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IMPACT OF POSITIVE AND NEGATIVE INFORMATION ON ECONOMIC OUTCOMES

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Abstract: This thesis investigates the impact of information on economic outcomes. We find empirical evidence that the high level of information to which consumers are exposed has the ability to influence their behavior.

In the three chapters of our thesis, we analyze three different fields. First, analysing data on Sanremo Festival, we show, through a Regression Discontinuity Design, that receiving an award have an impact on the commercial success of songs. Second, analysing data on cars sales and stock prices, we show that the Dieselgate scandal has an impact on the stock prices but not on the sales of the Volkswagen group. We use a Differences-in-Differences model and a RDD. Third, we investigate the impact of terrorism on the touristic sector, running a panel data model in some countries of the Euro zone and in the USA. Results illustrate that the terrorist attacks have both a long-run and a short-run effect on tourism.

In all the chapters, we find that a positive or a negative information could have an effect on the behaviour of people, and this consequently generates a positive or a negative economic performance.

Abstract: questa tesi studia l'impatto delle informazioni sui risultati economici. Le nostre evidenze empiriche dimostrano che l'elevato livello di informazioni a cui sono esposti i consumatori ha la capacità di influenzare il loro comportamento.

Nei tre capitoli della nostra tesi, analizziamo tre diversi ambiti. Innanzitutto, analizzando i dati sul Festival di Sanremo, mostriamo, attraverso un Regression Discontinuity Design, che ricevere un premio ha un impatto sul successo commerciale delle canzoni. In secondo luogo, analizzando i dati relativi alle vendite di automobili e ai prezzi delle azioni, dimostriamo che lo scandalo Dieselgate ha un impatto sui prezzi delle azioni ma non sulle vendite del gruppo Volkswagen. Usiamo in questo caso un modello Differences-in-Differences e un RDD. In terzo luogo, esaminiamo l'impatto del terrorismo sul settore turistico, eseguendo un panel data model in alcuni paesi della zona Euro e negli Stati Uniti. I risultati mostrano che gli attacchi terroristici hanno sia un effetto a lungo termine che a breve termine sul turismo.

In tutti i capitoli, scopriamo che un'informazione positiva o negativa potrebbe avere un effetto sul comportamento delle persone e questo di conseguenza genera una performance economica positiva o negativa.

Impact of positive and negative information on economic outcomes

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Impact of positive and negative information on economic outcomes

Introduction

This thesis investigates the impact of information on economic outcomes in different fields. The word information derives from the verb "to inform", that means the knowledge that people gain from studying or experiences. In particular, we are interested to the effect of information that people receive from the media.

The technological development of the last decades has had the great merit of bringing information to a global level. Acquiring information turns out to be now easy and immediate for most of the inhabitants of the world, who access quickly to any kind of news through internet, television, radio, newspapers. This high level of access to information has the ability to influence the judgments and assessments of consumers who have direct contact with what is happening in every part of the world.

We find that a positive or a negative information could have an effect on the behaviour of people, and this consequently generates a positive or a negative economic performance for the subject to which the information refers.

The thesis is divided into three chapters, each of which is referred to a research in a different field. The titles of the researches are:

- Cultural prize and economic success: evidence from the Italian Sanremo Music Festival
- Impact on sales and on market value of a negative product information: evidence from the Dieselgate scandal
- Terrorist attacks and impact on tourism: evidence from Europe and USA

The first research investigates the impact of the Sanremo music prize on the economic success of songs in the Italian market. It refers to the cultural field, with the purpose of adding new evidence to the line of literature to which it refers. Using a Regression Discontinuity Design, we show that receiving an award have an impact on the commercial success of songs.

In the second research, we analyse data on cars sales and stock prices of the major companies of the automotive industry, with the aim of estimating the effect of the Dieselgate scandal on economic performances of the sector. We use a Differences-in-Differences and a Regression Discontinuity Design, showing that the scandal had an effect on the stock prices of the companies involved, but not on the sales.

The aim of the third research is to estimate the impact of terrorism on the touristic sector. We analyse, in 16 different countries (Europe and USA), the principal terrorist attacks of the last 3

decades and their impact on indicators of tourism performance. The panel data model used show us that terrorist attacks have both a long-run and a short-run effect on tourism.
All the three researches are united by the theme of ‘information’. In the first case the information is positive, referred to the assignment of a cultural prize; in the second and third cases the information is negative, referred respectively to negative features of a product and to negative events in a nation. In each case, we analyse the effect of an information that is made public and that negatively or positively have an impact on economic performances in different fields.

In order to prove our hypotheses, we consider a wide literature regarding the effect that information has on consumer choice. We analyse the role of information in three different scopes: artistic products, physical products and experience products.

With reference to the information related to artistic products, artists such as musician, singers, writers, filmmakers, painters, have to produce appreciated goods, in order to intercept the cultural taste of consumers. This allows a good reputation of cultural products and consequently a higher volume of sales. In this market, awards have a great influence on the perception the consumers have on products. For example, if a film wins the Oscar or it receives an Oscar nomination, it is more likely to be seen by the consumers. This behaviour is driven by expert judgement, that gives information a priori about the high quality of the cultural product. Therefore, information given by the assignment of a prize is perceived as synonymous of good quality: the consumer is more inclined to buy a product which is already marked by a quality title. They exist interesting empirical results about this thesis.
Jerrell and Peltzman (1985) test any losses incurred by entrepreneurs following the withdrawal from the market of products judged defective. The report takes into consideration the markets of two goods: cars and medicines. The main conclusion is that the market penalizes entrepreneurs considerably, resulting in a total cost higher than the simple direct costs, due to a deterioration of the company's image.
Another important result of the study by Jerrell and Peltzman is that any loss of credibility of a single company causes disadvantages to the entire sector of reference.
A wide literature range confirms that positive information influence consumer choices. In the field of cultural products, in markets with imperfect information, consumers tend to trust experts. Ponzo and Scoppa (2015) show that winning the Strega Prize significantly increases the cumulated sales of a book.

Berger, Sorensen and Rasmussen (2010) demonstrate that also negative publicity can increase sales by increasing product awareness, but this is valid especially if it is referred to less known writers: even if negative reviews have a negative impact on the most popular author's books, they have a positive effect for not famous author's books.
The influence of information is also verified in the branch of cinema. It has been proved that Oscar nomination positively affects the financial success of the movie, in relation to the weekly returns and to the survival time (Deuchert, Adjamah and Pauly, 2005). A similar research conducted by Nelson et al. (2001) examines how information about Oscar nomination and award for best picture, best actor, and best supporting actor can influence movie sales.
All these researches inspire our interest in testing if the information has a real effect on the sales in an artistic field. We focus our first research on the Sanremo Music Festival.

With reference to the information related to physical products, different researches prove that product quality affects consumer demand and stock prices.
Markets characterized by asymmetric information are based on reputational mechanisms. For this reason, firms aim to produce quality products. Consumers pay attention to information about the quality of products they would like to buy: negative news about the functioning of a product, bad reviews on a website of e-commerce, unfavourable word of mouth concerning a good shift negatively the demand for the product. If firms want to preserve their reputation, and consequently the rents on future sales, they have to maintain high quality standards of their products and services.
Another element affected by the bad or good reputation is the financial performance of a company (McGuire et al., 1990). The information is relevant in the short period as in the long period. (Roberts and Dowling, 2002).
Bachmann et al. (2018) conduct a research on the same theme of our research, the Dieselgate scandal, to provide causal evidence that group reputation externalities matter for firms. They show significant declines in the U.S. sales and stock returns of some German car brands, due to the fact that Volkswagen's episode injured the reputation of all the "German car engineering" group in the United States. They show that not only the Volkswagen group, but also BMW, Mercedes-Benz, and Smart reputation results damaged by the Volkswagen scandal.
De Paola and Scoppa (2013) analyse a product recall in the food industry, computing the effects of negative information on the sales of involved brands. In 2008, in Italy, a fraud has involved some leading firms in the cheese sector. The research shows how the negative publicity on product quality has led to a consumers' demand shift from involved to not involved brands, and these effects continue in the long-term. The consequences of the negative information affect the retailers.

Roberts and Grahame (2002) prove that there is a positive relationship between reputation and financial performance: good corporate reputations create value for the company. Firms with relatively good reputations are better able to sustain superior profit outcomes over time.

With reference to the information related to experiential products, an event may affect the sales of this kind of goods. When the event is represented by a terrorist attack, the negative effect provoked by information could affect the sales of an entire country. Some researches show that there is a relationship between terrorist attacks and tourism: there is unidirectional causality from terrorism to tourism in the short-run and in the long-run, with no evidence of reverse causality (Liu and Pratt, 2017).

Kosová and Enz (2012) study the impact of the terrorist attacks of September 11, 2001 on US hotel performance. They control for market factors, such as inflation and seasonality, and for hotel characteristics, such as size, segment, or operation type. They find that New York's luxury hotels were the most affected by the terrorist attack.

Tourists have to take into account the unpredictability of terrorism when they organize their travels. Also the research of Pizam and Smith (2000) sustains that terrorism acts have effects on tourism destinations. They investigate the major terrorism events around the world from 1985 to 1998, classified by date, location, victims, weapons used, severity of damage, motive, effect on tourism demand, and length of effect. They conclude that information on terrorism appear to be inextricably linked to tourism performance of a country.

Since our three researches treat different economic fields, the literature's review is expressed differently in each chapter.

The thesis is organized as follows. In Chapter 1 we expose the research on the Sanremo Prize. In Chapter 2 we set out the research on the Dieselgate scandal. In Chapter 3 we present the research on terrorist attacks. In the last section, we draw concluding remarks, exposing the economic outputs common to the three researches.

1. Cultural prize and economic success: evidence from the Italian Sanremo Music Festival

Abstract: Analysing data on Sanremo Festival, the most popular Italian music Prize, we show that receiving an award have an impact on the commercial success of songs. We model a Regression Discontinuity Design, using as dependent variable two different measures for song sales, expressed by the ranking in Hit-parade (a national musical ranking) and the presence in different weeks in Hit-Parade.

1.1 Introduction

We are interested on the prize effect on the economic success of songs and of artists. This would confirm the empirical evidence that prizes express quality and that they affect consumer choices. We try to understand if awards affect consumers' choices or, conversely, if awards are conferred to the highest quality products.

A serious econometric problem in estimating the impact of the awards on the sales is the omission from the regression of an unobservable variable: the song's true quality. This variable has surely an impact on sales. We can also observe that prizes are normally given to high-quality products. Then, if we estimate a regression of sales on a variable "Prize", that indicates whether an award is obtained while omitting a measure of product quality, then the variable "Prize" might gather the effect of quality without having any independent effect on sales. Therefore, the coefficient on the prize will be upward biased.

In order to avoid estimation biases, we use a regression discontinuity design (RDD) using a measure for song sales as the dependent variable and, as a forcing variable, the ranking of the Sanremo Festival. Each year, the competing songs receive votes from different juries, some composed by experts and other by normal people, and the song that receives the largest number of votes wins the Sanremo Festival. In our RDD model, the evidence of treatment effects are the jumps in the relationship between sales and votes near the threshold of votes percentage necessary to win the Sanremo competition.

As a dependent variable, we should use data on song sales, but these are rarely available, therefore we use the Hit Parade ranking, that is a good proxy for the weekly sales, because it gives a position to the most sold songs of the market, for each week.

We use data on the Sanremo Festival ranking, the most famous Italian music competition, for 59 years, from 1959 to 2017.

1.2 Literature

A wide literature investigates the effect of cultural awards on success, in different artistic contexts, such as music, books or films.

Ponzo and Scoppa (2015) perform a research in literary context. Using data on the Strega Prize, the most important literary prize in Italy, they find a strong influence of the prize on book sales, showing that most of the impact happens in the weeks following the announcement of the Prize. The authors show therefore that expert's judgment influences books success.

They use data from three different datasets:

- the Strega prize ranking, with the number of votes that each book received from the expert's jury, over a period of 66 years
- number of copies of each book owned by members of aNobii, an international website for book lovers
- the bestseller lists published weekly by the leading Italian newspaper "La Stampa", over a period of 30 years.

The authors use two different models for the analysis: a sharp Regression Discontinuity Design (RDD) model and a difference-in-differences model.

In the RDD model they use the jury votes as a proxy for quality, that is the forcing variable, and they study the relationship with the sales. The votes are normalized subtracting from the effective number of votes received the votes received by the second ranked book in the competition plus one. Zero is the threshold: when the variable vote is equal to or greater than zero, the treatment of winning the Strega prize is received. In order to estimate the treatment effect, they compare the sales of those books that receive a number of normalized votes just above and below the cut-off of zero.

The estimates of the RDD model are clear: there is a jump in the relationship between the proxy of sales and the number of votes near the cut-off. Then the positive effect of the Strega Prize on sales is confirmed: winning the prize increases by about 500% the cumulated sales of a book.

The difference-in-differences model uses the average number of weeks on the bestseller lists for winners and non-winners of the Strega Prize. There is a comparison before and after the Strega Prize assignment, between these two measures. The authors find that, under the hypothesis that no other differences affect the two categories of books contemporaneously to the treatment, the difference-in-differences can be interpreted as the direct effect of the prizes on awarded books.

The authors also analyse data based on weekly level instead of that aggregated for longer spells. The regression shows that the effect on sales of winning Strega Prize is huge: the prize is

announced in July, in this period the probability of being on bestseller list increases by 45.7%, while the probability for non-awarded books slightly decreases when the Prize is announced.
Ponzo and Scoppa (2015) conclude that winning the Strega Prize increases by about 500% the cumulated sales of a book (RDD) and that the Prize has an immediate effect when it is announced, but this decreases in the following weeks (difference-in-differences). The authors are confident they are capturing a causal effect of the Prize because they use two different measures of book sales and two different econometric strategies. It is confirmed that the awards are a signal for the quality of a cultural product in markets with imperfect information: consumers tend to trust experts.

Ginsburgh and Van Ours (2003) analyse the Queen Elizabeth music competition, the best-known international competition for piano and violin, organized in Belgium.
Their key question is whether experts' opinions reflect true quality, or whether they influence economic outcomes independently of their value as a signal of quality. It turns out that a critical determinant of success in the competition is the order in which musicians perform and this order is assigned randomly.
They use data on the Queen Elizabeth competition ranking for 11 years, held between 1952 and 1991. The total number of musicians is 132, they collect data about some individual characteristics like sex, nationality, age at the moment of the competition, time elapsed between the competition and the date at which the success indicator is observed, order of performance, and final rank (one to 12). They also collect indicators of success such as the presence in catalogues and ratings by Belgian music critics.
The authors estimate the effect of ranking on success using a Two Stage Least Squares model. The order of appearance is used as an instrument for success. In fact, the order of appearance, that is randomly chosen, is not correlated with quality or with any observable characteristic of performers, it can be used to identify the nature and effect of ranking on success.
The research uses a probit equation and a tobit equation, both estimated through maximum-likelihood methods.
The results show that the order of appearance has a positive effect on both success indicators. This indicates that musicians that appear before seem to lead to more success.
The authors also investigated whether characteristics other than the order of appearance possibly contribute to success: gender, age at the time of the finals, nationality, and year of the competition have no significant effect.
In conclusion, musicians with high scores are more likely to record their music work and the opinion of music critics is more influenced by the ranking than by the quality of the pianist.

Ginsburgh (2003) illustrates that prizes awarded shortly after the production of an artwork or rankings that result from competitions are correlated with economic success and may even influence or predict it, but are often poor predictors of true aesthetic quality or survival of the work.
The research investigates awards taken from three different artistic contexts: movies, books and music.
The first research is about movies. Part of the data derives from three different lists of all-time best movies (America's 100 greatest movies, Mr. Showbiz critics pics, The 100 must-see films of the 20th century) in which they are cited 77 movies produced between 1950 and 1980.
Other data are information about the economic success of the film. Since it was difficult to measure box office gross ticket sales, it is considered the amount of money paid by movie theatres to producers and distributors to show a film. The final sample contains 559 movies, taking together the movies nominated for or winning Oscars, the movies from the top 100 lists and the top five film rentals in each year.
The model is a simple OLS with three different equations. The first one shows that winners are significantly associated with higher success, but it is difficult to say whether awards influence the success or whether the prize is assigned to the most popular film, since the movies are projected in cinemas before the award assignment. In the second equation, a standard F-test shows that movies listed in the top 100 do better than others, but the number of lists on which a movie is present makes no difference. The third equation takes both groups of variables together and shows that Oscar winners and nominees still pick up significant coefficients, while only those movies that are cited in all three best movies lists are then associated with short-run success.
The second research is about books, it investigates the Booker Prize, rewarding the best novel of the year written in English. Data about success of the book are measured by the number of editions published during the ten years after the selection. These are taken from the website Amazon.com. Other data derive from the online catalogue of the Library of Congress: the number of titles different from the winner book but belonging to the same author.
The OLS model, divided into three equations, shows that winners are not more successful than nominees.
The third research is that of Ginsburgh and Van Ours (2003) on the Queen Elizabeth competition, explained before.
In conclusion, despite there are some differences in the three case studies, the main results are very similar: awards, prizes and critics may have an impact on success.

Haan, Dijkstra and Dijkstra (2005) find that expert judgement is a better expression of quality, compared to popular judgment. Indeed, expert judgement is less sensitive to factors unrelated to quality than public judgment. The popular jury could be influenced the most by the singer's former success. Their research, unlike the others, is not about the economic success of the song, but only about the jury composition.
They refer to the Eurovision Song Contest, the European song competition, that has had different juries' composition among the years. The authors collect data for 41 years, from 1957 to 1997, about the order of appearance and the final ranking of the contest. Since not all festivals have the same number of contestants, they normalize these values. In total, there are 758 contestants in the dataset, divided into four categories: male singers, female singers, duos and groups.
An OLS estimation regresses the final ranking on the order of appearance and on other characteristics of the singer. It comes out that a song that is performed later during the contest stands a much better chance of obtaining a good position in the ranking.
To test the hypothesis of this research, the authors collect another dataset, with data for a total of 70 national finals. Many countries use both the expert and the popular jury for the national competition. The OLS regression shows that the song that is performed first has a rank that is lower than the song that is performed last, this has a great impact on the position in the final ranking. Furthermore, it shows that experts are a better judge of quality than the general public.
This study has two main conclusions. First, it provides evidence that there are ordering effects when judging music contests. An ordering effect exists not only for contests judged by experts but also for those judged by the general public.
Order effects can be a major source of economic inefficiency, not only in cultural contests but also in other contexts where the quality of several candidates needs to be compared (i.e. job interviews and the grading of exams).
The second contribution of this paper is that experts are unambiguously better judges of quality, at least in the sense that the outcomes of contests judged by experts are less sensitive to exogenous factors that clearly do not influence the quality of output. Nevertheless, experts are not perfect, because their judgment does depend on such factors.

Berger, Sorensen and Rasmussen (2010) argue that negative publicity can increase purchase likelihood and sales by increasing product awareness. In three different studies they show that, in the New York Times, even if negative reviews have a negative impact on the most popular author's books, they have a positive effect for less known author's books. Their results are in contrast with all the existing studies of negative publicity, that have found its effects to be negative.

The first study uses weekly sales data to estimate the impact of New York Times book reviews on the sales of more than 200 hardcover fiction titles. The OLS regression shows that for books by established authors, a negative review led to a 15% decrease in sales. For books by relatively unknown and new authors, negative publicity has the opposite effect, increasing sales by 45%.
The second study provides a more controlled experiment of the effects of negative publicity. The authors directly manipulated both publicity valence and product awareness to examine how they influence purchase likelihood. Few consumers want to read a bad book or see a movie they know will be terrible, but over time, the valence of publicity for unknown products may be forgotten, leading positive and negative reviews to have a similar effect. To test this possibility, the authors manipulated whether people reported purchase likelihood either right after reading a product review or after a delay. The group of experiment is composed by 252 participants. The model used is an analysis of variance (ANOVA) of type 2 (review valence: positive versus negative) x 2 (time: delay versus no delay) x 2 product awareness (well known versus unknown). Participants reported they would be more likely to purchase well-known products that were positively reviewed, regardless of whether they reported purchase likelihood right away or after a delay. In contrast, for unknown products, a delay moderated the effect of review valence on purchase likelihood. Viewed another way, the effect of a negative review for an unknown product became more positive after a delay such that purchase likelihood after a delay was similar after a positive or negative review.
The third study examines whether positive effects of negative publicity are driven by increased awareness. The authors use a 2 (prior product awareness) x 2 (review valence) x 2 (product reviewed) full-factorial mixed design.
Results of Study 3 again demonstrate conditions under which negative publicity will have positive versus negative effects. Compared to no publicity at all, whether the same negative review increased or decreased purchase likelihood depended on existing awareness about the cultural product being reviewed. Whereas a negative review decreased purchase likelihood of a book that was already well known, it increased purchase likelihood for a previously unknown book.
The result of the three studies is that the paper is the first to demonstrate beneficial effects of negative publicity, and then to delineate conditions under which negative publicity will have positive versus negative effects.

Sorensen (2007) performs a research on the impact of the bestseller list published on the New York Times and on sales and product variety. It comes out that appearing on the list leads to a modest increase in sales for the average book, and that the effect is more dramatic for bestsellers by debut authors.

The dataset is composed by weekly national sales for over 1,200 hardcover fiction titles that were released in 2001 or 2002, provided by the market research firm Nielsen BookScan. Information about the individual titles, such as the publication date, subject, and author information, was obtained from a variety of sources, including Amazon.com and a volunteer website called Overbooked.org.

In a first analysis of the data, Sorensen finds that book sales are remarkably skewed in two important ways. First, the distribution of sales across books is heavily skewed. Second, book sales tend to be skewed with respect to time for any given title: sales tend to be heavily concentrated in the first few weeks after a book's release.

The author models book sales as an autoregressive process in which the autoregression parameter is a function of covariates. The model can accommodate unobserved, book-specific heterogeneity in both the level and trajectory of sales.

The regression results confirm that appearances on a bestseller list have a direct impact on sales. But why the list has an impact? The author explains the idea that bestseller status is informative: for example, bestseller appearances could signal high quality, or signal what other people are reading. Another possibility is that sales increases result from promotional activities undertaken for bestsellers. A third explanation would be that the increases are merely price effects, resulting from the automatic discount that many stores offer on current bestsellers.

Another question the author tries to answer is "Do bestseller lists affect product variety?". In other words, to what extent are those extra sales 'stolen' from non-bestselling titles?

If substitution between non-bestsellers and bestsellers is important, then, presuming that books in the same genre are closer substitutes than books in different genres, sales of non-bestselling books should decline when the bestseller list is comprised of books in similar genres. To capture these kinds of substitution patterns, a variable summarizing each book's similarity to the current set of bestsellers is constructed by comparing the book's genres to the genres of all books on the current bestseller list. It is launched a regression with sales used as dependent variable, and all bestsellers, new on list, weeks out, week dummies and subject dummies as independent variables. The results suggest a complementarity between bestsellers and non-bestsellers. The effect seems to be most pronounced for books appearing on the list for the first time: when the similarity measure is defined only for the subset of bestsellers whose first appearance was in the given week, the positive effect of the similarity is stronger.

The final remarks of this research confirm that appearing on the New York Times bestseller list has a direct impact on the book's sales. However, given the amount of attention paid to the New York Times list, the estimates of its impact may seem surprisingly small, because the magnitude of the effect is modest. The analysis ignores two effects that could be quite significant to authors and publishers. First, while appearing on the bestseller list may have only a modest immediate impact on the book's sales, it may dramatically increase the popularity of future books by the same author. Second, paperback sales may be influenced by whether the hardcover edition was a bestseller. Unfortunately, these effects can't be measured with the data owned by the author.

Deuchert, Adjamah and Pauly (2005) investigate the effect of Oscar nomination and awards on the financial success of the movie, in relation to the weekly returns and to the survival time.
The movies analysed are all released in the US in the years from 1990 to 2000. Excluding some outliers, the movies that have total box office revenues of less than 10000$, the final sample includes 32040 observations, for a total of 2244 movies. 144 of these movies were nominated in at least one of the five categories under consideration which are "best picture", "best actor/actress in a leading role", and "best actor/actress in a supporting role". 40 movies won in at least one of these categories. Data on box office returns, release dates, and details on genre and distributor are taken from Variety's Weekly Box Office Chart, on the website www.variety.com. Data on nominations, awards and the dates of Oscar ceremonies are available from the Internet Movie Database on the website www.IMDb.com.
To analyse the effect of quality on financial success the authors consider two different directions of causality: first, movies with higher quality might attract larger audiences in a given week and, hence, should show significantly higher average weekly box office revenues. Second, movie theatres are constrained by their seating capacities and thus only a certain number of tickets can be sold per time unit.
The output comes out from two different models.
In the first model, there is a focus on the impact of nomination and award on weekly returns. There is the assumption that the effects of nomination and awards do not diminish but are constant over time. The logarithm of the weekly box office revenue is the dependent variable. The independent variables are the number of weeks a movie has already been released, the logarithm of the box office revenue of the opening week, seasonal effects which are captured by dummy variables for the quarter of the year, movie-specific variables captured by dummy variables for genre and for each of the five major distributors, and the nominations and awards by including dummy variables in each of the categories. The Academy Awards categories considered are "best picture", "best actor/actress in a leading role", and "best actor/actress in a supporting role", because they are the most prominent ones.

Coefficients show that where 1% higher box office results of the opening week results in 0.3% higher box office revenue in the following weeks. However, there isn't a snowball effect of the first week's revenue that drives the weekly box office revenues of the following weeks up because the effect of the opening week is rather small. It seems more likely that blockbusters are successful from the first week onwards. Outputs show that a nomination in the categories "best picture" or "best actor in a leading role" increases the weekly box office revenue of the following weeks by more than 200%, while a nomination for "best actress in a leading role" increases weekly box office revenue by almost 150%. The coefficients for winning an award are not significant, so surprisingly there is no evidence for the hypothesis that winning an award generates revenue in addition to nominations.

In the second model, there is a time-dependent impact of nominations. In the model are introduced dummy variables for the nomination of Oscar winners and only nominated movies are set equal to one for all weeks following the announcement, including the week of the announcement itself. There are also dummy variables that capture whether a movie was still shown in movie theatres in the weeks following the nomination and on the week of the nomination.

Three hypotheses are tested in this second model: hypothesis 1, awards generate revenues in addition to the effects of nominations, then Oscar winning movies should show a significant jump in weekly box office revenue after the announcement of the winners (in week 7 after the announcement of nominations and the following weeks); hypothesis 2, the audience punishes movies that are nominated but do not win, with lower attention. Thus, these movies should show a significant fall in weekly box office revenue after the announcement of the winners; hypothesis 3, Oscar winners benefit more from a nomination than movies that are nominated but do not win, then the parameter estimates for winning movies should be considerably larger than the corresponding parameters for only nominated movies in the weeks before Oscar night.

The duration of nomination effects on box office revenue differs widely within categories, ranging from 29 weeks in the category "best picture" to only four weeks for "best actress in a supporting role". The impact of nominations exceeds the announcement of winners even for those movies that do not win. Surprisingly, longer-lasting nomination effects can be found for movies that did not win. Significant nomination effects of movies that did not win can be found until 20 weeks after the announcement of the nominations. Winning movies tend to enjoy a higher initial boost in revenues, until week 7, but this effect seems to diminish very quickly, while nomination effects for movies that did not win seem to be more constant.

The results show that, for the first hypothesis, there is no immediate effect of winning, since the parameters of week 7 and week 8 do not differ significantly from the parameters of week 6. For the

second hypothesis, there is no immediate punishment for not winning, as there are not significant differences for week 7 and week 8. For the third hypothesis, winning movies are not significantly different from only nominated movies.
In conclusion, the paper shows that the awards have a positive effect on the sales, but the main box office effect is generated primarily by the nominations.

Nelson et al. (2001) examine the impact of an Oscar nomination and award for best picture, best actor, and best supporting actor on a film's market share of theatres. Furthermore, they examine the average revenue per screen and the film's probability of survival.
The research data were obtained from Variety, a weekly trade journal for the entertainment industry. In the period 1978-1987, of 131 films were nominated for best picture, best actor, or best supporting actor awards. In addition, it was created a control sample of 131 non-nominated films: for each nominated film, a non-nominated film released in the same week was chosen, the highest ranked non-nominated film that remained on the top 50 charts for a minimum of five weeks was selected. The final combined sample of nominated and non-nominated films totals 4,544 observations. For each film, the authors compute the percentage of total screens on which the film appears and the average revenue per screen.
Observing the descriptive statistics, the authors find evidence of seasonal fluctuations, generally reaching a peak around Christmas, declining in the late winter and spring months, increasing during the summer vacation months, and then declining again in early fall.
Two OLS models are created for the estimation of the award's effect. In model 1 the impact of a nomination is captured by the number of nominations a film receives for best supporting actor, best actor, and best picture. The model 2 is more flexible, it has more variables that allow to overcome some shortcomings of the first model.
The parameter estimates common to both models are similar in sign, magnitude, and statistical significance. A nomination or award for best supporting actor appears to have little if any impact on the percentage of total screens on which the film appears and on the average revenue per screen. A nomination for best actor has a positive and statistically significant impact on the percentage of total screens on which the film appears in both models and a positive but insignificant effect on the average revenue per screen. An award for best actor has a positive and statistically significant effect on both the variables listed above in both models. Finally, a nomination and award for best picture have a positive and significant impact on both the variables in model 1.
Using a likelihood ratio test in model 2, the authors are unable to reject the null hypothesis that

the impacts of a nomination and award are independent of the release date and constant in the weeks following the announcements of the nominations and awards. On the basis of these test, results they employ the estimates from model 1 in calculating the predicted values of an Oscar.
In the final step, they determine the impact of a nomination or award on the film's probability of survival. Films that receive Oscar nominations or awards generally remain on the Variety Top 50 chart longer than non-nominated films; an Oscar nomination or award thus enhances a film's probability of survival. A parametric survival function is used, based on the assumption of a Weibull distribution. The Weibull distribution allows for duration dependence and facilitates the incorporation of covariates. The results indicate that a nomination or an award for best picture has a positive and statistically significant effect on the survival of a film. In the weeks following the announcement of the awards, however, the films receiving an Oscar for best actor and best supporting actor experience a positive and statistically significant increase in the probability of survival. Finally, the negative and statistically significant coefficient for the lagged duration variable indicates that the probability of survival in the next spell is inversely related to the length of the previous spell. Thus, for example, films that were in the theatres for 20 weeks prior to the nominations have a lower probability of survival following the nominations than films that were in the theatres for 10 weeks prior to the nominations.
In conclusion, the results indicate that a nomination or award for the "top" prizes, such as best picture and actor, generally has a positive impact on a film's probability of survival, its market share of screens, and the average revenue per screen, while a nomination or award for "lesser" prizes, such as best supporting actor, has little if any impact on these variables. The authors conclude that Rosen's (1981) theory of superstars, in which small differences in talent or quality translate into large differences in earnings, may well be applicable to the motion picture industry. Finally, the competition for an Oscar may be viewed as a two-stage, single-elimination tournament, in which films first compete for a nomination with the survivors then competing for the award.

1.3 The Sanremo Festival

The Sanremo Festival is the most important Italian music prize, it is also called "Italian song festival". In 1951 Angelo Nicola Amato, the director of public relationships of the Sanremo casino, and the radio speaker Angelo Nizza, organized the first edition of the Sanremo Festival. From that year, the contest takes place every year in the period of February March. At the beginning, it took place in the Casinò theatre until 1976 and, from the following year, in the Ariston theatre; both the theatres are in the city of Sanremo; only in 1990 it took place in a different place, in the occasion of the 40th edition, because there was a larger audience to accommodate.

Until 1954, the Festival editions were transmitted exclusively through the radio. Subsequently to this date, the contest became a TV show, transmitted in Eurovision from the TV channel Rai Uno.
During the exhibition, the singer is always accompanied by an orchestra. Only during the 80s, the singers performed without the orchestra accompaniment, singing live on a previously registered musical base, or in playback.
The television audience peak was reached in 1987, with a share of 61%, followed by the year 1995 with a share of 66,42%.
The Eurovision Song Contest is inspired to the Sanremo Festival: in 1955 Europe had just emerged from the war and there was the expectation of a TV program which could involve different nations, therefore, it was created a Broadcasting European Union committee that inspired to the Italian Sanremo competition for the creation of the ESC.
The jury composition, that expresses an opinion for the final ranking, was different in the years.
There are two types of juries: a committee selects the songs that will participate to the Festival, a different jury votes for the final ranking.
Below we list the different juries typologies, which have followed during the years: experts jury, also called quality jury, composed by important people in the environment of art, music, entertainment and television; demoscopic jury, composed by a sample extracted by the usual music audiences; popular jury, composed by the live audience of the Festival and by different popular juries, spread in different Italian region, selected by age, sex and social class (in the years people were drawn from subscribers to the RAI Radio Televisione Italiana, subscribers to the principal Italian newspapers, telephone subscribers, components of social communities like barracks and hospices); televoting jury, composed by each Italian citizen who wants to vote using the telephone.

1.4 The data

We have data on the final ranking of the Sanremo Festival for 59 years, from 1959 to 2017, collected from the website of the RAI Radio Televisione Italiana *www.rai.it*, which organizes the event, and from the website *www.hitparadeitalia.it*, that faithfully collects data on the final ranking of the Festival. For all the years we have: name of the song, name of the artist, position in the final ranking. From 2002 to 2017 we have more detailed data on the percentage of votes attributed to each song in the ranking. The votes are expressed in percentage, not in absolute value, because the number of participants to the Festival, the number of judges and the jury composition are different for each year. Furthermore, for 8 years, from 2010 to 2017, we have the vote percentage of the different jury: demoscopic jury, expert jury, televoting, quality jury, orchestra jury, golden share pressroom jury. The final ranking for the last 8 years of the Festival is double, because in the final evening of the event, in a first moment, all the songs in competition receive a vote, then in a second moment, only the first three ranked receive another vote that ultimately decides the winner of the Prize.

For the same period of 59 years, we collected data on the Hit parade from the website *www.hitparadeitalia.it*. Hit parade is a weekly ranking of the most sold songs in Italy. It considers, from different official sources, the songs with the highest sales in Italy. It contains, obviously, not only Italian songs but also international songs sold in Italy. For the last years, it considers the revenues that derive from new ways to listen to music: the streaming. From the website are available data for each week for the first 100 songs from 2009 to 2017, for the first 20 songs from 1985 to 2008, and for the first 10 songs from 1959 to 1984.

The best choice for data on economic success was to have precise data on the weekly sales, but unfortunately these are not available; consequently, the weekly Hit parade ranking is a good proxy for sales. For each week we have the song title, the singer, the ranking position, the position of the previous week and the date of the week.

1.5 Descriptive statistics

We have data on 59 years of the Sanremo Festival, from 1959 to 2017. For each year we have 3 finalists of which one is the winner of the Sanremo Prize (the prize is assigned to the first, but also the second and the third ranked songs in the Festival have visibility because they are on the podium). In our sample we have in total 1651 songs: the 203 that are the finalists for the Prize are considered as "treated" units in our analysis (in some years we have more than three finalists because competition rules change over the years, for this reason, the finalist songs are in total 203 and not $177 = 59 \times 3$), while the remaining 1448 constitute our control units.

We use a Regression Discontinuity Design to measure the impact that winning the Sanremo Festival has on a song's economic success. We employ a sharp RDD, following the model of Ponzo and Scoppa (2015).

We create a variable that gives points to each song, with reference to their ranking position. The variable gives 100 points to the first ranked song in the Hit-parade ranking, and one point less to the other songs, as they are under in the ranking. We impute zero to songs not ranked in the Hit-parade. This variable is called "Points in Hit-parade".

Another ranking variable is "Ranking in Sanremo", a variable that gives increasing points to the songs, as they are under in the ranking.

We set a dummy "Finalists (first 3 songs)" equal to one for the finalists of the Sanremo Festival.

The first variable we use as a proxy for song sales is the sum of the points that we created for the Hit-parade ranking: we sum the points of the song in the different weeks a song is present in the Hit-parade. We call this variable “Total Points in Hit-parade”.

The second variable we use as a proxy for song sales is the sum of the number of weeks that this song is present in the Hit-parade. We call this variable “Weeks in Hit-parade”.

Table 1 shows the descriptive statistics of our variables. Our sample is limited to the songs that participate to the Sanremo Festival. We drop all the other songs.

Table 1: Descriptive statistics. Analyses on Total Points in Hit-parade (Years 1959-2017)

Variables	Obs	Mean	Std. Dev.	Min	Max
Total Points in Hit-parade	1651	2.334	5.036	0	63.03
Winner (First Song)	1651	0.043	0.204	0	1
Finalists (First 3 Songs)	1651	0.122	0.328	0	1
Presence in Hit-parade	1651	0.331	0.471	0	1
Weeks in Hit-parade	1651	3.056	6.519	0	95
Year of Sanremo	1651	1982.263	17.084	1959	2017
Ranking in Sanremo	1651	17.899	10.862	1	29
Previous Weeks in Hit-parade	1651	16.226	30.886	0	253
Female	1651	0.368	0.482	0	1
Featuring	1651	0.039	0.194	0	1
Group	1651	0.145	0.352	0	1
Foreign	1651	0.125	0.331	0	1
Votes % Normalized 1st Place	313	-0.089	0.090	-0.310	0.366
Votes % Normalized 3rd place	313	-0.021	0.071	-0.120	0.576

The forcing variable of our RDD model is the variable “Ranking in Sanremo”. For this variable, the cut-off is the third place in the Sanremo ranking, and it refers to the songs that win the Prize. The treatment status “Finalists (first 3 songs)” is a deterministic and discontinuous function of the Sanremo ranking.

In order to estimate a treatment effect, the sharp RDD compares the outcome of units just above the threshold with the outcome of units just below the threshold. In terms of our research, we compare the sales of those songs that arrive in the final, that are the songs above the fourth position in the Sanremo ranking, with the songs that don’t receive the prize, that are the songs below the third position in the Sanremo ranking. The Sanremo ranking should express the intrinsic quality of the songs. We take into account this using a flexible polynomial function of Sanremo ranking. We assume that, in the absence of a treatment, the relationship between the outcome variable and the Sanremo ranking position is continuous in the neighbourhood of the cut-off point. For this reason, any jump of the dependent variable in proximity of the cut-off can be interpreted as evidence of a treatment effect.

We use a parametric approach, in line with most of the papers analysed in the literature.

1.6 First application: effects on total points in hit-parade (a proxy for sales)

The following equation (1) models the dependent variable "Total points in Hit-parade" of song *i* competing in year *t*:

$$Total\ points\ in\ Hit\ parade_{it} = \beta_0 + \beta_1 Finalists3_{it} + \beta_2 Ranking\ in\ Sanremo_{it} + \lambda_t + \gamma_t + \varepsilon_{it} \tag{1}$$

Total points in Hit-parade, the dependent variable, is a proxy for song sales.

Finalists is the dummy variable referred to the three songs that each year receive the Sanremo Prize.

Ranking in Sanremo is the variable referred to the Sanremo ranking, we use the threshold at the 3rd place of the Sanremo ranking to verify if there is a jump in the RDD plot.

In addition to the variables explained above, there are other dummy variables:

λ_t represents the time dummies, for each different year;

γ_t represents the Hit-parade ranking dummies, for each different range of the Hit-parade ranking, that can differ in the years according to the number of positions expressed in the ranking. There could be 10, 20, 100 or 200 positions in the Hit-parade rankings, in different years. In Table 2 we show the outcomes of this analysis. We create a linear trend model and OLS estimates of the equation, using the Hit-parade ranking as the dependent variable and as a proxy for the sales, are the following:

- in column (1) we only control for the finalists, without the time dummies and without the Hit-Parade dummies. The coefficient on Finalists is large and highly statistically significant, with a t-stat of 5.53. As expected, the position in the Sanremo Ranking is negatively related to the proxy for sales: the best ranked songs in Sanremo have more points in Hit-parade, then higher sales on the music market. Arriving at the first three positions in Sanremo ranking increases by 3.28 the points used as a proxy for sales. The coefficient on Ranking in Sanremo is negative and highly statistically significant, with a t-stat of -6.15. This is in line with our expectations: the first ranked songs of Sanremo Festival have the lowest points in the Ranking (1 for the first, 2 for the second, and so on);
- in column (2), we control for time dummies (one for each year). We find that the effect of the Sanremo Prize is smaller in column (2) respect to that in column (1), however the results are statistically significant;
- in column (3), we control for Hit-parade ranking dummies, because in different years we collected data with different range of the Hit-parade ranking (there could be 10, 20, 100 or

200 positions in the Hit-parade rankings). We find that the effect of the Sanremo Prize is smaller in column (3) respect to that in column (2), and the statistical significance is maintained only for the variable Finalists, not for the Ranking in Sanremo;

- in column (4) we control for both time dummies and Hit-parade ranking dummies. We have a higher adjusted R-squared, this implies that column (4) is a more complete specification of our estimates;
- in column (5) we add some control variables referred to the singer: Female (the gender, equal to 1 if the artist is female, equal to 0 otherwise), Featuring (equal to 1 if the artist sings his song in couple with another singer, equal to 0 otherwise), Group (equal to 1 if there is more than one artist that form a musical group, equal to 0 otherwise), Foreign (equal to 1 if the artist comes from a foreign country different from Italy, equal to 0 otherwise). Within these control variables, the only significant one is Foreign: it has a statistical significance, with a t-value of -2.39 and it has a negative impact on the dependent variable;
- column (6) expresses the most complete interpretation, because we control for time dummies, Hit-parade ranking dummies, for the four control variables expressed in column (5) and for another control variable: Previous Weeks in Hit-parade, that expresses the presence in Hit-parade of the same singer, in the weeks and years previous to that specific Sanremo Festival. With this variable, we can control for the popularity of the artist, it represents an index of fame: the more week the singer is present in Hit-parade, the more it is famous. The variable Finalists is statistically significant with a t-stat of 4.85 and a coefficient of 2.625. The variable Ranking in Sanremo maintains its relevance, with a t-stat of -5.36, and it is negatively related to the dependent variable, with a coefficient of -0.081. The control variable Foreign maintains its negative and low statistical significance.

Table 2: Regressions for the impact of the Sanremo Prize on Total Points in Hit-parade.

Dependent variable: Total Points in Hit-parade	(1)	(2)	(3)	(4)	(5)	(6)
Finalists (First 3 Songs)	3.280***	2.904***	2.032***	1.739***	2.915***	2.625***
	(0.593)	(0.567)	(0.511)	(0.507)	(0.568)	(0.541)
Ranking in Sanremo	-0.078***	-0.096***	-0.002	-0.021*	-0.095***	-0.081***
	(0.013)	(0.016)	(0.010)	(0.012)	(0.016)	(0.015)
Previous Weeks in Hit-parade						0.039***
						(0.006)
Female					-0.246	-0.182
					(0.226)	(0.220)
Featuring					-0.131	-0.168
					(0.701)	(0.705)
Group					0.387	0.496
					(0.383)	(0.378)
Foreign					-0.895**	-0.668*
					(0.375)	(0.367)
Constant	3.324***	4.904***	0.000	4.000***	5.045***	3.978***
	(0.304)	(0.676)	(0.221)	(0.796)	(0.696)	(0.826)
Time dummies	NO	YES	NO	YES	YES	YES
Hit-parade ranking dummies	NO	NO	YES	YES	YES	YES
Observations	1,651	1,651	1,651	1,651	1,651	1,651
R-squared	0.113	0.217	0.450	0.482	0.221	0.271

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

In Table 3 we show an in-depth analysis of our first model. We try to control one of the most important threats to the internal validity of RDD (we want to capture the possible discontinuity) with the adding of the second and the third degree of Sanremo Ranking, and with different degrees of the interaction term. We assume different polynomial form in our regression to test if the functional form between the outcome and the forcing variable is different. We use polynomials of second or third degree to capture possible existing non-linearities. Our aim is to avoid confusing these non-linearities for discontinuities. We also use interaction terms between Ranking and Finalists to model different functional forms on the two sides of the cutoff:

- in column (1) we control for time dummies and for Hit-Parade dummies. The coefficient on Finalists is large and highly statistically significant, with a t-stat of 3.43. The coefficient on Ranking in Sanremo is negative and statistically significant, with a t-stat of -1.75; as expected, the position in the Sanremo Ranking is negatively related to the Total points in Hit-parade and to the music market sales. Arriving to the first three positions in Sanremo ranking increases by 1.74 the points used as a proxy for sales;

- in column (2) we add the variable Ranking in Sanremo^2 with the aim of testing the significance at the second degree of our forcing variable. The statistical significance is respected, although not highly, for the second degree, with a t-stat of 1.85;
- in column (3) we add also the third degree of the variable Ranking in Sanremo. With the addition of the third degree in Ranking, we lose the statistical significance of the Finalists variable, even if the positive value of the coefficient is confirmed, but the t-value is 1.15;
- in column (4) we add the interaction term: a variable that tests the interaction between the ranking in Sanremo and the Finalists songs (first 3 positions) to control for different functional forms on the two sides of the cutoff. Like in column (1), it is respected the coefficient direction and the statistical significance of Finalists and Ranking in Sanremo;
- in column (5) and (6) and we add the interaction term respectively squared and cubed. Here the coefficient of the Finalist variable turns out to be not significant, whit a t-stat of respectively 0.90 and 1.19, anyway the coefficient is positive.

In these models, we notice high instability regard to the estimate of the coefficient of Finalists. The instability is accentuated in columns (3), (5) and (6) of Table 3, probably due to the fact that, inserting in the model different degrees of ranking and interaction terms, it is more difficult to respect the statistical significance if the effect is not strong. The situation will be the same in Table 6. In both cases, we consider columns (1), (2), (4) and (5) as the most affordable models, because we lose significance with the adding of third degree functional forms that corresponds to columns (3) and (6) of both the tables.

Table 3: Regressions for the impact of the Sanremo Prize on Total Points in Hit-parade: first, second and third degree of Sanremo ranking. With the addition of the interaction term.

Dependent variable: Total Points in Hit-parade	(1)	(2)	(3)	(4)	(5)	(6)
Finalists (First 3 Songs)	1.739***	1.213*	0.947	2.531**	3.093	1.996
	(0.507)	(0.657)	(0.822)	(1.049)	(3.441)	(1.672)
Ranking in Sanremo	-0.021*	-0.149*	-0.295	-0.020	-0.132	-0.177
	(0.012)	(0.087)	(0.292)	(0.012)	(0.087)	(0.311)
Ranking in Sanremo^2		0.004	0.015		0.003	0.007
		(0.002)	(0.021)		(0.002)	(0.023)
Ranking in Sanremo^3			-0.000			-0.000
			(0.000)			(0.000)
Interaction				-0.394	-1.759	-1.893
				(0.433)	(4.198)	(4.317)
Interaction^2					0.366	-0.573
					(1.045)	(1.276)
Interaction^3						0.156
						(0.385)
Constant	4.000***	4.796***	5.319***	3.990***	4.685***	4.854***
	(0.796)	(0.989)	(1.425)	(0.795)	(0.987)	(1.486)
Time dummies	YES	YES	YES	YES	YES	YES
Hit-parade ranking dummies	YES	YES	YES	YES	YES	YES
Observations	1,651	1,651	1,651	1,651	1,651	1,651
R-squared	0.482	0.483	0.483	0.482	0.483	0.483

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

The following plots offer a better explanation of our results. The aim of an RDD model is to find a jump on the threshold variable. We show now the graphs that confirm the validity of our research.
Figure 1 expresses a transparent graphical analysis for our RDD model, showing the impact of the Sanremo Prize on the Total points in Hit-parade. It is a second-degree function, referred to the column (2) of Table 3. We clearly recognize a jump on the variable Ranking of Sanremo, corresponding to the threshold of the 3rd place. The predicted values refer to a regression of Total Points in Hit-parade on a second order polynomial in Ranking of Sanremo. The clear jump showed in the figure represents the effect of the Sanremo Prize on the song sales.
The first three best ranked songs of Sanremo have a better placement in the Hit-parade, compared with the other ranked songs in the Sanremo ranking. This means that the first three songs that are in the Sanremo final each year have greater sales.
Figure 2 is the graphical representation of column (3) Table 3. It expresses the third-degree function of the model. Here the jump is less clear, related to the fact that the variable Finalists loses its statistical significance.

Figure 3 and Figure 4 express respectively the second and the third degree of the RDD model, with the addition of the interaction term. They are a graphical representation of column (5) and (6) Table 3. The jump is clear, despite the statistical significance of Finalists is not established.

Figure 1: RD plot for the impact of the Sanremo Prize on the Total points in Hit-parade. Cut-off 3rd place of the Sanremo ranking. Second degree function.

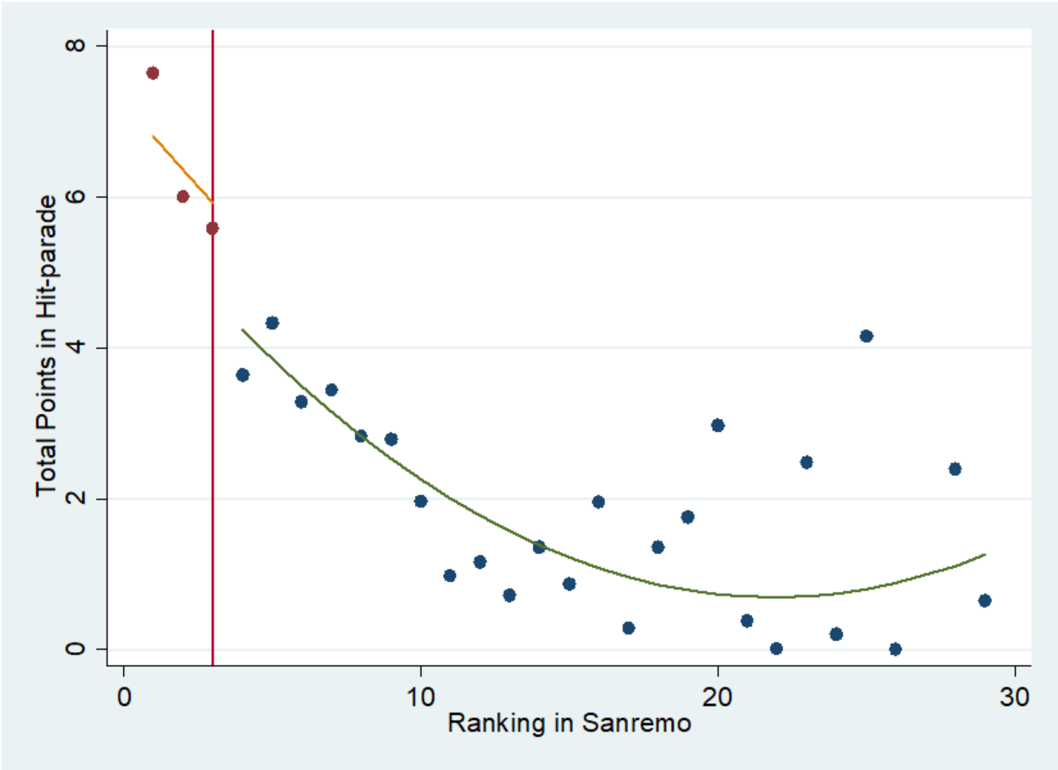


Figure 2: RD plot for the impact of the Sanremo Prize on the Total points in Hit-parade. Cut-off 3rd place of the Sanremo ranking. Third degree function.

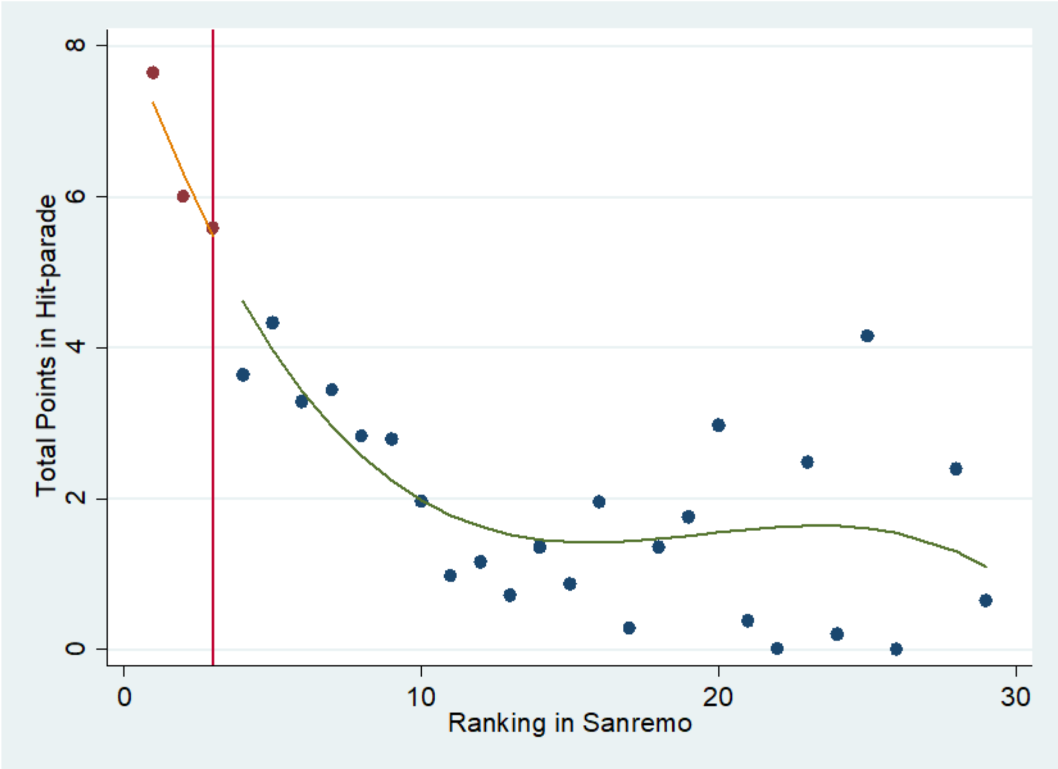


Figure 3: RD plot for the impact of the Sanremo Prize on the Total points in Hit-parade. Cut-off 3rd place of the Sanremo ranking. Second degree function. With the interaction term.

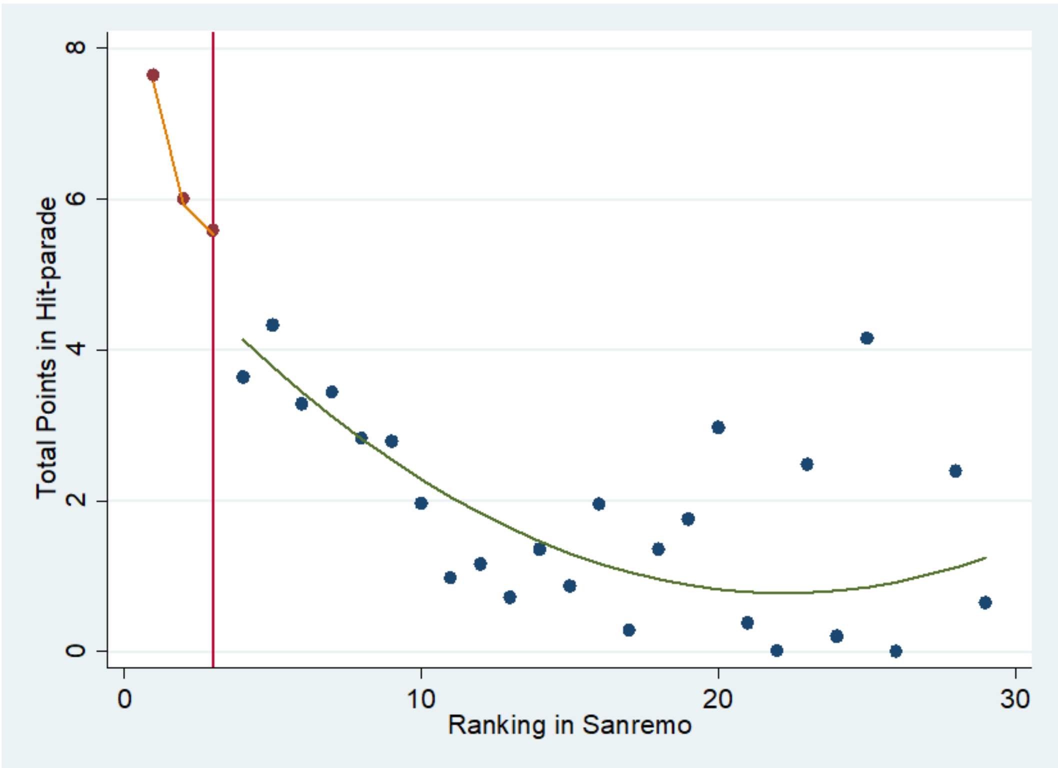
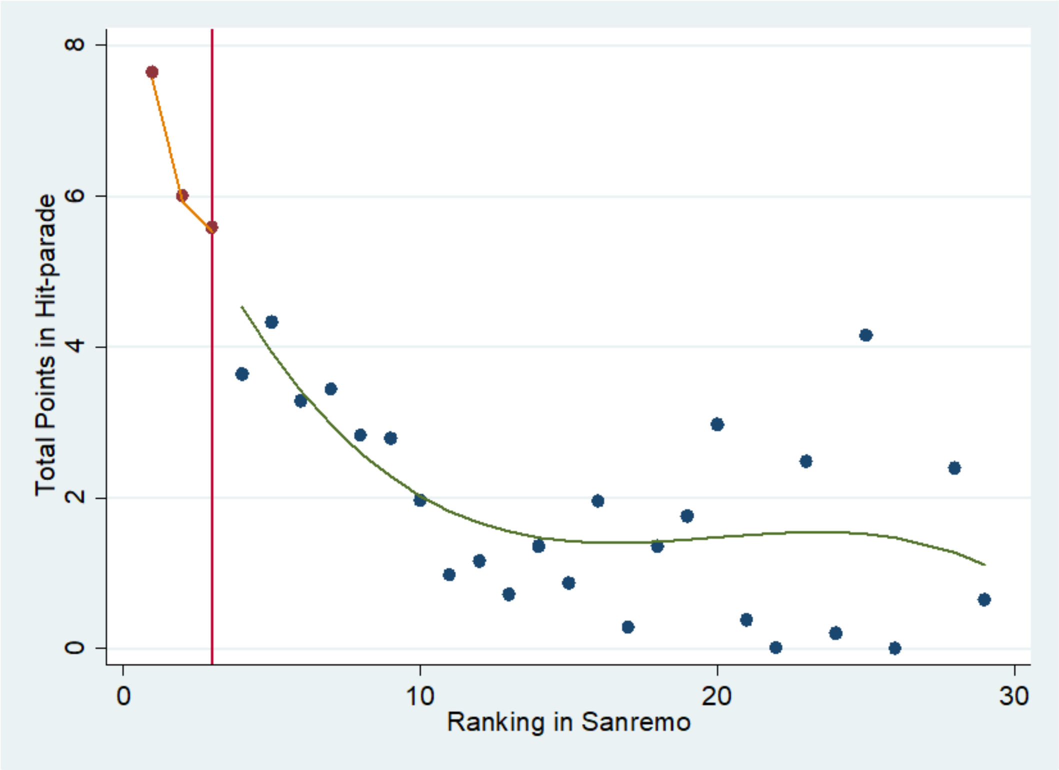


Figure 4: RD plot for the impact of the Sanremo Prize on the Total points in Hit-parade. Cut-off 3rd place of the Sanremo ranking. Third degree function. With the interaction term.



In Table 4 are expressed the local windows output of the regressions for the impact of the Sanremo Prize on Total Points in Hit-parade, with the addition of the interaction term. Local windows are used for control if, reducing the sample around the threshold, the effects remain the same or if it changes. If the jump is verified also in the local windows, our results gain a major robustness. In these regressions, local windows refer respectively to the first 28, 15 and 10 songs in the Ranking of Sanremo.

The statistical significance of Finalists is respected until column (3), that corresponds to the first 10 ranked songs, with a descending t-stat and a positive sign. The variable Ranking in Sanremo maintains his negative sign and it is also significant until column (3).

Table 4: Regressions for the impact of the Sanremo Prize on Total Points in Hit-parade. With the addition of the interaction term. Local window for the first 28, 15, 10 and 6 songs in the ranking.

Dependent variable Total Points in Hit-parade	(1)	(2)	(3)
Finalists (First 3 Songs)	3.959***	2.783**	2.783*
	(1.345)	(1.307)	(1.494)
Ranking in Sanremo	-0.142***	-0.347***	-0.340***
	(0.042)	(0.058)	(0.131)
Constant	6.014***	8.104***	9.319***
	(0.884)	(0.891)	(1.183)
Interaction	-0.778	-0.751	-0.756
	(0.544)	(0.504)	(0.520)
Time dummies	YES	YES	YES
Hit-parade ranking dummies	NO	NO	NO
Local Windows	28 ranking	15 ranking	10 ranking
Observations	1,148	772	587
R-squared	0.209	0.284	0.268

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

Here are the graphical RDD explanation of the four different local windows showed in Table 3.2. In Figures 5, 6, 7 and 8 the threshold remains stable at the 3rd place of the Sanremo Ranking, it changes only the size of the Ranking because we cut the final tail. What is common in all the figures is that the slope of the line is different on the right and on the left of the cut-off: this confirms the significant effect of interaction term Finalists*Ranking in Sanremo. Local windows are a robustness check for the consistency on our hypothesis. We can affirm that the hypothesis that the First three ranked songs have more points in the Hit-parade ranking, then they sell more on the music market, is also confirmed by the restriction of our sample, until the first 10 ranked songs in the Sanremo Ranking.

Figure 5: RD plot for the impact of the Sanremo Prize on the Total points in Hit-parade. Cut-off 3rd place of the Sanremo ranking. With the interaction term. Local window for the first 28 songs.

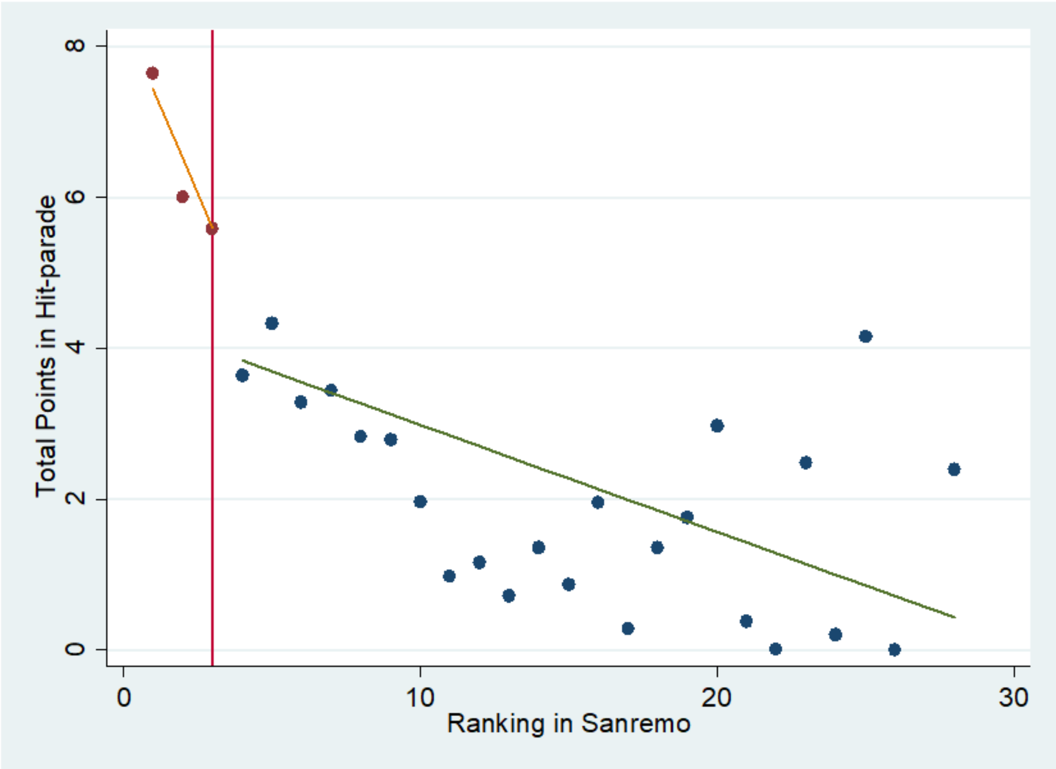


Figure 6: RD plot for the impact of the Sanremo Prize on the Total points in Hit-parade. Cut-off 3rd place of the Sanremo ranking. With the interaction term. Local window for the first 15 songs.

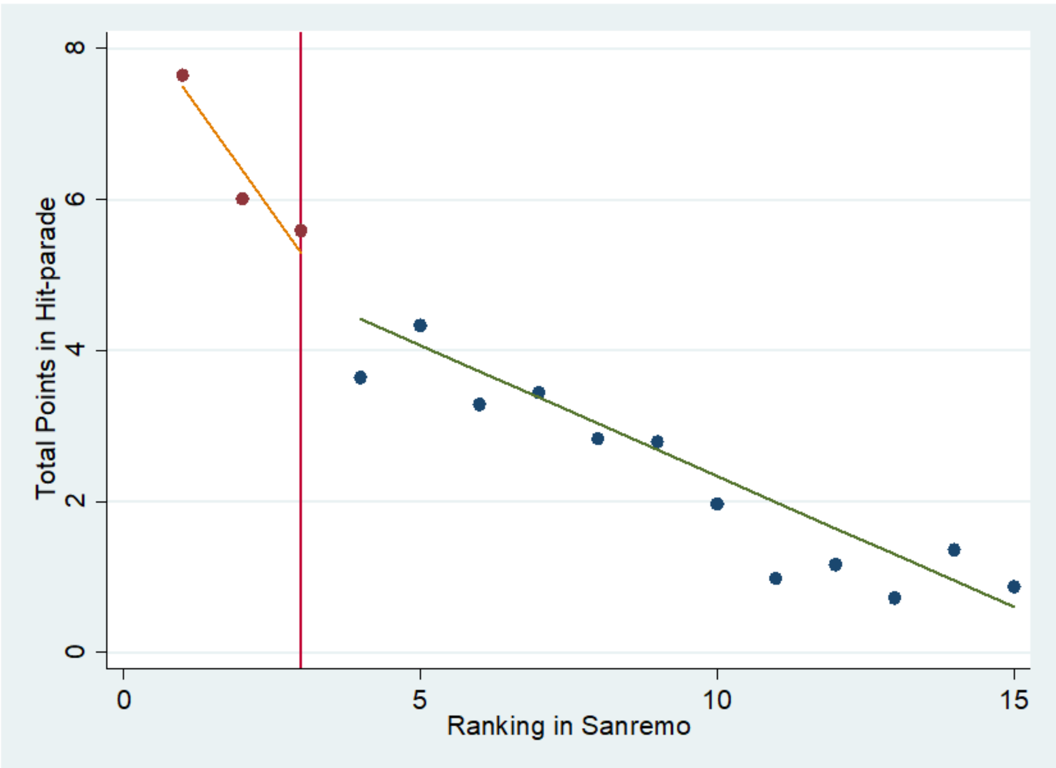


Figure 7: RD plot for the impact of the Sanremo Prize on the Total points in Hit-parade. Cut-off 3rd place of the Sanremo ranking. With the interaction term. Local window for the first 10 songs.

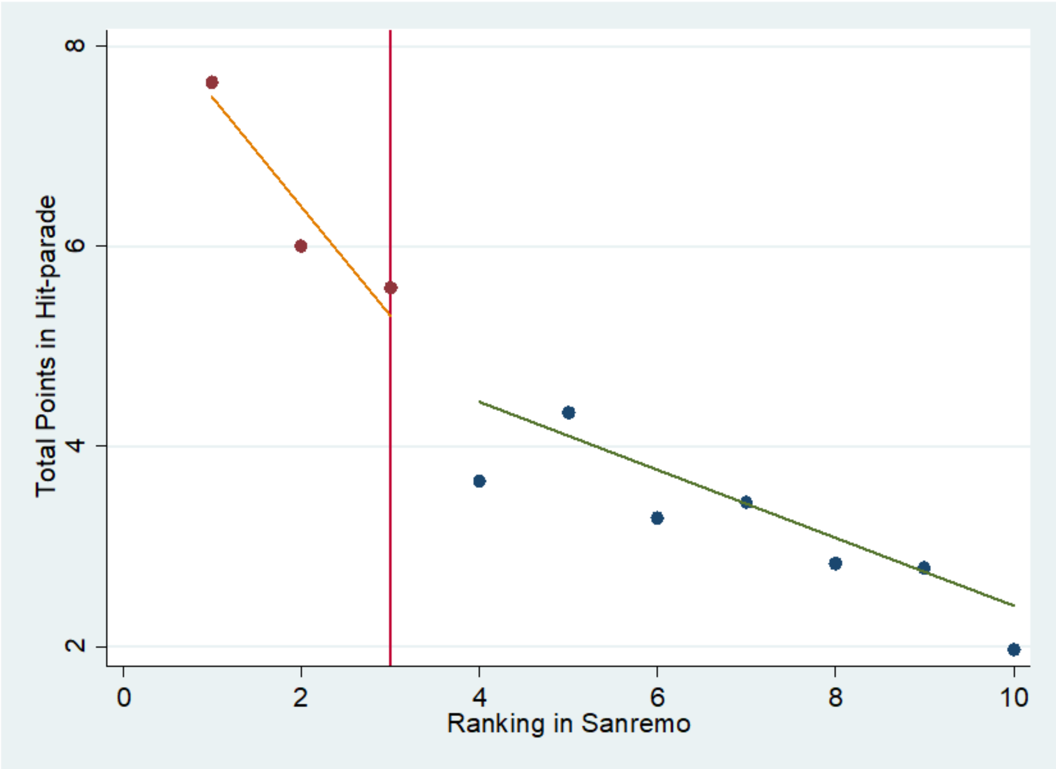
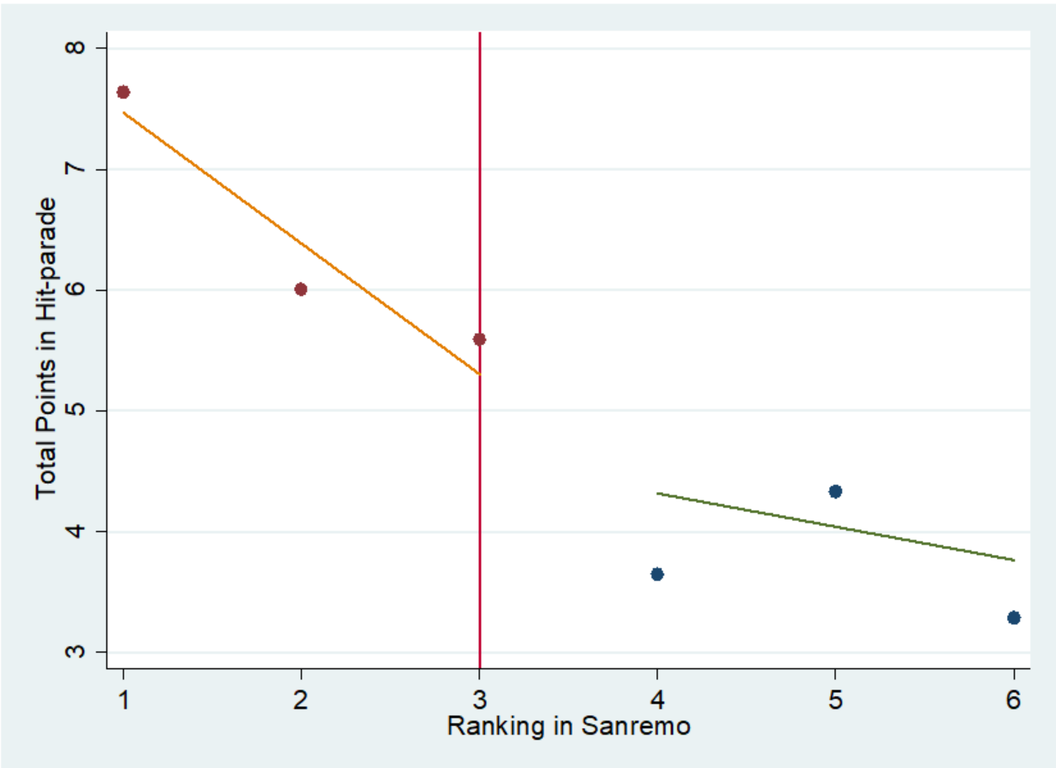


Figure 8: RD plot for the impact of the Sanremo Prize on the Total points in Hit-parade. Cut-off 3rd place of the Sanremo ranking. With the interaction term. Local window for the first 6 songs.



1.7 Second application: effects on weeks in hit-parade

The following equation (2) models the dependent variable "Weeks in Hit-Parade" of song *i* competing in year *t*:

$$Weeks\ in\ Hit\ parade_{it} = \beta_0 + \beta_1 Ranking\ in\ Sanremo_{it} + \beta_2 Finalists_{it} + \lambda_t + \gamma_t + \varepsilon_{it} \tag{2}$$

Weeks in Hit-Parade is a proxy for song sales, we sum the number of weeks that this song is present in the Hit-parade.

The other variables are the same as the previous equation (1). We use equation (2) for control the same effect of the Sanremo Prize on a proxy for Sales, different from our main proxy. The results confirm that of the first model.

In Table 4 we show the outcomes of our second analysis. OLS estimates on the equation (2), using the weekly presence in Hit-parade as the dependent variable and as a proxy for the sales, are the following:

- as in the previous table, in column (1) we only control for the three finalists, without the time dummies and without the Hit-Parade dummies. Also here, the coefficient on Finalists is large and highly statistically significant, with a t-stat of 4.61, and the position in the Sanremo Ranking is negatively related to Total points in Hit-parade with the same t-stat of -6.54. Reaching the first three positions in Sanremo ranking increases by 3.681 the number of weeks in which a song is present in the Hit-parade;
- in column (2), we control for time dummies. Also here, we find that the effect of the Sanremo Prize is smaller in column (2) respect to that in column (1), and the results maintain their statistical significance;
- in column (3) we control for Hit-parade ranking dummies because in different years we collected data with different range of the Hit-parade ranking. Also here, we find that the effect of the Sanremo Prize is smaller in column (3) respect to that in column (2), and the statistical significance is maintained only for the variable Finalists, not for the Ranking in Sanremo;
- in column (4) we control for both time dummies and Hit-parade ranking dummies. We have a higher adjusted R-squared, this implies that column (4) is a more complete specification of our estimates;
- in column (5) we add the same control variables referred to the singer: Female, Featuring, Group, Foreign. These control variables are not statistically significant;

- column (6) expresses the most complete outcome because we control for time dummies, Hit-parade ranking dummies, for the four control variables expressed in column (5) and for the control variable Previous Weeks in Hit-parade. The last one is statistically significant, with a t-stat of 2.98 and it is positively related to Total Points in Hit-parade. The variable Finalists is statistically significant with a t-stat of 3.08 and a coefficient of 2.020. The variable Ranking in Sanremo does not maintain its significance, with a t-stat of -1.13, despite it continues to be negatively related to the dependent variable, with a coefficient of -0.017.

The outcomes of Table 5 are in line with that of Table 2, this makes us confident that our results are robust because we obtain similar outcomes (that are slightly less statistically significant for Table 4) using two different type of measures that approximates the product sales

Table 5: Regressions for the impact of the Sanremo Prize on Number of weeks the song is present in Hit-parade.

Dependent variable: Weeks in Hit-parade	(1)	(2)	(3)	(4)	(5)	(6)
Finalists (First 3 Songs)	3.681***	3.444***	2.388***	2.118***	2.128***	2.020***
	(0.799)	(0.746)	(0.684)	(0.684)	(0.683)	(0.657)
Ranking in Sanremo	-0.106***	-0.105***	-0.007	-0.021	-0.021	-0.017
	(0.016)	(0.019)	(0.013)	(0.016)	(0.015)	(0.016)
Female					-0.283	-0.244
					(0.235)	(0.236)
Featuring					-0.126	-0.167
					(0.757)	(0.759)
Group					0.227	0.304
					(0.379)	(0.380)
Foreign					-0.162	-0.066
					(0.272)	(0.281)
Previous Weeks in Hit-parade						0.024***
						(0.008)
Constant	4.498***	9.422***	0.165	8.415***	8.553***	7.954***
	(0.391)	(0.768)	(0.286)	(0.885)	(0.894)	(0.997)
Time dummies	NO	YES	NO	YES	YES	YES
Hit-parade ranking dummies	NO	NO	YES	YES	YES	YES
Observations	1,651	1,651	1,651	1,651	1,651	1,651
R-squared	0.101	0.267	0.448	0.493	0.494	0.505

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

In Table 6 we show the analysis of our second model. We implement the OLS estimates of the equation (2), with the addition of the second and the third degree of Sanremo Ranking, and with different degrees of the interaction term:

- in column (1) we control for time dummies and for Hit-Parade dummies, without the interaction term. The coefficient on Finalists is large and highly statistically significant, with a t-stat of 3.09. As in the other tables, the position in the Sanremo Ranking is negatively related to Total points in Hit-parade and consequently to the music market sales. Reaching first three positions in Sanremo ranking increases by 2.19 the points used as a proxy for sales. The coefficient on Ranking in Sanremo is negative but not statistically significant, with a t-stat of -1.31;
- in column (2) we add the variable Ranking in Sanremo^2. The second degree of our forcing variable reduces the statistical significance of the variable Finalists, with a t-stat of 1.77. The coefficient is 1.49;
- in column (3) we add the third degree of the variable Ranking in Sanremo. Like in Table 2, with the addition of the third degree in Ranking we lose the statistical significance of the Finalists variable, even if the positive value of the coefficient is confirmed. The t-value is 1.01;
- in column (4) we add the interaction term between the Ranking in Sanremo and the Finalists songs (first 3 positions). Like in column (1), the coefficient has the expected sign and the statistical significance of Finalists and Ranking in Sanremo, with a high coefficient of Finalists 3.624;
- in column (5) and (6) and we add the interaction term respectively squared and cubed. Here the coefficient of the Finalist variable turns out to be not significant, whit a t-stat of respectively 0.73 and 1.23. Anyway, the coefficient is positive. While the variable Ranking of Sanremo continues to be not significant.

Table 6 is in line with the results of Table 3.

Table 6: Regressions for the impact of the Sanremo Prize on the Number of weeks the song is present in Hit-parade: first, second and third degree of Sanremo ranking. With the addition of the interaction term.

Dependent variable: Weeks in Hit-Parade	(1)	(2)	(3)	(4)	(5)	(6)
Finalists (First 3 Songs)	2.118***	1.494*	0.994	3.624***	3.523	2.646
	(0.684)	(0.844)	(0.989)	(1.399)	(4.821)	(2.160)
Ranking in Sanremo	-0.021	-0.173	-0.448	-0.020	-0.136	-0.184
	(0.016)	(0.107)	(0.358)	(0.016)	(0.105)	(0.367)
Ranking in Sanremo^2		0.004	0.025		0.003	0.007
		(0.003)	(0.026)		(0.003)	(0.027)
Ranking in Sanremo^3			-0.000			-0.000
			(0.001)			(0.001)
Interaction				-0.748	-1.340	-0.816
				(0.545)	(5.959)	(1.052)
Interaction^2					0.173	-0.536
					(1.477)	(1.811)
Interaction^3						0.118
						(0.547)
Constant	8.415***	9.359***	10.343***	8.396***	9.117***	9.297***
	(0.885)	(1.131)	(1.657)	(0.889)	(1.137)	(1.699)
Time dummies	YES	YES	YES	YES	YES	YES
Hit-parade ranking dummies	YES	YES	YES	YES	YES	YES
Observations	1,651	1,651	1,651	1,651	1,651	1,651
R-squared	0.493	0.494	0.494	0.494	0.494	0.494

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

The following figures offer a better explanation of our results with Number of weeks in Hit-parade as the dependent variable and confirm previous results.

Figure 9 shows the impact of the Sanremo Prize on the Number of weeks in Hit-parade. It is a second-degree function, referred to the column (2) of Table 5. Like in the previous figures, we clearly recognize a jump on the variable Ranking of Sanremo, corresponding to the threshold of the 3rd place, that confirms the effect of the Sanremo Prize on the song sales.

The first three best ranked songs of Sanremo have a major number of weeks of permanence in the Hit-parade, compared with the other ranked songs in the Sanremo ranking.

Figure 10 is the graphical explanation of column (3) Table 5. It expresses the third-degree function of the model. Here the jump is less clear, related to the fact that the variable Finalists lose its statistical significance.

Figure 11 and Figure 12 show respectively the second and the third degree of the RDD model, with the addition of the interaction term. They are a graphical explanation of column (5) and (6) Table 5. The jump is clear in Figure 11, despite Finalists is not statistically significant.

Figure 9: RD plot for the impact of the Sanremo Prize on the Number of weeks in Hit-parade. Cut-off 3rd place of the Sanremo ranking. Second degree function.

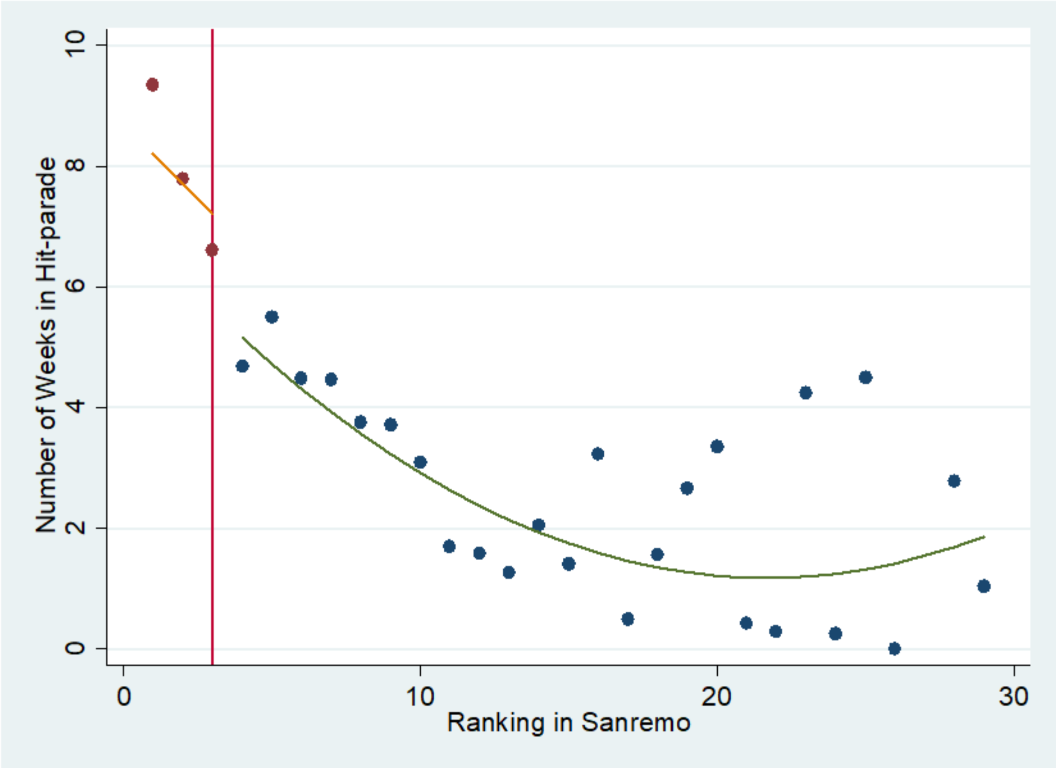


Figure 10: RD plot for the impact of the Sanremo Prize on the Number of weeks in Hit-parade. Cut-off 3rd place of the Sanremo ranking. Third degree function.

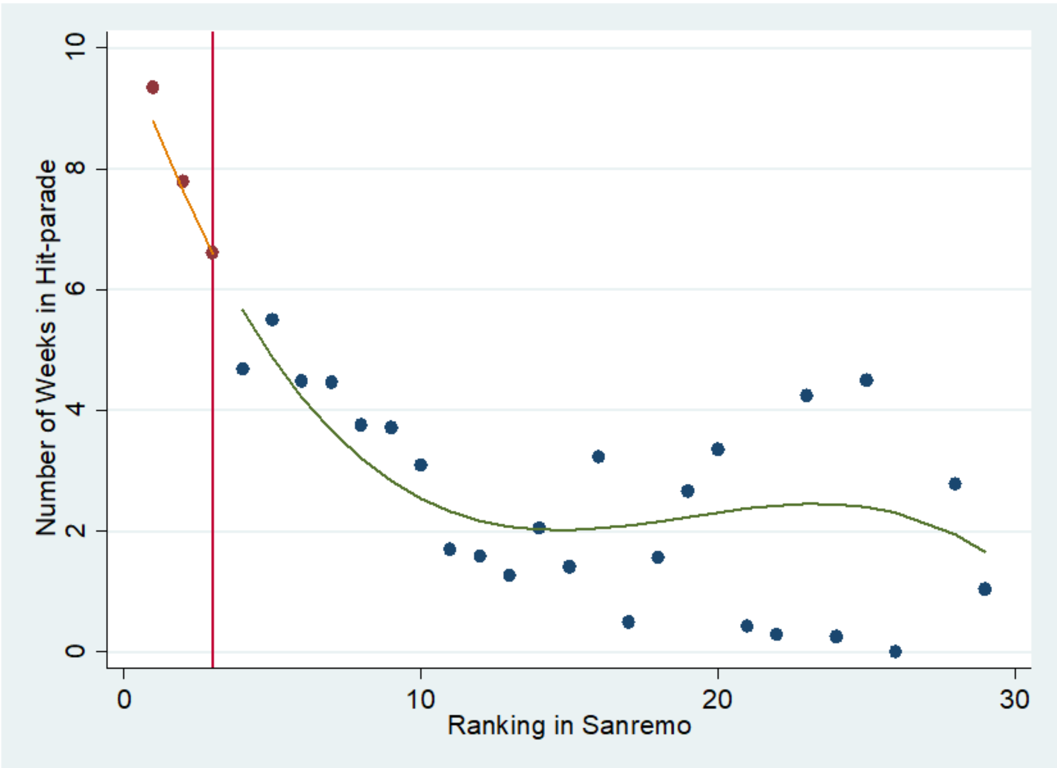


Figure 11: RD plot for the impact of the Sanremo Prize on the Number of weeks in Hit-parade. Cut-off 3rd place of the Sanremo ranking. Second degree function. With the interaction term.

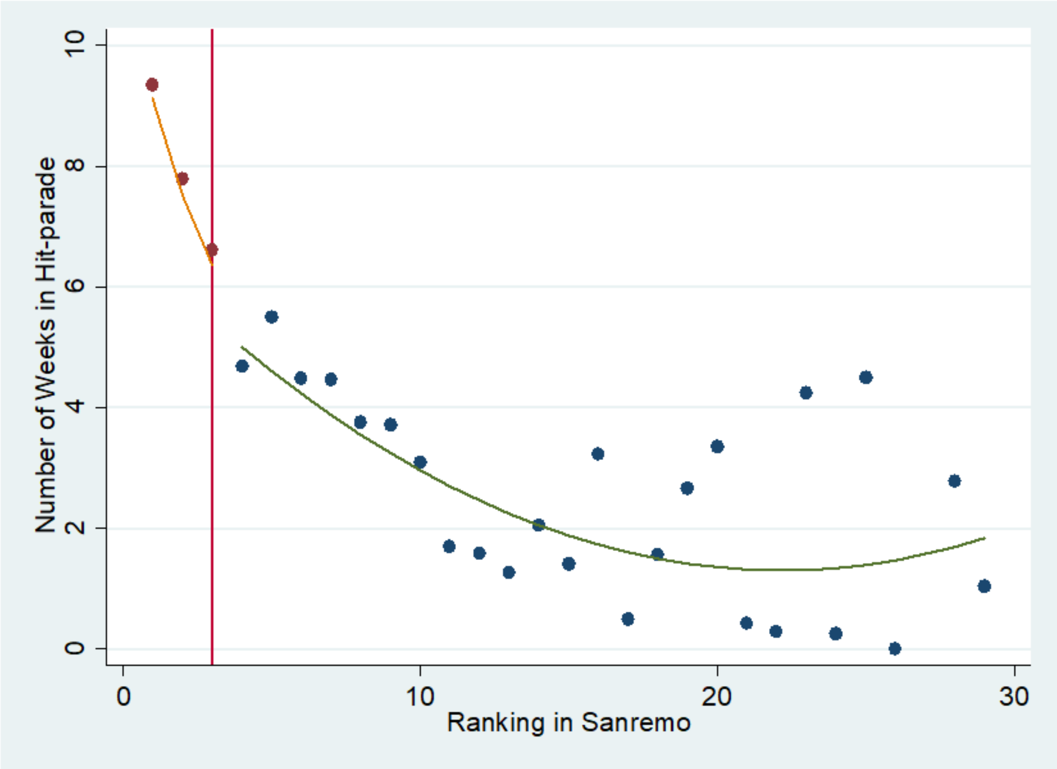


Figure 12: RD plot for the impact of the Sanremo Prize on the Number of weeks in Hit-parade. Cut-off 3rd place of the Sanremo ranking. Third degree function. With the interaction term.

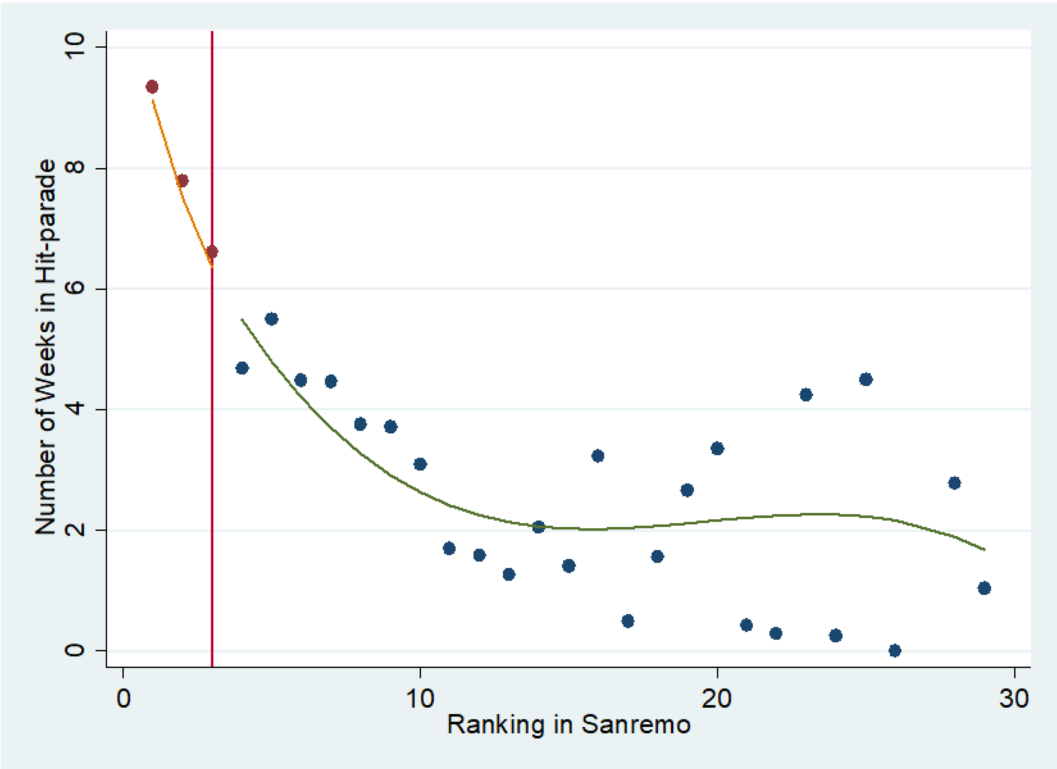


Table 7 shows the local windows output of the regressions for the impact of the Sanremo Prize on Number of Weeks in Hit-parade, with the addition of the interaction term. Similarly to the first model, also in our second model local windows refer respectively to the first 28, 15 and 10 songs in the Ranking of Sanremo, with a gradual reduction of our sample. Confirming our results, the statistical significance of Finalists is respected until column (3), that corresponds to the first 10 ranked songs, with a descending t-stat and a positive sign. The variable Ranking in Sanremo maintains his negative sign and it is also significant until column (3).

Table 7: Regressions for the impact of the Sanremo Prize on the Number of weeks the song is present in Hit-parade. With the addition of the interaction term. Local window for the first 28, 15, 10 and 6 songs in the ranking.

Dependent variable: Weeks in Hit-Parade	(1)	(2)	(3)
Finalists (First 3 Songs)	5.275***	3.918**	4.012**
	(1.733)	(1.713)	(1.913)
Ranking in Sanremo	-0.144***	-0.393***	-0.371**
	(0.050)	(0.069)	(0.161)
Interaction	-1.137*	-1.121*	-1.140*
	(0.667)	(0.641)	(0.657)
Constant	10.790***	13.345***	14.323***
	(0.940)	(0.944)	(1.329)
Observations	1,148	772	587
R-squared	0.270	0.333	0.320
Time dummies	YES	YES	YES
Hit-parade ranking dummies	NO	NO	NO
Interaction term	YES	YES	YES
Local Window	28	15	10

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

We report the RDD graphs below. These figures represent the four different local windows showed in Table 7.

Like in the previous local windows, in the Figures 13, 14, 15 and 16 the threshold remains stable at the 3rd place of the Sanremo Ranking, it changes only the size of the Ranking because we cut the final tail. Also in this case, the slope of the line is different on the right side and on the left side of the cut-off: the effect of interaction term Finalists*Ranking in Sanremo is significant. Furthermore, in our second model, thanks to the local windows robustness check, we can affirm that the hypothesis that the First three ranked songs remain for more weeks in the Hit-parade ranking.

Figure 13: RD plot for the impact of the Sanremo Prize on the Number of weeks in Hit-parade. Cut-off 3rd place of the Sanremo ranking. With the interaction term. Local window for the first 28 songs.

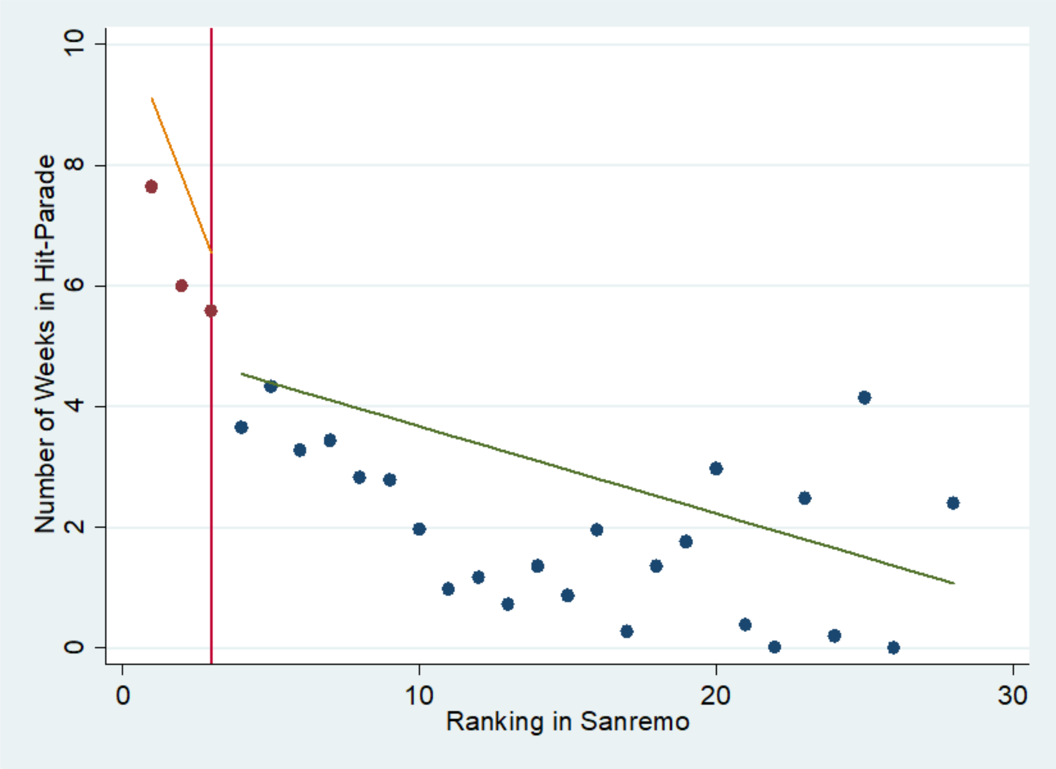


Figure 14: RD plot for the impact of the Sanremo Prize on the Total points in Hit-parade. Cut-off 3rd place of the Sanremo ranking. With the interaction term. Local window for the first 15 songs.

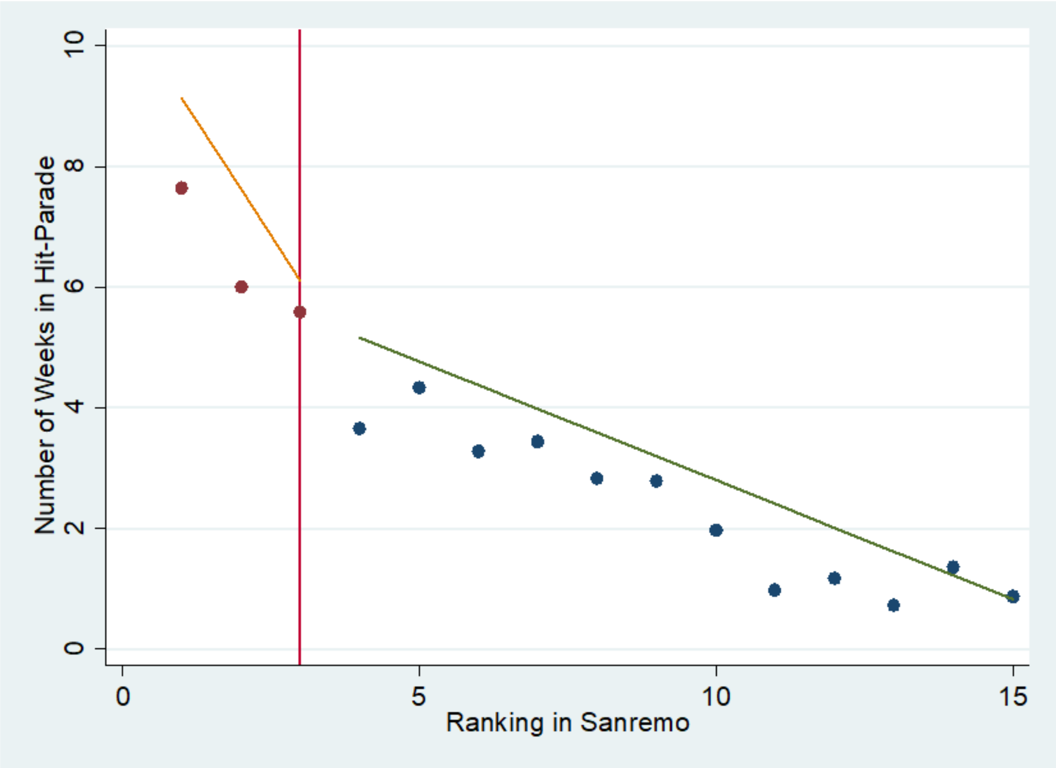


Figure 15: RD plot for the impact of the Sanremo Prize on the Total points in Hit-parade. Cut-off 3rd place of the Sanremo ranking. With the interaction term. Local window for the first 10 songs.

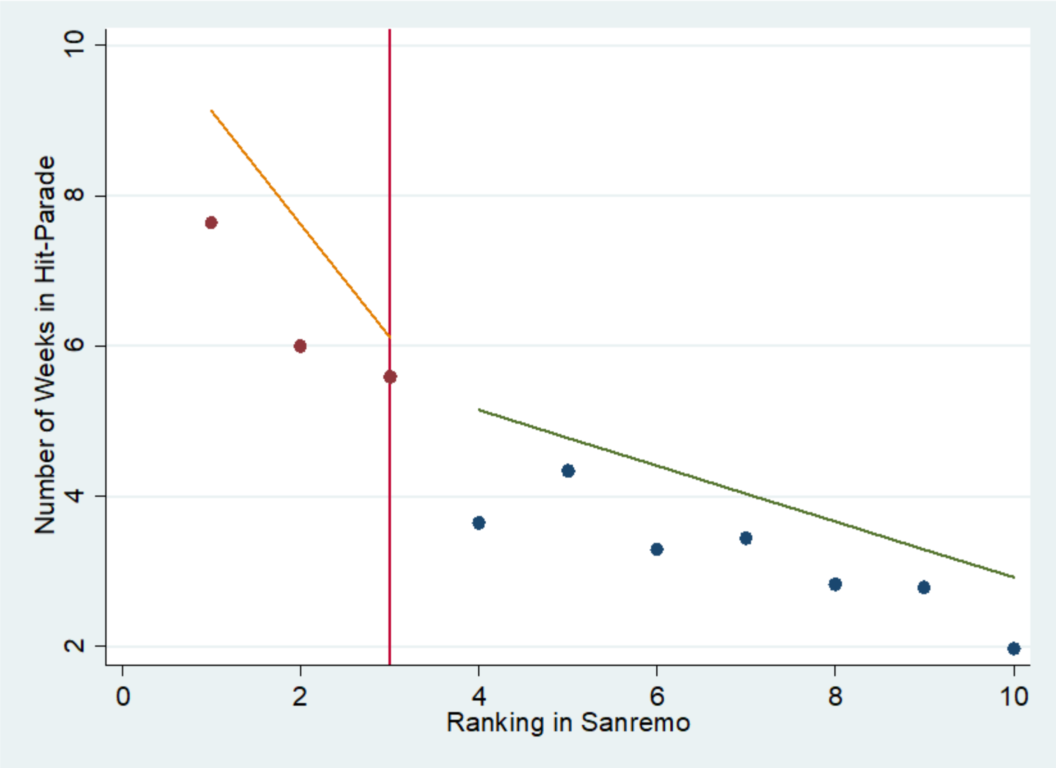
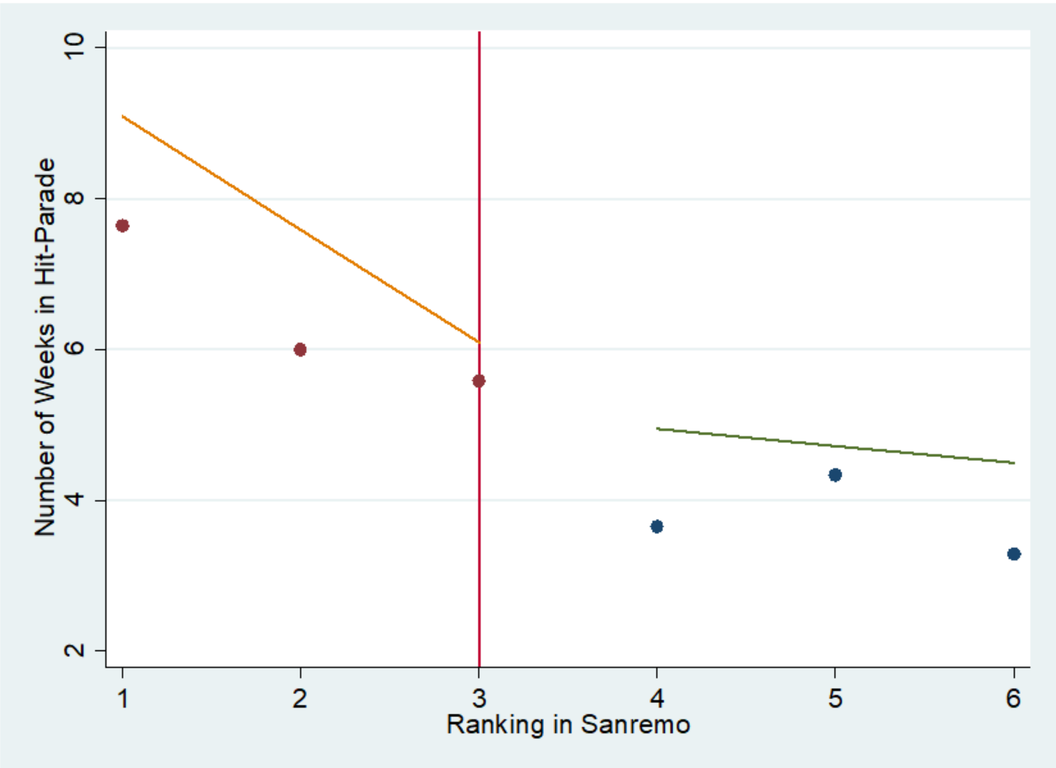


Figure 16: RD plot for the impact of the Sanremo Prize on the Total points in Hit-parade. Cut-off 3rd place of the Sanremo ranking. With the interaction term. Local window for the first 6 songs.



1.8 Third application: effects on total points in hit-parade using votes percentage

A third equation is used for the last 16 years of our database, from 2002 to 2017, because we have data on Votes percentage of the songs in the Sanremo Ranking only for these years.

$$Total\ points\ in\ Hit\ parade_{it} = \beta_0 + \beta_1 Finalists3_{it} + \beta_2 Votes\_normalized_{it} + \lambda_t + \gamma_t + \varepsilon_{it} \tag{3}$$

To construct the forcing variable *Votes*, we normalize the percentage number of jury votes received by each song (indexed by *i*) in each competition year (indexed by *t*) by subtracting from the real number of votes received, the votes received by the fourth ranked song in the competition plus one:

$$Votes\_normalized_{it} = Votes\_normalized_{it} - Votes\_normalized_{Ft} \tag{3.1}$$

Where *F* is the fourth ranked song in year *t*. Therefore, 0 is the cut-off: when $Votes\_normalized_{it}$ is equal to or greater than zero, the treatment of winning the Sanremo festival is received:

$$Sanremo\_Festival_{it} = \begin{cases} 1 & if \quad Votes\_normalized_{it} \geq 0 \\ 0 & if \quad Votes\_normalized_{it} < 0 \end{cases}$$

In Table 8 we show the outcomes of our equation (3). We use the Hit-parade ranking as the dependent variable and, as a forcing variable, we use the Votes Percentage normalized to the 3rd place of the Sanremo Ranking (normalization explained in Section 5). We collect the votes percentage only for the last 16 years of our dataset, for this reason, the number of observations is minor compared to the first two models:

- in column (1) we only control for the finalists, without the time dummies and without the Hit-parade dummies. The coefficient on Finalists is positive and statistically significant, with a t-stat of 1.91. As expected, the Votes Percentage in Sanremo Ranking is positively related to the Total points in Hit-parade: the songs that receive more votes in Sanremo have better points in Hit-parade, then better sales on the music market. Rising to the first three positions in Sanremo ranking increases by 1.888 the points used as a proxy for sales. The coefficient on Ranking in Sanremo is positive and highly statistically significant, with a t-stat of 4.26 and a coefficient of 14.911. This is in line with our expectations;

- in column (2), (3) and (4) we control respectively for time dummies, for Hit-parade ranking dummies and for both. We find that the effects of the Sanremo Prize and that of the Votes Percentage remains stable respect to that in column (1);
- in column (5) we add the same control variables referred to the singer: Female, Featuring, Group, Foreign. The significant variables within these are Female, with a positive coefficient, Featuring and Group, with a negative coefficient;
- even here column (6) expresses the most complete interpretation because we control for time dummies, Hit-parade ranking dummies, for the four control variables expressed in column (5) and for the variable Previous Weeks in Hit-parade. The variable Finalists is statistically significant with a t-stat of 1.94 and a coefficient of 1.858. The variable Votes Percentage maintains its validity, with a t-stat of 4.32, and it is positively related to the dependent variable, with a coefficient of 13.886. The added control variable Previous Weeks in Hit-parade is positively related to the dependent variable (coefficient 1.509), the other variables maintain significance and sign and it is added the significance of the variable Foreign, with a positive coefficient.

Table 8: Regressions for the impact of the Sanremo Prize on Total Points in Hit-parade, in terms of votes percentage for the last 16 years (2002-2016). Cut-off 3rd Place in the Sanremo ranking.

Dependent variable: Total Points in Hit-parade	(1)	(2)	(3)	(4)	(5)	(6)
Finalists (First 3 Songs)	1.888*	1.802*	1.807*	1.596*	1.815*	1.858*
	(0.989)	(0.970)	(0.991)	(0.913)	(0.947)	(0.959)
Votes % Normalized 3rd Place	14.911***	14.003***	14.722***	13.207***	14.606***	13.886***
	(3.503)	(4.001)	(3.579)	(3.882)	(3.463)	(3.212)
Previous Weeks in Hit-parade						1.509**
						(0.764)
Female					0.897*	0.826*
					(0.493)	(0.480)
Featuring					-1.749***	-1.787***
					(0.594)	(0.600)
Group					-0.889*	-0.828*
					(0.496)	(0.501)
Foreign					2.137	2.322*
					(1.352)	(1.360)
Constant	3.424***	4.575***	3.163***	4.476***	3.089***	2.894***
	(0.284)	(0.598)	(0.298)	(0.589)	(0.330)	(0.338)
Time dummies	NO	YES	NO	YES	YES	YES
Hit-parade ranking dummies	NO	NO	YES	YES	YES	YES
Observations	300	300	300	300	300	300
R-squared	0.140	0.276	0.168	0.387	0.202	0.215

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

Table 9 is a more complete analysis of our third model. There are OLS estimates of the equation (3), with the adding of the second and the third degree of Votes Percentage normalized to the 3rd place of the Sanremo Ranking, and with different degrees of the interaction term:

- in column (1) the coefficient on Finalists is positive and statistically significant, with a t-stat of 1.86. As expected, the votes percentage is positively related to the Total points in Hit-parade and to the music market sales. Arriving to the first three positions in Sanremo ranking increases by 1.802 the points used as a proxy for sales, in the last 16 years of the sample. The coefficient of Votes percentage has a t-stat of 3.50;
- in column (2) and (3) we add the variables Votes percentage squared and Votes percentage cubed, with the aim of testing the significance at the second and third degree of our forcing variable. The statistical significance is not respected for the variable Finalists, even if the coefficient maintains its sign in both the outputs;
- in column (4) we add the interaction term: a variable that tests the interaction between the Votes percentage and the Finalists songs (first 3 positions). Here is not respected the statistical significance of Finalist, even if it is positive and its value is similar to the other column;
- in column (5) and (6) and we add the interaction term respectively squared and cubed. Here the statistical significance for the Finalist variable is respected, whit a t-stat of respectively 1.75 and 1.66, anyway the coefficient is positive. Also for the variable Votes percentage is respected the statistical significance and the positive effect, with a t-stat of respectively 2.60 and 1.71.

Table 9: Regressions for the impact of the Sanremo Prize on Total Points in Hit-parade, in terms of votes percentage for the last 16 years (2002-2016): first, second and third degree of Sanremo ranking. Cut-off 3rd Place in the Sanremo ranking. With the addition of the interaction term.

Dependent variable: Total Points in Hit-parade	(1)	(2)	(3)	(4)	(5)	(6)
Finalists (First 3 Songs)	1.802*	1.285	1.337	1.375	1.992*	2.236*
	(0.970)	(1.101)	(1.110)	(0.990)	(1.139)	(1.346)
Votes % Normalized 3rd Place	14.003***	25.651**	32.180**	38.999***	29.632***	25.125*
	(4.001)	(10.505)	(15.289)	(9.748)	(11.387)	(14.670)
Votes % Normalized 3rd Place^2		-26.103	-80.998		84.639**	148.169
		(18.040)	(93.955)		(34.296)	(117.146)
Votes % Normalized 3rd Place^3			79.824			-130.350
			(128.489)			(187.735)
Interaction				-21.754**	-34.622**	-29.621
				(8.475)	(15.728)	(36.575)
Interaction^2					-34.466	-75.593
					(29.883)	(184.812)
Interaction^3						53.933
						(189.735)
Constant	4.575***	4.935***	5.005***	5.586***	5.558***	5.601***
	(0.598)	(0.678)	(0.688)	(0.702)	(0.705)	(0.713)
Time dummies	NO	NO	NO	NO	NO	NO
Hit-parade ranking dummies	NO	NO	NO	NO	NO	NO
Observations	300	300	300	300	300	300
R-squared	0.276	0.281	0.282	0.302	0.311	0.312

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

Figures 17, 18 and 19 clearly show the jump that confirms the RDD regression with the interaction term. They are referred to column 4, 5 and 6 of Table 7. The jump visibly illustrates the discontinuity in the votes percentage, that corresponds to the third place of Sanremo Ranking. Now the threshold is 0, because we Normalized our Votes percentage, as explained in the previous section.

Figure 17: RD plot for the impact of the votes percentage in the final Sanremo ranking on the Total points in Hit-parade. Cut-off 3rd place of the Sanremo ranking. First degree function. With interaction.

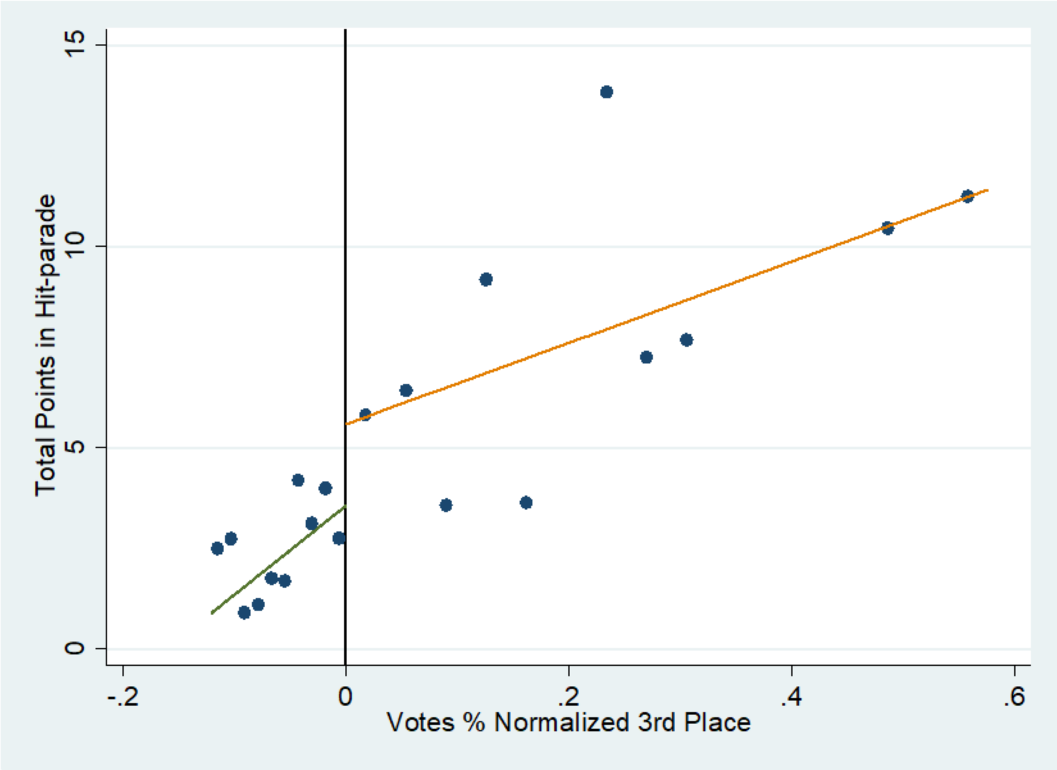


Figure 18: RD plot for the impact of the votes percentage in the final Sanremo ranking on the Total points in Hit-parade. Cut-off 3rd place of the Sanremo ranking. Second degree function. With interaction.

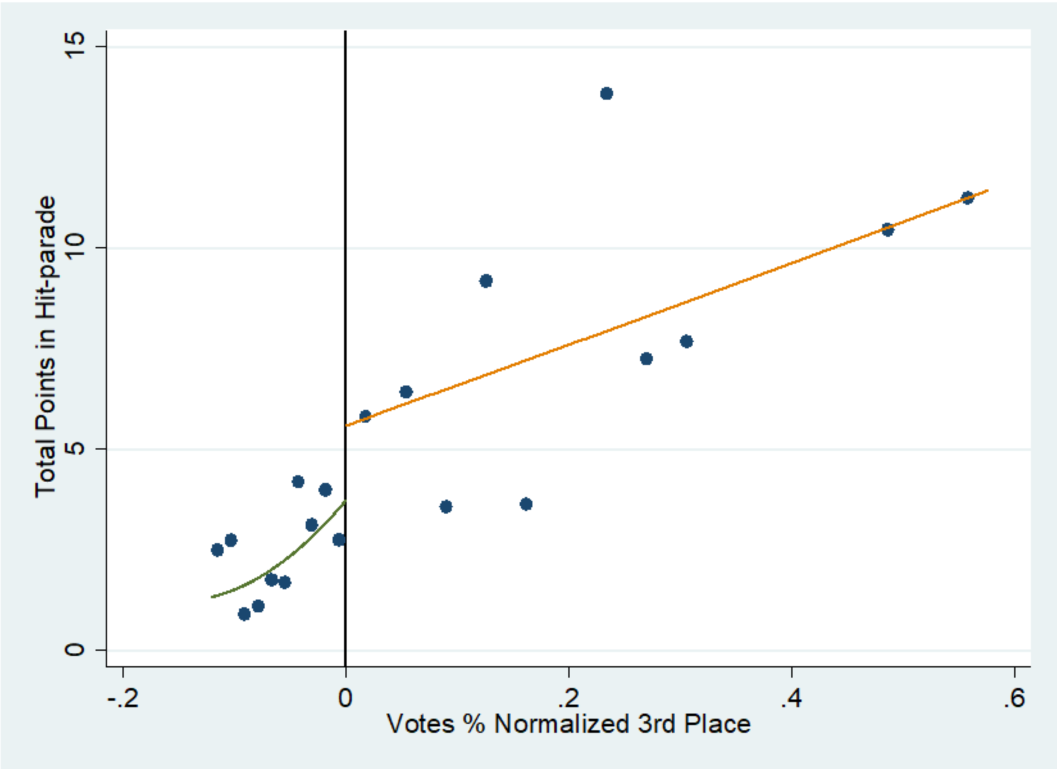
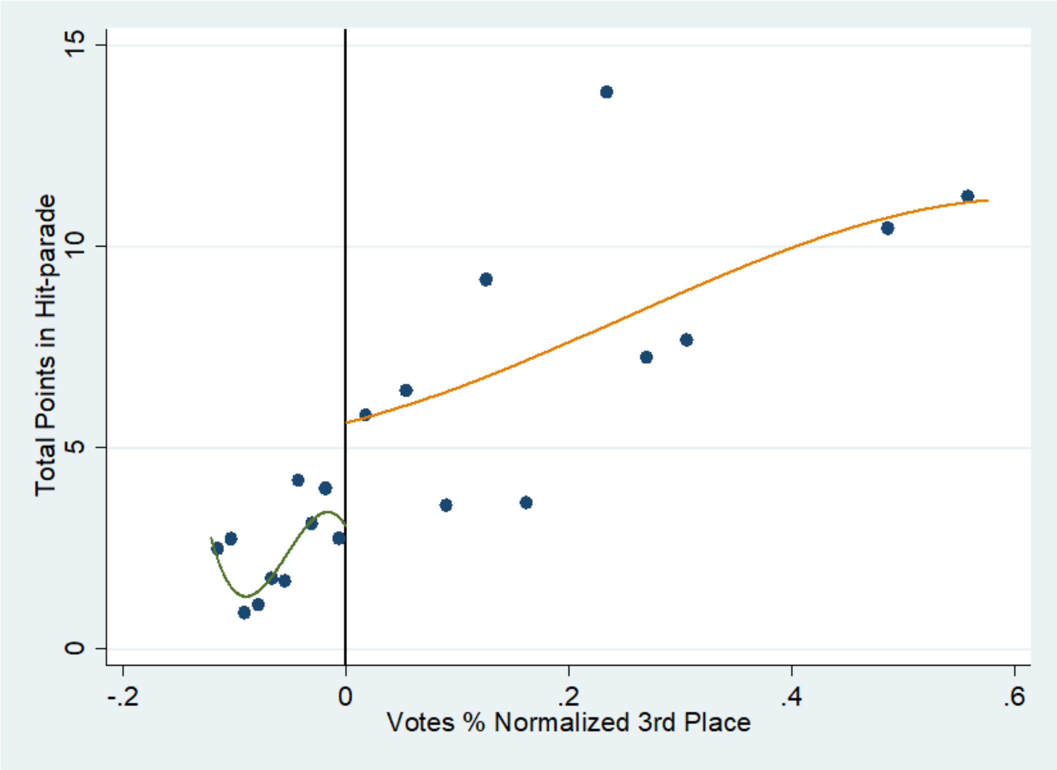


Figure 19: RD plot for the impact of the votes percentage in the final Sanremo ranking on the Total points in Hit-parade. Cut-off 3rd place of the Sanremo ranking. Third degree function. With interaction.



Similar to the expression (1) and (2), we have also the fourth expression that shows the model of the last 16 years (3) changing point of view with respect to the forcing variable: here we use the 1st place in the Sanremo Ranking as the threshold point, instead of the third place. Therefore, here the variable $Finalist1_{it}$ is referred to the first song of the Sanremo Festival, and the variable $Votes\_normalized_{it}$ is normalized for the Second (and not for the Fourth) place in the ranking.

$$Total\ points\ in\ Hit\ parade_{it} = \beta_0 + \beta_1 Finalist1_{it} + \beta_2 Votes\_normalized_{it} + \lambda_t + \gamma_t + \varepsilon_{it} \tag{4}$$

In the next section, we will show the empirical results of our equation models, using the data of our sample.

In Table 10 we use as a forcing variable the Votes percentage, for the last 16 years in which the data are available, normalized to the second place. In this case, we examine if the First song of the Festival (and not the first three songs as in previous models) sells larger quantities respect to the other ranked songs. The estimates express our equation (4), with the adding of the second and the third degree of Votes Percentage normalized to the 3rd place of the Sanremo Ranking, and with different degrees of the interaction term. The aim is to find if, using the votes percentage as a forcing variable, reaching the first place of the Sanremo Festival has a significant effect on the positions in different weeks of the Hit-parade ranking, expression for the song economic success. We also tried to test the significance of the first place using the Ranking position as a forcing variable, but with poor results. These are the column of Table 10:

- in column (1) the coefficient on Finalist is positive and highly statistically significant, with a t-stat of 2.71 and a coefficient of 3.24. As expected, the votes percentage is positively related to the dependent variable, with a t-stat of 3.88;
- in column (2) and (3) we add the variable Votes percentage relatively squared and cubed. The statistical significance is respected for both the variables. In the third column the coefficient of Finalist decreases and that of Votes percentage increases;
- in column (4), (5) and (6) we add the interaction term, as in the previous Table, respectively linear, squared and cubed. For the fourth and the fifth column is respected the sign and statistical significance of Finalist coefficient, with a t-stat of respectively 2.56 and 1.91, and the coefficient has a similar intensity of approximately 3.35. In the sixth column, the statistical significance for the Finalist variable is not respected, whit a t-stat of 1.27, anyway the coefficient is positive. In this column we find high statistical significance and high intensity for the coefficient of Votes percentage, with a t-stat of 2.68 and a value of 65.955, that is surprisingly higher respect to the previous Tables and columns.

This alternative specification that takes into exam the first ranked song instead the first three is interesting, but we cannot test it for all the 59 years present in our dataset, because data on the votes percentage are available only for the last 16 years. Also, we tried to test the same hypothesis only watching to the ranking of Sanremo, without the votes percentages, but the results are not statistically significant. So we can conclude that the song ranked to the first place in Sanremo Festival have a major economic success respect to the other songs of the Festival but we can confirm this result only for the last 16 years.

We also tried, for a robustness check, to express all the models with a logarithmic functional form, but the results have a low statistical significance. For this reason, we are not capable to confer more robustness to our results.

Table 10: Regressions for the impact of the Sanremo Prize on Total Points in Hit-parade, in terms of votes percentage for the last 16 years (2002-2016): first, second and third degree of Sanremo ranking. Cut-off 1st Place in the Sanremo ranking. With the addition of the interaction term.

Dependent variable: Total Points in Hit-parade	(1)	(2)	(3)	(4)	(5)	(6)
Winner (First Place)	3.242***	3.135**	2.863**	3.408**	3.292*	2.428
	(1.195)	(1.323)	(1.392)	(1.330)	(1.723)	(1.910)
Votes % Normalized 1st Place	11.411***	11.999***	17.124**	11.830***	25.835**	65.955***
	(2.938)	(3.042)	(7.747)	(3.340)	(11.938)	(24.596)
Votes % Normalized 1st Place^2		3.079	4.215		50.999	440.377**
		(9.132)	(9.676)		(40.007)	(198.850)
Votes % Normalized 1st Place^3			-63.625			924.686**
			(74.515)			(449.459)
Interaction				-3.170	-34.040	-66.068
				(6.347)	(37.367)	(68.103)
Interaction^2					-4.439	-488.094
					(95.074)	(412.404)
Interaction^3						-712.585
						(835.620)
Constant	5.061***	5.087***	5.404***	5.087***	5.770***	6.719***
	(0.636)	(0.639)	(0.780)	(0.643)	(0.865)	(1.036)
Time dummies	YES	YES	YES	YES	YES	YES
Hit-parade ranking dummies	NO	NO	NO	NO	NO	NO
Observations	300	300	300	300	300	300
R-squared	0.268	0.268	0.270	0.268	0.274	0.285

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

Figures 20 and 21 illustrate the jump of the RDD regression with the interaction term. They are referred to column 4 and 5 of Table 8. Also for the first place in the Sanremo Ranking, for the last 16 years of our sample, it is confirmed the discontinuity in the votes percentage.

Figure 20: RD plot for the impact of the votes percentage in the final Sanremo ranking on the Total points in Hit-parade. Cut-off 1st place of the Sanremo ranking. First degree function. With interaction.

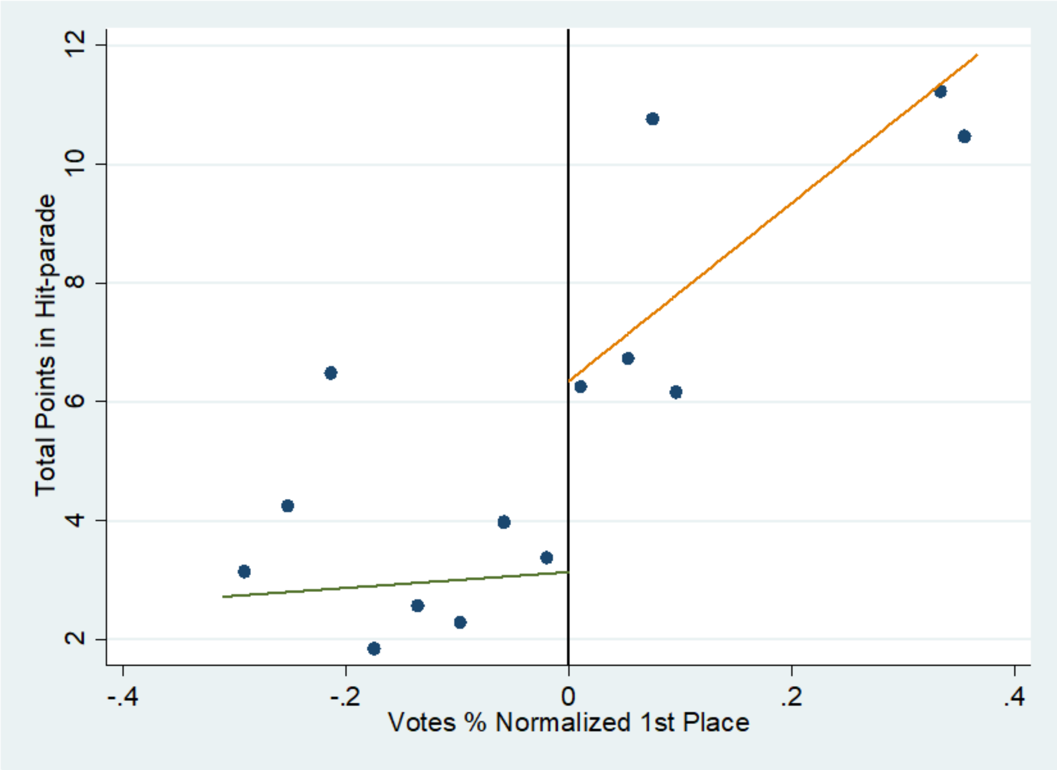
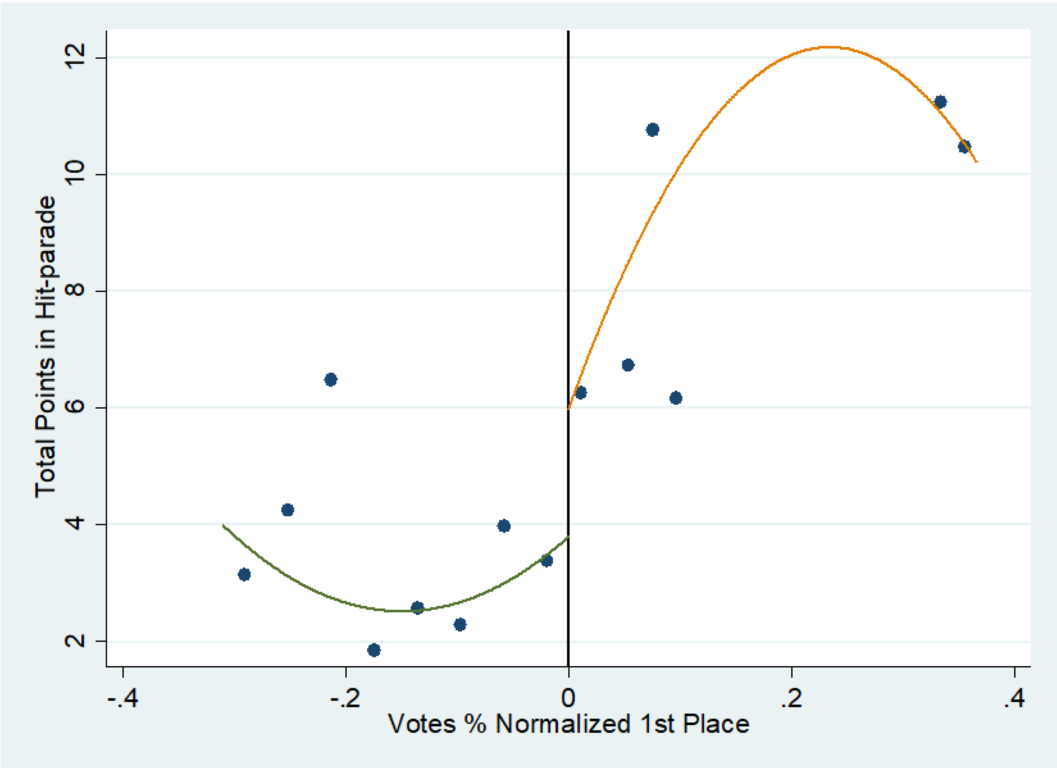


Figure 21: RD plot for the impact of the votes percentage in the final Sanremo ranking on the Total points in Hit-parade. Cut-off 1st place of the Sanremo ranking. Second degree function. With interaction.



1.9 Concluding remarks

Analysing data on the most popular Italian music Prize, together with measures of song sales expressed by the ranking and the presence in different weeks in Hit-Parade, we have investigated whether receiving an award have an impact on the commercial success of experience goods.

Our method is based on a Regression Discontinuity Design and exploits the votes given by different juries to select the best song of the Sanremo Festival. Comparing the success of awarded and non-awarded songs, we show that arriving at the Sanremo final to the first three places increases the cumulated sales of a song.

We verify the effect using two different forcing variables: the position in the Sanremo Ranking and the Votes Percentage of Sanremo. Our results are clear: in the RDD regressions there is always a jump corresponding to the third place of Sanremo Ranking. This confirm our hypothesis: getting the first three positions of the Sanremo Festival has an effect on the Hit-parade ranking position of the song, then on the commercial success of the song awarded.

The same hypothesis is confirmed for the first place of the ranking only using data on votes percentage in the last 16 years.

In conclusion, the aim of this study is to verify the impact of the Sanremo Festival cultural Prize on song’s sales. This research adds evidence to the existing literature on cultural awards.

In further research, our findings could be expanded using better data on the percentage of votes received by each song and comparing the Italian Sanremo Music Festival to other European or international music competition.

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2. Impact on sales and on market value of a negative product information: evidence from the Dieselgate scandal

Abstract: Analysing data on cars sales and stock prices, with reference to the major companies in the automotive market, we show that the Dieselgate scandal has an impact on the stock prices but not on the sales of the Volkswagen group. We use two models to draw this conclusion: a Differences-in-Differences model is used for testing a long-term effect of the scandal on sales and on stock prices; a Regression Discontinuity Design is adopted for expanding the stock price effect and it gives us also a graphical illustration of the jump.

2.1 Introduction

We test the effect of an information about the sustainability of a product on the product sales and on the stock value of the firm in the car industry. This would check the empirical evidence that negative information may affect consumer choices and the market response. Our aim is to understand if negative information affects sales and/or the firm stock prices or, conversely, if the information doesn't have any effect.

The car market is concentrated, most large countries having only one or two major manufacturers; thus, it is an oligopoly. The market is segmented. Domestic producers take the largest share of their market although there has been a tendency for this feature to become less marked. Furthermore, foreign competitors are also evenly distributed in each country. Thus, none of them has a share which is of the same magnitude or even close to domestic manufacturers (Kirman, Alan, Schueller, 1990).

Cars are classified as consumer durables: a class of products whose quality cannot easily be judged before purchase (Shapiro, 1982). In fact, when a new model automobile appears, there simply is no way of knowing what its repair record will be. All consumers value an unobservable characteristic: the quality of a product. Examples include durability, safety, and speed of service.

Automotive market, as many other markets, is generally characterized by informational asymmetries on product quality: while quality is well-known to the producer, consumers cannot evaluate fully and accurately the product they buy (De Paola, Scoppa, 2013).

Markets afflicted by asymmetric information are based on reputational mechanisms. There are incentives for firms to produce high-quality goods, they get up from the reputational costs imposed upon firms responsible for selling low quality or unsafe products. Consumer's demand would shift away from opportunistic firms and the latter would lose the stream of rents on future sales.

Therefore, it is important to deliver evidence about the consumer reaction to the news on product quality.

Firm reputation is also important for financial performance. Reputation research suggests that a reputation–performance effect may operate in both directions: a firm's financial performance affects its reputation and its reputation affects its performance (McGuire et al., 1990). Therefore, we provide empirical evidence to the effect of a negative information on a firm reputation on the stock market. The topic is relevant not only in the short period, but it could be significant for the market value of a firm in a long period perspective. Roberts and Dowling (2002) demonstrate that superior-performing firms have a greater chance of sustaining superior performance over time if they also possess relatively good reputations.

In order to demonstrate empirical evidence to our hypothesis, we use two different models for both the effect of consumer responses and market value in consequence to negative news. Firstly, we adopt a difference in differences estimation strategy, testing the Dieselgate effect on sales and on stock prices, before and after the scandal. We do it using all the company different from Volkswagen in the car industry as the control group and using the companies involved in the scandal, belonging to the Volkswagen group, as the treatment group. Secondly, we adopt a regression discontinuity design (RDD) testing the same effect, for a better explanation of the effect. This also offers us a graphical evidence of the Dieselgate scandal. In the RDD models we use car sales and firm stock price as dependent variables and, as a forcing variable, the months (for sales) and days (for stock price) in which data are available to us. In this case, the evidence of treatment effects are the jumps in the relationship between sales/stock price and the months/days near the threshold of the Dieselgate day.

We use data on the car industry, daily for the stock price and monthly for the sales, for 8 years, from 2010 to 2017.

The paper is organized as follows. In Section 2 we analyse the literature about negative information on consumer choice and about firm reputation on the stock market. In Section 3 we will deepen in the Dieselgate scandal and in the car industry. In Section 4 we describe our datasets. In section 5 we define the models. In Section 6 the outcomes are explained and commented. In Section 7 we do our concluding remarks.

2.2 Literature

Different studies have tried to analyse the effects of product quality information on consumer demand and stock prices. However, results are not univocal. Here is a literature review of the works that inspired our research.

De Paola and Scoppa (2013) make a research concerning the food industry, whose aim is to calculate the effects of negative information on the sales of involved and not involved brands. Essentially, they focus on a fraud that took place in 2008, which has involved some Italian leading firms in the cheese sector. Since media (Italian newspapers and television broadcasting news services) mentioned only some brands as being implicated in that fraud, the authors choose to use a difference-in-differences estimation strategy.

The authors use daily scanner data coming from 17 stores operating in Rome and other towns, provided by Despar, a large Italian supermarket chain. Data give information on daily purchases concerning 40 different items, belonging to the category "Grated Cheese", commercialized by 17 different brands and covering the period going from the 1st January 2005 to the 31st December 2009, for 5 years, with a total of 154,000 observations.

Firstly, they examine the short-run effects of the negative publicity, comparing the changes in the average sales of the brands in the treatment and in the control group during the period of time in which the cheese fraud received media attention. The dependent variable, the logarithm of the quantity of cheese sold, is regressed on an interaction between two variables: Media coverage, that measures the attention dedicated to the cheese fraud by the media, and Involved Brands, a dummy variable for the different brands affected by negative publicity. The results indicate a statistically significant decrease in sales of brands directly affected by such a negative publicity and, on the other hand, a growth regarding the sales of brands that were not mentioned by media at all.

Furthermore, the authors examine the persistence of the effects due to the media's negative publicity over time. The dependent variable remains the same, the interaction term is between Involved Brands and the variable Post, a dummy variable that takes the value of one for the period after the 4th July 2008 and zero otherwise. From the output table, it emerges that after the 4th July 2008 consumers' purchases have increased for "Not Involved Brands" and also the coefficients on the interaction term is negative and statistically significant.

This research shows how the negative publicity on product quality has led to a consumers' demand shift from involved to not involved brands; also, these effects persist in the long-term, even when the media wasn't giving attention to the issue anymore. The direct consequences of the negative information affect the retailers: the margin gained on brands directly mentioned by media has decreased after the negative publicity.

Bachmann et al. (2018) use the 2015 Volkswagen emissions scandal as a natural experiment to provide causal evidence that group reputation externalities matter for firms.
They use the 18th September 2015 as the date from which the U.S. Environmental Protection Agency (EPA) served a Notice of Violation to the VW Group (this episode is the same of our research and it will be better explained in the next section).
For this natural experiment, the authors notice that the German auto manufacturers featured the notion of “German car engineering” prominently in their U.S. advertising, creating a natural reputational group. For this reason, non-German automakers can serve as a control group for understanding the effects of a German-specific shock. The authors underline the importance of the car manufacturing industry in Germany: in 2014, the year preceding the scandal, cars amounted to 18 percent of Germany’s total exports.
Different data are used for the research:

- data from the Newsbank news aggregator on print media mentions of “Volkswagen” in the United States, that covers approximately 5,000 U.S. newspapers, newswires, journals, and magazines;
- novel sentiment measures from Networked Insights to measure the scandal’s effect on Volkswagen’s reputation, for 13 months;
- the 12-month growth rate of unit sales from January 2011 to August 2016.

The main result is that the scandal reduced the U.S. sales growth of the other German auto manufacturers relative to their non-German counterparts: they were sold about 76,070 fewer sales units for the non-Volkswagen German auto manufacturers between September 2015 and August 2016. The joint revenue loss to BMW, Mercedes-Benz, and Smart is $3.70 billion dollars. Furthermore, the authors, using a graphic method, show that the sales of the non-VW German automakers suffered a decline during the time following the scandal, and that, thanks to the month-by-month sales differential between non-VW German and non-German automakers after the scandal, the sales declines were concentrated in the immediate aftermath in the scandal.
Another outcome is noticeable in stock prices; in fact, German auto manufacturers’ U.S. stock returns fell right after the scandal relative to the returns of non-German auto manufacturers. The authors interpret these economic spillovers as reflective of reputational spillovers to the non-VW German car manufacturers. The cumulative abnormal return for German auto manufacturers excluding Volkswagen was negative 10 percent within two trading days of the scandal. This event

materially harmed the financial valuations of automakers linked to the scandal through their collective reputation as German automakers.

Overall, the estimates show statistically and economically significant declines in the U.S. sales and stock returns of (as well as public sentiment towards) BMW, Mercedes-Benz, and Smart, as a result of the Volkswagen scandal. Volkswagen's episode materially harmed the group reputation of "German car engineering" in the United States.

The research of Roberts and Grahame (2002) confirm that there is a positive relationship between reputation and financial performance. The authors sustain that good corporate reputations are critical because of their potential for value creation, but also because their intangible character makes replication by competing firms considerably more difficult. This paper shows that firms with relatively good reputations are better able to sustain superior profit outcomes over time.

To support their hypotheses, they use the survey "America's Most Admired Corporations", published by Fortune from 1984 to 1998. It is an annual reputation survey that covers Fortune 1000 firms and is based on responses from company executives and directors, as well as from financial analysts, that gives an output of firm's overall reputation score from ratings on eight scales. The authors link each firm observation for each year with data on firm profitability (after-tax return on total assets, ROA), market-to-book value (market value divided by total shareholder's equity) and firm size (total sales). The complete dataset contains 4444 observations.

Two models are launched in the paper: autoregressive profit model and proportional hazards regression model.

The results of the autoregressive profit model suggest that firms with better reputations demonstrate greater profit persistence.

Proportional hazards regression model suggests that firms with better reputations are less likely to exit a superior performance position at any point in time, and this supports their reputation hypotheses. The coefficients on the relative market-to-book value variable suggest that a firm's remaining stock of intangible assets is not related to its ability to sustain superior profit outcomes over time.

The results of both the models suggest that superior-performing firms have a greater chance of sustaining superior performance over time if they also possess relatively good reputations. The authors also decompose overall reputation into a component that is predicted by previous financial performance and find that each element supports the persistence of above-average profits over time.

A study of Dean (2004) observes the corporate crises that often result in negative publicity, threatening the image of the company. The research investigates the effects of company reputation for social responsibility prior to a crisis event, response to a crisis event, and responsibility for the event on overall consumer regard for the firm.

The study focuses on three factors that may affect consumer reaction to negative publicity: company response to the event (appropriate vs. inappropriate), company reputation for social responsibility prior to the event (good vs. bad), and company responsibility for the event (not responsible vs. responsible). The three factors are used as independent variables in a 2 × 2 × 2 factorial ANOVA experiment. The dependent variable data were collected at three different time points, immediately after the presentation of each independent variable stimulus. It captures the consumer attitude toward the company and it represents consumer perceptions of corporate image.

Data are collected on students enrolled in an introductory marketing course at a large Southeastern University in the United States volunteered to serve as participants. They present to the students some written scenarios on corporate reputation, response to an event, and responsibility for an event, each followed by a series of questionnaire scale items.

Here are the results of the model, that are the validations of the 4 hypotheses advanced by the authors:

- an inappropriate response would further diminish regard for a bad company, but the same response would not significantly impair regard for a good company;
- firms responding to the crisis with fairness and compassion for those affected were more highly regarded than firms whose response lacked these elements and attempted to shift the blame for the tragedy;
- in the absence of other explanations, consumers attribute the negative event to the company and hold it liable for the outcome;
- participants significantly downgraded their opinion of a good firm that responded appropriately but was responsible for the tragic event.

Each of the three factors was found to exhibit a significant main effect. The authors find an unexpected result: an inappropriate response by a “bad” company resulted in an increase in regard toward the firm, whereas the same response by a “good” company resulted in a decrease in regard for the firm.

The study of Chen, Shankar, and Yong (2009) is about product harm crises, that often result in product recalls, which can have a significant impact on a firm's reputation, sales, and financial value.

The authors sustain that in managing the recall process, some firms adopt a proactive strategy in responding to consumer complaints, while others are more passive. They examine the impact of these strategic alternatives on firm value using Consumer Product Safety Commission (CPSC) recalls during a 12-year period from 1996 to 2007.

The authors make an event study, in which the event is a product-recall announcement from the CPSC. The event study identifies an investigation period during which there are no confounding events that could obscure the effects associated with the event under consideration. The CPSC data provide a unique and accurate event day when a recall was announced. The final sample counts 153 recalls.

Standard & Poor's S&P 500 index is used for the independent variable definition: Returns on a typical market portfolio. Returns of the company for which the recall was issued is the dependent variable. To calculate the abnormal return, the authors subtract the expected return from the actual return.

The results provide consistent evidence that the proactive recalls are associated with significantly more negative abnormal returns than the passive recalls. On average, the abnormal return for proactive strategies is approximately 0.7% lower than that for passive strategies. Thus, the stock market interprets a proactive product-recall strategy as a signal of severe financial losses.

In the second part of the study, the authors examine the source of abnormal returns to complement the event study and show that product-recall strategies are a significant influencer of abnormal returns. The empirical model includes both recall strategies and important firm and product characteristics. Some firm characteristics may influence abnormal returns in different ways: the level of firm reputation, firm size in terms of sales revenue, the level of financial liability, and whether the recalled product used the company name in its brand or carried an individual brand name. The estimation results support the previous findings of the event study that proactive recall strategies are associated with more negative abnormal returns than passive strategies. First, the estimation shows that a product-recall strategy is an important influencer of abnormal stock returns. Second, proactive strategies have a more negative effect on firm financial value than passive strategies. Third, among independent variables, Hazard, Year trend, and Outdoor also significantly influence abnormal returns. However, firm characteristics, such as Reputation, Firm size, and Brand, do not have a significant impact.

Therefore, the authors show that regardless of firm and product characteristics, proactive strategies have a more negative effect on firm value than more passive strategies. The authors try to explain this result supposing that the stock market interprets proactive strategies as a signal of substantial financial losses to the firm: when a firm proactively manages a product recall, the stock market infers that the consequence of the product-harm crisis is sufficiently severe that the firm had no choice but to act quickly to reduce potential financial losses.

The research of Jarrell and Peltzman (1985) analyse the reaction of the wealth of shareholders of firms producing defective products. They estimate the losses borne by owners of a firm that recalls a defective product from the market.
The authors use the event study methodology. In the experiments, there are producers of drugs and autos that were recalled from the market.
The first study is on drug products. They start from the assumption that when a drug product is found to be defective, the manufacturer is required to remove it from the market. Several hundred recalls occur in a typical year, and most involve minor health or financial consequences. For the data, the authors consulted the weekly reports of FDA Recalls and Court Actions in the Food, Drug and Cosmetic Reporter. They also include those recalls where direct cost estimates are reported in the Wall Street Journal (WSJ). The sample period runs from 1974 through 1982. All the cases comprehend stock returns data for the manufacturer. Results of the first research show that the stock market is imposing a substantial goodwill loss on a firm over and above the product-specific costs. The stock market appears to expect that news of a recall will reduce consumers' demand, or raise costs, for other products sold by the firm and thereby impose additional losses on the firm.
The second study is on the automotive sector. The authors previously announced that the number of cars per recall is highly skewed. The sample is composed of all recall announcements reported in the WSJ for 1967-81 that exceeded 50,000 cars for GM, 20,000 for Ford, and 10,000 for Chrysler. These cut-offs are consistent with the relative market shares and stock market values of these firms. In this case, they cannot compare the direct cost of auto recalls with the stock market loss, as for drugs, because they have no estimates of the former. The result is similar to the previous study on drugs: competitors lose rather than gain also during an auto recall. And, as with drugs, the spill over effects are substantial. There is a significant company-specific component to recall losses over and above a company's share in the industry-wide loss.
Shareholder’s losses are substantially greater than the costs directly emanating from the recall, for example, costs of destroying or repairing defective products. They are larger than all the costs attributable specifically to the recalled product. The losses spill over to the firm's goodwill and they also spill over to competitors, producing a negative externality.

The previous article of Jarrell and Peltzman (1985) is re-examined by Hoffer, Pruitt, and Reilly (1988). The paper presents several modifications to the Jarrell-Peltzman study, that are shown to

have a pronounced effect on the conclusions to be drawn with respect to the automobile industry. In particular, after these modifications are made, little evidence remains in the study that share prices are significantly affected by automotive recalls. On careful examination of the 63 recalls used by Jarrell and Peltzman over the 1975-81 period, the authors found that 21 did not meet their criteria. The finding of Jarrell and Peltzman that GM shareholders suffered significantly greater wealth losses from Ford and Chrysler recalls than they did from recalls of their own firm is eliminated under the revised analysis of Hoffer, Pruitt, and Reilly.
Following the revisions, little significant evidence remains from the previous study, indicating that securities markets penalize shareholders for an automotive recall by driving down share prices. For the most part, neither shareholders of the firm recalling the automobile nor shareholders of competitor firms are significantly affected.

Marsh, Schroeder and Mintert (2004) analyse the impact of meat product recall events on consumer demand in the USA. They empirically test beef, pork, and poultry recall, through some indices that are constructed from both the Food Safety Inspection Service's meat recall events and from newspaper reports over the period 1982–1998.
The empirical analysis is divided in two steps:

- in the first step, they estimate demand models that include meat price and expenditure variables along with recall indices. Models are estimated for lag lengths with likelihood ratio test statistics calculated for each lag length;
- in the second step, they estimate a final simple model in which restrictions are imposed on the number of recall lags.

The authors presuppose that in their research could be present potential misspecification problems, because of the persistent presence of autocorrelation in the demand models. Results suggest that there are diminishing returns to multiple media reports on a single recall event. Price and expenditure elasticities at the mean demonstrate that beef and pork are normal goods, whereas poultry is an inferior good. Meat recalls also have spill over or cross-effects: increases in beef recalls have a negative and significant impact on pork and a positive impact on poultry demand. Similarly, increases in pork recalls had a negative and significant impact on beef and a positive impact on poultry consumption.
The principal results of the paper are the following:

- consumers appear to perceive current and lagged meat recall information as a decrease in product quality for beef and pork;
- only current period poultry recalls appear to significantly shift poultry demand down;

- there are significant spillover effects within the meats group;
- there is a general negative effect on meat demand, coinciding with a perceived drop in quality for meat products: consumers often prefer other consumption goods when meat recalls occur;
- regarding the source of information, Food Safety Inspection Service's meat recall events significantly impact demand, and newspaper reports do not;
- although elasticities related to recall events are significant, they are small in magnitude relative to price and income effects.

The study of De Matos and Rossi (2007) evaluates the factors influencing consumers' responses to product recalls.
The authors conducted two surveys among Brazilian automobile owners and they run two different regression models.
In the first study, 643 undergraduate students from two colleges participate to a survey. Participants receive a product recall information about cars, from a company that had announced a product recall in one of the main Brazilian newspapers, chosen by the authors. The message of product recall affirmed that the brake system could not function properly if heated by heavy use and it was valid for three models of car manufactured in the year 2002.
For this study were used two models: the first approach explains the variance in product judgement by some predictors; in the second approach, predictors explain the variance in the behavioural intentions variable.
In the first approach, product judgement was significantly affected by three predictor variables: ownership of a car from a certain company, the perceived social responsibility of and the blame attributed to this company for the defect presented in the message. In the second approach, behavioural intentions were significantly affected by these predictors: whether the participant owned the brand recalled or not, the importance attributed to the message, the danger perceived in the defect presented and the product judgement: consumers owning a car made by a certain brand have positive behavioural intentions toward this brand, consumers giving more importance to the product recall message also have positive behavioural intentions, as also do the consumers who have a positive product evaluation. It emerges also an inverse relationship: the higher the danger perceived in the product because of the defect presented in the recall message, the smaller the behavioural intentions toward the brand recalled.
In the second study, it is replicated the first study, but this time considering a new product recall message from the same automobile company and a non-student sample: 158 car owners voluntarily

participating in the study. The recall message was also related to a similar defect in the brake system of a recent car launched by the company. The instrument and variables measured are the same as in the first study. Behavioural intentions are significantly influenced by product judgement, whether or not consumer had a car made by a certain company and the perceived social responsibility of the company. The explanatory variables with the highest predictive power are product judgement, ownership of the brand and social responsibility.

Final results indicate that:

- product judgement is significantly affected by corporate social responsibility (CSR), blame attributed to the company and whether or not consumers had a car made by the brand considered;
- behavioural intentions are significantly affected by CSR, consumers' involvement with the message, perceived danger, product judgement and whether or not consumers had a car made by the brand considered.

The paper of Magno (2012) investigates the effect of four recall brand attitudes: the time taken to start the recall after the primary signals of potential injuries arose; responsible recall management; opportunistic recall management; the blame attributed to the company for the defective, unsafe or dangerous products.

The authors underline the size of the problem: in 2010, in the European Union, 2,244 notifications of measures taken against dangerous products were notified to the EU rapid alert system for all non-food dangerous consumer products; in 2003 they were just 139.

Data for the experiment were collected from 217 undergraduate students of a strategic management course. Each participant was invited to read the recall letter and asked to think as she had received the recall letter as the owner of a computer potentially involved in the recall program. Participants completed a questionnaire which included the measurement of four independent variables:

- consumers' perception about the time span between the primary signals of potential injuries and the date when the recall was issued;
- responsible recall management;
- opportunistic recall management;
- blame attribution to the company.

The dependent variable of the model is Post-recall brand attitude, measured on a five-point scale including three items: bad/good; dislike/like; unpleasant/pleasant.

The results of the linear regression highlight that all the independent variables have significant effects on consumer's post-recall brand attitude. Brand attitude after the crisis is negatively linked to the time taken to issue the recall: if the company does not start the recall immediately after the first malfunction, consumers' attitude will deteriorate. Consumers appreciate the firm's spontaneous and responsible effort to recall the product to safeguard consumers' health, but they don't appreciate the opportunistic behaviour of the firm. If consumers blame the company for the product crisis, their post-recall brand attitude will deteriorate.

Overall the model shows that responsible recall management is positively related to post-recall brand attitude, while time, opportunistic recall management and blame have a negative relationship with post-recall brand attitude.

2.3 The Dieselgate emission scandal

The Dieselgate emission scandal, or emissiongate, is the name by which we refer to the episode that affected the automobile company Volkswagen starting from September 2015. During that month, the United States Environmental Protection Agency (EPA), the federal agency for the protection of the environment that attests the regularity of cars' consumptions regarding America, issued a notice of violation of the Clean Air Act to German automaker Volkswagen Group. The matter of this charge concerns that the well-known German industry had intentionally programmed turbocharged direct injection (TDI) diesel engines to activate their emissions controls only during laboratory emissions testing which caused the vehicles' nitrogen oxides output, extremely significant in terms of air pollution, to perfectly fit in the US standards during regulatory testing. Instead, the cars end up emanating about 40 times more nitrogen oxides while used for real, actual driving. Volkswagen installed this programming software in about 11 million cars worldwide, counting about a number of 500,000 in the United States, from 2009 to 2015.

The 18th of September 2015 is the date the EPA accuses Volkswagen group of the suspected rigged software, in order to investigate even further.

A study conducted by the European branch of the American non-profit society ICCT (International Council for Clean Transportation) back in 2014 was the turning point to bring to light such an important fact: this study was then repeated in the United States in collaboration with a team of researchers from West Virginia University. As a consequence of the outcomes deriving from this study, the EPA starts a survey involving the German car company, looking for answers about the huge, unacceptable variance between the amount of emissions detected during the approval phase and the real road one. On 18th September 2015 the EPA, receiving scarce and unsatisfactory explanations from the charged company, notifies Volkswagen a notice of violation, accusing it of having altered polluting emissions of their vehicles, denying approvals to the new range of car

models made by Volkswagen group and prohibiting the sale of those already approved, until obtaining convincing and precise clarifications regarding the previously mentioned problem.
On 21st September 2015 Volkswagen company admits its guilt by declaring to have intentionally altered polluting emissions of their vehicles and, in order to fix the whole case, it announces a big recall campaign for the car models involved in that scandal. The recall would allow them to restore the automobiles to the legal standards through the updating of the engine control unit. About 11 million vehicles between Europe and America were involved in the case, including cars equipped with diesel engine, EA 189 series, of engine displacement 1200, 1600, 2000 and 3000.

2.4 The data

For the purposes of our research, we gathered data on vehicle sales and stock prices for the automobile manufacturer.
We collected data on sales from the European Automobile Manufacturer Association ACEA (website www.acea.be). Data contains the units of new passenger cars sold in Western Europe (EU 15) with a monthly frequency, from January 2010 to October 2017. Data on sales are normalized to the first month available in the dataset: each monthly value is divided by the value of January 2010. The normalization makes the sales values more similar to each other, therefore we can do a better comparison between companies. There are 28 brands in the dataset, with a total of 2,726 observations. In the final dataset for sales, we compute the mean of sales for all the company different from Volkswagen, to create a control variable called Other Brands, for this reason, the observations are compacted to 188.
Furthermore, we gathered stock prices data through Datastream. These data have a daily frequency, from November 2010 to November 2017, in order to investigate the daily impact on stocks. Data on stock prices are normalized to the first day available in the dataset: each daily value is divided by the value of 18th November 2010. We have a total of 47,784 observations. Also, data on stock prices are normalized to the first month available in the dataset: each month is divided by November 2010. As the dataset on sales, also in the final dataset for stock prices we compute the mean of stock prices for all the company different from Volkswagen, for this reason, the observations are compacted to 3,668.
From Datastream we collected data on control variables: fuel price, GDP, unemployment, workforce, Stoxx Euro 600, volatility Stoxx international. We will explain these variables in the description of table 1 and 2.

Table 1: Descriptive statistics. Analyses on car sales (years 2010-2017)

Variables	Obs	Mean	Std. Dev.	Min	Max	Measure
Sales	188	1.086	0.237	0.553	1.780	Vol. norm.
Volkswagen	188	0.5	0.501	0	1	Dummy
Other Brands	188	0.5	0.501	0	1	Dummy
After	188	0.266	0.443	0	1	Dummy
After*Volkswagen	188	0.133	0.340	0	1	Dummy
Time	188	-21.5	27.206	-68	25	Month norm.
Fuel Price	188	0.206	0.020	0.166	0.240	Euro norm.
GDP	180	16.149	1.074	14.323	17.975	Euro norm.
Unemployment/workforce	178	0.116	0.011	0.094	0.133	Vol./vol. norm.

Table 2: Descriptive statistics. Analyses on car industry stock price (years 2010-2017)

Variables	Obs	Mean	Std. Dev.	Min	Max	Measure
Stock Price	3,668	1.300	0.268	0.792	2.323	Euro norm.
Volkswagen	3,668	0.5	0.500	0	1	Dummy
Other Brands	3,668	0.5	0.500	0	1	Dummy
After	3,668	0.311	0.463	0	1	Dummy
After*Volkswagen	3,668	0.156	0.363	0	1	Dummy
Time	3,668	-345.5	529.502	-1262	571	Month norm.
Stoxx Euro 600	3,668	1.185	0.179	0.792	1.527	Euro norm.
Volatility Stoxx International	3,668	0.964	0.296	0.482	2.336	Euro norm.

Tables 1 and 2 illustrate respectively the descriptive statistics of our samples on Sales and on Stock Prices.

In Table 1 we find the dependent variable Sales, which represents the volume number of new cars, normalized to the first month available, January 2010. We takes into account of the different models of purchased cars with the following two variables. Volkswagen is a dummy variable set equal to 1 when the variable Sales is referred to the company. Other Brands is another dummy variable equal to 1 when the variable Sales is referred to sales mean of all the other company different from Volkswagen present in our sample. The variable After is a dummy equal to 1 after the scandal, in this case after the 21st of September. After*Volkswagen is the interaction variable between After and Volkswagen, it is equal to 1 if the variable Sales is referred to Volkswagen after the scandal. The variable Time is zero on the 21st September 2015, the data in which the company admits its guilt. For this reason, all the months and days before this date are negative. Fuel price is the price of fuel expressed in thousand euros, in particular, liquid fuels and lubricants for personal transport equipment for the European Union. We use this variable because it takes into account that the purchases of new automobiles could be influenced by changes of the fuel price. GDP is the quarterly Gross Domestic Product of the European Union, expressed in Euro million units, collected from OECD dataset. This control variable is useful because the ability to purchase depends from the GDP of a country, in this case the entire European region. Unemployment/workforce is an index that divides the monthly unemployment on the workforce of the European Union, collected from the Eurostat labour force survey. This control variable is useful because unemployment influences the purchase power. We use the workforce volume for a normalization of the unemployment.

In Table 2 we find the dependent variable Stock price, that expresses the value of stock price normalized to the first day available in our sample, 18th November 2010. Also, here we have the dummy variables Volkswagen, Other Brands, After, After*Volkswagen that have the same meaning of the previous table. Also, the variable Time has the same meaning of Table 1, but it has a larger scale. Stoxx Euro 600 is a daily index, that represents large, mid and small capitalization companies across 17 countries of the European region. We use this index because it covers about the 90% of market capitalization in Europe, therefore, daily changes in stock prices are intercepted by this measure. Volatility Stoxx international is a daily index (also called Vstoxx), based on Stoxx, designed to reflect the market expectations of near-term up to long-term volatility by measuring the square root of the implied variance across all options of a given time to expiration. We use this index because the market volatility influences the stock prices.
In section 5 we will explain our model.

2.5 First application: differences-in-differences analysis on car sales

We run two different models that investigate the long-run effect of the Dieselgate scandal on the sales and on the stock prices of Volkswagen. Our aim is to understand if the effects deriving from the negative publicity on product quality persist over time, for all the months available after the scandal date.
Our first model investigates the negative news effect on the car industry sales, we adopt a differences-in-differences estimation:

$$Sales_{it} = \beta_0 + \beta_1\{After_t * Volkswagen_i\} + \beta_2 After_t + \beta_3 Volkswagen_i + \gamma_t + \varepsilon_{it} \tag{1}$$

The variables expressed in equation (1) represents:

$Sales_{it}$ the quantity of vehicles sold monthly by the different company of the automotive sector, expressed in normalized volumes, of the brand *i* sold to the month *t*;

$After_t$ is a dummy variable equal to 1 for all months after September 2015, the month in which the scandal took place;

$Volkswagen_i$ is one of the brand dummies, that assumes value 1 if the volume of vehicles is sold by the Volkswagen group, 0 if it's sold by other brands;

$After_t * Volkswagen_i$ is a variable of interaction between the two dummy variables After and Volkswagen, that assumes value 1 if the sales are referred to Volkswagen after the scandal;

γ_t is a vector of 12 months and 8 years dummies;

ε_{it} is an error term.

Figure 1 is the plot of sales for all the months available in our sample. The orange line represents the Volkswagen sales, while the blue line represents the sales of Other Brands (it is a mean of all the other brand's sales). A vertical line is on the 21st September 2015, the date on which the scandal occurred. The figure shows seasonal trends, but we cannot clearly see a difference in sales. The following differences-in-differences analysis can help us to understand if the Dieselgate influences sales of Volkswagen and other brands.

Figure 1: Sales plot for Volkswagen (orange) and for Other Brands (blue). The line is on 21th September 2015, the date on which the scandal occurred, that coincide with the normalized Time variable 0.

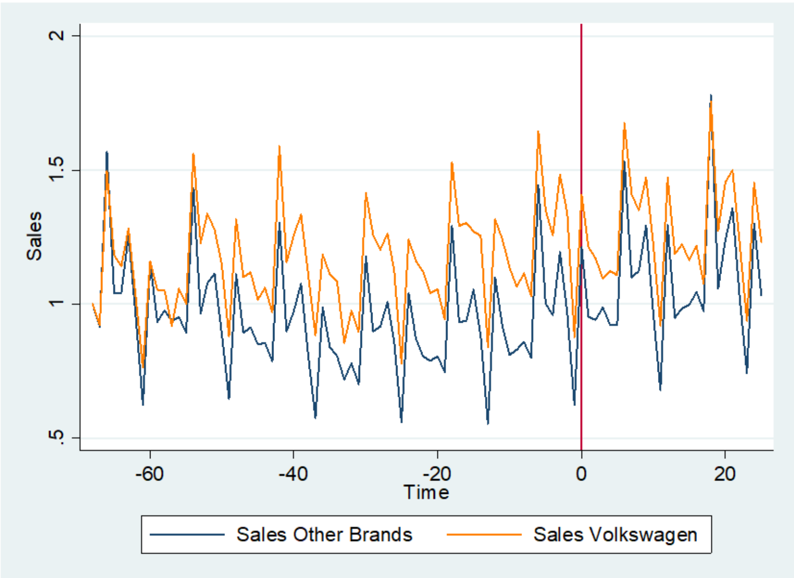


Table 3 shows the output of the differences-in-differences analysis on sales. We have 69 observations before and 25 after the scandal. The two different counterparts are Volkswagen, in which are collected all the sales of Volkswagen brands, and Other brands, in which there is a mean of all the brands different from Volkswagen. In Table 4 we have a better idea of the differences-in-differences: in mean, Volkswagen decreases its sales of about -0.025 points after the scandal, compared to the other brands. However, this result doesn't give us an idea of the statistical significance of the effect. For this reason, we analyse OLS regressions in the next tables.

Table 3: Descriptive statistics for Differences in Differences on sales.

	Obs	Mean	Std. Dev.	Min	Max
Sales (Volkswagen=1, After=0)	69	1.158	0.197	0.765	1.645
Sales (Volkswagen=1, After=1)	25	1.277	0.206	0.919	1.756
Sales (Volkswagen=0, After=0)	69	0.943	0.202	0.553	1.569
Sales (Volkswagen=0, After=1)	25	1.088	0.239	0.679	1.780

Table 4: Differences in differences. Analyses on car sales (years 2010-2017)

	After (A)	Before (B)	Difference (A-B)
Treated (T=Volkswagen)	1.277	1.158	0.120
Control (C=Other Brands)	1.088	0.943	0.145
Difference (T-C)	0.189	0.214	**-0.025**

In table 5 we show the outcomes of the OLS estimates on the equation (1) in which Sales is the dependent variable.

- In column (1) we control the interaction variable After*Volkswagen, that is the most important in our analyses: we try to understand how the Dieselgate scandal influences sales of Volkswagen. For this reason, we are interested to the interaction of two variables: After that is 1 in all the months after the scandal date, and Volkswagen, that is 1 only if the sales belong to the company. The interaction variable coefficient results statistically not significant, with a t-stat of -0.352. This coefficient suggests that sales for Volkswagen after the scandal decreases by -0.025 points, but we have no statistical significance. The variables Volkswagen and After are highly significant with a t-stat respectively of 6.29 and 2.73, but these results are not useful to our purpose that is to understand the conjoint effect of both the variables. In this column, we don't consider the dummies Month, Year and all the others control variables.

- In column (2) we add only the control variable GDP that results not significant. The variable Volkswagen maintains its significance, while the significance of the variable After results lower than column (1) as its t-stat becomes 1.93.
- In column (3) we consider the three principal variables of column (1) and we add the variable Fuel Price. Its impact on the sales is negative, but the variable results not significant.
- In column (4) we add the variable Unemployment on the workforce, an index that divides the monthly unemployment on the workforce of the European Union, that is negatively related with the dependent variable: if Unemployment/workforce decrease, sales increase as we expected. This variable result highly significant with a t-stat of -2.86.
- In column (5) we consider the control variables of column (2), (3) and (4) all together. The only two variables that result significant are Volkswagen, with a t-stat of 6.41, and Unemployment/workforce, with a t-stat of -2.70.
- In column (6) we come back to the situation explored in column (1) but we add the two dummies Month and Year in order to control for a temporal effect that can variate between months of different years, for this reason we compute both. We built this variables firstly conferring value 1 to the first month and value 1 to the first year present in our dataset, than the value is normalized, as explained in the description of tables 1 and 2. Also here the interaction variable coefficient results statistically not significant, with a t-stat of -1.19. The variable Volkswagen maintains its significance, with a t-stat of 17.83. The variable After has a t-stat of 2.65.
- In column (7) we add again the GDP control variable. Compared to column (2) where we tested the same variables without the time dummies (Month and Year), it becomes significant with a t-stat of 2.27, but we lost the significance of the variable After.
- In column (8) we analyse the same situation of column (3) with the addition of time dummies. As we can see, the situation remains the same, but the significance of both the variables Volkswagen and After, increases with a t-stat of respectively 17.83 and 2.32.
- In column (9) we analyse the same variable of column (4) adding the time dummies. Variables that already resulted significant increases their significance, in fact, the t-stat of Volkswagen become 18.16 and the t-stat of the variable Unemployment/workforce become 2.88. Even the variable After becomes significant, with a t-stat of 2.43.
- Column (10) is the more complete interpretation of our table because we consider all the control variables and the time dummies. Also here, our variable of interest After*Volkswagen results still not significant with a t-stat of -1.22. The variables

statistically significant are Volkswagen, with its coefficient 0.218 and a t-stat of 19.82; GDP, with its coefficient 0.041 and a t-stat of 3.73; Fuel Price, that is negatively related to the dependent variable Sales, with its coefficient -1.511 and the t-stat of -1.76; Unemployment/workforce that is negatively related to the variable Sales with its coefficient -4.027 and the t-stat of 2.88.

From the results of this table, we can affirm that the variable After*Volkswagen, that is our variable of interest, is negatively related with the variable Sales, as we expect, but it never became significant in all the 10 columns, after the adding of all the control variables. Its t-stat remains always in the range between -0.31 and 1.21. Based on our analyses we conclude that the Dieselgate doesn't affect the Sales for Volkswagen. This result is not in line with our thesis, because we expected an effect on sales of negative information. Probably the problem that affects the Volkswagen cars doesn't affect directly the consumer: it affects the environment, with more emissions which lead to more pollution, but probably the perception of the problem is not so strong as to significantly impact the consumer behaviour.

Table 5: Regression for Differences in differences. Analyses on car sales.

Dependent variable: Sales	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
After*Volkswagen	-0.025	-0.024	-0.025	-0.028	-0.028	-0.025	-0.024	-0.025	-0.028	-0.028
	(0.071)	(0.077)	(0.072)	(0.075)	(0.075)	(0.021)	(0.023)	(0.021)	(0.023)	(0.023)
Volkswagen	0.214***	0.214***	0.214***	0.218***	0.218***	0.214***	0.214***	0.214***	0.218***	0.218***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)
After	0.145***	0.137*	0.116*	0.078	-0.002	0.069***	0.026	0.065**	0.068**	-0.018
	(0.053)	(0.071)	(0.064)	(0.063)	(0.088)	(0.026)	(0.029)	(0.028)	(0.028)	(0.030)
GDP		0.010			0.037		0.025**			0.041***
		(0.023)			(0.027)		(0.011)			(0.011)
Fuel Price			-0.940		0.592			-0.464		-1.511*
			(1.051)		(1.329)			(0.944)		(0.859)
Unemployment/workforce				-4.885***	-6.719***				-0.790	-4.027***
				(1.798)	(2.352)				(1.584)	(1.399)
Constant	0.943***	0.779**	1.145***	1.531***	1.038**	0.881***	0.494***	0.967***	0.965***	0.984***
	(0.024)	(0.370)	(0.230)	(0.222)	(0.438)	(0.020)	(0.174)	(0.182)	(0.189)	(0.248)
Month dummies	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES
Year dummies	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES
Observations	188	180	188	178	178	188	180	188	178	178
R-squared	0.255	0.262	0.259	0.290	0.301	0.927	0.930	0.927	0.928	0.936

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

In the next table, our aim is to understand more in depth if the effect has a significance: we run a robustness check on the same variables. In Table 6 are expressed some robustness checks for the impact of the Dieselgate on Volkswagen car sales. We added all the control variables of the previous table to reduce the risks of endogeneity, as these variables could be correlated with the variables of interest whose effect is to be estimated. Our robustness checks are used to control if, reducing the sample around the date of the scandal, the effect continues to be not statistically significant or if it changes. If the difference-in-difference is not verified also in the robustness checks, our results gain a major robustness. In these regressions, we reduce the sample respectively to 28, 14 and 10 months around the Dieselgate date. The months are computed around the scandal date, it means that for example, in the first column, 28 months are divided: 14 months before and 14 months after the scandal.

We focus our attention on the interaction variable After*Volkswagen that is statistically significant in column (1) and (2), with a t-stat that decreases from -2.48 to -2.63 and a negative sign of the coefficient. Even if this result is in line with our hypothesis, it is not in line with the previous table, and this is a threat to the robustness of our findings. In column (3) the interaction variable returns to be not statistically significant, in line with the previous table's results. In summary, our robustness check works only if we restrict the sample on 10 months, while if the sample is of 28 and 14 months, the interaction variable is statistically significant. This represents a problem: even if the coefficient sign remains the same, negative, it has a significance only in the first two columns. This means that the Volkswagen sales decrease respectively of -0.062 (1), -0.092 (2) and -0.082 (3) points after the scandal, and the effect on the consumer is significant only for the first two columns. In conclusion of our first method, we can conclude that, for most of our regressions, the Dieselgate scandal has a negative but not significant effect on consumer choice. It is significant only in two situations, for this reason in further researches we could deepen the analysis adding new variables or with different methods.

Table 6: Regression for Difference in differences. Analyses on car sales. With robustness test at 28, 14 and 10 months.

Dependent variable: Sales	(1)	(2)	(3)
After*Volkswagen	-0.062**	-0.092**	-0.082
	(0.025)	(0.035)	(0.044)
Volkswagen	0.274***	0.280***	0.282***
	(0.018)	(0.026)	(0.030)
After	0.068	0.064	0.064
	(0.053)	(0.057)	(0.057)
Constant	-14.637	2.314**	0.302
	(17.148)	(0.798)	(0.354)
Control variables	YES	YES	YES
Month dummies	YES	YES	YES
Year dummies	YES	YES	YES
Local Window	28 months	14 months	10 months
Observations	54	26	18
R-squared	0.979	0.987	0.980

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

2.6 Second application: differences-in-differences analysis on stock prices

The second equation studies the negative publicity effect on the car industry stock prices, we adopt a differences-in-differences estimation similar to the equation (1):

$$Stock\ prices_{it} = \beta_0 + \beta_1\{After_t * Volkswagen_i\} + \beta_2 After_t + \beta_3 Volkswagen_i + \gamma_t + \varepsilon_{it} \quad (2)$$

In the equation (2) we change the dependent variable respect to the previous model: $Stock\ prices_{it}$ expresses the stock prices of different brands i to the time t. Now the time has a daily frequency. The variable $After_t$ assumes value 1 from the day after the guilt admission of Volkswagen, corresponding to 21st September 2015, the day in which the company also announces a big recall campaign for the implicated car models. All the other variables are equal to the previous model.

Figure 2 represents the plot of stock prices for all the months available in our sample. The orange line represents the Volkswagen stock prices, while the blue line represents the stock prices of Other Brands (it is a mean of all the other brand's stock prices). A vertical line is on the 21st September 2015, the date on which the scandal occurred. The figure shows seasonal trends and we can clearly identify a difference in stock prices. The following differences-in-differences analysis can help us to understand if the Dieselgate scandal influences stock prices of Volkswagen and other brands.

Figure 2: Stock Price plot for Volkswagen (orange) and for Other Brands (blue). The line is on 21th September 2015, the date on which the scandal occurred, that coincide with the normalized Time variable 0.

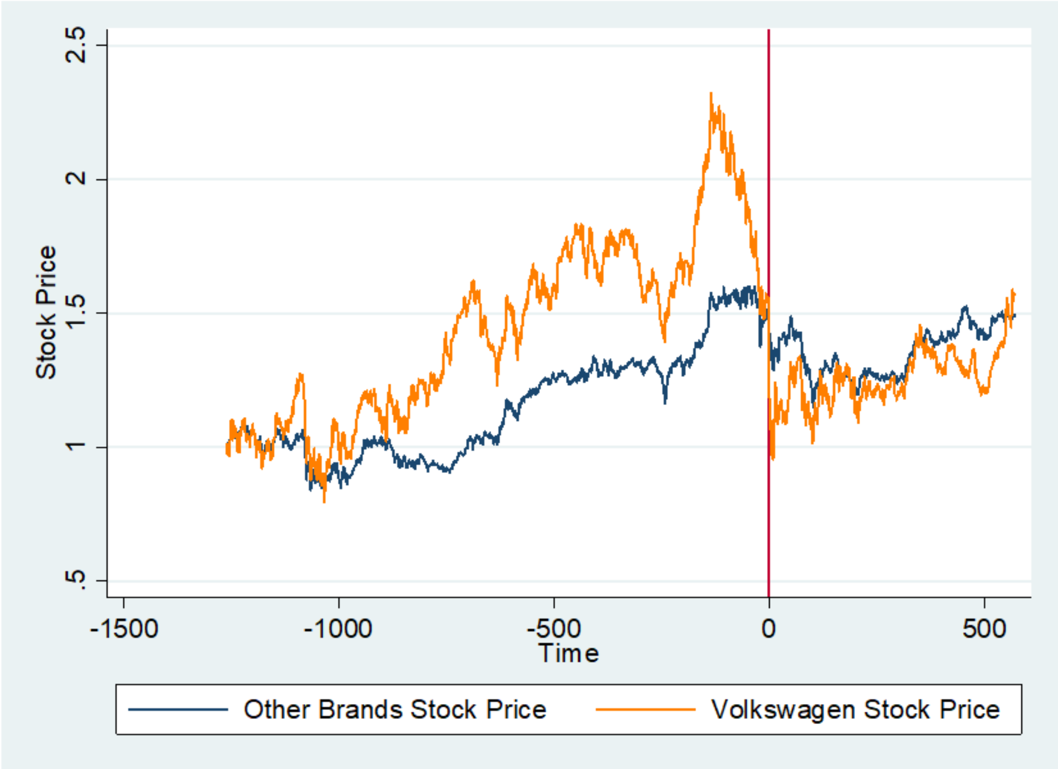


Table 8 shows the output of the differences-in-differences analysis on the stock prices. We have 1263 observations before and 571 after the scandal. In this case, we analyse daily data. Our two different counterparts are Volkswagen, in which are collected all the Volkswagen brands' Stock Price; and Other brands, in which there is a mean of all the Stock Price of the brands different from Volkswagen. In Table 9 we better analyse the situation with the differences-in-differences method: in mean, the Stock Price of the Volkswagen brand decreases of about 0.389 points after the scandal, compared to the other brands. We need to be more specific about the statistical significance of the effect, therefore, in the following tables, we will analyse OLS regressions.

Table 8: Descriptive statistics for Differences in Differences on car industry stock price.

Variables	Obs	Mean	Std. Dev.	Min	Max
Stock Price (Volkswagen=1, After=0)	1,263	1.441	0.340	0.792	2.323
Stock Price (Volkswagen=1, After=1)	571	1.258	0.103	0.953	1.588
Stock Price (Volkswagen=0, After=0)	1,263	1.153	0.203	0.824	1.601
Stock Price (Volkswagen=0, After=1)	571	1.358	0.090	1.147	1.526

Table 9: Differences in differences. Analyses on car industry stock price (years 2010-2017)

	After (A)	Before (B)	Difference (A-B)
Treated (T=Volkswagen)	1.258	1.441	-0.183
Control (C=Other Brands)	1.358	1.153	0.206
Difference (T-C)	-0.100	0.289	**-0.389**

In table 10 we show the outcomes of the OLS estimates on the equation (2) in which Stock Prices is the dependent variable.

- In column (1) we analyse the interaction variable, that, as we previously explained, is our variable of interest. It results that the variable is highly significant thanks to its t-stat of -29.92, and it is negatively related to the variable Stock Price with a coefficient of -0.389. This is what we expected, in fact, our aim is to prove that, after the scandal, the stock price of Volkswagen falls, reflecting the distrust of investors. Also, the variables Volkswagen and the variable After singularly taken are highly significant with their coefficients 0.289 and 0.206 and with high t-stat's values of 26.27 and 29.43 respectively. We notice that the sign is positive in both cases, as opposed to the interaction variable. This fact points out the importance of the interaction between the two terms and the validity of the differences-in-differences method used. In this column, we don't consider the time dummies and all our control variables.
- In column (2) we add the variable STOXX index, that is the Stoxx Euro 600, a daily index that represents large, mid and small capitalization companies Europe. The variable coefficient results highly significant with its coefficient of 1.415 and a t-stat of 108,85. It doesn't affect the statistical significance of the other variable even if it increases their t-value, but it changes the sign of the variable After, in fact, it becomes negative.
- In column (3) we add the variable Volatility STOXX, a daily index based on Stoxx that reflects the market expectations of near-term up to long-term volatility. The variable is negatively related to the dependent variable with its coefficient -0.396 and it results highly

significant with a t-stat of -44. The adding of the variable takes us to the beginning situation with the variable After positively related to the dependent variable and the significance of all the variable maintained stable.

- In column (4) we evaluate both the control variables without the time dummies. All the variables result significant except for the variable Volatility STOXX that lost its significance with a t-stat of -0.875. The coefficient of After returns to be negative.
- In column (5) we start again the analysis of the three principal variables but this time we include the time dummies of Months and Years. This different point of view led our analysis to an increasing of the significance of our variable of interest After*Volkswagen, with a t-stat of -48.63, compared to column (1). Also the variable Volkswagen increases its significance with a t-stat of 48.17, and the variable After becomes negatively related to the dependent variable with its coefficient of -0.107.
- In column (6) we use, in addition to time variables, the variable STOXX index that results highly significant with its t-stat of 39.91 and compared to column (2) it doesn't affect the After's coefficient sign.
- In column (7) we control for the variable Volatility index, with the time dummies. It results less significant respect to column (3) with a t-stat of 18.7. The adding of these variables increases the t-stat of the two variables After*Volkswagen and Volkswagen, leading them to 55.57 and 48.17. Only the variable After decreases its significance with a t-stat of 5.8.
- In column (8) we consider all the variable plus the time dummies. All the control variables result highly significant with very high t-stats. Our variable of interaction's t-stat reaches its higher value of -64.83, this proves our thesis that, after the scandal, the stock prices of the Volkswagen group decreases because of the negative publicity. The variable Volkswagen increases its t-stat reaching the value of 72.25, the variable After results significant with a t-stat of 11.45, the variable STOXX index is highly significant with a t-stat of 39.55 also the variable Volatility STOXX results significant with a t-stat of 9.64. In conclusion, column (8) is the more complete and it is totally in line with our hypothesis: after the scandal, Volkswagen stock price significantly decreases its value of about -0.389 points.

This analysis proves that the consequence of the negative news about Volkswagen products is a decrease of the stock price, that is expression of the company perceived value. As we can see, our variable of interest is always significant, with a very high t-stat in each column, and it's always negatively related to the dependent variable. This means that in each scenario we analyse after the scandal, the stock prices of the Volkswagen group decreases.

Table 10: Regression for Differences in differences. Analyses on car industry Stock Prices.

Dependent variable: Stock Prices	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
After*Volkswagen	-0.389***	-0.389***	-0.389***	-0.389***	-0.389***	-0.389***	-0.389***	-0.389***
	(0.013)	(0.006)	(0.011)	(0.006)	(0.008)	(0.006)	(0.007)	(0.006)
Volkswagen	0.289***	0.289***	0.289***	0.289***	0.289***	0.289***	0.289***	0.289***
	(0.011)	(0.005)	(0.010)	(0.005)	(0.006)	(0.004)	(0.006)	(0.004)
After	0.206***	-0.089***	0.155***	-0.089***	-0.107***	-0.122***	-0.104***	-0.126***
	(0.007)	(0.004)	(0.006)	(0.004)	(0.018)	(0.011)	(0.018)	(0.011)
STOXX Index		1.415***		1.408***		1.397***		1.582***
		(0.013)		(0.016)		(0.035)		(0.040)
Volatility STOXX			-0.396***	-0.007			-0.187***	0.106***
			(0.009)	(0.008)			(0.010)	(0.011)
Constant	1.153***	-0.431***	1.550***	-0.417***	1.450***	-0.416***	1.648***	-0.775***
	(0.006)	(0.015)	(0.010)	(0.024)	(0.013)	(0.048)	(0.016)	(0.061)
Month dummies	NO	NO	NO	NO	YES	YES	YES	YES
Year dummies	NO	NO	NO	NO	YES	YES	YES	YES
Observations	3,668	3,668	3,668	3,668	3,668	3,668	3,668	3,668
R-squared	0.211	0.845	0.395	0.845	0.738	0.869	0.760	0.874

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

Table 11 reports some robustness checks outputs of the regressions for the impact of the Dieselgate on Volkswagen group's stock prices. As we have done previously in table 6, we restrict our sample, this time we consider the ranges of 132, 75 and 50 days around the day in which the Volkswagen admit its responsibility. The restriction of our sample is a way to prove that the interaction variable maintains its significance. Confirming our results, the statistical significance of the interaction term is respected for all the three columns. In column (3), that expresses the highest restriction of our sample, the t-stat settles on the value of -26.2 and the coefficient maintains its negative sign: stock prices for Volkswagen decrease by -0.393 after the scandal, watching only the 50 days around the scandal. In the previous two columns, the interaction variable coefficient has the same sign and significance, but the intensity is higher as the sample is larger: -0.550 points with the restriction to 132 days, and -0.438 points with the restriction to 75 days.

This is a good result for our thesis: shrinking the sample, the negative effect of the Dieselgate on the stock prices of Volkswagen after the scandal is statistically significant, compared to the effect on other brand's stock prices in the same period. The robustness checks enhance the validity of the method that we use.

Table 11: Regression for Differences in differences. Analyses on car industry Stock Prices. With robustness test at 132, 75 and 50 days.

Dependent variable: Stock Prices	(1)	(2)	(3)
After*Volkswagen	-0.550***	-0.438***	-0.393***
	(0.016)	(0.016)	(0.015)
Volkswagen	0.375***	0.218***	0.130***
	(0.014)	(0.014)	(0.011)
After	0.032	-0.018	-0.038
	(0.042)	(0.030)	(0.026)
STOXX Index	1.123***	1.297***	1.256***
	(0.228)	(0.249)	(0.349)
Volatility STOXX	0.057	0.103*	0.025
	(0.054)	(0.058)	(0.085)
Constant	-0.040	-0.329	-0.327
	(0.385)	(0.419)	(0.587)
Month dummies	YES	YES	YES
Year dummies	YES	YES	YES
Local Window	132 days	75 days	50 days
Observations	526	298	198
R-squared	0.919	0.915	0.946

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

2.7 Third application: RDD analysis on stock prices

In this model, we examine from another perspective the negative news effect on the car industry stock prices. This time we adopt a sharp Regression Discontinuity Design (RDD), that gives us also a graphical image of the cut-off date of the scandal:

$$Stock\ prices_t = \beta_0 + \beta_1 Dieselgate_t + \beta_2 Time_t + \gamma_t + \varepsilon_{it} \tag{3}$$

In this model, we use the variable $Time_t$ as a forcing variable, and we expect a jump on the cut-off day *t*, that coincides with the scandal. The variable $Dieselgate_t$ is a dummy that assumes value 1 after the scandal, it expresses the treatment status and it is a deterministic and discontinuous function of the Time variable. All the other variables are in line with previous models.

In the next section, we will illustrate the empirical results of our models.

In this part of our analysis we want to analyse if the Dieselgate has an impact on the prices of the other brand's stock, and if so what kind of influence it had, also we want to compare the effect on the stock prices of Volkswagen brand whit the effect on the other brands. In the two table that follow there are the outcomes of our evaluation. In Tables 12 and 13 we compare two different RDD: the first one is referred to the stock prices of all the car industry brands present in our sample, except Volkswagen; the second one is referred to Volkswagen stock prices only.

Table 12: Regressions for the impact of the Dieselgate on Other Brands Stock Prices (considering a mean of stock prices of all the brands different from Volkswagen).

Dependent variable: Stock Prices of Other Brands	(1)	(2)	(3)	(4)
Dieselgate	-0.227***	-0.053***	-0.227***	-0.046***
	(0.009)	(0.003)	(0.008)	(0.003)
Time	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
STOXX Index		0.004***		0.004***
		(0.000)		(0.000)
Volatility STOXX		0.003***		0.003***
		(0.000)		(0.000)
Constant	1.441***	-0.148***	1.451***	-0.175***
	(0.005)	(0.020)	(0.008)	(0.018)
Month dummies	NO	NO	YES	YES
Observations	1,833	1,833	1,833	1,833
R-squared	0.787	0.959	0.798	0.962

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

Table 13: Regressions for the impact of the Dieselgate on Volkswagen Stock Prices.

Dependent variable: Stock Prices of Volkswagen	(1)	(2)	(3)	(4)
Dieselgate	-0.922***	-0.755***	-0.938***	-0.791***
	(0.015)	(0.012)	(0.013)	(0.011)
Time	0.001***	0.000***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
STOXX Index		0.003***		0.003***
		(0.000)		(0.000)
Volatility STOXX		-0.004***		-0.004***
		(0.001)		(0.000)
Constant	1.950***	0.852***	2.028***	1.081***
	(0.011)	(0.058)	(0.013)	(0.056)
Month dummies	NO	NO	YES	YES
Observations	1,833	1,833	1,833	1,833
R-squared	0.800	0.869	0.842	0.887

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

As we can see, we have a strong statistical significance in both the tables for the coefficient of the variable Dieselgate. Also, as we expected, the sign is equal, negative for both. What changes is the intensity of the coefficient: for Volkswagen we have a greater intensity downwards. This fact confirms the previous models discovering: Dieselgate scandal have a more negative effect on the stock prices of Volkswagen, compared to that on other brands. In particular, as shown in columns (4), the Dieselgate effect has an intensity of -0.791 points of normalized stock prices for Volkswagen, on the other side, it has an intensity of only -0.046 on other brands. The difference is remarkable: 0.745 points of normalized stock prices less for Volkswagen compared to Other Brands. In conclusion, the bad publicity deriving from Dieselgate affected more the Volkswagen group than the other brand.

Table 14 shows the impact of Dieselgate on other brands' stock prices, we maintain the variable Dieselgate at the base of our analysis, with the variables STOXX index and volatility STOXX. Now we are going to analyse what happens to our model adding the time variable in different polynomial orders: Time, Time^2, Time^3. Also the interaction variables are of different orders as Dieselgate*Time, Dieselgate*Time^2 and Dieselgate*Time^3. The reason why we use these polynomial forms is that we want to control one of the most important threats to the internal validity of RDD, with the adding of the second and the third degree of Time, and with different degrees of the interaction term. We run the regressions with polynomials of second and third degree to attempt for possible existing non-linearities. Our aim is to avoid confusing these non-linearities for discontinuities. We adopt different polynomial forms in our regression to test if the functional form between the outcome and the forcing variable is different.

- In column (1) we analyse the influence of the variables Dieselgate and Time on the stock prices of other brands. As we expected, the Dieselgate has a negative effect on the prices of the other brands stock prices. It is negatively related to the dependent variable and it is statistically significant with a t-stat of -15.33.
- In column (2) we add the variable Time^2 that results not significant and that led to a decrease of the Dieselgate variable's significance, reducing its t-stat to the value of -12.57.
- In column (3) we add the variable Time^3. It results significant for our analysis and it improves the significance of the variable Time^2, however, our variable of interest (Dieselgate) remains significant with a t-stat that decrease to the value -9.67.

From now on we will add the variables of interaction to the initial variables of previous columns.

- In column (4) we consider the variable of interaction Dieselgate*Time, it isn't statistically significant. Our variable of interest remains significant with a t-stat of -11.5.
- In column (5) we add the variable Dieselgate*Time^2, that led to an increasing significance of the other variables, but our variable of interest decreases in significance with a t-stat value of -8.16.
- In column (6) we consider all the variables including the last variable of interaction Dieselgate*Time^3 that affects the significance of the Dieselgate's t-stat reducing it to a value of -3.86.

In conclusion, from our analysis, it is evident that the Dieselgate scandal led to a decrement of the Stock prices of another brand. In the next table we expect that this decrement is smaller for other brands compared to that for the Volkswagen group.

Table 14: Regressions for the impact of the Dieselgate on Other Brands' Stock Prices (considering a mean of stock prices of all the brands different from Volkswagen). With Time^2 and Time^3. With the addition of interaction variables.

Dependent variable: Stock Prices of Other Brands	(1)	(2)	(3)	(4)	(5)	(6)
Dieselgate	-0.046***	-0.051***	-0.058***	-0.046***	-0.049***	-0.027***
	(0.003)	(0.004)	(0.006)	(0.004)	(0.006)	(0.007)
Time	0.000***	0.000***	0.000***	0.000***	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time^2		0.000	-0.000*		0.000***	-0.000***
		(0.000)	(0.000)		(0.000)	(0.000)
Time^3			-0.000**			-0.000***
			(0.000)			(0.000)
Dieselgate*Time				0.000	-0.001***	-0.000***
				(0.000)	(0.000)	(0.000)
Dieselgate*Time^2					0.000***	0.000***
					(0.000)	(0.000)
Dieselgate*Time^3						0.000
						(0.000)
STOXX Index	0.004***	0.004***	0.004***	0.004***	0.004***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volatility STOXX	0.003***	0.003***	0.002***	0.003***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.175***	-0.169***	-0.121***	-0.176***	0.124***	0.132**
	(0.018)	(0.018)	(0.025)	(0.019)	(0.045)	(0.055)
Month dummies	YES	YES	YES	YES	YES	YES
Observations	1,833	1,833	1,833	1,833	1,833	1,833
R-squared	0.962	0.962	0.962	0.962	0.963	0.965

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

In Table 15 we analyse the outcomes of the Regression for the impact of the Dieselgate on Volkswagen stock prices. The base of our analyse remains the same as the previous one.

- In column (1) we note that the Dieselgate has a negative impact on the Volkswagen stock prices, as we expected, it is highly significant with a t-stat of -71.91.
- In column (2) we add the variable Time^2 that results significant and led to a decrease of the Dieselgate variable's significance, reducing its t-stat to the value of -40,33.
- In column (3) we add the variable Time^3, it results significant for our analysis, but it worsens the significance of the variable Time^2 and it eliminates the significance of the variable Time. The variable Dieselgate remains significant but its t-stat decreases again to the value of -25.48.

From now on, we will add the variables of interaction to the initial variables of previous columns.

- In column (4) we consider the variable of interaction Dieselgate*Time, our variable of interest remains significant with a t-stat of -58.5, that is minor compared to its t-stat in column (1).
- In column (5) we add the variable Dieselgate*Time^2 that makes all the other variables significant, but our variable of interest decreases in significance with a t-stat value of -24.75.
- In column (6) we consider all the variables including the last variable of interaction Dieselgate*Time^3, that affected the significance of the t-stat of the Dieselgate variable, reducing it to a value of -23.63. In this column, the effect of Dieselgate is strong and relevant: after the scandal, Volkswagen stock prices decrease their value of -0.638 normalized points.

The outcomes show us that the Dieselgate had a negative impact on the Volkswagen stock prices and that, as we expected, this effect is higher for Volkswagen compared to that of other brands. We quantify this difference in 0.611 points of normalized stock prices: comparing column (6) of table 14 and 15, Volkswagen stock prices decrease its value of -0.611 after the scandal, compared to other brands stock prices.

This effect could have negative consequences on financing strategies of Volkswagen, as the perception of the company is worse for the investors after the scandal.

We want to clarify that the reduction of Volkswagen stock price could be related, in part, to variations not due to the Dieselgate, but, since our results have a strong statistical significance and since we added different control variables, we can affirm with certainty that at least a part of our model captures the effect of Dieselgate on Volkswagen stock prices.

The results of the RDD model underlines our theory, already tested with the differences-in-differences method. It makes our empirical analysis more robust.

Table 15: Regressions for the impact of the Dieselgate on Volkswagen Stock Prices. With Time^2 and Time^3. With the addition of interaction variables.

Dependent variable: Volkswagen Stock Prices	(1)	(2)	(3)	(4)	(5)	(6)
Dieselgate	-0.791***	-0.605***	-0.535***	-0.702***	-0.495***	-0.638***
	(0.011)	(0.015)	(0.021)	(0.012)	(0.020)	(0.027)
Time	0.000***	0.000***	-0.000	0.001***	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time^2		-0.000***	-0.000*		-0.000***	-0.000***
		(0.000)	(0.000)		(0.000)	(0.000)
Time^3			0.000***			0.000
			(0.000)			(0.000)
Dieselgate*Time				-0.000***	0.003***	0.008***
				(0.000)	(0.000)	(0.000)
Dieselgate*Time^2					-0.000***	-0.000***
					(0.000)	(0.000)
Dieselgate*Time^3						0.000***
						(0.000)
STOXX Index	0.003***	0.003***	0.004***	0.002***	0.007***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volatility STOXX	-0.004***	-0.005***	-0.002***	-0.007***	0.004***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Constant	1.081***	0.835***	0.371***	1.331***	-0.947***	-1.814***
	(0.056)	(0.060)	(0.097)	(0.058)	(0.124)	(0.113)
Month dummies	YES	YES	YES	YES	YES	YES
Observations	1,833	1,833	1,833	1,833	1,833	1,833
R-squared	0.887	0.912	0.916	0.902	0.928	0.946

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

Figure 3: RD plot for the impact of the Dieselgate on Other Brands Stock Prices (different from Volkswagen). Cut-off is 21th September 2015, the date on which the scandal occurred. First degree function. With interaction term.

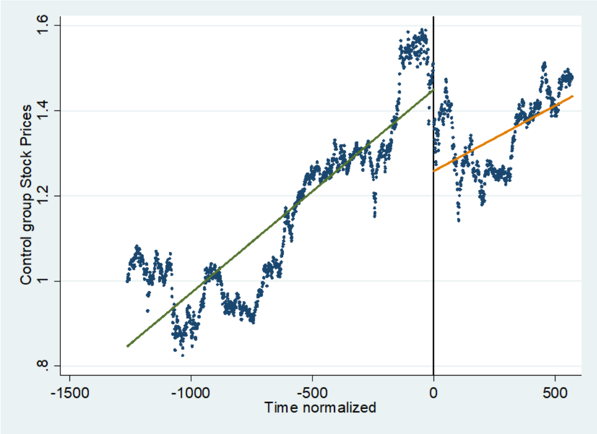


Figure 4: RD plot for the impact of the Dieselgate on Other Brands Stock Prices (different from Volkswagen). Cut-off is 21th September 2015, the date on which the scandal occurred. Second degree function. With interaction term.

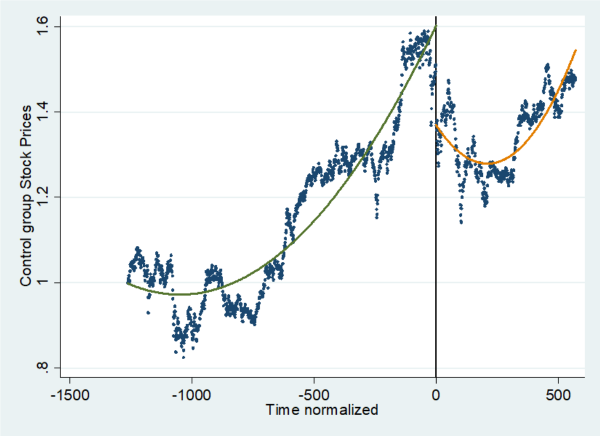


Figure 5: RD plot for the impact of the Dieselgate on Other Brands Stock Prices (different from Volkswagen). Cut-off is 21th September 2015, the date on which the scandal occurred. Third degree function. With interaction term.

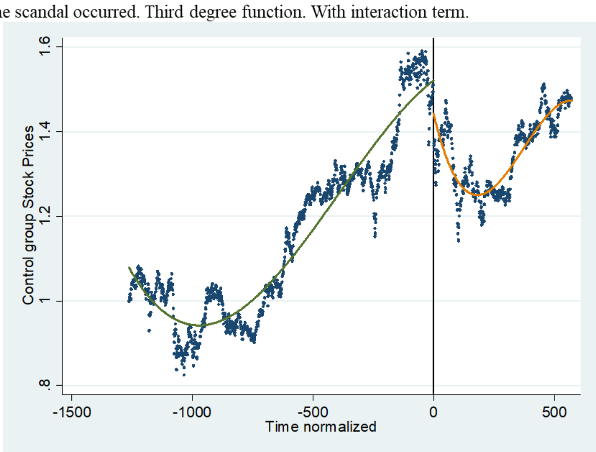


Figure 6: RD plot for the impact of the Dieselgate on Volkswagen Stock Prices. Cut-off is 21th September 2015, the date on which the scandal occurred. First degree function. With interaction term.

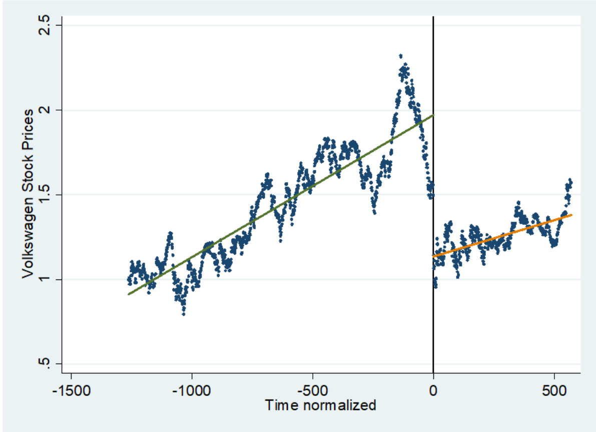


Figure 7: RD plot for the impact of the Dieselgate on Volkswagen Stock Prices. Cut-off is 21th September 2015, the date on which the scandal occurred. Second degree function. With interaction term.

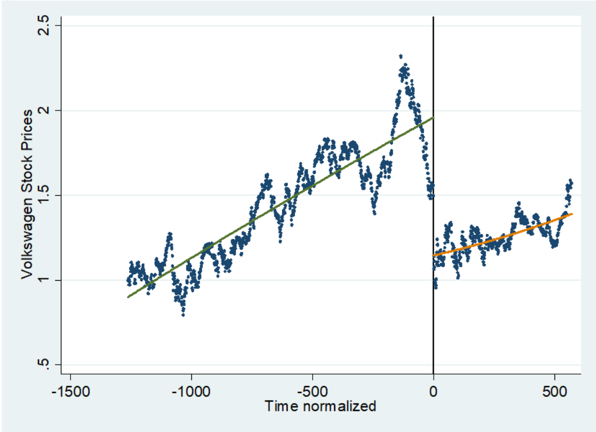
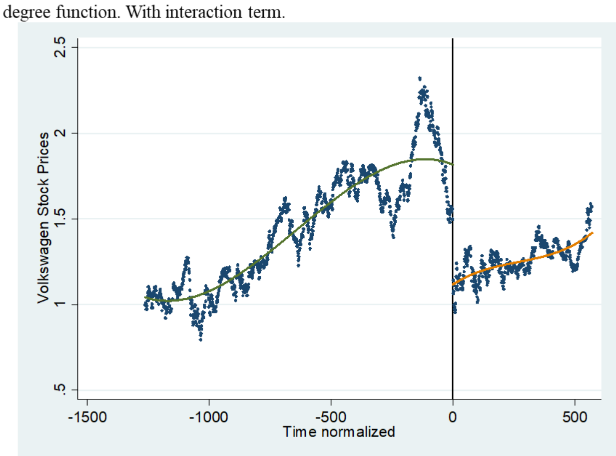


Figure 8: RD plot for the impact of the Dieselgate on Volkswagen Stock Prices. Cut-off is 21th September 2015, the date on which the scandal occurred. Third degree function. With interaction term.



Figures 3, 4 and 5 represents the RDD plots for the 1st, 2nd and 3rd degree of the regression in Table 14, that measures the impact of the Dieselgate on Other Brands Stock Prices (considering a mean of stock prices of all the brands different from Volkswagen).
Figures 6, 7 and 8 represents the RDD plots for the 1st, 2nd and 3rd degree of the regression in Table 15, that measures the impact of the Dieselgate on Volkswagen Stock Prices.
Also comparing the RDD plots we can see that the effect of Dieselgate on Volkswagen stock prices has a major and negative intensity, compared to that on other brands stock prices. In all the figures we can recognize the jump, typical of the RDD model, that expresses the validity of the coefficient of our variable of interest, Dieselgate. We clearly identify a larger jump in figures 4, 5 and 6, compared to figures 1, 2 and 3: for Volkswagen, in correspondence of the cut-off period, stock prices have a major negative gap, compared to that of other brands. Also these figures contribute to increase the validity of our thesis.

2.8 Concluding remarks

We analysed data on car sales in the European Union (EU 15) and data on stock prices of the 27 principal car industry companies. Our aim is to understand if the scandal that hit Volkswagen on the 21st September 2015 had long-run effects on the sales and on the stock prices of the company, compared to that of the entire car industry. Our purpose is dual, we tried to understand if the scandal influenced the consumers and the shareholders.
We created two models: the first one is a differences in differences model used for the monthly sales and for the daily stock prices, the second one is a regression discontinuity design model used only for the stock prices.
Our models include, as control variables, the fuel price, that could affect car consumers; the Gross Domestic Product of the European Union; unemployment/workforce of the European Union; Stoxx Euro 600 that represents 600 capitalization companies across the European region; volatility Stoxx international that reflect the market expectations of near-term up to long-term volatility.
The results are different.
For the effect of the scandal on sales, we find a negative effect, but it isn't statistically significant. For this reason, we cannot confirm that the Dieselgate influenced consumer reaction. This conclusion is not in line with the literature on consumer reaction to negative information. We suppose that the reason is that, in this case, the negative feature of the product, brought to light by the scandal, do not regards directly the consumer. In fact, the Dieselgate scandal highlight that the cars produce polluting emissions. These impact directly on the environment, but not directly on the single consumer. For the consumer, the feature of the product remains the same: a reliable car of

German manufacture. In this case, the scandal emphasised a negative externality produced by the firms, that have an impact on the environment, but it doesn't have a statistically significant impact on the consumer choice.

On the other hand, the effect of the scandal on the stock market is strongly statistically significant and negative, confirmed by both the models used. We can confirm that the Dieselgate scandal had a negative effect on the stock market, which coincides with a collapse of the stock price of the Volkswagen company. This negative market reaction to bad news about products is in line with most of the researches that analyse this field, and it points out that a negative information about a product could have catastrophic consequences for the value of a company. In this case, investor trust in the company is affected by negative information.

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3. Terrorist attacks and impact on tourism: evidence from Europe and USA

Abstract: As a result of the various terrorist attacks in recent years, the fear of a terrorist attack is widespread among travellers. We investigate the impact of terrorism on the touristic sector. We run a panel data model, using monthly data on non-resident nights spent in hotels in the last three decades, in some countries of the Euro zone and in the USA. Results illustrate that the terrorist attacks have both a long-run and a short-run effect on tourism.

3.1 Introduction

In the last three decades, several terrorist attacks affected the USA and different nations in Europe. The increasing frequency of terrorist events worldwide has resulted in a growing demand for research investigating the economic consequences of terrorism. Several studies examine the effects of terrorist attacks on stock markets, but we notice a considerable gap in the economic literature considering the impact on tourism of terrorist attacks.

Starting from the attack of the 11^{th} September 2001 in USA to the World Trade Center's twin towers and to the Pentagon in New York City, several other attacks were made in Europe, causing innocent deaths and injuries. In particular, we focus on terrorist attacks made in Belgium, UK, France and Spain, because we have data available for these countries, and because the Global Terrorism Database gives evidence of terrorist attacks of a certain thickness, comparing them to other European countries that didn't receive any attack. The panel data model allows us to determine the effect of terrorism on tourism outcomes.

The study of terrorism has been an active field of research in international relations since the early 1970s. Terrorist attacks caused catastrophic consequences not only to the tourism industry. For example, the losses associated with the attack in USA 2001 topped 80 billion dollars and caused insurance companies to end automatic coverage of terrorist-induced losses. Consequently, many companies have been unable to afford terrorism insurance (Enders and Sandler, 2011). Furthermore, the occurrence mobilized a huge reallocation of resources to homeland security: since 2002, the US Department of Homeland Security (DHS) budget has grown by over 60% to 36.2 billion dollars for the fiscal year 2004 (DHS, 2003). This is a low expenditure compared to proactive measures taken in fighting the "war on terror," including the invasion against the Taliban and al-Qaida in Afghanistan on 7 October 2001. Still other proactive spending involves improving intelligence, tracking terrorist assets, and fostering cooperative linkages with other countries. All these protective actions taken by rich developed countries have transferred some attacks to poorer countries, for example, the attacks in Egypt, Indonesia, Morocco, Kenya, Saudi Arabia, and Turkey in the last decades.

The Madrid train bombings on 11 March 2004 have made Europe more aware that large-scale terrorist events can occur on European soil. These events heightened anxiety worldwide and resulted in trade-offs in terms of trading reduced freedom for greater security. The anxiety that terrorists seek to create is amplified by people's proclivity to overreact to low-probability but ghastly events.

We test the effect of several terrorist attacks on the nights spent in hotels by non-resident people, aggregated for nations. This research would add empirical evidence to the existing literature on terrorist attacks and their effects on economic performances of the nations.

We use data on the non-resident nights spent in hotel, with a monthly frequency for the sales, for 29 years, from 1990 to 2018. We also use data on migration fear, computed quarterly for the same period.

The paper is organized as follows. In Section 2 we analyse the literature about the economic effect of terrorist attacks. In Section 3 we analyse the attacks that are the object of our study. In Section 4 we describe our datasets. In section 5 we define the models. In Section 6 the outcomes are explained and commented. In Section 7 we do our concluding remarks.

3.2 Literature

The influence of terrorist attacks on economic performance indicators has been extensively discussed in the literature, but most of the research is about the implications for the stock markets. In fact, the literature on the effect of terrorism on tourism is not so wide. Also for this reason, our research aims to fill this gap in the research.

We report below a literature review. In the first part, we review articles related to the effect of terrorism on tourism, in the second part, we review papers on the effect of terrorism on financial markets, which are still useful for our research purposes.

The research of Liu and Pratt (2017) analyse the relationship between terrorism and tourism in 95 different countries. This sample of countries is taken from the United Nations World Tourism Organization and the selected countries cover all the regions of the world.

One of the variables used in the model is an index for the terrorist attacks called Global Terrorism Index GTI, that captures the direct effects of terrorist-related violence. The GTI is based on data from the Global Terrorism Database. The index is based on four factors to give a country's annual index: the total number of terrorist incidents in a given year; the total number of fatalities caused by terrorism in a given year; the total number of injuries caused by terrorism in a given year; and the approximate level of total property damage from terrorist incidents in a given year.

The analysis is performed through the ARDL methodology: an autoregressive distributed lag model is used to estimate the impact of terrorism on tourism demand. These kinds of models are adopted in the tourism field by using both panel data and time series data. The model investigates both long run and short run influences of terrorism on tourism demand. In particular, a panel data model is employed to explore the effect of terrorism on tourism demand from a global view, while time series models are used to look at the impact on specific countries.

The dependent variable is the total tourist arrivals to a destination. This variable lagged is also used as an independent variable. Other independent variables are the weighted GDP index of the top 10 source markets to a certain destination, GTI index (before explained), and other dummies.

The overall findings are the following

- there is no long run effect of terrorism on international tourism demand, only nine countries out of the 95 show a long run impact of terrorism on tourism;
- the short run effect is present, 25 countries out of the 95 show a short run impact using time series models. This implies that international tourism is resilient to terrorism.
- The influence of terrorism is diverse in destinations with different political instability, income levels and tourism intensities.

Samitas et al. (2018) study the terrorism effect on tourism demand of only one nation: Greece. Their aim is to investigate the possible bidirectionality of the relationship terrorism-tourism and to study the effect in a long run perspective.

Two databases are used for the research:

- the statistical databases of National Statistical Services of Greece (NSSG), that provides monthly data from 1977 to 2012 on tourist arrivals
- the Global Terrorism database, that provides data on terrorist incidents, filtered by nations.

The final sample includes 664 terrorist incidents, of which 39 caused a total of 112 deaths. It is assembled a time series with 432 months of observations. Each observation includes the monthly number of all the incidents, the monthly number of incidents with casualties and the name of the terrorist group responsible for the attack.

The authors examine the existence of cointegration among the variables in order to confirm the use of the model, which tests for the long run persistence of the relationship between terrorism and tourism demand. It is used the unrestricted vector autoregression VAR model. Data are corrected for cyclical seasonality. The PCA method is applied in order to extract a common factor from the three terrorism proxies, that is expression of the severity of the incident. This factor is used as a proxy for the terror variable in the empirical analysis.

The empirical results show that terrorism has a significant negative impact on tourist arrivals to Greece. The analysis also examines the direction of causality among the two variables: there is unidirectional causality from terror to tourism in the short-run and in the long-run, with no evidence of reverse causality, so the causality direction is from terrorism to tourism demand in Greece.

The authors suggest that authorities should establish firm measures against terrorism and that additional actions should be taken to promote tourism, safety and security, as a response to terrorist incidents.

The study of Kosová and Enz (2012) investigates the impact of two external shocks on US hotel performance: the terrorist attacks of September 11, 2001, and the financial crisis of 2008.

To isolate the specific effects of the two shocks, the authors controlled for market factors that affect hotels' daily operations (such as inflation and seasonality) and hotel characteristics (such as size, segment, or operation type).

Data on monthly hotel performance, which comprehends room demand, room supply, and room revenue, as well as other hotel characteristics, including hotel opening date, segment, operation type, and geographic location, are obtained from Smith Travel Research (STR). The STR database contains data on 34,695 hotels in the US from 2000 to 2009, covering more than 98% of US hotel properties.

The authors analyse the impact of September 11 and the financial crisis on three main performance measures: hotel-level occupancy, average daily rate (ADR), and monthly revenue per available room (RevPAR) within the US lodging industry.

Monthly price indexes are taken from the Bureau of Labor Statistics (BLS) to obtain monthly real ADR and real RevPAR. To take into account time-varying market characteristics, the authors combine STR data with annual information from the US Census Bureau and BLS on county demographics and employment. The sample includes 34,695 hotels, observed monthly for 10 years. The final number of observations is equal to 3,454,362.

The independent variables in the models are:

- a dummy variable equal to 1 in the month and year when the terrorist attack or the financial crisis occurred and equal to 0 otherwise;

- the set of hotel characteristics including hotel age, monthly number of room-nights available; dummies for each segment and hotel operation-type dummies;
- the set of market characteristics measured across 2,283 counties in the sample: population, unemployment rate percentage, employment and number of establishments in the accommodation industry;
- the set of dummies for each of the twelve months to capture seasonal variation in performance typical for the hotel industry;
- dummies for the ten years in the sample.

The results show that both shocks, the terrorist attacks of September 11, 2001, and the financial crisis of 2008, significantly affect hotels. They started to recover from the negative effects of each shock within four months. The terrorist attack had an immediate and dramatic impact on reducing hotels' occupancy. In contrast, the effects of the financial crisis were less striking and most hotel managers appeared to handle well this shock. Examining specifically hotels in New York City, which is the location most affected by both shocks, the study found an impact on occupancy, ADR, and RevPAR similar to that of the nation as a whole. New York's luxury hotels were the most affected by the shocks, but they were able to recover. Overall, the main implication of this work is that the hotel industry is able to address the negative effects of environmental shocks and that it focuses on revenue management.

Pizam and Smith (2000) sustain that, before the end of the Cold War, terrorism acts have had major effects on tourism destinations. Therefore, tourists have to take into account the unpredictability of terrorism when they organize their travels. The study provides a quantitative analysis of major terrorism events around the world from 1985 to 1998, classified by date, location, victims, weapons used, severity of damage, motive, effect on tourism demand, and length of effect.

The authors identified 70 major incidents that occurred in 28 countries identifying in the Lexis/Nexis Academic Universe database all newspapers and magazine articles discussing the topics of tourism and terrorism for the period 1985–98.

The study focuses on the impact of acts of terrorism happening at tourism destinations on tourism demand and on the effects of different typologies of acts of terrorism.

The majority (54%) of terrorist events analysed occurred in the Middle East, followed by Europe (27%) and Asia (12%). In 71% of the incidents, tourists were among the victims of terrorist acts. The motives for terrorist acts were equally split between 'independence' and 'social injustice'.

The places in which the events occurred are urban location in the 44% of the cases, mode of transportation in the 32%, and rural location in the 23% of the cases. In three-quarters of the cases, the acts decreased tourism demand. The median length of the decline in demand was 1–3 months, with more than one-third of the cases causing a decline of 4–6 months.

The main findings regarding the relationship between terrorism characteristics and tourism demand are:

- acts of terrorism motivated by ‘social injustice’ had a stronger negative effect on tourism demand than those motivated by ‘independence’;
- acts of terrorism that victimized both tourists and residents had a stronger impact on tourism demand than those that victimized residents only;
- acts of terrorism that resulted in bodily harm had a longer negative effect on tourism demand than acts that resulted in property loss;
- acts of terrorism committed with guns had a more negative and longer lasting effect on tourism demand than those committed with bombs;
- no statistically significant differences were found between the location of the terrorist act and the effect on tourism demand.

Overall, the main implication of this study is that terrorism and tourism appear to be inextricably linked.

The paper of Estrada and Koutronas (2016) aims to establish conceptual foundations of the economic impact of terrorism, investigating the recent terrorist attacks in Paris November 2015 and in Brussels March 2016. The economic impact of terrorist attack model (EITA-Model), in fact, attempts to estimate the optimum number of potential terrorist incidents that can affect the regional economic performance.

The model suggests a three-phase of terrorist operations: *i*) the terrorist group attack setting; *ii*) the terrorist group attack behaviour; *iii*) the post-effect of the terrorist group attack. The model investigates.

In this EITA-Model, participants interact in a simple, complete information, two-player game. The first player P1 is the local owner (defender), while the second player P2 is the intruder (enemy). For example, a terrorist group P2 may try to invade the space of local owner P1 to take over all available resources. The terrorist attack consists of two phases: pre-attack and the actual attack phase.

The model comprehends five different risk indicators for the assessment of terrorist attacks: the maximum level of terrorist group attack targets; terrorist group attack destruction; economic terrorist wear; economic degrowth; the multidimensional graphical sub-strategic national security sector analysis.

The authors expect that terrorist incidents have the potential to cause diffused economic disruption. Their findings indicate that the likelihood and magnitude of terrorist attacks are related to economic dynamics of the corresponding region.

In particular, the magnitude of the impact of terrorist attacks in Paris and Brussels depends on the nature of the attacks, the economic resilience of French and Belgian economies and the security levels.

Given this setting, Paris and Brussels may experience significant economic losses. The public perception of terrorist attacks as a one-time event or as a recurring threat will have an impact on the tourism to Paris. In addition, IHS Global Insight expects the Brussels attacks to have a short-term negative impact on the Belgian economy. The most affected factors should be the consumer spending on recreation and leisure, as well as tourism to the popular destinations of the country.

The second part of our literature review is based on researches that analyse the effect of terrorism on stock markets. Despite these researches don’t deal directly to the tourism sector, they are very interesting for the theory that presents and for their empirical conclusion, that could be expanded to our ambit of research on tourism.

Mnasri and Nechi (2016) adopt an event study methodology, combined with an improved bootstrapping test, to evaluate the impact of terrorist attacks on the volatility of stock markets in 12 Middle East and North Africa countries. They do not include Iraq, Syria, Libya and Yemen in their sample because these countries have been experiencing civil wars for the last 5 years (at least) and a terrorist attack could be interpreted as an expected event. Therefore, their final sample includes the seven stock exchange markets of the GCC (Bahrain, Kuwait, Qatar, Saudi Arabia, Oman, Dubai and Abu Dhabi), three stock exchange markets in the Middle East (Jordan, Lebanon and Turkey) and three exchange markets from North Africa (Egypt, Morocco and Tunisia). The authors collected the terrorist attacks from the Global Terrorism Database, considering all incidents of terrorism across the globe since 1970. For countries subject to a relatively high frequency of terrorist attacks, the authors select the “important” attacks only. They define as “important” an attack that causes significant fatalities and financial losses or that targeted an important facility, such as an oil or gas site and refinery plant, or a large city.

A generalized autoregressive conditional heteroscedasticity (GARCH) model is adopted to capture the characteristics of the second moment of stock returns' distribution. The dependent variable is the daily returns of local stock market index for different countries in different times, the independent variable is the global stock market index returns. They estimate the equations, using the maximum

likelihood method, over the period immediately preceding the event by adopting a time window of 500 days. This time frame allows a more accurate analysis of the impact than a standard period of 250 days.
Their results show that terrorist attacks significantly affect the stock market volatility of the sample countries and that there is evidence of regional financial integration. In addition, they also investigate the duration of the impact of terrorist attacks on the emerging markets in two ways.
The authors show that there is no evidence of a significant reaction in the volatility of the stock markets for the first five days following the events, while they find a significant impact in the following days. In fact, their results show that the impact of terrorist attacks on financial markets' volatility lasts about 20 trading days, which is a particularly long-term compared to the term effect of similar events in developed markets. Therefore, regional markets react to the event but with delays. This may be explained by the fear of investors that subsequent attacks may occur.

Kollias et al. (2011) examine the effect of terrorist attacks on stock markets, looking at the question from three different points of view: *i*) they study if markets' reactions to terrorism have changed through time; *ii*) they control if market size and maturity determine reactions; and *iii*) they examine whether reactions depend upon either the type of targets or the perpetrators of the attack.
The authors analyse a large capitalization market (the London stock exchange) and a small capitalization market (the Athens stock exchange) by adopting an event study methodology and a conditional volatility model, considering the fact that both UK and Greece have been subject to terrorist attacks over the years both by domestic terrorist groups and also by transnational terrorist organisations, such as Al-Qaeda in UK and Hezbollah and the Abu Nidal organisation in Greece.
Also these authors retrieve data on terrorist incidents from the Global Terrorism Database. They separate terrorist attacks by type of target (government vs civilian), perpetrator (domestic vs transnational) and the number of fatalities and injuries.
To carry out the event study, in line with the efficient market hypothesis, the authors assume that market agents will take into account new information stemming from an unpredictable event when it becomes available. Under this view, investors are able to reassess values of individual firms after the information release considering economic, environmental, political, social and demographic changes due to the exogenous event. The event study methodology allows estimating such abnormal changes in the market value of each traded stock, reflecting the general valuation of market investors.
The dependent variable of their event study is the daily return for the stock index; while, the independent variables are one period lag of the dependent variable and the returns of the US

S&P500 stock market index. In the second stage, they calculate daily abnormal returns as the difference of the actual returns minus the expected returns. Finally, they estimate cumulated abnormal returns (CARs), aggregating these returns in time windows after the attack.
The authors replicate the same methodology by replacing stock returns with stock market volatility.
With regard to the different impact of domestic and transnational attacks, in the case of the UK, there were two terrorist attacks committed by transnational perpetrators. Only the 2005 incident caused a significant negative effect on stock market returns, while attacks committed by domestic terrorist groups led to statistically significant negative returns. Qualitatively similar findings are observed in the case of Greece. A significant result for Greece is that, when prominent businesspersons are the victims of an attack, the market seems to be affected for a longer period with negative and statistically significant CARs. This may suggest that small capitalisation markets are more sensitive to attacks involving economic targets and such attacks have a comparatively stronger negative impact. Overall, results reported in this study suggest that specific attributes of terrorist incidents are possible determinants of markets' reactions.

Procasky and Ujah (2016) study the costs of terrorism by examining its long-term impact on financial markets. Specifically, the authors analyse the effect of terrorism on the sovereign risk of 102 countries.
They adopt the Institute for Economics and Peace's Global Terrorism Index (GTI), which incorporates both the economic and social dimensions of terrorism, based on the Global Terrorism Database that covers 104,000 documented incidents.
The authors use country level data for the period 2002–2011 to estimate a cross-sectional OLS model. They adopt S&P credit rating to measure sovereign credit rating and the GTI to measure terrorism risk at the country level.
The results of this study indicate that terrorism leads to a higher cost of debt for sovereigns and, consequently, for firms established in affected countries. A two-point increase in terrorism on the 10-point scale, on average, reduces sovereign's credit ratings of a half notch. This impact is more pronounced in developing markets. A comparable two-point increase in terrorism, on average, results in a one-notch downgrade in the sovereign credit rating.
These findings remain significant also after estimating several robustness checks, such as tobit, ordered probit, 2SLS, GMM and dynamic panel estimations, to ensure that they are not driven by choice of methodology.

The research of Crijns, Cauberghe and Hudders (2017) analyses the terrorist threat that happened on November 2015 in Belgium. They conduct a national survey among 805 respondents, with three purposes. First, the authors aim to explore how Belgians deal with the threat by investigating if citizens change their behaviour in public places and seek information about the threat. The second aim of the research is the analysis of how people seek and process information about the terrorism threat, which is namely based on their level of involvement with the threat, the expert efficacy of the government, and attitudes towards mass media communication. Finally, this study focuses on perceived governmental efficacy, examining how governmental reputation is affected by institutional trust and governmental responsibility.

Data are collected through a national research agency, that sent surveys by mail to a random sample of 805 Belgian residents. Since this quota sampling does not frequently provide an accurate representation of the target population, the data are weighted to improve its representativeness. The survey was distributed on the 27th of November 2015, two weeks after the terrorist attacks in Paris. At that date, the terrorist threat level in Belgium was on the second highest level, which indicates that the threat is severe and a terrorist attack is possible and probable to take place.

The model was tested in two different stages: an assessment of the construct validity of the measurement model through confirmatory factor analysis (CFA) and the assessment of the structural model.

Their results show that the terrorism threat leads citizens to be more alert in public places and to a lower participation in mass events. Moreover, one fifth of respondents stopped travelling by public transport. Belgian citizens searched for information several times a day, mostly via traditional media such as television and radio. Furthermore, relying on structural equation modelling, the cognitive assessment of the risk determines information seeking and processing behaviour. This cognitive risk assessment is, in turn, positively affected by individual risk involvement and perceived governmental expert efficacy. However, if respondents perceive that the mass media focus too much on drama and sensationalism, then the perception of risk decreases and, in turn, it reduces information seeking behaviour. Finally, the findings of this study indicate that a perception of governmental expert efficacy is able to increase trust and decrease the level of governmental responsibility, which is in turn beneficial for governmental reputation.

Drakos (2010) hypothesizes that terrorist activity affects investors' attitude. The research investigates whether terrorism has a significant negative impact on daily stock market returns in a sample of 22 countries. The main hypothesis is that the negative impact of a terrorist activity on stock markets is greater when the incident is more severe.

For the research are employed information regarding the exact calendar date and the country of terrorist incidents extracted by the Global Terrorism Database. The database also provides information regarding the psychosocial impact of terrorist attacks, classifying them as having no, minor, moderate, or major impact, for the period after 1998. Stock market data are obtained from Datastream. The sample comprehends daily closing prices of 22 indices from January 1994 to December 2004.

The empirical specification assumes a one-factor setting in which the relevant source of global risk is a benchmark portfolio proxied by the World Morgan Stanley Capital International equity market index (MSCI World). It is also conducted a sensitivity analysis by assuming a three-factor model.

The dependent variable is the daily stock index returns of the country subject to a terrorist incident. The independent variables are the daily return of the world market portfolio, the daily return lagged by one year, the variables of year, month and day. In an additional model, there are introduced dummies to take into account the psychological impact: major, moderate, minor or no impact.

The findings indicate that national returns are significantly affected by the world market portfolio returns whose impact declines monotonically with the lag order. National returns are significantly lower on days when terrorist attacks occur. Furthermore, the null hypothesis that all psychosocial dummies' coefficients are insignificant was rejected at all levels of significance, suggesting that the effect on returns is not uniform across levels of psychosocial impact.

Overall, this analysis suggests that terrorist activity leads to significantly lower returns on the day a terrorist attack occurs and that the negative effect of terrorist activity is substantially amplified as the level of psychosocial effects increases.

Kolaric and Schiereck (2016) analyse the dynamics of airline stock prices surrounding the terrorist attacks that took place in Paris, on 13th November 2015, and in Brussels, on 22nd March 2016. The authors analyse 27 of the largest U.S., Canadian, and European airlines. Their final sample has 51 observations, 25 for the Paris terrorist attacks and 26 for the attacks in Brussels.

They employed the standard market model event study methodology. The cumulative abnormal return (CAR) of airline stocks is the dependent variable of the OLS model. The independent variables are: Brussels, that is defined as 1 for the attacks in Brussels on 22 March 2016; EU, that is defined as 1 if the airline's headquarter is located in Europe; Size is the logarithm of the total assets of a firm in U.S. dollars in the year prior to the event; Net Income is the logarithm of the net income of a firm in U.S. dollars in the year prior to the event. The stock market data and balance sheet data are obtained from Datastream and Worldscope, respectively.

The results document significantly negative market reactions to both events on the announcement day and after one day from the event. In contrast, there is not a significant impact in the event window following the attacks (from day one to day five). These findings may imply that capital markets react exceedingly rational immediately after the attacks, with a stock price adjustment largely made on the event day itself. This strongly supports the efficient capital markets hypothesis.
In particular, CARs observed after the attacks in Paris are significantly more negative than that registered after the subsequent attacks in Brussels, implying that equity markets already adjusted to the threat of potential future terror attacks in Europe after the events in Paris. Also this result is consistent with the assumption of efficient capital markets, given that price adjustments become less severe if an event occurs repeatedly.
In addition, the study underlines that larger airlines seem more affected by terrorism than smaller and regionally focused airlines.

Arin, Ciferri and Spagnolo (2008) investigate the effects of terrorism on the financial markets of Indonesia, Israel, Spain, Thailand, Turkey and UK.
The authors obtained data from Datastream. They extracted the daily stock market index returns, domestic interest rates, 90 days Treasury Bills, US stock market index returns, over the period 2002–2006, for a total of 1368 observations. They define a daily terror index as the natural logarithm of *e* plus the number of human casualties, the number of people injured, the number of terrorist attacks occurred each day. Data for the terror events are collected from the MIPT Terrorism Knowledge Base's Database.
The authors model the joint process governing stock market returns and terrorism index with the bivariate VAR–GARCH-in-mean model. They control for exogenous shocks including in the mean equation the domestic 90-days Treasury Bill rate and the US stock market returns as a proxy for the global market.
They find that there is a negative and significant causality effect for all countries analysed, especially for Indonesia, Turkey and Spain. There is also evidence of the effect of terror events volatility on the stock market returns.
Overall, the findings presented in this study show that terror significantly affects stock markets, both in terms of returns and volatility, and the magnitude of these effects are larger in emerging markets.

3.3 Terrorism: definition and attacks

Terrorism means premeditated, politically motivated violence perpetrated against non-combatant targets by subnational groups or clandestine agents, usually intended to influence an audience (US Department of State, 2003). It is also defined as the premeditated use or threat to use violence by individuals or subnational groups in order to obtain a political or social objective through the intimidation of a large audience beyond that of the immediate victims. Two essential ingredients characterize any modern definition of terrorism: the presence or threat of violence and a political/social motive (Enders and Sandler, 2011). Terrorism is defined by White (2003) as the unlawful use or threatened use of force or violence against individuals or property to coerce or intimidate governments or societies, often to achieve political, religious, or ideological objectives.

In our research, we analyse the most relevant terrorist attacks from 2000 to 2016 that hit some European nations and the USA. For this purpose, we use data that come from the Global Terrorism Database (GTD), regarding terrorist attacks that have had a certain importance between 2000 and 2016, measured in terms of victims (fatalities and injured). In fact, we include in our dataset only the attacks with more than 101 victims, both injuries and deaths, in the 16 countries present in our sample.

In our sample, nations affected by relevant terrorist attacks are USA, Spain, UK, France and Belgium. These events are reported in Table 1, which gives us information about the size and the importance of the attacks, indicating the number of killed and injured people. Also the perpetrator group, that often refers to Islamic extremist groups, is reported in the table.

Table 1 Global Terrorism Database: terrorist attacks between 2000 and 2016 with more than 101 casualities, both injuries and deaths, in the 16 countries present in the dataset.

DATE	COUNTRY	CITY	PERPETRATOR GROUP	FATALITIES	INJURED
14/07/2016	France	Nice	Jihadi-inspired extremists	87	433
12/06/2016	USA	Orlando	Jihadi-inspired extremists	50	53
22/03/2016	Belgium	Zaventem	Islamic State of Iraq and the Levant (ISIL)	18	135
13/11/2015	France	Paris	Islamic State of Iraq and the Levant (ISIL)	93	217
17/04/2013	USA	West	Unknown	15	151
15/04/2013	USA	Boston	Muslim extremists	2	132
07/07/2005	UK	London	Secret Organization of al-Qaida in Europe	27	340
11/03/2004	Spain	Madrid	Abu Hafs al-Masri Brigades (suspected)	73	450
11/09/2001	USA	Arlington	Al-Qaida	189	106
11/09/2001	USA	New York	Al-Qaida	1383	7366

3.4 The data

We collected data on total nights spent by non-residents at tourist accommodation establishments: hotels, camping grounds, recreational vehicle parks and trailer parks, holiday and other short-stay accommodation. These data are available monthly, for 29 years (340 months), from 1990 to 2018, for 15 European countries and the USA, for a total of 5,276 observations. These are the countries present in the dataset: Belgium, Italy, Germany, Sweden, Denmark, France, Spain, Portugal, UK, Iceland, Netherlands, Greece, Austria, Finland, Luxembourg, USA. The data source is Datastream. In order to have a normalized index that allows the comparison between countries of different size, we calculate the fraction between the number of non-resident nights in hotels and square kilometres of the country. The output is the dependent variable of our model, named Nights in Hotels (per square Km), and it represents a proxy of tourism performance in a single country.

From Datastream we also collected data on control variables used in the model:

- GDP, the national Gross Domestic Product of the 16 countries in our sample, with a quarterly frequency;
- Exchange rate, the real effective exchange rate, consumer price index based, with a monthly frequency, different for each of the 16 countries;
- Oil price, the crude oil price, taken from the Brent market of London, with a monthly frequency, that could influence the travels between countries.

Data on the terrorist attacks are taken from the Global Terrorism Database and, as showed in Table 1, they concern terrorist attacks between 2000 and 2016 with more than 101 casualities, both injured and death, in the 16 countries present in our sample.

Table 2 shows the descriptive statistics observed in our sample. Nights in Hotels (per square Km) is the dependent variable and it represents a touristic performance indicator to a national level. Nights are divided for the square kilometres of the country in order to have a normalization for the size. It assumes positive and negative values because it is normalized to the first year available in the sample. Attack is a dummy variable, equal to 1 after the terrorist attack in a certain country. Attack 18 months is equal to 1 only for the 18 months after the attack, then it is 0. The same is for Attack 36 months. These temporal differences are used to compute a short-run, a mid-run and a long-run effect of the terrorist attack. Terrorist attack cumulated is a variable similar to Attack, but it cumulates the attacks in the time: for example in the USA there is an attack in the year 1, and another attack in the year 3, the variable takes value 1 for the year 1 and 2, then split to 2 for the year 3 and so on. The same logic is used for the two following variables in the table, respectively for 18 and 36 months. The variable Fatalities take count of the number of deaths occurred in a terrorist attack, and it cumulates the number of deaths of the eventual following attacks for the same country. This variable also exists for 18 months and 36 months. With the same logic, the variable Injured take count of the injured people in a certain attack, also for 18 and 36 months. The variable Oil price Brent is the crude oil price, taken from the Brent market of London, that we use as a control variable because it could influence the travels between countries. The variable Time measures continuously the months from 1990 to 2018, in which 1 is the value of the first month captured, January 1990, and 340 is the value for the last month measured, April 2018. Nights in hotels (not normalized) is our dependent variable, explained above, before the normalization with the square kilometres.

Table 2: Descriptive statistics. Analyses on country level non-resident nights in hotels per square kilometres (years 1990-2018)

Variables	Obs	Mean	Std. Dev.	Min	Max
Nights in Hotels (per square Km)	4,953	68.9635	435.956	-1864.08	6675.73
Attack	5,440	0.10662	0.30865	0	1
Attack 18 months	5,440	0.02463	0.15502	0	1
Attack 36 months	5,440	0.04099	0.19829	0	1
Terrorist attack cumulated	5,440	0.13732	0.46823	0	4
Terrorist attack 18 months cumulated	5,440	0.03125	0.20861	0	2
Terrorist attack 36 months cumulated	5,440	0.05165	0.26518	0	2
Fatalities	5,440	62.1925	297.688	0	1639
Fatalities 18 months	5,440	6.54283	91.0255	0	1572
Fatalities 36 months	5,440	12.3393	128.071	0	1572
Injured	5,440	305.384	1422.32	0	7808
Injured 18 months	5,440	31.3658	432.017	0	7472
Injured 36 months	5,440	60.3649	608.609	0	7472
Oil price Brent	5,440	48.1341	33.4705	10.27	133.86
Time	5,440	170.5	98.1581	1	340
Nights in Hotels (not normalized)	4,953	0.19133	1.1853	-0.758	34.923

In section 3.5 we will explain our model.

3.5 Model

The research is based on a panel data model that investigates the long-run and the short-run effect of different terrorist attacks on the nights spent in hotels and other accommodations of the respective countries in which the attack took place. Our panel data model is unbalanced because few individuals are not observed for all the periods in the sample (data were not available for some months). We use fixed effects.

Our aim is to understand if the effects deriving from the negative event on the country tourism persist over time, for all the months available after the attack date.

The model examines the terrorist attack effect on the nights spent in hotels and other accommodations:

(1)

$$\begin{aligned} Nights\ in\ hotels_{it} &= \beta_0 + \beta_1 Terrorist\ attack_{it} + \beta_2 Exchange\ rate_{it} + \beta_3 GDP_{it} + \beta_4 Oil\ price_t \\ &+ \beta_5 Country_i + \beta_6 Month_t + \beta_7 Year_t + \varepsilon_{it} \end{aligned}$$

The variables expressed in equation (1) are the following:

$Nights\ in\ hotels_{it}$ the number of nights spent by non-residents at tourist accommodation establishments: hotels, camping grounds, recreational vehicle parks and trailer parks, holiday and other short-stay accommodation, monthly expressed for the different countries of our sample, expressed in volumes, of the country *i* referred to the month *t*;

$Terrorist\ attack_{it}$ is a dummy variable that assumes value 1 from the day after the terrorist attack, for the country attacked, and maintains its value for all the months after that date. The variable variates in the different estimation, becoming a variable that measures the short-term effect of 36 months (it assumes value 1 only for the 36 months after the attack, then returns to 0) and 18 months (it assumes value 1 only for the 36 months after the attack, then returns to 0). We use the word Terrorist attack to indicate our different variables that measure the attack and that we will run in the different regressions separately: Attack, Terrorist attack cumulated, Fatalities and Injured;

$Exchange\ rate_{it}$ is the value of the real effective exchange rate, consumer price index based, monthly expressed, for each country;

GDP_{it} is the value of the Gross Domestic Product, quarterly expressed, for each country;

$Oil\ price_{t}$ is the crude oil price, taken from the Brent market of London, that could influence the travels between countries;

$Country_{i}$ represents the 16 country dummy, that assumes value 1 if the nights in hotel is referred to the respective country, 0 if it refers to another country;

$Month_{t}$ is a vector of 11 month dummies, that assumes different values, according to the month;

$Year_{t}$ is a vector of 28 year dummies, that assumes different values, according to the year;

ε_{it} is an error term.

In the next section we will illustrate the empirical results of our models.

3.6 Estimations and outcomes

In this section, we analyse the outcomes of our panel data model. We use a panel data model because our data are combined time-series and cross-sectional. This kind of model allows in general a great flexibility in demonstrating differences in behaviour across individuals.

In a panel data model, there is a set of individual or group specific variables which may be observed or unobserved. These variables, combined with a constant term, form the individual effect, also called heterogeneity.

If the heterogeneity is observed for all individuals, we can treat the model as an ordinary linear model, using OLS.

If the heterogeneity is unobserved but correlated with the independent variables, then the coefficients of the independent variables are biased and inconsistent as a consequence of an omitted variable. In this case, we add a term to the regression that incorporates all the observable effects and defines an estimable conditional mean. This is the fixed effects approach. It takes the variable that we add to be a group-specific constant term in the regression model. The effect is called "fixed" because it indicates that the term does not vary over time.

If the heterogeneity is unobserved and uncorrelated with the included variables, then we have to formulate another kind of model: a linear regression model with a combined disturbance that may be consistently, though inefficiently, estimated by least squares. This is the random effects approach. It specifies that there is a group specific random element, similar to the error term, except that for each group there is but a single draw that enters the regression identically in each period.

To understand if we have to use fixed effects or random effects, we run the Hausman test. The specification test devised by Hausman (1978) is used to test for orthogonality of the random effects and the regressors. The test is based on the idea that, under the hypothesis of no correlation, both OLS in the LSDV model and GLS are consistent, but OLS is inefficient. Instead, under the alternative hypothesis of correlation, OLS is consistent, but GLS is not (Greene, 2002). Therefore the test is based on the difference.

The chi-square of our Hausman test is minor than 0.05, this suggests that these effects are correlated with the other variables in the model, we would conclude that of the two alternatives we have considered, the fixed effects model is the better choice.

In our dataset we have some missing data due to the way the data were recorded. We use an unbalanced panel. This is a very common situation in panel data sets.

We report below the results of our panel data model using fixed effects.

Table 3 shows the outcomes of the analysis of terrorist attacks on the occupancy of the hotels by non-resident. It is referred to a long-term period.

- In column (1) we analyse only the effect of the variable Terrorist attack on the dependent variable Nights in hotels. The coefficient of the variable terrorist attack has a negative sign, with a value of -77.446. It has a large impact on the dependent variable, it is also highly significant with its t-stat of -11.10. From this first simple analysis, we note an effect of terrorism on tourism, but we need to add other control variables to confirm the effect.
- In column (2) we add the control variable Oil price, that could affect tourism because it affects the price of travels, and that results significant with a t-stat of 5.32. Our variable of

interest remains significant with a t-stat of -9.45 and its coefficient decreases to the value of -108.119, reaching an even bigger level of impact on the dependent variable.

- In column (3) we add the month dummies that led the variable Terrorist attack and the variable Oil price to a slightly less significance compared to column (2), with a t-stat value of respectively -9.38 and 5.35.
- In table (4) we add the year dummies that decrease considerably the Terrorist attack's coefficient (-133.690). It remains significant with a t-stat of -9.09. The variable Oil price becomes not significant and it changes its sign that becomes negative.
- In column (5) we add the country dummies to make our analysis more specific. There is a considerable decrease of both the variable's coefficients. The coefficient of Terrorist attack variable has a value of -45.451 and its t-stat becomes -4.52. The variable Oil price remains not significant.
- In column (6) we add the control variable Exchange rate per nation, its only effect is to change the Oil price sign that becomes positive, but the variable remains not significant.
- In column (7) we add the last control variable GDP per nation, that indicates the Gross Domestic Product. In this last analysis, the variable of interest results negatively related to the dependent variable with a coefficient of -63.812 and it results significant with a t-stat of -4.70. The variable Oil price results not significant.

From this first table, we can affirm that terrorist attacks affect negatively the hotel business, for the countries that we are analysing. This table takes into account all the months available in our sample, it is a long-term analysis.

Table 3: Panel regression: long-term effect of terrorist attacks on country level non-resident nights in hotels per square kilometres (years 1990-2018).

Dependent variable: Nights in hotels	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Terrorist attack	-77.446***	-108.119***	-109.058***	-133.690***	-45.451***	-45.476***	-63.812***
	(6.974)	(11.440)	(11.624)	(14.701)	(10.053)	(10.181)	(13.589)
Oil price		1.244***	1.268***	-0.343	-0.308	0.049	1.999
		(0.234)	(0.237)	(0.852)	(0.633)	(0.949)	(1.404)
Constant	77.720***	19.256**	46.455*	59.256*	78.081***	-208.899	5,321.867*
	(6.974)	(8.858)	(27.229)	(30.646)	(23.756)	(1,172.911)	(2,760.173)
Month dummies	NO	NO	YES	YES	YES	YES	YES
Year dummies	NO	NO	NO	YES	YES	YES	YES
Country dummies	NO	NO	NO	NO	YES	YES	YES
Exchange rate per nation	NO	NO	NO	NO	NO	YES	YES
GDP per nation	NO	NO	NO	NO	NO	NO	YES
Observations	4,953	4,953	4,953	4,953	4,953	4,953	3,907
R-squared	0.003	0.012	0.014	0.034	0.477	0.477	0.478

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

In Table 4 we show for a shorter period the results of the analysis of terrorist attacks on the occupancy of hotels by non-resident. This time we refer to a period of 36 months after the attacks. We create a dummy variable that is 1 for the 36 months after the attack and 0 otherwise, one for each country. Therefore, we analyse here a middle time period after the attacks.

- In column (1) we analyse only the effect of the variable Terrorist attacks on the dependent variable, Night spent in hotel. It results negatively related, as expected, in line with the first column of the previous table. The coefficient results statistically significant with a t-stat of -11.11 and a value of -71.917.
- In column (2) we add the control variable Oil price that results significant with a t-stat of 4.8 and that is positively related to the dependent variable, Nights in hotels. Our variable of interest remains significant with a t-stat of -10.46 and its coefficient decreases to the value of -108.119, amplifying its negative impact on the dependent variable.
- In column (3) we add the month dummies that led the variable Terrorist attack and the variable Oil price to a slightly less significance compared to column (2) with a t-stat value of respectively -9.38 and 5.35.
- In table (4) we add the year dummies that diminish considerably the Terrorist attack's coefficient (-133.690). It remains significant with a t-stat of -9.09. But the variable Oil price

becomes not significant and also it changes its sign into negative, this is not in line with the previous results.

- In column (5) we add the country dummies to complete our analysis. It led to a considerable decrease of both the coefficients of our variables. In fact, the coefficient of Terrorist attacks becomes -45.451 and its t-stat becomes -4.52. The variable Oil price remains not significant.
- In column (6) we add the Exchange rate per nation control variable, its effect is enough to change the Oil price sign that becomes positive again, but still the variable remains not significant.
- In column (7) we add the last control variable Gross Domestic Product per nation. In this last column, the variable of interest results negatively related to the dependent variable with a coefficient of -28.469 and it results significant with a t-stat of -2.48. The variable Oil price results not significant.

From this table of outcomes, we confirm that terrorist attacks affect negatively the nights spent in hotels, with reference to a middle period of 36 months after the attack.

Table 4: Panel regression: effect after 36 months of terrorist attacks on country level non-resident nights in hotels per square kilometres (years 1990-2018).

Dependent variable: Nights in hotels	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Terrorist attack 36 months	-71.917***	-79.072***	-79.573***	-123.843***	-26.512**	-26.390**	-28.469**
	(6.473)	(7.557)	(7.759)	(16.660)	(10.305)	(10.556)	(11.439)
Oil price		1.032***	1.053***	-0.330	-0.306	0.055	2.007
		(0.215)	(0.217)	(0.854)	(0.633)	(0.950)	(1.405)
Constant	72.085***	21.010**	47.673*	59.203*	63.139***	-241.479	5,239.040*
	(6.473)	(8.873)	(27.310)	(30.718)	(23.390)	(1,173.913)	(2,758.584)
Month dummies	NO	NO	YES	YES	YES	YES	YES
Year dummies	NO	NO	NO	YES	YES	YES	YES
Country dummies	NO	NO	NO	NO	YES	YES	YES
Exchange rate per nation	NO	NO	NO	NO	NO	YES	YES
GDP per nation	NO	NO	NO	NO	NO	NO	YES
Observations	4,953	4,953	4,953	4,953	4,953	4,953	3,907
R-squared	0.001	0.008	0.009	0.028	0.476	0.477	0.477

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

In table 5 are reported the outcomes of our analysis for a shorter period respect to the previous table. This time we focus on a period of 18 months after the attacks. Also here we introduce a dummy variable that is 1 for the 18 months after the attack and 0 otherwise, one for each country. Therefore, we analyse here a short-term after the attacks.

- In column (1) the variable Terrorism continues to result negatively related to the dependent variable, as we have seen in the previous table. The effect is statistically significant with a coefficient of -70.917 and t-stat of -11.14.
- In column (2) we add the control variable Oil price, that results significant with a t-stat of 4.78. Our principal variable remains significant with a t-stat of -10.4.
- In column (3) we add the month dummies that slightly affects the variable Terrorist attacks and Oil price, leaving the situation almost equal to the previous column.
- In column (4) we add the year dummies that drop the Terrorist attack's coefficient (-127.937). It remains significant with a t-stat of -6.09. The variable Oil price becomes not significant and also its sign becomes negative.
- In column (5) we add the country dummies, it leads to a consistent change of the coefficient of the variable Terrorist attacks, in fact its coefficient becomes -29.570 and its t-stat becomes -2.14. Also in this column, the control variable results not significant.
- In column (6) we add the control variable Exchange rate per nation. Its effect is to change the Oil price sign that becomes positive again, but still the variable remains not significant. The significance of the principal variable Terrorist attacks decreases again to the t-value -2.03, but the statistical significance is still maintained.
- In column (7) we add the last control variable GDP per nation. In this last column, the variable of interest results negatively related to the dependent variable with a coefficient of -29.291 and a t-stat of -1.89. The significance is reduced respect to previous columns, but it is still confirmed with a p-value of 0.10.

From this table we can deduce that, as we reduce the time interval, the Terrorist attacks continue to have an impact on the hotel reservations.

Table 5: Panel regression: effect after 18 months of terrorist attacks on country level non-resident nights in hotels per square kilometres (years 1990-2018).

Dependent variable: Nights in hotels	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Terrorist attack 36 months	-70.917***	-76.389***	-75.137***	-127.937***	-29.570**	-29.485**	-29.291*
	(6.367)	(7.342)	(7.341)	(20.995)	(13.802)	(14.481)	(15.531)
Oil price		1.022***	1.042***	-0.319	-0.303	0.057	2.011
		(0.214)	(0.217)	(0.855)	(0.633)	(0.950)	(1.405)
Constant	70.882***	20.162**	46.517*	58.742*	61.012***	-234.321	5,256.368*
	(6.365)	(8.887)	(27.305)	(30.749)	(23.240)	(1,173.820)	(2,758.936)
Month dummies	NO	NO	YES	YES	YES	YES	YES
Year dummies	NO	NO	NO	YES	YES	YES	YES
Country dummies	NO	NO	NO	NO	YES	YES	YES
Exchange rate per nation	NO	NO	NO	NO	NO	YES	YES
GDP per nation	NO	NO	NO	NO	NO	NO	YES
Observations	4,953	4,953	4,953	4,953	4,953	4,953	3,907
R-squared	0.001	0.007	0.009	0.027	0.476	0.477	0.477

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

In tables 3, 4 and 5 we analyse respectively the long, the middle and the short-term effect of the Terrorist attacks on the Nights spent in hotel by non-resident. We note that, in the long period, the negative effect is higher, with a coefficient of -63.812, compared to that of the middle period of -28.469, and to that of the short period of -29.291. The significance of these effects, according to the last columns of the tables, increases in time: we have a t-value of -1.89 for the short time, -2.48 for the middle time and -4.70 for the long time. The increasing significance in time is unexpected because we would wait that, immediately after the attack, the effect would be stronger than in the long period. Probably this fact is a symptom that in this first part of our research there is a lack of control variables. In the next pages we hope to solve this issue. However, this is only the first part of the research, this means that the quality of our results could be better in the next tables because we will take into account also the cumulated terrorist attacks and the number of fatalities and injuries.

In tables 6, 7 and 8 we analyse the cumulated terrorist attacks. We use the term “cumulated” because in one country it could be present various terrorist attacks, so we sum the terrorist attacks in order to have a major value for countries affected by multiple attacks. In this case, the variable Terrorist attacks assumes value 0 when the country has not attacks, 1 when the country receives an attack, 2 after the second attack received and so on.

In table 6 we analyse the outcomes of the cumulated terrorist attacks effect on the hotel's reservations on the long-term (we use all the months present in our sample).

- In column (1), as usual, we analyse only the effect of the principal independent variable, Terrorist attacks, on the dependent variable, Nights spent in hotel by non-residents. The first difference we can note is that the coefficient of the variable of interest is considerably smaller than the previous analyses (table 3), in fact it is -42.925, but it is still negatively related to the dependent variable and it is statistically significant with a t-stat of -10.05.
- In column (2) we add the control variable Oil price that results significant with a t-stat of 5.14. Our variable of interest remains significant with a t-stat of -8.71, and its coefficient diminishes to -57.771.
- In column (3) we add the month dummies that slightly affects the variables Terrorist attacks and Oil price, leaving the situation almost equal to that of column 2.
- In column (4) we add the year dummies that almost double the Terrorist attacks coefficient (-86.829). It remains significant with a t-stat of -8.23, but the control variable Oil price becomes not significant and again it changes its sign into negative.
- In column (5) we add the country dummies, it leads to a drastic drop of the coefficient of Terrorist attacks, in fact its coefficient becomes -38.840 and its t-stat is -5.4. The variable Oil price remains not significant.
- In column (6) we add the control variable Exchange rate per nation. Its effect is to change the other control variable sign, Oil price, that becomes positive again, but still the variable remains not significant. The variable Terrorist attacks significance remains stable with a t-stat of -5.27 and a coefficient of -39.071.
- In column (7) we add the control variable Gross Domestic Product per nation. In this more complete column, the variable Terrorist attacks results negatively related to the dependent variable, with a coefficient that returns almost equal to that of the first column, with a value of -49.694, and it results significant with a t-stat of -5.3.

We can conclude again that terrorist attacks have an important impact on the hotels' reservations. This result is also confirmed for cumulated values of the attacks in the long-term, considering all the months present in our sample.

Table 6: Panel regression: long-term effect of cumulated terrorist attacks on country level non-resident nights in hotels per square kilometres (years 1990-2018).

Dependent variable: Nights in hotels	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Terrorist attack cumulated	-42.925***	-57.771***	-58.249***	-86.829***	-38.840***	-39.071***	-49.694***
	(4.272)	(6.626)	(6.731)	(10.546)	(7.193)	(7.409)	(9.373)
Oil price		1.162***	1.184***	-0.335	-0.305	0.056	2.004
		(0.226)	(0.229)	(0.851)	(0.633)	(0.949)	(1.403)
Constant	75.229***	19.553**	46.559*	58.710*	88.490***	-206.942	5,287.336*
	(6.751)	(8.854)	(27.256)	(30.638)	(24.263)	(1,172.329)	(2,757.897)
Month dummies	NO	NO	YES	YES	YES	YES	YES
Year dummies	NO	NO	NO	YES	YES	YES	YES
Country dummies	NO	NO	NO	NO	YES	YES	YES
Exchange rate per nation	NO	NO	NO	NO	NO	YES	YES
GDP per nation	NO	NO	NO	NO	NO	NO	YES
Observations	4,953	4,953	4,953	4,953	4,953	4,953	3,907
R-squared	0.002	0.010	0.012	0.033	0.477	0.478	0.478

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

In table 7 we examine the mid-term effect of terrorism on tourism. The outcomes refer to 36 months after the terrorist attack. The table refers to the cumulated frequency of terrorist attacks.

- Column (1) expresses the effect of the variable Terrorist attacks on the Nights spent in hotel. Even in the middle-term, it is negatively related to the dependent variable, with a t-stat of -10.64 and an intensity of -51.072.
- In column (2) we add our first control variable, Oil price, that results significant with a t-stat of 4.83. The terrorism variable remains significant with a t-stat of -10.05, and its coefficient decreases of about 7 points.
- In column (3) we add the month dummies and the situation remains stable.
- In column (4) we add the year dummies that again lead to an important decrease of the Terrorist attacks coefficient (-99.033), it remains significant with a t-stat of -7.76, but the variable Oil price becomes not significant and again it changes its sign into negative.
- In column (5) we add the country dummies that cause a drop of the coefficient of the Terrorist attacks variable, it becomes -32.724 and its t-stat becomes -4.24.
- In column (6) we add the Exchange rate per nation, a control variable. Its effect is to change Oil price sign that becomes positive again, but still the variable remains not significant. The variable Terrorist attacks significance remains stable with a t-stat of -4.123.

- In column (7) we add the variable GDP per nation. The results remain similar to that of previous columns: the coefficient of terrorist attacks is -34.724 and it results significant with a t-stat of -4.02; the variable Oil price results not significant.

We can conclude that, also in the middle-term and with cumulated frequencies, terrorist attacks have a negative impact on tourism of a certain country.

Table 7: Panel regression: effect after 36 months of cumulated terrorist attacks on country level non-resident nights in hotels per square kilometres (years 1990-2018).

Dependent variable: Nights in hotels	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Terrorist attack 36 months cumulated	-51.072***	-58.415***	-58.737***	-99.033***	-32.724***	-32.744***	-34.724***
	(4.800)	(5.815)	(5.956)	(12.761)	(7.720)	(7.941)	(8.634)
Oil price		1.038***	1.060***	-0.338	-0.308	0.054	2.002
		(0.215)	(0.218)	(0.854)	(0.633)	(0.949)	(1.404)
Constant	71.737***	20.429**	47.079*	59.316*	67.687***	-244.093	5,224.284*
	(6.441)	(8.867)	(27.302)	(30.712)	(23.484)	(1,173.735)	(2,758.037)
Month dummies	NO	NO	YES	YES	YES	YES	YES
Year dummies	NO	NO	NO	YES	YES	YES	YES
Country dummies	NO	NO	NO	NO	YES	YES	YES
Exchange rate per nation	NO	NO	NO	NO	NO	YES	YES
GDP per nation	NO	NO	NO	NO	NO	NO	YES
Observations	4,953	4,953	4,953	4,953	4,953	4,953	3,907
R-squared	0.001	0.008	0.009	0.029	0.477	0.477	0.477

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

Table 8 expresses the short-term outcomes of our research, considering the cumulated terrorist attack effect on tourism. For the short-term analysis we use a period of 18 months after the attack.

- Column (1) shows the primary short-term effect. The variable Terrorist attacks is negatively related to the dependent variable. The effect results statistically significant with a t-stat of -10.43. Both the t-stat and the intensity of the coefficient result similar to that in the previous table, that expresses a mid-term analysis.
- In column (2) it is present the control variable Oil price that results significant with a t-stat of 4.79. Our variable of interest remains significant with a t-stat of -9.95, and its coefficient slightly decreases, amplifying its negative effect on the dependent variable.
- In column (3) we add the month dummies that slightly affects the variables Terrorist attacks and Oil price leaving the situation almost equal to that of column 2.

- In column (4) we add the year dummies that again lead to an important drop of the Terrorist attacks coefficient (-99.090) that almost doubles with a negative sign. It remains significant with a t-stat of -6.37, but the control variable Oil price becomes not significant and again it changes its sign into negative.
- In column (5) we add the country dummies, it leads to an intense rise of the coefficient of the Terrorist attacks variable, it becomes -31.166 and its t-stat becomes -3.09. The variable Oil price remains not significant.
- In column (6) we add the Exchange rate per nation variable. The variable Terrorist attacks significance remains stable with a t-stat of -2.93. It changes the Oil price sign, that becomes positive again, but still the variable remains not significant.
- In column (7) we add the control variable GDP per nation. The variable of interest, Terrorist attacks, results negatively related to the dependent variable, its coefficient is -31.321 and its t-stat is -2.73. The variable Oil price results not significant.

Table 8: Panel regression: effect after 18 months of cumulated terrorist attacks on country level non-resident nights in hotels per square kilometres (years 1990-2018).

Dependent variable: Nights in hotels	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Terrorist attack 18 months cumulated	-49.644***	-57.364***	-56.334***	-99.090***	-31.166***	-31.212***	-31.321***
	(4.761)	(5.764)	(5.767)	(15.555)	(10.091)	(10.660)	(11.483)
Oil price		1.030***	1.051***	-0.301	-0.296	0.064	2.015
		(0.215)	(0.217)	(0.856)	(0.634)	(0.951)	(1.405)
Constant	70.667***	19.644**	45.994*	58.285*	62.534***	-233.635	5,252.601*
	(6.346)	(8.879)	(27.298)	(30.746)	(23.259)	(1,173.764)	(2,758.528)
Month dummies	NO	NO	YES	YES	YES	YES	YES
Year dummies	NO	NO	NO	YES	YES	YES	YES
Country dummies	NO	NO	NO	NO	YES	YES	YES
Exchange rate per nation	NO	NO	NO	NO	NO	YES	YES
GDP per nation	NO	NO	NO	NO	NO	NO	YES
Observations	4,953	4,953	4,953	4,953	4,953	4,953	3,907
R-squared	0.001	0.007	0.009	0.027	0.477	0.477	0.477

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

Here is an overview with our considerations about the analysis on cumulated frequency of terrorist attacks. In tables 6, 7 and 8 our research focuses respectively on the long, the middle and the short-term effect of terrorism on tourism. In the long period the effect is higher, with a coefficient of -49.694, compared to that of the middle period of -34.724, and to that of the short period of -31.321. The significance of these effects, according to the columns (7) of the tables, increases in time: we have a t-value of -2.73 for the short time, -4.02 for the middle time and -5.30 for the long time. Also here, as in the previous comparison of tables 3, 4 and 5, we notice an increasing significance in time of the terrorism variable that is unexpected. Even if here the difference between the middle and the short-term is little, and the distances are also shortened between the long and the mid-term. Therefore, the situation improves when we analyse the cumulative effect of terrorist attacks on tourism, even if we expected that, in the short period, close to the terrorist attack, the effect would be stronger than in the long period. Probably, with the adding of more control variables, the results could be more similar to our expectations and this could be improved in further research.

To confirm our thesis, we expand our panel data model, using, as indicators of terrorist attacks, the number of fatalities and injured people. These measures give us a more detailed idea on the size of the attack. In the next three analyses, we test if a terrorist attack of greater intensity has major effects on our tourism indicator, hotel nights.

In Table 9 we show the results of the panel regression that uses number of fatalities in the terrorist attack as the only variable that measures terrorism. We use, as the dependent variable, the same of previous regressions: Nights spent in hotels by non-resident.

- In column (1) we study the effect of the number of fatalities on tourism. The variable Fatalities results negatively related to the dependent variable and it’s statistically significant, with a t-value of -12. This is exactly what we expected: the number of fatalities affects the willingness of tourists to visit the places damaged by terrorism.
- In column (2) we add the control variable Oil price that results significant with a t-stat of 4.93. It influences negatively the coefficient of the variable of interest, but it doesn’t affect the significance that remains stable with a t-stat of -8.86.
- In column (3) we consider the month dummies that don’t affect the significance of the two variables, and slightly increases the intensity of their coefficients.
- In column (4) we add the year dummies, that, as we had seen before, changes the sign of the variable Oil price and makes it not significant. While the variable of interest remains significant with a t-stat of 8.75.
- In column (5) we consider the country dummies. The coefficient of the variable Fatalities rises up to the value of -0.014. Its statistical significance is confirmed, even if it is smaller than the previous column, with a t-stat value of -2.33. The variable Oil price remains not significant.
- In column (6) we add the control variable Exchange rate per nation that doesn’t change the situation of column (5).

- In the last column (7) we add the variable GDP per nation. Its presence slightly decreases the coefficient of the variable of interest to the value of -0.029, and it results a higher statistical significance, with a t-stat of 3.22. The variable Oil price results not significant. If we compare the value in the last column with the value in the first column, we can see that the coefficient of the variable of interest is smaller in the last column than in the first, because of the adding of control variables. We can conclude that the number of fatalities due to a terrorist attack significantly affects the hotel's reservations.

Table 9: Panel regression: effect of the number of fatalities on country level non-resident nights in hotels per square kilometres (years 1990-2018).

Dependent variable: Nights in hotels	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fatalities	-0.048***	-0.062***	-0.063***	-0.070***	-0.014**	-0.014**	-0.029***
	(0.004)	(0.007)	(0.007)	(0.008)	(0.006)	(0.006)	(0.009)
Oil price		1.080***	1.102***	-0.351	-0.310	0.051	2.014
		(0.219)	(0.222)	(0.854)	(0.633)	(0.949)	(1.405)
Constant	72.250***	19.439**	46.498*	60.004*	69.050***	-227.732	5,298.604*
	(6.487)	(8.867)	(27.284)	(30.740)	(23.433)	(1,174.037)	(2,760.550)
Month dummies	NO	NO	YES	YES	YES	YES	YES
Year dummies	NO	NO	NO	YES	YES	YES	YES
Country dummies	NO	NO	NO	NO	YES	YES	YES
Exchange rate per nation	NO	NO	NO	NO	NO	YES	YES
GDP per nation	NO	NO	NO	NO	NO	NO	YES
Observations	4,953	4,953	4,953	4,953	4,953	4,953	3,907
R-squared	0.001	0.008	0.010	0.028	0.476	0.477	0.477

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

In table 10 we use the number of injured people due to the attack as a measure for terrorism.

- In column (1) we examine only the effect of the variable injured on the nights spent in hotels by non-resident. As the variable fatalities, also the variable injured is negatively related to the dependent variable, as we expected. It has a very small intensity of the coefficient (-0.010), but the statistical significance is very high, with a t-stat of -10.
- In column (2) we introduce in the regression our first control variable, Oil price, that results positively related to the dependent variable and it's statistically significant with a t-stat of 4.93. The variable Injured remains significant with a t-stat of -13.

- In column (3) we add the month dummies that slightly changes the situation of the previous column, maintaining the significance and the influence of the two variables on the dependent variable.
- In column (4) we add the year dummies, that, as we expected, changes the sign and the statistical significance of the variable Oil price. The significance of the variable of interest remains high, with a t-stat value of -7.5.
- In column (5) we use country dummies that lead to a dramatic increase of the coefficient of the variable Injured, that goes from 0.015 to 0.03, but it still it remains statistically significant, with a t-stat of -3.
- In column (6) we add the variable Exchange rate per nation, that maintains the situation similar to column (5).
- In column (7) we add the variable GDP per nation that lead to a small drop of the Injured coefficient, in fact it decreases to the value -0.007, and it remains statistically significant with a t-stat value of -3.5. The control variable Oil price remains not significant. We can conclude that the number of injured people less affects tourism, compared to the number of fatalities, but we can see that anyway it has an effect on hotels nights.

Table 10: Panel regression: effect of the number of injured on country level non-resident nights in hotels per square kilometres (years 1990-2018).

Dependent variable: Nights in hotels	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Injured	-0.010***	-0.013***	-0.014***	-0.015***	-0.003***	-0.003***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Oil price		1.085***	1.108***	-0.351	-0.310	0.051	2.013
		(0.220)	(0.222)	(0.854)	(0.633)	(0.949)	(1.405)
Constant	72.430***	19.417**	46.494*	60.002*	70.571***	-225.855	5,303.956*
	(6.503)	(8.867)	(27.282)	(30.737)	(23.464)	(1,174.020)	(2,760.577)
Month dummies	NO	NO	YES	YES	YES	YES	YES
Year dummies	NO	NO	NO	YES	YES	YES	YES
Country dummies	NO	NO	NO	NO	YES	YES	YES
Exchange rate per nation	NO	NO	NO	NO	NO	YES	YES
GDP per nation	NO	NO	NO	NO	NO	NO	YES
Observations	4,953	4,953	4,953	4,953	4,953	4,953	3,907
R-squared	0.001	0.008	0.010	0.028	0.476	0.477	0.477

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

In table 11 we show the last outcomes of our research, the analysis of the conjunct effect of both the variables that measure terrorist attacks, fatalities and injured, on the dependent variable that is a proxy for tourism, nights spent in hotels by non-resident people of a country. The variable called Fatalities and Injured is a simple sum of both the variables. It expresses the total number of people who were directly hit by the terrorist attack.

- In column (1) is expressed the basic regression using the effect of the combination of the two variables on the dependent variable. It results negatively related, as we expected, with a very low coefficient of -0.009, that is statistically significant with a t-stat value of -9.
- In column (2) we add the control variable Oil price that leads to a slight decrease of the variable of interest's coefficient, that reaches the value of -0.011 and maintains its statistical significance with a t-stat of -11. The variable Oil price is, as usual, statistically significant and positively related to the dependent variable, with a t-stat of 4.95.
- In column (3) we add the month dummies that doesn't affect the results obtained in the previous column.
- In column (4) we add the year dummies that lead the variable Oil price to be not significant, but it doesn't affect the significance of the variable of interest that has a t-stat of -12 and that maintains its coefficient stable to the value of -0.012.
- In column (5) we add the country dummies that lead to a strong increase of the coefficient of the variable Fatalities and injured, up to the value of -0.003, with a significance attested by the t-stat's value of -3.
- In column (6) we insert the control variable Exchange rate per nation that doesn't change the situation founded in column (5) with regard to the variable of interest, but it influences the sign of the variable Oil price that anyway remains not significant.
- In column (7) we add the last variable, GDP per nation, that led to a slight diminishing of the coefficient of Fatalities and injured, that reaches the value of -0.005, and it remains statistically significant with a t-stat value of 2.5. The control variable Oil price remains not significant.

Table 11: Panel regression: effect of the number of fatalities and injured per terrorist attack on country level non-resident nights in hotels per square kilometres (years 1990-2018).

Dependent variable: Nights in hotels	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fatalities and Injured	-0.009***	-0.011***	-0.011***	-0.012***	-0.003***	-0.003***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Oil price		1.084***	1.107***	-0.351	-0.310	0.051	2.013
		(0.219)	(0.222)	(0.854)	(0.633)	(0.949)	(1.405)
Constant	72.399***	19.421**	46.495*	60.002*	70.310***	-226.180	5,303.047*
	(6.500)	(8.867)	(27.283)	(30.737)	(23.458)	(1,174.023)	(2,760.574)
Month dummies	NO	NO	YES	YES	YES	YES	YES
Year dummies	NO	NO	NO	YES	YES	YES	YES
Country dummies	NO	NO	NO	NO	YES	YES	YES
Exchange rate per nation	NO	NO	NO	NO	NO	YES	YES
GDP per nation	NO	NO	NO	NO	NO	NO	YES
Observations	4,953	4,953	4,953	4,953	4,953	4,953	3,907
R-squared	0.001	0.008	0.010	0.028	0.476	0.477	0.477

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

The overview of the last three tables takes us to think that the number of fatalities and injured people leads tourists to reconsider the idea of spending time in places where terrorist attacks happened. According to tables 9 and 10, the number fatalities due to terrorist attacks affects tourism more than the number of injured people: nights spent in hotel diminish of 0.029 points in the first case and of 0.007 in the second one. Even if the effect is slight in terms of intensity, it has a strong statistical significance in all the cases. Also this result is in line with our hypotheses: terrorist attacks have a statistically significant effect on tourism.

3.7 Concluding remarks

We investigated data on terrorist attacks of the last two decades, in 15 European countries and the USA, with the aim of understanding the effect of terrorist attacks on tourism demand.

Crossing data on nights spent in hotel accommodations by non-residents and data on the size of different terrorist attacks, we run a panel data model regression. Our model includes, as control variables, the oil price, that could affect tourism transportations, the Gross Domestic Product of the 16 countries of our sample and the real exchange rate for each country.

We verify the effect of terrorism on tourism performance using different principal variables in the diverse regressions that we run: the simple Attack dummy variable, the cumulated attack variable, the number of fatalities, the number of injuries and the sum of both injured and death.

For the most these regressions we control for long-run, middle-run and short-run.

The results are univocal for all our models: terrorist attacks have a highly significant and negative effect on the tourism performance indicator in the short-run as in the mid-run and in the long run. In particular, the shortest period we control for is 18 months after the attack, then the mid-run counts 36 months after the attack. Instead, the long-run period lasts until the last month collected in our dataset, for 17 years.

However, we are faced with a problem: in the long-run the negative effect of terrorism on tourism is higher than in the short-run. For the theory also reviewed in the literature, the effect could conversely decrease over time. In further research our findings necessitate discovering the motivation of this unexpected trend of the effect over time. This could depend on some control variables not present in our model.

3.8 References

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Concluding remarks

We estimated the effect of positive and negative information on economic performance. Our three researches lead to the same conclusion: information has an effect on economic performance, that is positive or negative depending on the type of information that the information transmit.

We find a positive effect on sales when a cultural prize is assigned in the music Italian industry.

We find negative effects when the information is negative and it concerns the features of a product in the European automobile industry, and when the information is negative and it is about terrorist attacks in some countries of Europe and USA.

In our three researches we used different econometric methods: Regression Discontinuity Design, Differences-in-Differences and Panel data model.

In most cases, our research is in line with the previous findings of the scientific literature and it contributes to expand the empirical evidences that confirm the theory. In particular, in our first research we find that the Italian Sanremo cultural award have a positive effect on song sales, therefore there is a positive effect of cultural prize on consumer choice; in our second chapter we find that the Dieselgate scandal have a negative effect on financial markets, decreasing the stock prices of the Volkswagen company involved in the scandal; in our third work we find that terrorist attacks negatively influences the nights spent in hotels by non-resident people, a touristic performance indicator that expresses the negative consumer reaction to the event.

In one case only, we find results divergent from the previous literature. In our research on the Dieselgate scandal, analysing data on car sales, we find that these don’t have a statistically significant decrease after the scandal, in contrast with the previous findings in this field. We suppose that this fact is due to an indirect effect on the consumer of the negative features of the product: the cars involved in the scandal produce pollution that directly affects the environment but indirectly affects the consumers, which does not significantly change their purchase choice.

A more detailed overview of our findings is expressed in the final section of the research chapters, it also expresses some advices for further research.

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