Paris Terrorist Attacks and Hotel Word-of-Mouth

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Abstract

Using web-scraped consumer review data from booking.com, this paper examines the effect of the November 2015 Paris attacks on hotel word-of-mouth. I apply a difference-in-differences framework and find that the attacks led to a 3.4-5.4 percent increase in review scores and a 13.8-21.8 percent increase in positive review length in the wake of the attacks. I also find that the positive effect persist for 10-12 months, and that the short-term improvements in word-of-mouth is greater than the medium-term increases. I further provide theoretical and empirical evidence on the mechanism. There is no evidence that fear of terrorist threats is adversely correlated with customers' satisfaction with hotel stays immediately after the attacks. Using text mining techniques, I offer suggestive evidence that the improved hotel service quality plays a important role in enhancing customer experience during the attack period, whereas the improved breakfast quality, reduced hotel rates are more important in the medium term.

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Contents

1 Introduction

The November 2015 Paris attacks are considered among the worst acts of violence in Europe over the last few decades. The attacks generated huge economic impacts on travel and tourism, one of the world's largest industries. According to the French treasury, the attacks costed the French economy around two billion euros, mainly in consumer spending and tourism [Estrada and Koutronas, 2016].

The empirical literature investigating the effect of terrorism on the hotel industry and tourism is still scarce [Drakos and Kutan, 2003, Enz et al., 2011]. Enders and Sandler [1991] is among the first to examine the relationship between terrorism and tourism by using an vector autoregression (VAR) approach and find that terrorist events had huge negative impacts on the number of tourists in Spain. More recently, Enz et al. [2011] investigate how the 9/11 terrorist attacks affected the US hotel performance. They find an immediate drop in aggregate occupancy, hotel price, and revenue per available room but a strong rebound in hotel performance after four months. Besides the direct economic impacts, terrorist acts have large and lasting impacts on human behavior, and the indirect effect can be greater than the direct effect [Becker et al., 2004].

In this paper, I examine the effect of the November 2015 Paris terrorist attacks on word-of-mouth (WOM) in the hotel industry. Hotel word-of-mouth, as a reliable source of information about the quality of experience goods [Li and Hitt, 2010], provides an ideal setting to investigate how customers sentiments and subjective assessments of hotel value evolved in the wake of the terrorist attacks. It also provides a new perspective to observe the efforts of the hotel industry to response to negative exogenous shocks.

Unlike standard measures of hotel performance being rocked by terrorist attacks, hotel word-of-mouth may be affected in a more complex and uncertain way. On the one hand, terrorism generates a disproportionate amount of fear and stress [Becker et al., 2004]. Some research find that the attack-triggered fear can lead to less satisfaction with life [Frey et al., 2009] and work [Nandi et al., 2004]. Did the increased fear also brings about less satisfaction with hotel stays? On the other hand, hotels offered a range of promotion and marketing strategies to reduce losses in the face of the negative demand shock. Accroding to JacTravel, a supplier of hotel accommodations, a large number of hotels in Paris provided room upgrades, discounts and reduced minimum stay requirements to attract customers after the Paris attacks. Hotel guests thus enjoyed more benefits and may rate the overall experience in Paris hotels more positive.

I exploit rich web-scraped hotel reviews data from *booking.com* to construct comprehensive measures of hotel word-of-mouth. The first and foremost measure is review scores which directly reflects customers' subjective assessments of hotel quality. The second measure is consumer sentiments. I use the length of positive reviews and the length of negative reviews as proxies of consumer sentiments. The number of words show customers' willingness to provide feedback to their hotel stays. A longer positive review may suggest a higher evaluation, whereas a longer negative review reflects a worse assessment of the hotel quality.

I apply a generalized difference-in-differences framework to assess the effect of the Paris attacks on hotel word-of-mouth. By comparing changes in word-of-mouth three months before the attacks versus three months after the attacks for hotels in Paris to changes in word-of-mouth pre- versus post-attack for hotels in the top 6 European tourist cities other than Paris–London, Barcelona, Amsterdam, Milan and Vienna, I find positive and significant effects on hotel word-of-mouth. Specifically, review scores and the length of positive reviews in Paris increased relative to other cities, whereas the length of negative reviews decreased compared with the control group. I also find that the effects for all the three outcomes persist for approximately one year to the end of 2016.

Two major sources of threats to identification come from seasonality and selection bias. The divergence of word-of-mouth trends can be caused by cities' composition of traveler type. The share of leisure trip hotel guests in Paris is substantially higher than that in London and Milan, and high seasonality of the leisure trip may drive the Paris hotel word-of-mouth to differ from others. To reduce bias from seasonality, I control for differential time trends by cities' one year lead of composition of traveler type and include city specific time trends. The Paris attacks are still found to have positive effects on hotel word-of-mouth in the medium-term.

To address selection bias, I next examine whether those attack-exposed customers who stayed in Paris hotels when the attacks occurred rated hotels differently from those attacks-unaffected guests who just left the hotel before the attacks. I exploit the intertemporal variations in timing of hotel guests checking-in and checking-out around the attacks. The attack-exposed cohorts are those who checked-in before the attacks but checked-out after the attacks, and the attack-unexposed cohorts are those who left the hotel just before the attacks and checked-in within one week before the attacks. This strategy ensures randomness of the treatment status and therefore reduces self-selection bias arising from that high risk-averse visitors may avoid going to Paris after the attacks and those post-attack reviewers were inherently low risk-averse. I find that the attack-exposed cohorts rated the hotel quality higher then their attack-unexposed counterparts. Strikingly, the short-term positive effect is larger than the medium-term effect. For instance, the average review scores increased by approximately 3 percent in the three months after the attacks, but increased by around 5.5 percent immediately after the attacks. How could this happen given that customers experienced greater fear during and immediately after the attacks, which might reduce subjective assessments of hotel stays, and that hotels were difficult to make systematic and proactive responses to enhance the guest experience within a very short time after the attacks?

I propose a simple model and then provide suggestive evidence to explain why the Paris attacks had positive effects on hotel word-of-mouth and, more importantly, why the short-term word-of-mouth improvement was higher than the medium-term improvement. The effect on word-of-mouth, in the model, relies on a direct quality effect which was higher due to the improved service quality and attractive benefits hotels offered and on an indirect physiological effect emphasizing the rivalry between attack-triggered fear and hotel risk-management strategies mitigating customers' fear and counteracting the negative impacts of fear.

To examine whether fear of attack threats is correlated with hotel word-of-mouth, I test the relationship between guests' geographical distance to the targets of the Paris attacks and word-of-mouth. The results give no evidence that customers who stayed closer to the attack sites and thereby had greater fear gave worse assessments of hotel quality than customers who stayed further away. By using Google trends data on search scores for safety concerns, I also find that safety concerns had no sizeable and significant effects on hotel word-of-mouth. The above two results suggest that fear may play little role in affecting guests evaluating their hotel stays. What matters probably is what hotels do to reduce guests' fear and improve guests experience, which can indirectly increase hotel word-of-mouth.

I further use text mining techniques to extract high-frequency terms in hotel reviews. The evolution of words prominence over time suggests what customers care and how hotels did to improve visitor experience before and after the Paris terrorist attacks. I find "staff" and its associated words "friendly" "helpful" were highly prominent in positive reviews immediately after the attacks but were less salient before the attacks and in the following three months after the attacks, suggesting that the hotel staff and the improved service quality may explain the greater improvements in word-of-mouth in the short term. In addition, the relative changes of "breakfast" and "expensive" in the word prominence implies an improvement in breakfast and an reduction in hotel room prices in the medium term.

The word-use frequency helps infer the evolution of hotel crisis-management strategies and thus has clear managerial implications for the hotel industry to cope with negative exogenous shocks. During the attacks, helpful staff took good care of those attack-exposed hotel guests and made them feel less unsafe, so the indirect physiological gain from reducing guests' fear allowed hotel guests to rate their hotel stays more positive. In the later months after the attacks when abating guests' fear was no longer crucially in satisfying customers, reducing hotel prices, improving breakfast quality also helped raise hotel word-of-mouth, but to a lesser degree than providing good services did during the attack period. In a nutshell, well-trained and enthusiastic hotel staff is the secret to a good reputation during hard times.

Broadly speaking, this study adds to the literature on the economic consequences of terrorist attacks. Previous research mainly focuses on the negative effects of terrorism on the macro-economy. For example, terrorist attacks generate huge and adverse effects on airline demand [Drakos, 2004, Ito and Lee, 2005], tourism [Drakos and Kutan, 2003], investment and public spending [Blomberg et al., 2004], employment [Fainstein, 2002], capital markets [Drakos, 2004, Chen and Siems, 2004], GDP and productivity growth [Abadie and Gardeazabal, 2003, Bloom, 2009], and trade [Nitsch and Schumacher, 2004]. The most relevant study is by Enz et al. [2011] who examine how 9/11 attacks affected hotel performance using a simple control-of-variables strategy. My research relies on micro-level consumer review data and thus contributes to a better understanding of how terrorist attacks affect the hotel industry. To the best of my knowledge, this paper is the first to identify the magnitude of the causal impact of terrorism on the hotel industry.

This paper also contributes to the literature on the effect of terrorism on human behavior. A stream of political science literature studies how trust in public institutions evolves in the wake of terrorist attacks. Chanley [2002] and Perrin and Smolek [2009] find that trust in the government increased in the months after the 9/11 attack. The increased trust in public institutions reflects an appreciation and recognition of the institution' capacity to respond to the terrorist threats [Putnam, 2002]. In my study, the subjective assessments of hotel quality increased during and after the attacks, which can also be seen as a variant of "rally effect" which suggests an increase in approval and appreciation of the "institution"–the hotel, in the face of the attacks.

The rest of the paper is organized as follows. Section 2 introduces the data and provides an initial description of the data. Section 3 presents the identification strategy and illustrates how I address threats to the identification. Section 4 attempts to provide some suggestive evidence on the mechanism by proposing a simple theoretical model and then performing a range of tests. Section 5 presents robustness checks and section

6 offers concluding remarks.

2 Data

The primary source of data comes from web-scraped hotel customer review data from *booking.com*.[2] *Booking* is the biggest online travel agency for making hotel reservations. For each hotel, *booking.com* provides rich consumer review information. In the review section, a potential guest can observe previous guests' review scores, detailed review content including separate positive reviews and negative reviews, when guests post the review, where they come from, how long did they stay in the hotel, who did they go with. Figure 7 in the appendix displays how a typical review page looks like.

The dataset collects consumer review information of 1493 luxury hotels (4- and 5-star hotels) over a two-year period from August 3, 2015 to August 3, 2017 in the six most visited European destinations, namely, Paris, London, Barcelona, Amsterdam, Milan and Vienna. The total number of time-stamped hotel reviews is 514,146. This data covers review scores and separate content of positive and negative reviews, respectively. In addition, the data provides guests personal information, including customers' nationality,[3] night stays in the hotel, trip type–business trip or leisure trip, guest type–solo travelers, couples, stay with children or stay with others.

Online reviews are a good proxy for word-of-mouth [Dellarocas et al., 2004]. Existing studies have been using measures such as mean of review scores/rating [e.g., Dellarocas et al., 2004], number of reviews [e.g., Duan et al., 2008], and spread of reviews [e.g., Clemons et al., 2006] to measure word-of-mouth. I first use the average review scores, the most commonly used measure, as a proxy of hotel word-of-mouth. Review scores reflects customers' subjective evaluation to the hotel quality [Li and Hitt, 2010]. The

[2]The data was released by Kaggle.com, an online platform facilitating participation of data miners in competitions posted by companies.

[3]I group customers' nationality into North America, Europe, East Asia, West Asia, Australia and others.

second measure of word-of-mouth is consumer sentiments which help better understand the behavior of reviewers. I extract the length of positive reviews and length of negative reviews from the raw review content. The word counts reflect customers' willingness to provide feedback to their hotel stays. A lengthy positive review usually shows the guest's satisfaction with her hotel experience, while a long-winded negative review usually arises from the customer's discontent over her stays. That is, a longer positive review implies better word-of-mouth whereas a longer negative review reflects worse word-of mouth. This two metrics combined with review scores constitutes the measures of hotel online word-of-mouth in my research.

Summary statistics for all the important review variables are presented in table 1. Table 2 compares the pre-attack with post-attack variable information by city.

I also collect Google trends data on search volumes to supplement the research. Google trends provide relative frequency with which users search for certain terms over time in a certain place. Google assigns a index of 100 for the time/region with the highest search rate for the term. Indexes for other regions are being normalized to this highest score. I collect worldwide search scores for "Is is safe to go to city Amsterdam/Barcelona/Paris/London/Milan/Vienna",[4] The search scores serve as a proxy for safety concerns regarding city Amsterdam/Barcelona/Paris/London/Milan/Vienna. Figure 8 in the appendix shows the distribution of the google trends information.

[4] I also search for French, Germany, Spanish, Italian and Dutch versions of "Is is safe to go to city Amsterdam/Barcelona/Paris/London/Milan/Vienna", Google does not have enough data to show the trends. Since these six cities are top international tourist destinations and their hotel guests are quite international, it would be difficult to use terms in many languages to construct a unified measure of search scores. Using English terms alone would simplify the analysis without loss of generality.

3 The Empirical Framework and Results

3.1 The identification strategy

The identification strategy relies on an interpretation of the Paris terrorist attacks as a natural experiment. The terrorist attacks were completely unforeseen and hotel guests were unable to cancel or adjust their travel plans in anticipation of the event. Therefore, the timing of the attacks generated exogenous variations in consumer psychology, hotel strategies and thereafter subjective assessments of hotel quality. Paris hotels, the treated group, were unarguably subject to the terrorist attacks. To evaluate the causal effect of the terrorist attacks on Paris hotel industry, ideally, we need to know how Paris hotels would evolve in the absence of the terrorist attacks. A widely-used strategy is to construct a control group that resembles the Paris hotel industry the most. Then the pre- to after-attack time series variations on both groups can be used to identify the causal effect of the Paris terrorist attacks. This is the so-called difference-in-differences (DiD) strategy.

To motivate how to construct the comparison group, Figure 1 compares the evolution of the hotel word-of-mouth in Paris to the changes of the word-of-mouth in other five top European tourist destinations. In Figure 1, panel a and panel b, most cities (Amsterdam, Barcelona, London and Milan), prior to the attacks, experience similar paths of both the average review scores and the average length of positive reviews with Paris, and only Vienna displays a non-parallel pre-attack trend. In Figure 1 (panel c), the different pre-attack paths of the length of negative reviews for Amsterdam and London to path for Paris suggest these two cities offer bad a counterfactual.

There are several ways for constructing the control group such that its pre-attack trend is similar to trend for Paris. One is to simply take the average of all these five cities considering that these cities are top European tourist destinations after Paris and thus share similar economic and geographical characteristics with Paris. Another is to select one or several cities among these five that one could reasonably argue resemble Paris the most. For example, Barcelona may be a good candidate since its pre-attack paths of all the three outcome variables are parallel to trends for Paris. An alternative strategy would be to take a data-driven approach and to construct a weighted average of other five non-treated cities. The Synthetic control method, developed by Abadie and Gardeazabal [2003], Abadie et al. [2010], can be seen as a generalization of difference-in-differences and is an ideal approach to construct a synthetic control group.

It is worth noting that other cities may also be affected by the Paris attacks. In the wake of the attacks, potential visitors to Paris may change their holiday plans and turn to other European cities. To reduce the spillover effects, I look within a short time window around the attacks in my main analysis.

3.2 Initial Approach

In this section, I compare the basic results from the synthetic control method with the results from the traditional difference-in-differences method. By providing a graphical comparison, I illustrate why a conventional difference-in-differences approach is preferable.

3.2.1 Synthetic control methods

The objective of the synthetic control method is to choose a weighting vector to minimize distance in pre-treatment characteristics between the treated and the weighted average of control. We assume that X_1 is a vector of pre-attack predictors of the outcome variables for Paris, which also includes pre-attack values of the outcomes, and X_0 is a matrix of these variables for Amsterdam, Barcelona, London, Milan and Vienna. Specifically, X_1 and X_0 collect pre-attack values of share of leisure trip, average night stays, share of guests staying in the hotel alone and Google search volumes on safety concerns.

The weighting vector W is chosen by minimizing

$$\|X_1 - X_0W\| = \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)} \tag{1}$$

where V is an semidefinite matrix of weights. The optimal V is obtained after assigning weights to linear combinations of X_1 and X_0 to minimize the mean square error (MSE).

Table 3 displays the cities' received weights in the construction of synthetic Paris for three of our outcome variables. As can be seen, overall, Barcelona contributes the most to the synthetic control group. Barcelona received weights for all the three outcomes range from 0.462 for review scores to 0.938 for length of negative reviews. London is almost as important as Barcelona in constructing the control group for review scores and the length of positive reviews, but it receives zero weights for the length of negative reviews. By contrast, Amsterdam and Milan plays no role in the construction of the synthetic control group.

Table 4 compares the pre-attack characteristics of Paris hotels to those of hotels in the synthetic Paris, and also to those of a simple average of the five cities in the donor pool. The characteristics of the synthetic Paris is not more similar to characteristics of Paris than those of the city average.

Figure 2 presents trends of the three outcome variables for Paris and the comparable trends for its synthetic counterpart. For comparison, Figure 2 also compares trends for Paris to those for the average untreated cities. This figure can be regarded as a graphical comparison of results from the synthetic control method with results from the standard difference-in-differences method. Before the Paris terrorist attacks, Paris and the remaining top tourist cities average show similar paths of all the three word-of-mouth variables. The synthetic Paris almost exactly reproduces the path of the negative review length for Paris during the pre-attack period, but its fit for paths of both review scores and the length of positive reviews is not strictly better than the fit using the average of other cities. The moderate fit of the synthetic city is probably due to the fact that there are limited number of cities in the donor pool so that any combinations of those cities fail to closely reproduce the path for Paris. Considering the good pre-attack trends provided by the average of untreated cities, and conceptual difficulties with statistical inference in synthetic control methods, which uses placebo tests as foundation of inference [Abadie et al., 2010], I prefer to construct the control group using the average of other cities and therefore to stick to the conventional difference-in-differences approach.

In Figure 2 (panel a and panel b), Paris shows a strong increase in review scores and the length of positive reviews immediately after the terrorist attacks, with a noticeable drop in both measures around ten months after the attacks, suggesting a rebound of word-of-mouth. For the average of other cities and the synthetic Paris, a mild increase in review scores and the length of positive reviews can be observed in Figure 2 (panel a and panel b). It is clear that both review scores and the length positive reviews increase for Paris relative to the control group. As can be seen in Figure 2, panel (c), there is an evident decrease in the length of negative reviews in Paris, with a moderate increase three months after the attacks. The control group decreases immediately after the attacks, though to a lesser degree. To sum up, Figure 2 shows an visible increase in hotel word-of-mouth in the wake of the attacks. I will carefully estimate the magnitudes of the increase in the following sections.

3.2.2 Difference-in-Differences and basic results

As discussed in the last section, I prefer to use the average of attack-unexposed cities to construct the control group and therefore to employ a standard difference-in-differences approach to obtain the treatment effect of the Paris attacks on word-of-mouth in the hotel industry. I can run a difference-in-differences model on either individual level data or aggregate data at the city level. Both regressions give the same estimates since the regressors of interest vary at the city level. Although within-city variations provided by individual level data does not matter for identification, using micro data facilitates introducing covariates which may help reduce standard errors. For this reason, I mainly employ customer level data in my analysis. The generalized difference-in-differences model is set as the following:[5]

$$ln(WOM_{ihct}) = \beta(Paris_c \times Post_t) + \gamma_t + \alpha_c + \lambda_h + \epsilon_{ihct} \quad (2)$$

where WOM_{ihct} is the measure of word-of-mouth given by reviewer i for hotel h of city c in period t. To improve the model fit and ease interpretation, the outcome variables are transformed by taking the natural logarithm. For the length of positive reviews and negative reviews, add 1 to their original values before taking log since a large amount of their values take on 0. The next set of terms is: α_c, a city level fixed effect controlling for observed or unobserved city heterogeneity; γ_t, a month fixed effect capturing common economic or policy shocks that affect all cities equally; λ_h, a hotel fixed effect controlling for hotel heterogeneity; and ϵ_{ihct}, a random error term. $Paris_c$ is 1 if the city is Paris, 0 otherwise. $Post_t$ is 1 if the customer posted the review after Nov 14, 2015, the day when the Paris terrorist attacks occurred, 0 if the review was posted before the attacks. β, the coefficient of the interaction of $Paris_c$ and $Post_t$, gives us DiD estimates of the effect of the Paris attacks.[6] I define pre- and post-attack periods as three months before and after Nov 14, 2015 as I only observe three-months' information prior to the attacks in the data.

An easily ignored issue surrounding DiD inference is serial correlation when there are many groups and more than two time periods. This issue is particularly severe in this study since the outcome variables word-of-mouth is positively serially correlated. A common practice to address serial correlation is to cluster standard errors at group

[5]Alternatively, I can estimate a simple difference-in-differences model as the following:

$$ln(WOM_{ict}) = \beta_1(Paris_c \times Post_t) + \beta_2 Paris_c + \beta_3 Post_t + \epsilon_{ict}$$

Advantage of generalized differences-in-differences is that it can improve precision and provide better fit of model. It does not assume all cities in treatment or control group have same average WOM; it allows intercept to vary for each city. It does not assume that common change in WOM around the shock is a simple change in level; it allows common change in WOM to vary by month.

[6]In this generalized difference-in-differences model, $Paris_c$ and $Post_t$ dummies are absorbed by city and month fixed effect, respectively.

level. This approach, however, can potentially perform worse than standard robust errors when clusters are small. Wild bootstrap, based on simulation information, is generally accepted as the best method for clustered standard errors for few clusters [Cameron and Miller, 2015]. Cameron et al. [2008] provide simulation evidence suggesting this test works well even in situations with as few as five clusters. To examine the robustness of standard errors, I report robust (Heteroscedasticity-consistent) standard errors, clustered standard errors at city level, as well as wild cluster bootstrapped p-value.[7]

Table 5 reports the basic DiD regression results. For comparison, I also use Barcelona alone as the control group to obtain DiD estimates in column 2, 4, and 6 since Barcelona exhibits the most similar pre-attack trends of all the three outcome variables. Table 5 indicates that in the following three months after the attacks from Nov 14, 2015 to Jan 14, 2016, there is a 2.7 percent (column 1) increase in review scores and 6.9 percent (column 3) increase in length of positive reviews for Paris relative to other cities. Column 5 shows that the length of negative reviews drops by 5.9 percent for Paris compared with the remaining tourist destinations. In addition, results obtained by setting Barcelona as the control group are similar to results from comparing Paris with the average of Amsterdam, Barcelona, London, Milan and Vienna. Overall, Table 5 suggests that the Paris attacks had positive effects on word-of-mouth in the hotel industry.

As can be seen in Table 5, the simple robust (heteroscedasticity-consistent) standard errors are larger than the clustered standard errors for all the DiD estimates, though both methods lead to statistically significant results. For wild cluster bootstrapped p-value, although all the p-values are less than the threshold of significance (0.1), the explanatory power of the model declines compared with employing robust standard errors or clustered standard errors.

[7] The wild cluster bootstrap method is unable to provide standard errors or confidence intervals.

3.3 Dynamic specification and long-term impacts

The key identifying assumption in DiD models is that the treatment group have similar trends to the control group in the absence of treatment. To formally test whether the parallel trends hold and, more importantly, to investigate the dynamics of the effects of Paris attacks on hotel word-of-mouth, I estimate the following equation:

$$ln(WOM_{ihct}) = \sum_{j=-m}^{q} \beta_j (Paris_c \times Post_{t+j}) + \gamma_t + \alpha_c + \lambda_h + \epsilon_{ihct} \tag{3}$$

All variables are as defined above in equation 2 but β_j is a vector which takes on a unique value for each month period from Aug 4, 2015 to Aug 4, 2017. Equation 3 estimates q leads and m lags of the treatment. In this exercise, there are 21 lags and 2 leads after setting the period from Aug 4, 2015 to Sep 4, 2015 as the reference group. Figure 3 plots all the coefficients of the month-Paris interactions and 95% confidence intervals for each outcome generated from equation 3. For the sake of simplification, the confidence intervals are constructed based on the robust standards errors which are more conservative than clustered standard errors,[8] as can be seen in Table 5.

In Figure 3, the coefficients of the leads for all the three outcome variables are close to zero, suggesting no existing difference in trends prior to the Paris attacks. This dynamic DiD results are consistent with comparisons of raw trends in Figure 2. In Panel (a) of Figure 3, there is a sizeable and positive effect on review scores in the following ten months after the attacks, with the largest effect being observed after two months. The positive effect persists for the entire year 2016, though fades gradually. In year 2017, the positive effect is no longer exist–the point estimates fluctuate around zero and have wide confidence intervals. Panel (b) shows a noticeable positive effect for the length of positive reviews and panel (c) presents a negative effect for the length of negative reviews within one year of the attacks. However, for these two outcomes, the

[8]The wild cluster bootstrap method is unable to provide standard errors or confidence intervals. The wild cluster bootstrap method produces similar results in terms of explanatory power, so I report robust standard errors in my following analysis.

95% confidence intervals for most of the lags include zero, suggesting relatively weak explanatory power.

The economics of terrorism literature argue that the effects of terrorism can have a huge real impact, but rebound very soon [e.g., Lenain et al., 2002, Bloom, 2009]. For example, Bloom [2009] finds that output and employment rebound 6 months after 9/11, Enz et al. [2011] find that hotel performance measures return to pre-attack levels after 4 months of 9/11. Similar to existing studies, I also find rebounds of hotel word-of-mouth in Figure 3, though taking longer time (10-12 months) to return to pre-attack levels.

3.4 Threats to identification and preferable specifications

So far, I have compared luxury hotels before and after the Paris attacks between Paris and the controlled cities and found that hotels in Paris received higher review scores, longer positive reviews, shorter negative reviews in the wake of the attacks. To what extent should we believe these evidence? Even though the dynamic specification in Figure 3 suggests that the pre-treatment point estimates are close zero and statistically insignificant, a parallel trend prior to treatment is neither sufficient nor necessary for the parallel trends to continue in the absence of treatment [Kahn-Lang and Lang, 2020]. Meanwhile, due to data availability, the pre-treatment periods is not long enough to show the underlying trends. In this section, I will discuss several sources of threats to the identification and employ corresponding strategies to mitigate these threats.

3.4.1 Seasonality

First, there may be concerns that a seasonal effect can affects hotels in Paris differentially to other cities regardless of the attacks. For instance, The share of the leisure trip hotel guests in Paris is substantially higher than in London and Milan as can be seen in Table 2. Leisure trips are highly seasonal, and trends in hotel word-of-mouth are likely to diverge because of different trends in word-of-mouth driven by travel type (leisure trip or business trip). Leisure trip travelers are less picky in rating the hotel quality than business trip customers (I find that on average, leisure trip guests rate the hotel 5.79 percent higher business trip guests), and if Paris had a larger proportion leisure trip travelers in the absence of the attacks, the previous DiD estimates would overestimate the effects on hotel word-of-mouth.

An ideal strategy to address seasonality would be taking advantage of the preceding years' data and employing a de-trended difference-in-differences methodology. Recently, Draca et al. [2011] and Glover [2019] use de-trended difference-in-differences strategy to account for seasonality in their outcomes. Due to data restriction, I apply an alternative strategy to reduce concerns about seasonality.

I first include differential time trends by cities' one year lead of composition of leisure trip guests. The reason is because immediately after the attacks, composition of leisure trip travelers was also affected, directly including a so-called "bad control" would worse the estimates. But leisure trip composition of the following year (Aug 2016 to Jan 2017) can be more close to the true composition in the absence of the attacks since visitors usually have short memories [Löfstedt and Frewer, 1998] and travelers are less likely to adjust their travel plans after 6 months the terrorist attacks [Floyd et al., 2004].

Next, I include city specific time trends which can help relax the parallel trends assumption [Mora and Reggio, 2019]. For the parallel trends to hold, the slope of the trend for the treated and control group, or the first derivative must be similar. Including group specific linear time trends controls for the first derivative. I also introduce city specific quadratic time trends so that only the third derivative is required to be similar to satisfy the common trends assumption.

Table 6 presents the modified DiD results. Column 1 also presents the previous basic DiD estimates for comparison. Focusing on the average review scores first, in column 2 of panel (a), the point estimate slightly decreases from 2.71 percent to 2.69 percent after including the trip type specific time trend, which suggests that the varying composition of leisure trip customers is not a severe source of threats to identification. Introducing the group specific trends in columns 3 and 4 increase the size of the effect by around 0.5 percent to 3.3 percent. This can be because these trends reflect omitted variables, and thus adding group specific trends remedies the omitted variables bias. The size of the interaction terms increase since factors associated with higher word-of-mouth are negatively related to the Paris attacks. In panel (b) and panel (c), for the length of positive reviews and negative reviews, similarly, including trip type specific trends in column 2 has a small impact on the magnitudes of the DiD estimates. After adding city specific time trends, the effects on positive review length increases from 6.9 percent to around 14 percent. The estimates of the effect on negative review length become statistically significant in column 3 and 4.

3.4.2 Selection bias

Second, selection bias may exist. High risk-averse travelers may choose not go to Paris after the attacks and, as a result, those who still stayed in Paris after the attacks were more likely to be inherently less risk averse. The utility losses caused by the attacks were smaller for those less risk averse hotel guests and therefore, those post-attack guests had less fear of attack threats and were more likely to rate positively about their stays thanks to the reduced hotel rates, less crowded dining rooms, etc.

From the review information, we are able to identify when customers post reviews and how long they spent in the hotel. Li et al. [2020] take advantage of restaurant review data and find that most reviews are posted on the same day as the dining time and that consumers who have extreme experiences (strongly positive or negative) tend to post reviews earlier than consumers who have moderate experiences. We can infer the check-in date from the review date and nights stayed in the hotel by assuming that customers immediately leave the review on the same day when they check-out.[9]

Figure 4 tests whether there exists a discontinuity in review date and whether Nov 15, 2015 is the cutoff date. Panel (a) and panel (c) show that review scores and the length of negative reviews display a sharp jump on Nov 15, 2015, suggesting that customers experienced an exogenous shock on Nov 14, 2015, which had a significant

[9]For instance, if a reviewer posted the review on Nov 14, 2015 and he had stayed in the hotel for 3 days, we can infer that she checked-in on Nov 11, 2015.

impact on their assessments of hotel stays. Figure 4 also offers suggestive evidence that most customers post reviews on the same day as the check-out date, consistent with the finding of [Li et al., 2020]. Otherwise, it is hard to justify why the cutoff date is Nov 15, 2015.

After approximating check-in and check-out dates, I define attack-exposed cohorts as hotel guests who checked-in before November 14, 2015 and checked-out at least one day after the attacks. In the sample, only 4% those affected customers left the hotel after one week of the attacks (Nov 21, 2015). I restrict the analysis to the remaining 96% customers who checked-out within one week of the attacks. The attacks-unaffected cohorts are defined as guests who left the hotel before the attacks and checking-in within one week prior to the attacks (from Nov 6, 2015 to Nov 12, 2015). It should be noted that assuming the review date is the same as the check-out date only affect defining the attack-exposed cohorts. For example, if a customer in fact checked-out on Nov 10, 2015 but decided to write a review 10 days later, then we would mistakenly categorize this attack-unaffected customer into the treated cohorts. However, if she checked-out on Nov 1, 2015 but left the review on Nov 10, 2015, she would be still belong to the untreated cohorts. In other words, we would potentially underestimate the positive effects on hotel word-of-mouth if customers posted reviews a few days after they checked-out.

This strategy ensures customers having no control over treatment status. The attack-exposed cohorts stayed in the same hotel before the attacks and could not anticipate the terror acts before checking-in. Self-selection bias can thus be largely reduced. Moreover, restricting the analysis to such short time window around the attacks improves our confidence in attributing any pre- to after-attacks differences in hotel word-of-mouth between Paris and other cities to the Paris attacks without worrying the divergence of hotel word-of-mouth was driven by other events that occurred near but after the Paris attacks.

The first test is to simply focus on time-series variation within Paris and to compare differences in the outcome variables between attack-exposed and attack-unexposed cohorts. The causal interpretation relies on randomness of exposure to the terrorist attacks–the average word-of-mouth would have been same for treated cohorts and untreated cohorts in the absence of the attacks. Because those treated customers checked-in near Nov 14, 2015, their characteristics should be very similar to those untreated cohorts who happened to leave the hotel just before the attacks. The only difference between the two groups is the timing of check-in and check-out.

Table 7 presents the differences in word-of-mouth measures between attack-exposed cohorts and attacks-unexposed cohorts. Focusing on the most important outcome variable–review scores, the coefficient of the attack-exposed cohorts dummy in column 1 is 0.0582, showing that the treated cohorts gave 5.8 percent higher review scores than attack-unexposed cohorts. The magnitude of the estimate is higher than 3.3 percent, the medium-term DiD estimate in Table 6 (column 4). This suggests that there may exist a spillover effect in the previous DiD specification.[10] The Paris attacks posed threats to most European countries and deterred every potential visitor interested in Europe. If hotels in these controlled cities also strategically responded to the attacks and adjusted their pricing or marketing strategies which help improve word-of-mouth, the previous DiD estimates would underestimate the treatment effect on Paris hotels as other cities also witnessed an increase in hotel word-of-mouth after the attacks.

Similarly, for the remaining two outcomes, the effect on positive review length increases from 13.9 percent (column 4 of Table 6) to 18.6 percent (column 2 of Table 7), and the effect on negative review length changes from -4.1 percent (column 4 of Table 6) to -7.1 percent (column 3 of Table 7), though remaining insignificant.

A potential identification challenge in such a setting is that those highly risk averse customers may leave the hotel hurriedly and forgot to post reviews, and those post-attack reviewers may be inherently less risk averse or more satisfied with their hotel experience. If so, the treated cohort would be different to unaffected cohort in terms of risk aversion, financial conditions and other traits that may bias the results. If this

[10]There is a trade-off between endogeneity and spillovers since including city fixed effects can increase the bias due to spillovers. Because adding city fixed effects and focusing on within group variation are always subject to within-group spillovers to control units [Berg and Streitz, 2019].

is the case, we would expect to observe fewer reviews immediately after the attacks since only less risk averse or satisfied guests were willing to post reviews. Figure 9 in the appendix displays daily number of reviews in Paris around the attacks. There is no noticeable drop in the number of reviews immediately after the terror attacks. It is reasonable to conclude that such self-selection may not be a big issue in my analysis.

The second test is to apply a difference-in-differences framework to re-examine the effect of terrorism exposure on hotel word-of-mouth. The sources of identification now come from the inter-temporal variation across cohorts and the spatial variation across cities. Considering the following relationship between the online review (WOM_{ijc}) given by customer i, from cohort j, in city c, and her exposure to the Paris attacks:

$$ln(WOM_{ijc}) = \beta_1 \text{Affect\_Cohort}_{ij} + \beta_2(\text{Affect\_Cohort}_{ij} \times Paris_c) + \alpha_c + \epsilon_{ijc} \quad (4)$$

where $\text{Affect\_Cohort}_{ij}$ is a dummy indicating whether individual i is from the attacks-affected cohort. $Paris_c$ dummy is absorbed by the city fixed effect α_c.

Table 8 shows the DiD regression results. Overall, the results are similar to previous time-series difference results. In column 1, the estimated effect on review scores is 5.42 percent and significant at 10% level, suggesting that the attack-exposed customers gave a 5.4 percent higher review scores in Paris than the attacks-unexposed cohorts relative to other top European tourist destinations. The effect on positive review length is 21.8 percent and marginally significant. Again, the estimated effect on negative review length is not statistically different from 0.

4 Further Discussion on the Mechanism

The Paris terrorist attacks is found to have a positive effect on hotel word-of-mouth. For example, in the next three months after the attacks, there is a 3.3 percent increase in review scores. Surprisingly, the positive effect increases to 5.4 percent for the attack-exposed guests. How could it happen? In the medium-term, hotels could implement a series of promotion and marketing strategies to improve the hotel quality. During and immediately after the attacks, however, hotels were difficult to make proactive and systematic strategies (e.g., lowering hotel rates) in the response to the shock to improve customer experience. More importantly, one might expect guests who stayed in the hotel during the attack had greater fear and therefore, the physiological loss would translate their fear and worry into lower subjective evaluations of the hotel value. In this section, I first propose a simple model to explain the puzzle and then offer some suggestive evidence on the mechanism.

4.1 Theoretical motivation

Hotel word-of-mouth (W), the subjective evaluations of hotel stays, are mainly determined by hotel quality q. W is a stochastic function of q

$$W = F(q) + \epsilon \tag{5}$$

where ϵ is the individual idiosyncratic taste. After terrorist attacks, hotel guests usually suffer from strong anxiety and fear. The fear can bring about utility losses and adversely affect how they evaluate their hotel stays. Meanwhile, terrorism can trigger a series of hotel risk management strategies such as providing discounts, room upgrades, free breakfasts, etc. These initiatives can directly improve hotel quality, mitigate the fear of guests through which indirectly reduce the psychological loss due to terror attacks. I therefore model $F(q)$ as

$$F(q(\tau, \pi)) = q\big(\pi(\tau), f(\tau, \pi(\tau))\big) \tag{6}$$

where the quality q is affected by attack-triggered hotel risk-management strategies, π, and by customers' worry and fear, f. The amount of fear is affected not only by the degree of terrorism τ, but also by whether the hotel can ease or control the fear through a series of initiatives π. It is reasonable to assume that terrorism trigger more hotel initiatives in response to the crisis ($\pi_\tau > 0$), and hotel strategies directly improve hotel quality ($q_\pi > 0$). Terrorist attacks can unarguably incite more fear ($f_\tau > 0$) which negatively affects the subjective assessments of hotel quality ($q_f < 0$). It is also reasonable to assume hotel initiatives can mitigate customers' fear ($f_\pi < 0$). To detect how terrorist attacks affect hotel word-of-mouth, take the derivative of W with respect to τ:

$$\frac{dW(.)}{d\tau} = \frac{dF(q)}{d\tau} = \overbrace{\underbrace{\frac{\partial q(.)}{\partial \pi(\tau)}}_{+} \cdot \underbrace{\frac{\partial \pi(\tau)}{\partial \tau}}_{+}}^{\text{direct quality effect}(+)} + \overbrace{\underbrace{\frac{\partial q(.)}{\partial f(\tau,\pi)}}_{-} \cdot \underbrace{\frac{\partial f(\tau,\pi)}{\partial \tau}}_{+} + \underbrace{\frac{\partial q(.)}{\partial f(\tau,\pi)}}_{-} \cdot \underbrace{\frac{\partial f(\tau,\pi)}{\partial \pi(\pi(\tau))}}_{-} \cdot \underbrace{\frac{\partial \pi(\tau)}{\partial \tau}}_{+}}^{\text{indirect psychological effect}(\pm)} \tag{7}$$

The first part in Equation 7 is a direct quality effect–terrorist attacks induce hotels to raise service quality and offer some attractive schemes (e.g., room upgrades, free breakfasts), which leads to higher customer satisfaction. The whole second part in Equation 7 is an indirect psychological effect emphasizing the trade-off between attack-triggered fear which generates a negative impact on customer experience and hotel initiatives which mitigate customers' fear and counteract the negative effect of fear. The sign of the effect of terrorist attacks on hotel word-of-mouth relies on the rivalry between utility losses due to fear of terrorist threats and improved hotel quality arising from a series of risk management strategies.

To obtain a positive effect of terrorist attacks on hotel word-of-mouth, the hotel need to operate a series of risk management strategies to improve hotel quality and to simultaneously mitigate customers' fear so that the direct quality improvements and the indirect physiological gains are greater than physiological losses due to fear,

$$\underbrace{\frac{\partial q(.)}{\partial \pi(\tau)} \cdot \frac{\partial \pi(\tau)}{\partial \tau}}_{\text{direct quality improvements}} + \underbrace{\frac{\partial q(.)}{\partial f(\tau,\pi)} \cdot \frac{\partial f(\tau,\pi)}{\partial \pi(\pi(\tau))} \cdot \frac{\partial \pi(\tau)}{\partial \tau}}_{\text{indirect fear reductions}} > \underbrace{\frac{\partial q(.)}{\partial f(\tau,\pi)} \cdot \frac{\partial f(\tau,\pi)}{\partial \tau}}_{\text{negative fear effect}}$$

4.2 How large is the negative fear effect

Fear of terrorist threats may be an important channel via which terrorist attacks influence hotel word-of-mouth immediately after the attacks. However, I have found that the positive short-term effect on word-of-mouth is greater than the medium-term impact. The most possible reason is that the negative fear effect was small–hotel guests rarely shift their negative emotions caused by uncontrollable exogenous shocks to the victimized hotel.

To test whether the psychological fear effect exists, I first exploit geographic variation in attack exposure across different locations within Paris. Taking advantage of the longitude and latitude information of each hotel, I calculate the average distance of each hotel guest to the exact locations where attacks occurred.[11] If the fear effect was important, a customer who stayed closer to the attack targets during the attack period would expect to give lower assessments of the hotel value.

Table 9 reports the simple OLS estimates using different time windows. Overall, the estimates for all the 6 models are very small in magnitudes and non-significant. For example, in the first week after the attacks, 1 km further away from the attack targets in Paris region is associated with a 0.25 percent increase in review scores (column 1), a 0.19 percent increase in length of positive reviews (column 3) and a 0.99 percent decrease in length of negative reviews (column 5). Considering the relatively large standard errors, we can conclude that there is no evidence that the distance to attack targets is correlated with hotel word-of-mouth.

Customers who stayed closer to the terrorist targets were unarguably more sensitive to the terrorism risks and had more fear. But the fear was not translated into dissatisfaction with the hotel quality. Does it because hotels near the attack-hit places did better in enhancing customer experience such that an improved hotel quality counteracted the negative fear effect. Probably no. Using text-mining techniques, I present

[11] Stade de France; Rues Bichat and Alibert Le Petit Cambodge; Rue de la Fontaine-au-Roi; The Bataclan theatre; Rue de Charonne; Boulevard Voltaire.

the top 10 most frequently used words in reviews of Paris hotels one week following the attacks in Table 13 of the appendix. Hotels could not change their address or enlarge the room size immediately after the attacks, but they could, for instance, adjust the service quality after the attacks. Thus when investigating whether hotels that closer to the attack targets reacted more to the terrorist attacks, we need pay less attention to terms like "location", "small" which used to describe unchanged hotel characteristics but more attention to words like "staff", "helpful", etc. Table 13 shows that overall, there is a lot of similarity in word prominence between hotels closer to the attacks and hotels further away from the attacks. However, "location" was the most mentioned positive term for hotels closer to the attack targets, whereas "staff" was used the most for hotels further away from the attacks. Interestingly, the positive term "safe" ranks higher for hotel less close to the attacks than hotels closer to the attacks. To sum up, there is little evidence that hotels closer to the attacks improved the service quality to a greater degree or made guests feel safer than hotels less close to the attacks.

Does it because people stayed in the hotel closer to the terrorist targets were systematically different from customers who went to hotels less close to the terrorist locations? Even though I control for several guests characteristics including trip type, guest type, stay length and national region, omitted variable bias may still a concern.

An additional test is to take advantage of Google trends data and to explore the relationship between safety concerns and hotel word-of-mouth. Google global search rates for the item "Is is safe to go to Amsterdam/Barcelona/Paris/London/Milan/Vienna" reflect people's safety concerns over a specific city. I first specify the following two-way fixed effect model:

$$ln(WOM_{ct}) = \beta ln(Score_{ct}) + \alpha_c + \gamma_t + \epsilon_{ct} \tag{8}$$

where $score_{ct}$ denotes the Google trend search scores for safety concerns over city c in week t. α_c and γ_t are city and week fixed effects, respectively. This two-way fixed effect model adjusts for unobserved group-specific and time-specific confounders simultaneously. The two-way fixed effect estimator is equivalent to the DiD estimator under setting with two groups and two periods [Bertrand et al., 2004].

As a comparison, I aggregate the city-week level Google search scores into a city level measure and specify the following DiD model:

$$ln(WOM_{ct}) = \beta(lnScore_c \times Post\_t) + \alpha_c + \gamma_t + \epsilon_{ct} \tag{9}$$

where $score_c$, a continuous treatment variable, is the intensity of Google search volumes for safety concerns in city c, and $Post_t$ is a post-attack dummy.

Table 10 reports the regression results. There is no evidence that the Google search volumes for safety concerns have sizable and significant effects on hotel word-of-mouth. In the first column of Panel (a), the coefficient of google search scores is -0.0001, which implies that a 10 percent increase in google search scores for safety concerns is correlated with a 0.001 percent decrease in reviewer scores. The size of the estimated effect in column 1 of Panel (b) is also small and insignificant at conventional level. In column 2, although the two-way fixed effect estimate and DiD estimate is marginally significant at 10% level, the magnitudes of their coefficients (0.0059 and 0.0406, respectively) are very small. These results suggest that Worrying about the safety has little impact on how guests rate the hotel.

In a nutshell, I do not find evidence that fear or safety concerns could influence hotel word-of-mouth. A possible explanation might be hotel guests are rational when evaluating their hotel stays and they cannot be easily governed by irrational fear and exogenous shocks out of the hotel industry' control. The dominant factor affecting word-of-mouth is probably what the hotel do to improve customer experience.

4.3 How Paris hotels responded to the crisis

In this section, I use text-mining techniques to investigate how Paris hotels responded to the Paris attacks. This section also helps explain why the short-term hotel word-of-mouth improvements are higher than the medium-term word-of-mouth improvements.

The Text mining method enables us to highlight the most frequently used keywords from a big text corpus. To understand the prominence of terms that appear more frequently in reviews, I first process the textual data by removing unnecessary white space, converting the text to lower case letters, removing common stop-words like "the", "we","was" "also". I then create a term document matrix, a mathematical matrix describes the frequency of terms that occur in the documents. I finally plot word clouds in Figure 5 and Figure 6. The size of a word in the word cloud shows how important it is, e.g. how often it appears in a text. In Table 11, I summarize the top ten most frequently used words in both positive reviews and negative reviews of Paris hotels. By comparing what customers wrote at varying time, we can infer what matters to customers and what Paris hotels did before and after the Paris terrorist attacks.

As can be seen in Table 11, in positive reviews, "location" is the most importance element, "staff" and its associated words "helpful" and "friendly" rank the 2rd, 5th and 6th, respectively, in prominence of words for all periods except for the first week after the terrorist attacks. During the first week after the attacks, "staff" becomes the most frequently used word, "friendly" and "helpful" climb up to the top four key words. This change in word frequency suggests that the improved service quality was the decisive factor of positive hotel reviews immediately after the Paris attacks. Interestingly, "safe" becomes a highly used word within one week of the terrorist attacks but is no longer mentioned a lot by reviewers when we zoom the post-attack period on three months or longer, suggesting that the hotel made guests feel safe during the attack period. After the attacks, "breakfast" comes into view, though ranking the 9th in positive reviews for all the selected after-attack periods. At the other end, "breakfast" is the second leading complaint before the attacks and in the first week after the attacks, but down to 4th highly used word in negative reviews in the following three months after the attacks. The relative change of "breakfast" in the word prominence implies a constantly improved breakfast after the attacks.

Another interesting term is "expensive" which is marginally important before and immediately after the attacks, but no longer a major worry in the medium term. During the attack period, hotel room prices were fixed to some extent given that most guests made bookings before the attacks. However, after some periods of time, hotels could flexibly lower hotel rates to attract customers. Lacking detailed hotel price data, I am unable to precisely measure the contribution of the reduced hotel prices to the improved word-of-mouth after the attacks, but the evolution of "expensive" yields some indirect evidence on the role of hotel rates.

Taken together, a higher short-term word-of-mouth than medium-term word-of-mouth may arise from friendly and helpful hotel staff taking good care of customers and making them feel safe during the attacks. The indirect physiological gains from mitigating fear allow customers to highly rate their hotel stays during the attack. After some time when fear of terrorism faded, hotels made proactive strategies–lowering hotel rates, improving breakfast quality to enhance customer experience. Some scattered evidence drawn from the review content can help reinforce my findings. For example, on Nov 15, 2015, a customer wrote "The staff took good care of us during a stressful time the attacks in Paris". On Nov 16, 2015, another guest wrote "We were very impressed with your staff. We happened to stay the night of the ISIS attacks in Paris. They were very helpful in arranging a shuttle and a taxi so that our family was safely able to get to the airport to catch our flights out". On Nov 17, 2015, "Excellent customer service, my wife and I stayed during the recent attacks, hotel staff could not be any more helpful. Great people Pray for Paris". Such reviews help reveal the secret of the higher short-term hotel word-of-mouth.

4.4 Heterogeneity in impacts

Heterogeneity of the effect on different types of customers is potentially important. The pattern of the heterogeneous impact can help increase the understanding of why the Paris attacks improved the word-of-mouth in the hotel industry.

The fear-of-crime literature argues that unfamiliar environments are more likely to trigger fear of victimization [e.g., Warr, 1990, Yechiam et al., 2005]. Customers from Islamic countries are more likely to be familiar with Islam State militant group (ISIS) and ISIS terrorist attacks. The familiarity may lower customers' perceived risks.

Therefore, during the attacks, the attack-triggered fear may be smaller for them than for hotel guests from non-Islamic countries. If the fear effect exists, I would expect customers from Islamic countries to given higher evaluations to hotels after the Paris attacks than customers from non-Islamic societies. I specify the following difference-difference-differences (DDD) model:

$$
\begin{aligned}
ln(WOM_{icj}) = &\beta_1 Islam_i + \beta_2 \text{Affected\_Cohort}_{ij} + \beta_3 (Paris_c \times \text{Affected\_Cohort}_{ij}) \\
&+ \beta_4 (Islam_i \times Paris_c) + \beta_5 (Islam_i \times \text{Affected\_Cohort}_{ij}) \\
&+ \beta_6 (Paris_c \times \text{Affected\_Cohort}_{ij} \times Islam_i) + \alpha_c + \epsilon_{ict}
\end{aligned} \tag{10}
$$

where $Islam_i$ is a dummy variable taking on 1 if the customer comes from an Islamic country.[12] β_3 is the DiD estimate for customers from non-Islamic countries, β_6 is the DDD estimate which captures how much larger effect is for the Islamic cohort.

Table 12 reports the DDD results. The loss of degrees of freedom reduces our power to detect a true effect. The DDD estimates in all the three models are not different from 0. Overall, I find no evidence that attack-exposed Islamic customers who had less fear gave higher assessments of the hotel quality than non-Islamic customers who had greater fear. The results suggest that fear of attack threats may play little role in affecting hotel word-of-mouth, consistent with my previous findings.

5 Robustness Checks

5.1 A Placebo test

I perform a placebo test by estimating additional DiD models using a "fake" treatment group from city Amsterdam, Barcelona, London, Milan and Vienna. The pre-attack and post-attack periods are defined as three months before and after the attacks. Hotel fixed effect and linear time trends are also introduced to improve the model fit.

[12] I group guests' nationality into Islam and Non-Islam societies based on the country's dominant religion.

Figure 10 presents the placebos test results. For outcomes reviewer scores and the length of positive reviews, using all the cities other than Paris as the placebo treatment group produces non-significant estimated effects. For outcome variable negative review length, the point estimate obtained by treating London as the affected city is positive and significant at 95% level, but estimates by using Amsterdam, Barcelona, Milan and Vienna as placebo treated groups remain non-significant. Overall, the placebo test shows that only treat Paris as the treatment group could generate statistically significant effects of the Paris terrorist attacks on hotel word-of-mouth.

5.2 Aggregated Data to Two Time Periods

An alternative way to deal with serial correlation in difference-in-differences models is aggregating data into one pre- and one post-intervention periods. This approach performs well also with small number of groups [Donald and Lang, 2007]. I aggregate data into city level with two time periods each: pre- and post-attack periods. Pre- and post-treatment periods are defined as three months before and after the Paris attacks, respectively.

Table 14 in the appendix shows the results. For all the three outcomes, the interactions of Post and Paris dummies are statistically significant and the size of the effect is close to that from disaggregated data.

6 Conclusion Remarks

In this paper I provide new evidence on the causal impact of terrorist attacks on hotel word-of-mouth. I find strong evidence that the November 2015 Paris attacks lead to substantial increases in average review scores, increases in the length of positive reviews and reductions in negative reviews. The effect on hotel word-of-mouth persist for approximately 10 months. Furthermore, I present evidence that the positive effect is greater in the short term than in the medium term. I propose a simple model in which the effect of terrorist attacks on hotel word-of-mouth relies on the competition between utility losses due to fear of terrorist threats and improved hotel quality. I find striking evidence that the fear effect is small and insignificant. I further use text mining techniques to extract the word-use frequency in reviews, and present suggestive evidence that the improved hotel service explains the increase in word-of-mouth immediately after the attacks and that an improved breakfast and a reduced hotel price in the following months after the attacks play an important role in enhancing customer experience.

In this research, although the parallel trends hold for all the three outcome variables, the identification may still be undermined since the pre-attack period is not long enough to show the underlying trends. Future research could supplement the data by obtaining longer periods of pre-treatment information and by extracting review data from other platforms such as *Yelp.com*, *Tripadvisor.com* to improve the robustness of the results.

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Tables and Figures

Table 1: Summary Statistics of Review Variables

	N	Mean	S.D.	Min.	Max.
WOM measures					
Review scores	514,146	8.32	1.64	2.36	10.20
Length of positive reviews	514,146	17.79	21.80	0.00	395.00
Length of negative reviews	514,146	18.52	29.69	0.00	408.00
Guests' information					
Leisure trip	499,171	0.83	0.37	0.00	1.00
Night stayed	513,953	2.36	1.65	1.00	30.00
Solo traveler	514,146	0.21	0.41	0.00	1.00

Table 2: Descriptive Statistics by City

	Paris		Amsterdam		Barcelona		London		Milan		Vienna	
	Pre-attacks	Post-attacks	Pre-attacks	Post-attacks	Pre-attacks	Post-attacks	Pre-attacks	Post-attacks	Pre-attacks	Post-attacks	Pre-attacks	Post-attacks
WOM measures												
Review scores	8.212	8.571	8.443	8.594	8.465	8.716	8.181	8.401	8.113	8.327	8.503	8.642
Positive review length	16.562	18.421	17.36	19.845	17.38	18.282	14.768	15.887	15.562	16.579	17.238	18.552
Negative review length	15.853	16.214	16.763	18.105	16.378	15.089	17.795	17.372	15.944	16.214	15.557	15.751
Guests' information												
Leisure trip	0.871	0.769	0.864	0.844	0.909	0.875	0.809	0.803	0.792	0.722	0.831	0.843
Night stayed	2.819	2.628	2.669	2.457	3.201	2.973	2.197	1.879	2.318	2.349	2.736	2.688
Solo traveller	0.176	0.261	0.196	0.206	0.145	0.191	0.239	0.231	0.223	0.279	0.204	0.193
Num of Reviews	*9908*	*6323*	*6329*	*6973*	*8564*	*6053*	*31239*	*36707*	*5092*	*3668*	*5129*	*4855*
Num of Hotels	*394*	*398*	*89*	*94*	*182*	*187*	*368*	*372*	*149*	*151*	*143*	*142*

Notes: Pre-attack and post-attack periods are define as three months before and after Nov 14, 2015.

Table 3: Cities Receiving Weights for the Synthetic Control Group

Review scores		Length of positive reviews		Length of negative reviews	
Amsterdam	0.000	Amsterdam	0.000	Amsterdam	0.000
Barcelona	0.462	Barcelona	0.534	Barcelona	0.938
London	0.538	London	0.345	London	0.000
Milan	0.000	Milan	0.000	Milan	0.000
Vienna	0.000	Vienna	0.121	Vienna	0.062

Table 4: Hotel WOM Predictor Means Before the Paris Terrorist Attacks

Pre-attack characteristics	Paris	Average of other cities	Synthetic Paris
Panel A: Review scores			
Leisure trip	0.840	0.820	0.840
Solo traveler	0.215	0.224	0.219
Night stay	2.773	2.591	2.681
Google search volumes	12.402	2.944	4.719
Panel B: Length of positive review			
Leisure trip	0.840	0.820	0.885
Solo traveler	0.215	0.224	0.220
Night stay	2.773	2.591	3.114
Google search volumes	12.402	2.944	2.677
Panel C: Length of negative review			
Leisure trip	0.840	0.820	0.829
Solo traveler	0.215	0.224	0.206
Night stay	2.773	2.591	2.458
Google search volumes	12.402	2.944	7.304

Notes: Google search volumes represents Google trend scores on searching for "Is is safe to go to Amsterdam/Barcelona/Paris/London/Milan/Vienna".

Table 5: Basic Difference-In-Differences Estimates, Paris attacks and WOM

Outcome variable:	**ln(review scores)**		**ln(length of positive reviews+1)**		**ln(length of negative reviews+1)**	
Control group:	Average of other cities	Barcelona	Average of other cities	Barcelona	Average of other cities	Barcelona
Paris× Post	0.0272	0.0200	0.0693	0.0788	-0.0591	-0.0539
	(0.0042)	(0.0056)	(0.0183)	(0.0255)	(0.0270)	(0.0261)
	[0.0016]	[0.0001]	[0.0044]	[0.0001]	[0.0141]	[0.0163]
Wild cluster bootstrapped p-value	0.0938	-	0.0625	-	0.0938	-
Average dependent variable	8.303	8.409	16.443	17.258	16.642	15.461
City FE or Paris dummy	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Hotel FE	Yes	Yes	Yes	Yes	Yes	Yes
N	115,872	27,929	115,872	27,929	115,872	27,929
adj. R^2	0.134	0.122	0.044	0.044	0.044	0.053

Notes: pre-attacks period and post-attacks period are defined as 3 months before and after the November 2015 Paris attacks. Robust standard errors in parentheses. clustered standard errors at city level in brackets.

Table 6: Address Seasonality by Introducing Trip Type Specific and City Specific Time Trends

	(1)	(2)	(3)	(4)
Panel A: Outcome variable: ln(reviewer scores)				
Paris× Post	0.0271***	0.0269***	0.0334***	0.0334***
	(0.0042)	(0.0042)	(0.0084)	(0.0085)
Average dependent variable	8.303	8.303	8.303	8.303
City FE & Month FE & Hotel FE	Yes	Yes	Yes	Yes
Trip type specific time trends	No	Yes	Yes	Yes
City specific linear trends	No	No	Yes	Yes
City specific quadratic trends	No	No	No	Yes
N	112,713	112,713	112,713	112,713
adj. R^2	0.150	0.150	0.150	0.151
Panel B: Outcome variable: ln(positive review length+1)				
Paris× Post	0.0693***	0.0682***	0.1471***	0.1393***
	(0.0184)	(0.0185)	(0.0372)	(0.0377)
Average dependent variable	16.443	16.443	16.443	16.443
City FE & Month FE & Hotel FE	Yes	Yes	Yes	Yes
Trip type specific time trends	No	Yes	Yes	Yes
City specific linear trends	No	No	Yes	Yes
City specific quadratic trends	No	No	No	Yes
N	112,713	112,713	112,713	112,713
adj. R^2	0.061	0.061	0.061	0.061
Panel C: Dependent variable: negative review length+1)				
Paris× Post	-0.0539***	-0.0531***	-0.0424	-0.0405
	(0.0261)	(0.0276)	(0.0558)	(0.0565)
Average dependent variable	16.642	16.642	16.642	16.642
City FE & Month FE & Hotel FE	Yes	Yes	Yes	Yes
Trip type specific time trends	No	Yes	Yes	Yes
City specific linear trends	No	No	Yes	Yes
City specific quadratic trends	No	No	No	Yes
N	112,713	112,713	112,713	112,713
adj. R^2	0.055	0.055	0.059	0.061

Notes: Pre- and post-period are defined as 3 months before and after November 14, 2015. The trip type specific time trends control for time trends by one year lead of cities' composition of leisure trip guests. Significance levels: * 0.10 ** 0.05 *** 0.01. Robust standard errors in parentheses.

Table 7: Relationship Between WOM and Attack Exposure During the Paris Attacks

	ln(review scores)	**ln(positive review length+1)**	**ln(negative review length+1)**
	(1)	(2)	(3)
Attack-exposed cohort	0.0582**	0.1860**	-0.0071
	(0.0275)	(0.0836)	(0.1716)
Average dependent variable	8.443	17.450	14.163
N	317	317	317
adj. R^2	0.007	0.016	-0.008

Notes: The sample is restricted to Paris. Affected cohort dummy equals 1 if customers checked-in just before the attacks and checked-out within 1 week after the attacks, equals 0 if customers checked-in 1 week before the attacks and check-out just before the attacks. Significance levels: * 0.10 ** 0.05 *** 0.01. Robust standard errors in parentheses.

Table 8: Re-examine the Relationship Between WOM and Attack Exposure During the Paris Attacks

	ln(review scores)	**ln(positive review length+1)**	**ln(negative review length+1)**
	(1)	(2)	(3)
Paris × Attack-affected cohort	0.0542*	0.2184*	-0.1306
	(0.0297)	(0.1161)	(0.1765)
Average dependent variable	8.236	15.811	16.561
Attack-affected cohort dummy	Yes	Yes	Yes
City FE	Yes	Yes	Yes
N	2046	2046	2046
adj. R^2	0.038	0.027	0.007

Notes: Affected cohort dummy equals 1 if customers checked-in just before the attacks and checked-out within 1 week after the attacks, equals 0 if customers checked-in 1 week before the attacks and check-out just before the attacks. Significance levels: * 0.10 ** 0.05 *** 0.01. Robust standard errors in parentheses.

Table 9: Relationship between Distance to Attack Targets and WOM in Paris

	ln(review scores)		**ln(positive review length+1)**		**ln(negative review length+1)**	
	post 1 week	post 1 month	post 1 week	post 1 month	post 1 week	post 1 month
Distance to the attack targets	0.0025	0.0004	0.0019	-0.0005	-0.0099	0.0008
	(0.0018)	(0.0006)	(0.0068)	(0.0025)	(0.0110)	(0.0038)
Average dependent variable	8.221	8.274	15.747	15.831	16.697	16.221
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	318	2291	318	2291	318	2291
adj. R^2	0.073	0.030	0.126	0.053	0.022	0.007

Notes: The sample is restricted to Paris customer who posted reviews after the Paris terrorist attacks. Control variables include: stay duration, guest type (solo customer, couple customers, stay with children), trip type (business trip or leisure trip), and reviewer's national location (North America, Europe, East Asia, West Asia, Australia and others). Robust standard errors in parentheses.

Table 10: Relationship between Safety Concerns and WOM

	ln(review scores)	**ln(positive review length+1)**	**ln(negative review length+1)**
	(1)	(2)	(3)
Panel A: two-way fixed effect model			
ln(Google search volumes)	-0.0001	0.0059*	0.0036
	(0.0010)	(0.0034)	(0.0049)
City FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
N	636	636	636
adj. R^2	0.497	0.663	0.391
Panel B: DiD model			
Post×ln(Google search volumes)	0.0092	0.0406*	0.0381
	(0.0085)	(0.0161)	(0.0300)
N	636	636	636
City FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
adj. R^2	0.504	0.670	0.397

Notes: Google search volumes represent google trend scores on searching for "Is is safe to go to Amsterdam/Barcelona/Paris/London/Milan/Vienna". In panel A, Google search volumes vary at city-week level. In panel B, Google search volumes vary at city level. Pre- and post-attack periods are defined as 3 months before and 12 months after the attacks, respectively. Significance levels: * 0.10 ** 0.05 *** 0.01. Robust standard errors in parentheses.

Table 11: Top 10 Most Frequently Used Words in Reviews of Paris Hotels

Positive reviews							
before the attacks		within one week		within three months		within one year	
word	frequent	word	frequent	word	frequent	word	frequent
location	4932	staff	156	location	2469	location	12994
staff	3967	location	148	staff	2253	staff	12170
good	1959	friendly	69	great	1137	great	6339
great	1884	helpful	67	good	1046	good	5959
helpful	1738	good	66	friendly	990	friendly	5325
friendly	1682	great	60	helpful	941	helpful	5298
clean	479	nice	57	nice	759	nice	5412
nice	1169	safe	51	clean	646	clean	3876
excellent	1031	breakfast	43	breakfast	588	breakfast	3633
comfortable	908	comfortable	41	excellent	554	comfortable	3387
Negative reviews							
before the attacks		within one week		within three months		within one year	
word	frequent	word	frequent	word	frequent	word	frequent
small	1241	small	41	small	642	small	3757
breakfast	1016	breakfast	38	rooms	366	rooms	2189
rooms	850	rooms	32	staff	271	staff	1731
staff	740	service	15	breakfast	260	breakfast	1297
bathroom	501	staff	15	bathroom	217	bathroom	1287
bed	405	night	14	night	216	shower	1073
night	393	front	14	shower	154	bed	1073
wifi	380	poor	13	service	154	night	1048
service	359	floor	12	poor	153	good	1073
expensive	358	expensive	12	bed	152	service	953

Table 12: Heterogeneous Impacts on Customers from Islamic or Non-Islamic Counties

	ln(review scores)	**ln(positive review length+1)**	**ln(negative review length+1)**
	(1)	(2)	(3)
Islam	-0.0468	-0.3234***	0.1678
	(0.0307)	(0.1213)	(0.1952)
Affected_cohort	-0.0043	0.0127	0.1024
	(0.0137)	(0.0542)	(0.0873)
Islam× Affected_cohort	0.0060	0.0866	-0.0404
	(0.0405)	(0.1603)	(0.2580)
Paris× Affected_cohorts	0.0071	0.1272	0.0328
	(0.0321)	(0.1271)	(0.2046)
Paris × Islam	-0.0799	-0.0833	0.0522
	(0.0660)	(0.2610)	(0.4202)
Paris× Islam× Affected_cohort	0.1153	0.2088	-0.3507
	(0.0845)	(0.3342)	(0.5380)
City FE	Yes	Yes	Yes
N	2029	2029	2029
adj. R^2	0.038	0.022	0.007

Notes: Islam is 1 if the customer is from an Islamic country, 0 otherwise. Affected cohort dummy equals 1 if customers checked-in just before the attacks and checked-out within 1 week after the attacks, equals 0 if customers checked-in 1 week before the attacks and check-out just before the attacks. Significance levels: *** 0.01. Robust standard errors in parentheses.

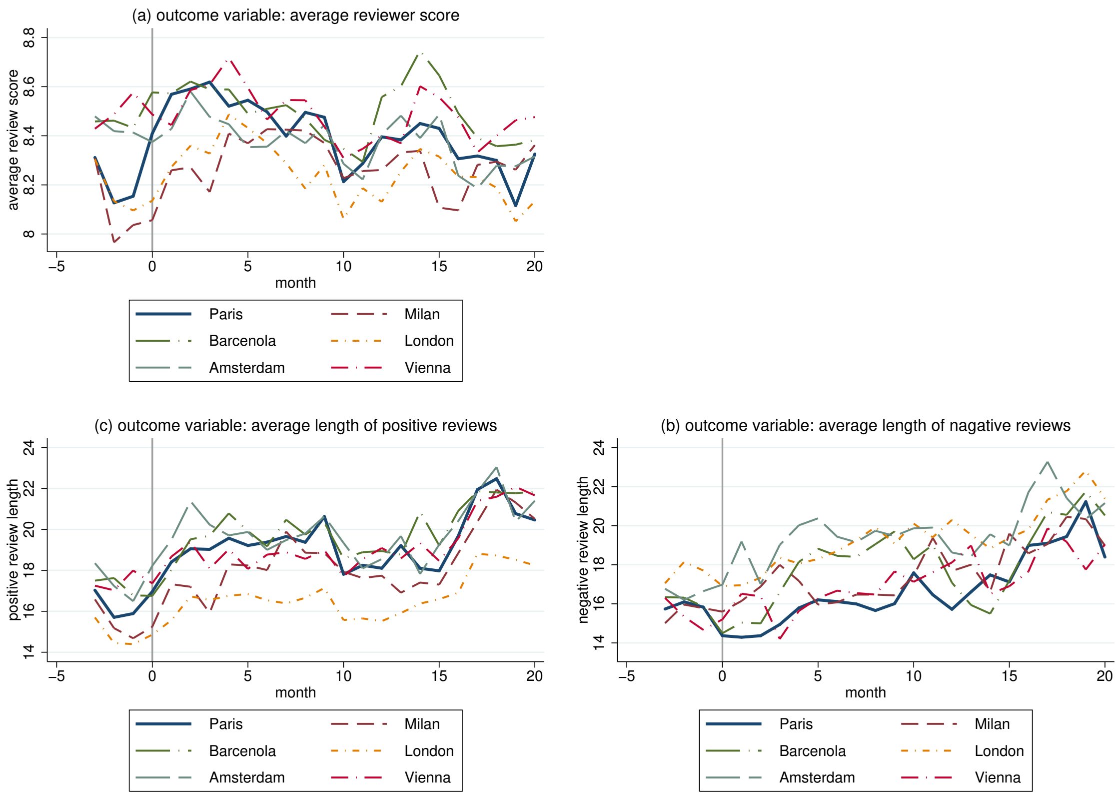


Figure 1: Raw Trends by City

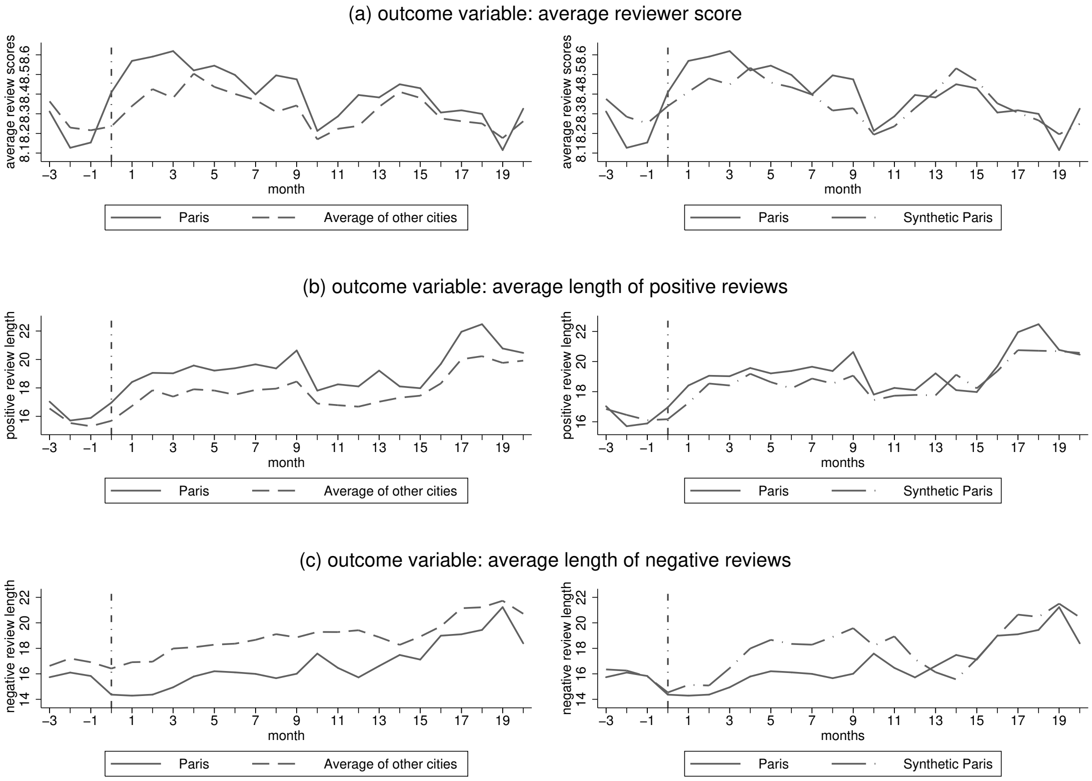


Figure 2: Compare Synthetic Paris with Average of the Untreated Cities

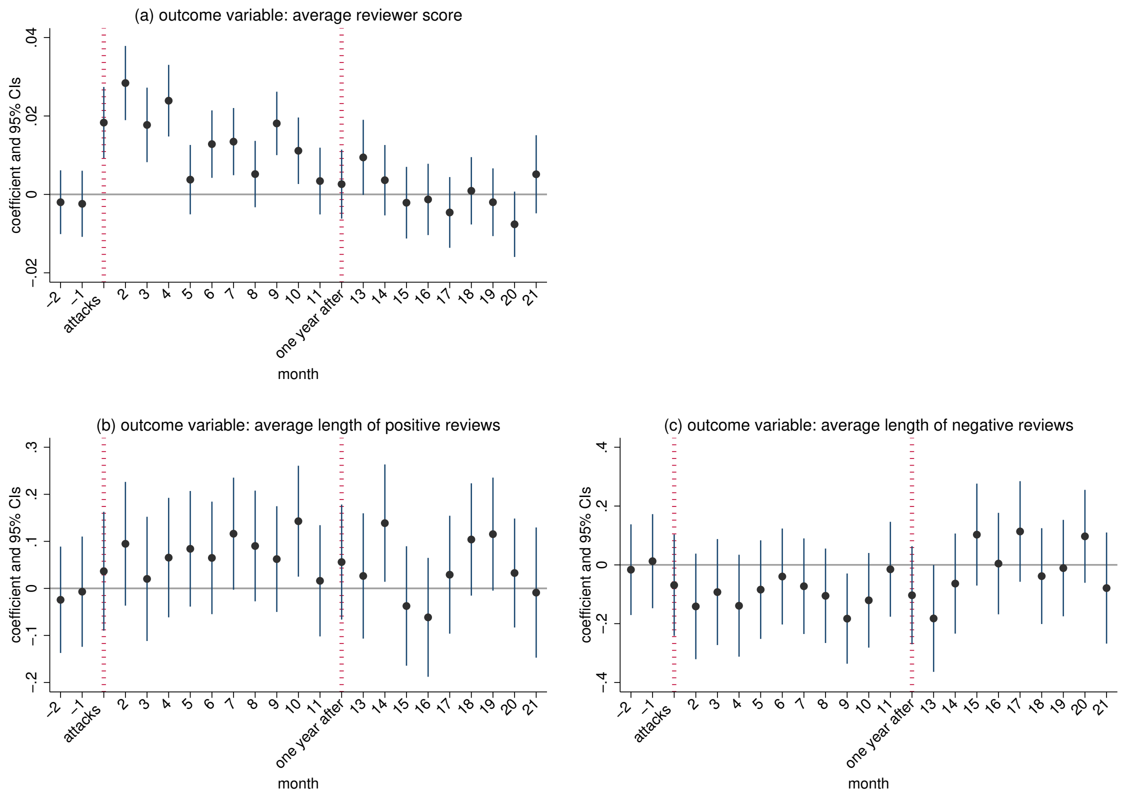


Figure 3: Month-by-month Treatment Effect Dynamics

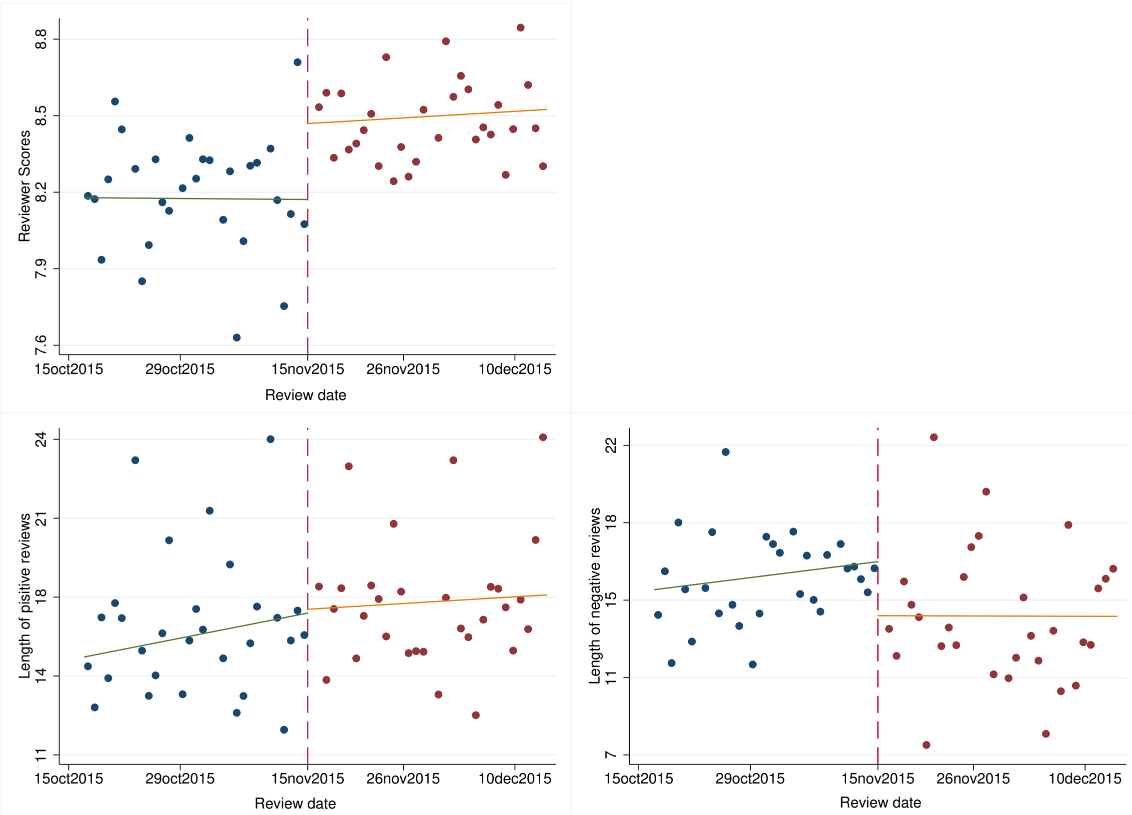
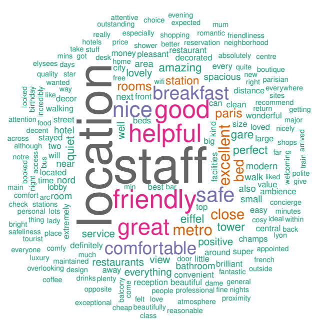


Figure 4: Time-series Comparison in Paris Around the Attacks

(a) Before the Paris attacks



(b) Within a week of the attacks

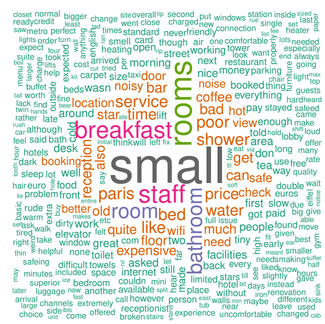
(c) Within three months of the attacks

(d) Within a year of the attacks

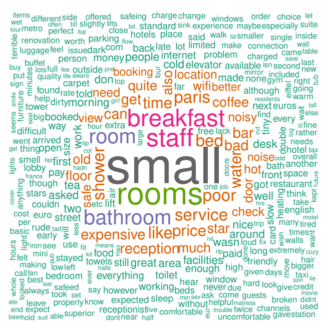
Figure 5: Word Clouds of Positive Reviews of Paris Hotels

(a) Before the Paris attacks

(b) Within a week of the attacks



(c) Within three months of the attacks



(d) Within a year of the attacks

Figure 6: Word Clouds of Negative Reviews of Paris Hotels

A Appendix

Table 13: Top 10 Most Frequently Used words in Reviews of Paris Hotels One Week following the Attacks

positive reviews				negative reviews			
closer hotels		further hotels		closer hotels		further hotels	
word	**frequency**	**word**	**frequency**	**word**	**frequency**	**word**	**frequency**
location	67	staff	97	room	15	breakfast	25
staff	59	location	81	breakfast	13	small	20
friendly	35	helpful	40	small	11	room	17
good	33	friendly	34	service	10	expensive	10
helpful	30	great	33	staff	9	poor	9
great	27	good	33	floor	8	front	8
nice	25	nice	32	bathroom	8	staff	7
breakfast	24	safe	31	door	7	old	7
comfortable	22	comfortable	23	price	7	morning	6
safe	20	excellent	22	bed	6	service	6

Table 14: Robustness Check: Aggregated Data to Two Time Periods

	ln(review scores)	**ln(positive review length+1)**	**ln(negative review length+1)**
	(1)	(2)	(3)
Paris × Post	0.0343***	0.0838**	-0.0947***
	(0.0074)	(0.0220)	(0.0309)
Post	0.0106**	0.0690***	0.0475
	(0.0030)	(0.0090)	(0.0249)
City FE	Yes	Yes	Yes
N	12	12	12
adj. R^2	0.957	0.968	0.879

Notes: Aggregate data to city level data with two time periods each: pre- and post-attacks periods. Pre- and post-treatment periods are defined as three months before and after the attacks, respectively. Significance levels: * 0.10 ** 0.05 *** 0.01. Standard errors in parentheses.

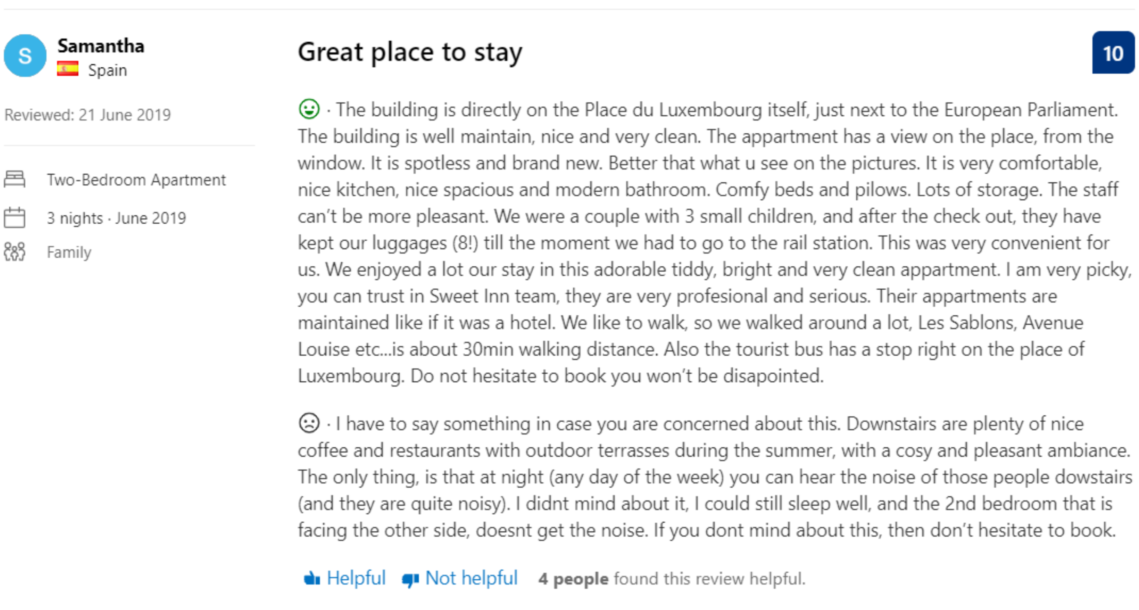


Figure 7: An Review Page in *booking.com*

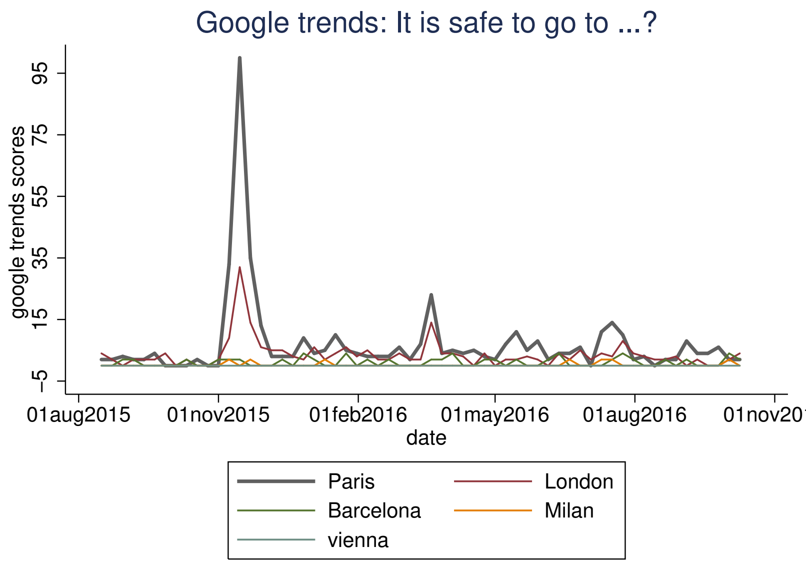


Figure 8: Google Trends on Safety Concerns

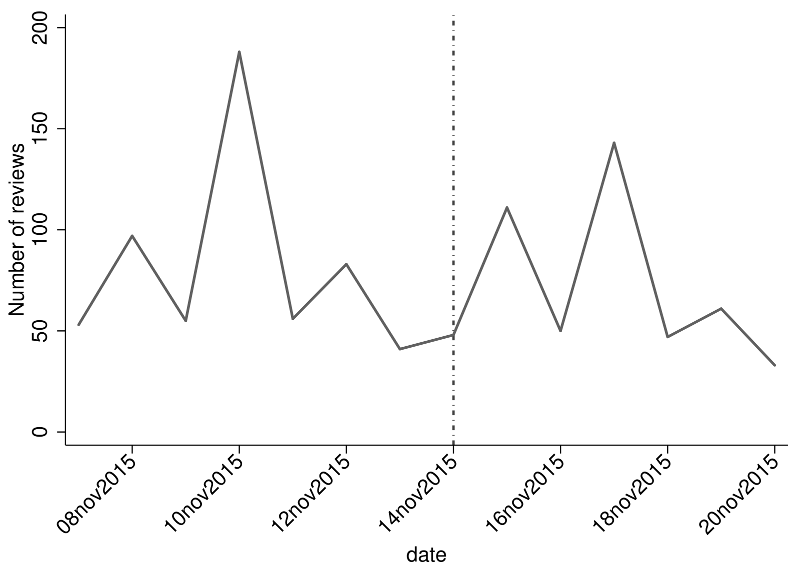


Figure 9: Paris Daily Number of Reviews Around the Attacks

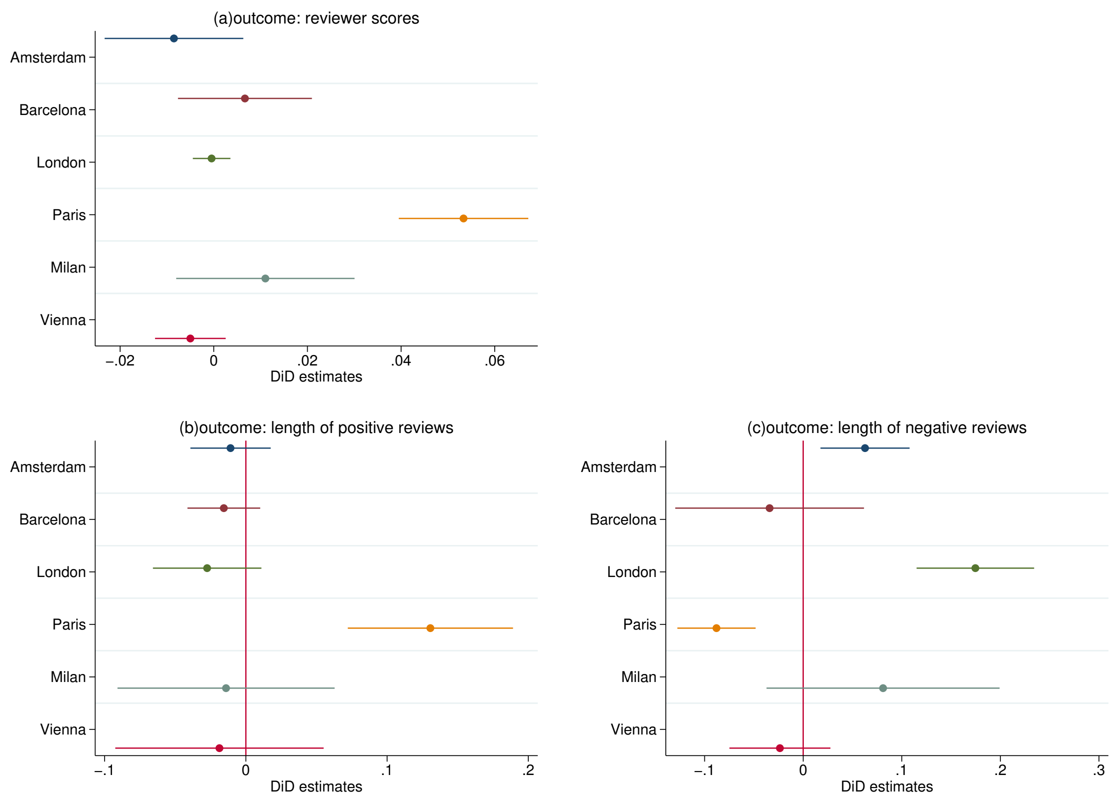


Figure 10: Robustness Check: Placebos Tests