Does a disaster in the backyard affect donations for a faraway cause? Evidence from a natural experiment in Flanders (Belgium)

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Abstract: In the midst of an ongoing nationwide campaign to collect funds for famine relief in Africa, a storm struck a locally famous open air music festival in Belgium. Five participants died, and several hundreds were wounded. We use this event to determine whether donations to an ongoing campaign for a cause located abroad can be affected by a local disaster. Applying a differences-in-differences identification strategy to campaign contributions at the municipality-day level, we show that, after the event, the municipalities affected by the disaster gave more money to the famine relief in Africa campaign than non-affected municipalities. We interpret this finding as evidence that donations to a faraway cause can be positively affected by a local disaster.

Keywords: Altruism, Charity, NGO, Giving, Disaster.
JEL codes: D10, D64, L31.

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1. Introduction

Fundraising is an essential part of the activity of charities. They invest resources in finding and building relationships with donors. In doing so, they compete to attract funds, which is a standard way to model their behavior, like in Bilodeau and Slivinski (1997) or Aldashev and Verdier (2009, 2010). Bilodeau and Steinberg (2006) remark that the fact that charities invest in the relationship with donors is evidence that the game they play involves some competition with other charities.

In understanding the competition among charities, a crucial assumption is whether the size of the pool of potential donations over which they compete is fixed, or may increase with the efforts of charities to communicate with and attract donors. If the pool of donations is fixed, then competing for donations is a zero-sum game, and the charity sector may be subject to a common pool problem as Eckel and Steinberg (1991, 1993, cited by Bilodeau and Steinberg 2006) argue. In a recent contribution where they study the competition between charities in a spatial model where the number of charities is endogenous, Aldashev and Verdier (2009) show that the efficiency of the charity market depends on that assumption. If the size of the market is fixed, then the number of charities may be larger than optimal from the point of view of beneficiaries, precisely because of the common pool problem. Charities devote too much resources to attract donors. Conversely, if the size of the market increases with communication efforts, then each charity generates a positive externality on others, because it raises the awareness of donors, thereby increasing the pool of donations. In that case, the number of charities can be too small.

Direct evidence on the size of the pool of potential donors is limited. There is indirect evidence that the number of charities on a market may adversely affect their performance. Feigenbaum (1987) finds that competition among health research charities increases the ratio of fundraising costs to gross receipts. The belief that charities compete is moreover widely held among professionals, as Aldashev and Verdier (2010) report. There is also evidence that charities must devote resources to elicit donations. Schokkaert (2006) underlines the "importance of being asked". Andreoni and Rao (2011) provide experimental evidence that communication raises donors' empathy, thereby increasing their donations. Using individual panel data, Reinstein (2011) finds that the within individual correlation of donations to different types of charity tends to be negative, suggesting that charities are indeed substitutes and compete for donations. Ek (2015) uses a real-donation laboratory experiment where participants can contribute to different charities supporting different causes. He finds that contributions are substitutes, in that contribution to one charity comes at the expenses of others. Conversely, Lange and Stocking (2012) use a field experiment to measure the response of donors to two charities to being invited by e-mail by one charity to volunteer for the other. They find that the total donations to the two charities of donors who were invited to volunteer were larger than those of donors who had not been invited. Accordingly, time and money donations seem complement.

Disasters provide natural experiments to test the competition between charities, because they exogenously raise the number of causes to donate to. Disasters can cause large donations. There is moreover evidence that donations to disaster relief charities increase with communication and media coverage of particular events. Olsen et al. (2003) argue that the sevenfold difference between the emergency aid received by India following the 1999 cyclone and Mozambique following the 2000 floods can be explained by the fourfold difference in media coverage received by the two disasters in the US and Western Europe. Brown and Minty (2008) use data on individual internet donations in the US following the December 2004 Indian Ocean tsunami. They find that an additional minute of nightly news coverage on network television increased Internet donations by up to 20.8% on the same day. However, the evidence reported by Brown and Minty (2008) pertains to the impact of communication about a given disaster on the donations that it receives, not on the overall amount of donations. It therefore does not tell us if increases in donations to one charity come at the expense of donations to others.

Anecdotal evidence may suggest that they do. For instance, in the aftermath of the 2004 Tsunami, the NGO Doctors Without Borders stopped accepting tsunami-relief donation and requested donators to donate to its general Emergency Relief Fund instead, because it had received enough funds to finance its operations related to the disaster. Recent empirical evidence however contradicts the standard view. Using household data from the U.S. Panel Study of Income Dynamics, Brown et al. (2012) observe that donations specifically for the victims of the 2004 Tsunami were positively correlated with subsequent donations to other charitable causes. Deryugina and Marx (2016) complement Brown et al. (2012) by studying the impact of tornado strikes in the United States on donations by US citizens as reported in tax declarations provided by the Internal Revenue Service. They observe that donations increase in a state in the two years after it was hit by a tornado that claimed more than five victims. Using a large dataset on charitable contributions in the United Kingdom, Scharf et al. (2016) study the impact of six fundraising appeals for disasters abroad on charitable contributions directly related to the appeals and donations to other charitable causes, domestic or foreign. They find that appeals increase charitable contributions to their own cause, but do not affect donations to other causes in the medium term.

These studies all study the impact of disasters on donations to permanent causes. In other words, they look at how unforeseen disasters affect recurrent donations. A more demanding test of whether causes compete would be to test whether a disaster can affect donations to an unforeseen emergency.

The aim of the present paper is precisely to perform such a test. To do so, we use data on donations to an ongoing campaign to collect funds in Belgium for famine relief in Africa around the time of a disaster that hit the Belgian open-air pop festival of Pukkelpop, in the Flemish region of Limburg, on 18 August 2011. On that day, a catastrophic storm struck the festival. Five participants died, several hundreds were wounded, and 60,000 festival participants were affected. The disaster received intense media coverage. A few weeks before the storm, a consortium of humanitarian organizations had made an appeal to solicit donations from the Belgian public to combat famine in the Horn of Africa. A single bank account was opened from 22 July to 1 October, 2011 for the duration of the campaign. The disaster thus occurred in the midst of the fundraising campaign. The consortium granted us access to the universe of donations received during the campaign. We can identify individual campaign contributions at the municipality-day level, and finely trace the impact of the disaster on donations not only over time, but also as a function of the characteristics of municipalities, among which geographic proximity to the disaster.

In addition to allowing us to study the impact of a disaster on a temporary appeal, our dataset has several desirable features that complement other studies. Firstly, by providing daily data, it allows us to finely track the timing of the effect of the disaster, while papers that use tax or survey data, such as Brown et al. (2012) or Deryugina and Marx (2016), can only assess the effect of disasters over a horizon of a year, at least. Secondly, donations for famine relief were made through a standard bank account. This means that there was no fixed cost of giving, because domestic bank transfers are free and simple in Belgium, making them a very standard way to make an invoice. Therefore anyone could contribute. In particular, donors did not have to register, and there was no lower limit on donations. We can therefore study the impact of the disaster on all donors, as opposed to a set of regular registered donors making above-average donations. This distinguishes our data from the one used by Scharf et al. (2016), because CAF accounts impose a minimum amount for donations, and also from the data used by Deryugina and Marx (2016), because the IRS does not report data for ZIP codes with fewer than a threshold number of donors, to preserve donors' anonymity.

Finally, our dataset draws a clear distinction between the location of the disaster and the location of the cause of the fundraising campaign. While the disaster took place at a Flemish music festival, the appeal was explicitly made for a famine relief in the Horn of Africa. We can therefore study the impact of a domestic disaster on donations to an overseas cause. In that respect, we contrast with Scharf et al. (2016) who study the impact of disasters abroad, and with Deryugina and Marx (2016), who study the impact of domestic disasters on total donations reported to the tax authority.

We observe that a positive gap emerged between donations to the famine relief campaign between the municipalities that were closer to the disaster and other municipalities in the days following the Pukkelpop festival disaster. The effect of the disaster was larger the closer the donators' municipalities to the municipality where the festival was organized. Other measures of proximity lead similar results. This suggests that a foreign alternative charitable cause in fact benefitted from the local disaster. The rest of the paper is organized as follows. The next section describes the context of the fund raising campaign and of the disaster. Section 3 introduces our empirical strategy and our data, while Section 4 reports our results. Section 5 concludes.

2. The famine relief campaign and the local disaster

2.1. The Campaign to Stop Famine in the Horn of Africa

Since the 1984 Ethiopian Famine, a consortium of five large humanitarian organisations – Caritas, Handicap International, Doctors of the World, Oxfam and UNICEF – has bundled forces to solicit donations from the Belgian public in the event of a large crisis. The do this though the common bank account with number 000-0000012-12, making the campaigns known to the public as "12-12". According to the president of the consortium, the single account and the accompanying campaign allow the public to express its solidarity at times when large amounts of money are needed in a short time span (Todts, 2011, p.2). The idea to work as a consortium boosts the visibility and the efficiency of collecting donations, far beyond the capacities of a single organisation. According to Todts (2011, p.6.) it reduces costs and avoids undue competition for the same goals.

Each campaign is a combination of radio, TV and social media events, documentaries, live testimonies and news bulletins. An average citizen using radio, TV, newspapers, or social media is aware of the campaign. It cannot escape one's attention.

By launching temporary appeals related to specific causes, the consortium aims at increasing visibility and leverage on the public's emotion. As Todts (2011) argues, "when the public makes a donation in the event of a large crisis, he or she is doing that spontaneously, out of emotion. The citizen does not want to express this emotion by contributing one's more to the NGO that he or she regularly supports, but rather looks for a channel to express his own humanity in the face of so much suffering" (p.7).

Figure 1. The 12-12 Consortium logo

Recently, the consortium organised nationwide campaigns at the occasion of the Asian Tsunami (2004-2005), the Earthquake in Haiti (2010), the flooding in Pakistan (2010), and the Campaign the Combat Famine in the Horn of Africa (2011, see Figure 1).

The consortium has been successful in raising money following several disasters. It, for instance, collected 54 million euro after the Asian Tsunami and 23 million euro after the Earthquake in Haiti. It collected 8.8 million euro for the Stop Famine in the Horn of Africa campaign we study in this paper (Todts, 2011, p. 24-27).

2.2. The Pukkelpop Festival

The Pukkelpop Festival is the second largest open air summer pop and rock festival organised in Belgium every year. Around 60,000 people, most between 15 and 35 years old, attend it every year. It enjoys an international reputation among rock bands and rock audience for the high quality of its organisation and its line-up. Every year too, the performances as well as the atmosphere at the festival ground are widely covered by Belgium's national media, television, radio and newspapers. Performers are interviewed, the organiser is invited into talk shows, ticket sales are monitored, members of the audience are interviewed and so on. The reason for this nationwide attention is that Belgium is a small country and that music events of this kind attract an audience from every corner of the country. During the summer, the music festival scene in Flanders and Belgium is very lively and can best be described as the place where participants socialize during the summer period. In its June 18, 2016 magazine (p.24), introducing the festivals this summer, the newspaper De Standaard, regarded as the leading journal in Flanders, described the experience of connectedness as the key ingredient of the summer festival scene.

The festival ground is a large meadow with a series of large trees providing shadow for participants in the event of a burning sun. The area is just outside Hasselt, which is the capital of the province of Limburg, part of the region of Flanders in the east of Belgium, about 25 km from the Dutch border.

2.3. The Development of a Super Cell and the Unfolding of the Disaster

In the early afternoon of 18 August 2011, some weather cells with a potential for storm arrived from France in south-west Belgium. Strong but not yet catastrophic winds, accompanied by heavy rain developed between the city of Mons and Brussels. The trajectory of the cells is depicted on Map 1. The storm continued its path over the northern part of the city of Leuven without much damage. It then went in the direction of the city of Hasselt increasing its power. Upon arrival above the Pukkelpop Festival venue, around 6 pm that day, everything became dark all of a sudden, with lightning striking and very heavy rains. Meteorologists describe a super cell as producing "falling winds" that destroy everything in their path. In technical terms the super cell became a bow echo with a booked echo (vortex) as can be derived from radar images (see Map 2 and Figure 1). Such a booked echo is well-known in the meteorological literature and signals very strong winds because of the presence of a vortex at the mid-level (Hamid, 2011, p.3).[1]

The power of the wind was so strong that it knocked down giant trees on the festival ground as if they were wooden matches. That is how festival participants described their experience. The first person to be killed was a young participant who died when the construction of one of a huge tent collapsed. One of the pillars fell on him. The British rock band Skunk Anansi was playing right at that moment and band leader Skunk later declared in an interview that she had never experienced something like that. She was literally blown of the stage and had to run for her life.

The unfolding of the disaster could be followed live on radio and television. Media was already at the venue before the storm given the nationwide coverage of the festival, so the entire Belgian public was informed immediately about what was going on. It is important to know that nationwide radio in Belgium is organized by regionalized public broadcasting companies (VRT for the Flemish part and RTBF for the Francophone part). No other broadcasting company has nationwide radio coverage. For news items, most Belgians

[1] The technical explanation of the development of the supercell into a bow echo with bookend echo (vortex) is based on a technical note from the Royal Meteorological Institute in Brussels. (Hamid, 2011).

listening to the radio are tuned to these public channels. As the evening progressed, Belgians turned their TV sets on and were informed that five people had died at the Festival, that all other acts at the festival were cancelled, and that thousands of participants were leaving the venue. Because of the overburdening of the local mobile phone antennas (60,000 people calling at the same time), many parents could not get hold of their children and jumped into their cars to find them and bring them back home. This caused a massive presence of cars several hours into the disaster. Belgian TV also reported that hundreds of local residents opened up their houses to give shelter to participants.

The morning after the disaster all Flemish newspapers put large pictures of the disaster on their front pages, with stories of sorrow, heroism, parents and children not finding one another, stories questioning the safety of the tents, interviews with weather specialists, and so on. The daily newspaper "Het Belang van Limburg", which is the most widely read newspaper in the province of Limburg, devoted almost its entire edition to the calamity. This amount of reporting would go on during the subsequent days.

Given the regionalized and linguistic political organization of Belgium (Flanders in the north, Wallonia in the south and Brussels as a bilingual capital in the center), we focus on Flanders as the disaster took place there. The reason is that the media is organized at the region-linguistic level, meaning that the Flemish audience rarely tunes into the francophone media and vice-versa. As the calamity happened in Flanders, that region was primarily affected.

Map 1: The Development of the super cell above the Pukkelpop Festival Location near the City of Hasselt

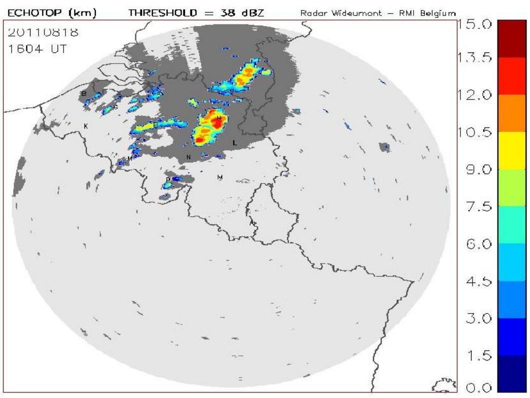


Figure 4: the power of the wind in the super cell

Figure 5: The day after, destruction at the Pukkelpop Festival camping side

All pictures taken by Hamid, K. (2011) and published in his technical note.

3. Data and Empirical Identification Strategy

3.1. Data

We had access to the detailed statement of account of Consortium 12-12 during the Combat Famine in the Horn of Africa campaign. The database was handed to us in an anonymized version by Consortium 12-12. The data contains information on the day each donation was received, the post code of the donor, and the amount of the donation (in euro). As the Combat Famine in the Horn of Africa campaign started on July 22, 2011 and lasted till

September 30, 2011, the disaster at the Pukkelpop Festival occurred almost in the middle of the campaign, to wit on August 18, 2011.

We combine these data with geographic information on the municipalities of the donors. We thus take into account the region to which the municipality belongs, or its distance from the festival venue. And we add administrative, municipality/NIS-level data such as gross income and merge this with the distance data and the donations file using the post codes of each municipality.

The data contains a total of 84,614 donations of which 779 (0.91 %) exceeded 1,000 euro. We exclude these large donations from our analysis, because they are most likely donated by institutional donors such as companies or banks.

For Flanders, there are 534 different zip codes in the donation data, representing all municipalities in Flanders. There are 308 municipalities in Flanders (589 in Belgium), many of which used to be subdivided in smaller entities that were merged into one larger municipality in a reform of 1977. Some of these smaller entities kept their own zip code, which is why we have more zip codes than municipalities in the data.

The average number of non-zero donations per zip code is 123, and the average amount of non-zero donations is 65 euro per zip code. In the province of Limburg, the average non-zero amount was 61 euro in the three weeks before the disaster and 67 euro in the three weeks after, whereas in the rest of Flanders it was 65 euro before and 66 euro after.

When we use distances from Hasselt, we do that by zip code as these are used in software to compute distances. To make things even more complicated, there is also a third set of codes, named NIS codes (after National Institute of Statistics) which are used to calculate tax income per statistical entity. The NIS codes mostly overlap with the zip codes of the municipalities. As we want to control for income in one of our regressions, we merged the donation data with tax income data using the NIS codes.

3.2. Method

Our identification strategy rests on the idea that Belgian municipalities received a treatment on 18 August 2011, and that the intensity of the treatment was related to their proximity to the disaster. All our estimations are therefore variants of the following equation:

$$donation_{it} = \gamma_i + \lambda_t + \beta.after_t{*}disaster_i + u_{it} \quad (1)$$

where: - $donation_{it}$ is the average donation from municipality i on day t;

- $after_t$ is a dummy variable taking the value one after 18 August 2011;
- $disaster_i$ is a variable measuring the proximity of municipality i to the disaster;
- γ_i is a municipality fixed effect;
- λ_t is a day fixed effect;
- β is a coefficient;
- u_{it} is the error term.

We include municipality fixed effects to control for the unobserved characteristics of municipalities that may result in different donations, for instance income. As we observe donations over a couple of months, the municipality fixed effect will capture most of the difference across municipalities, except those related to the disaster, as other characteristics of municipalities, such as income or demographics, are unlikely to evolve significantly over such a short time span. The day fixed effect allows controlling for the evolution of donations over time that is common to all municipalities, like the time that has elapsed since the beginning of the appeal.

The critical coefficient measuring the impact of the disaster on donations is β, which the coefficient of the interaction term. If it turns out significant, then it means that donations in municipalities hit by the disaster followed a different path from donations in other municipalities after the disaster. If it is significantly negative, it means that the local disaster resulted in lower donations for famine relief in Africa in the municipalities hit by the disaster. This would imply that the two causes are substitutes in the eyes of donors. Conversely, if the coefficient is significantly positive, it means that the local disaster prompted donors in affected municipalities to give more for famine relief. The two charities may therefore be complements.

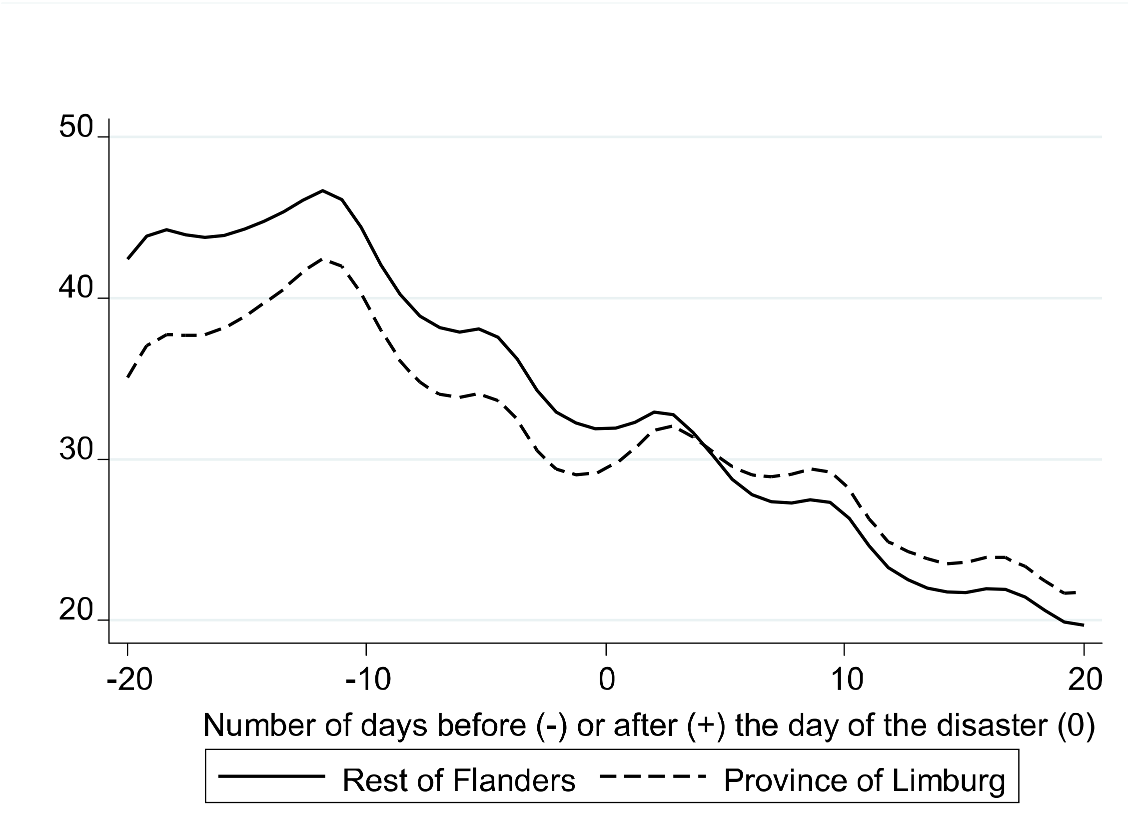
4. Findings

In this section we first describe the evolution of donations around the disaster. We then report our baseline econometric results.

4.1. A first look at the data

We illustrate our empirical identification strategy first by examining the non-parametric relationship between the amount of a donation and the date on which the donation took place. In Figure 6 we estimate a kernel-weighted local polynomial regression of the amount on the date of transfer using an Epanechnikov kernel. Our unit of analysis here as well as in the remainder of the analysis is the municipality-day level. The average non-zero donation was 32 euro per municipality per day. This includes days were donations were zero for some municipalities. Figure 6 separately plots the day by day evolution of average donations in municipalities located in Limburg and in the rest of Flanders for the three weeks before the disaster and the three weeks thereafter. The dotted line plots average donations in Limburg while the solid line those in the rest of Flanders.

Figure 6: Mean Amount per Donation before and after the Disaster (in euro), Province of Limburg versus the rest of Flanders



Both curves display a downward trend, with amounts being higher in the first weeks, which corresponds to the timing of the start of the campaign. This suggests some erosion of interest a few weeks after the beginning of the appeal for donations in July. One may also remark that average donations were initially lower in Limburg than in the rest of Flanders. This observation is in line with Limburg being the poorer province of Flanders. For our purpose however, the trend is not the key issue.

What really matters is the evolution of the difference in donations between Limburg and the rest of Flanders. Two points must be made here. First, before the disaster, the trend in Limburg follows that of the rest of Flanders. In other words, the trends were parallel in the treated and non-treated groups of municipalities before the disaster. The data therefore meet the common trend assumption necessary for a differences-in-differences estimation.[2]

Second, we observe a clear turning point right on the date of the disaster. Average donations in Limburg start increasing at a faster pace than donations in the rest of Flanders. After a couple of days, donations in Limburg end up exceeding those in the rest of Flanders. One can therefore observe a differential evolution of donations between the region hit by the disaster and the rest of Flanders after the disaster, and only after the disaster. The disaster accordingly had a positive impact on donations in Limburg.

4.2. Benchmark results

In our baseline specification, we consider that only the municipalities located in the same province as the festival were hit by the disaster. We therefore define $disaster_i$ as a dummy variable taking the value one if municipality i belongs to the province of Limburg. It therefore distinguishes Limburg from the rest of Flanders. The results of that specification are reported in Table 1 below.[3]

*** Insert Table 1 around here ***

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[2] Table A1 in the appendix substantiates that finding. In that table, we regress donations in municipalities on municipality fixed effects, a time-trend, and an interaction between the trend and a Limburg dummy, for several study-windows before the disaster. While the trend is statistically significant, the interaction term between the time trend and the Limburg dummy is insignificant in all four regressions. In other words, regardless of the width of the study window, the trend in Limburg can never be statistically distinguished from the trend in the rest of Flanders, at standard levels of confidence.

[3] For the differences-in-differences identification to work, trends must be parallel in Limburg and the rest of Flanders prior to the disaster. Table A1 in the appendix shows that it was the case by regressing donations on a trend and an interaction of the trend with the Limburg dummy, during the pre-disaster part of the window. While the trend is statistically significant, the interaction never is, implying that Limburg's trend did not differ from that of the rest of Flanders before the disaster.

The first column of the table reports the results of the estimation when the event window starts one week before the disaster and ends one week after the disaster. The second column considers an event-window starting two weeks before and ending two weeks after the disaster. The third column considers respectively three weeks before and after the disaster. In all four specifications, the coefficient of the interaction term between the Limburg and After dummies is significant at the five percent level or beyond. The coefficient is always positive implying that municipalities in the province where the disaster occurred started giving more for famine relief in Africa after the disaster. In addition, the magnitude of the coefficient is stable across specifications, ranging from 5.27 to 6.24. In other words, municipalities from Limburg started donating to famine relief between five and six euros more per day than other municipalities in Flanders.

5. Robustness checks and extensions

In another specification, we measure the intensity of the treatment by geographic distance to the city of Hasselt, the city of the disaster. To let the effect be non-linear, we define four concentric circles. The first includes all municipalities located within a 20 kilometers radius from Hasselt. The second circle includes all the municipalities located between 20 and 50 kilometers from Hasselt. The third circle features the municipalities that are located between 50 and 100 kilometers from Hasselt. Municipalities located further than 100 kilometers belong to the fourth circle. We created a dummy variable for each circle and interacted it with the After dummy. Table 2 below reports the results of the estimations using those interaction terms.

*** Insert Table 2 around here ***

Like in Table 1, we broaden the study window from one week to three weeks before and after the disaster. The first Column reports the results obtained with the narrowest study window. The coefficients of the interaction terms are all negative, but none is significant at standard levels of significance, suggesting that the window is likely too short to allow identifying reactions that are specific to concentric circles.

When the study period is extended to two weeks before and after the disaster, like in Column 2.2, the coefficients remain negative, and all become significant at the ten-percent level or beyond. This shows that, after the disaster, all concentric circles gave less than the first circle, which was the closest to the disaster. By symmetry, it means that municipalities located within twenty kilometers of the disaster started giving more than the others after the disaster. We obtain the same result when the study window is extended to six weeks, as reported in Column 2.3.

We performed a series of t-tests to compare the three coefficients. The tests cannot reject the hypothesis that the coefficients of "Circle 2 * After" and "Circle 3 * After" are equal. They however do reject the hypothesis that the coefficients of "Circle 3 * After" and "Circle 4 * After" are equal. The difference is significant at the ten-percent level, and nearly at the five-percent level. As the coefficient of "Circle 4 * After" is lower than the other two, it suggests that the effect of the disaster on donations was larger closer to the disaster.

The previous table allows the effect of distance to be non-linear, but pools together all the days following the disaster. Yet it stands to reason that the effect takes time to materialize, and probably fades away as time goes by. Moreover, a support fund was launched on August 25. Finally, the disaster occurred on a Thursday and was therefore followed by a week-end. To take into account the possibility that the effect varied over time, we estimated the differences in differences model with time-varying coefficients. Specifically, we defined three dummy variables capturing three periods: the week-end immediately following the disaster, the week following the disaster, and a period starting at the beginning of the second week. We defined three dummy variables over those periods, and interacted them with the Limburg dummy. Table 3 reports the outcome of the regressions controlling for those interactions.

*** Insert Table 3 around here ***

The first column of Table 3 reports the outcome of a regression where the study window is only two-weeks long. As the window does not go beyond the first week, it does not allow estimating the coefficient of the "Limburg * After the 1st week" interaction term. In the regression, the coefficient of the interaction of the disaster with the dummy variable capturing the first week-end is statistically insignificant, suggesting that donors did not really react to the disaster in the first two days following the disaster. The coefficient of the second interaction term is however positive and significant at the five-percent level, suggesting that donors living in the province of the disaster indeed reacted by giving more than other donors in the first week following the disaster.

Columns 3.2 and 3.3 report the same specification, but can include interaction terms for the period starting after the first week. Their results are consistent with those of Column

3.1. They show that donations in Limburg municipalities were not different from those of other municipalities during the week-end following the disaster. However, the coefficient of the interaction of "Limburg * 1^{st} week after" is positive and significant beyond the five-percent level in both regressions, like in Column 3.1. In addition, they show that the effect lasted after the first week, as the coefficient of the "Limburg * After the 1^{st} week" variable is positive and statistically significant in both regressions. In all regressions, t-test reject the hypothesis that the coefficient of the first interaction term is equal to the other two. The same test cannot reject the hypothesis that the other coefficients are equal. This is important, because it shows that the launch of the appeal for donations to the fund supporting the victims of the festival, at the end of the first week, did not affect donations for famine relief in Africa.

One may also remark that the magnitudes of the coefficients of the interaction terms in Regressions 3.2 and 3.3 are very close. This means that our results are robust to the length of the study window.

The timing of the disaster is critical to our identification strategy. One may therefore worry that the effect that we capture is an artifact or due to luck. To address that concern, we perform a series of placebo tests on the date of the disaster. Specifically, we run the same regressions as before, but move the date used to define the After dummy around the true day of the disaster. We move it forward and backward by ten and fifteen days around August 18. The results of the series of placebo tests is reported in Table 4.

*** Insert Table 4 around here ***

When doing so, we in general find that the coefficient of the interaction term fails to be significant at standard levels of statistical significance. This is true for any placebo date for the two, four, and six weeks windows. Accordingly, the effect that we capture truly reflects a change around the day of the disaster and is not driven by chance.

One may be wonder whether the effect of the disaster on average donations that we observe is driven by an increase in a subset of donations. To see if it is the case, we replace average donations by median donations in our baseline estimations. The result of those regressions is reported in Table 5.

*** Insert Table 5 around here ***

The results reported in Table 5 are strikingly in line with those of Table 1. Specifically, we observe that the coefficient of the interaction variable is positive and significant at the five-percent level or beyond, regardless of the length of the study window. Moreover, the magnitude of the estimated effect is the same as in the baseline regression, specifically between five and six euros per day. As the results obtained for the mean and the median donations are the same, we can conclude that the effect is not limited to a particular subset of donations, but likely affected all of them regardless of their size.

As an extension to our main results, and as a way to interpret our results, we also applied our baseline estimation to the number of donations per municipality instead of average donations. The idea is to test whether the impact of the disaster ran through the intensive or extensive margin. The results of that alternative estimation are reported in Table 6.

*** Insert Table 6 around here ***

The results show no effect of the disaster on the number of donations. More precisely, the coefficient of the interaction between Limburg and the after dummy is never significant at standard levels of statistical significance, regardless of the length of the study window. This suggests that the impact of the disaster essentially operated through the size of donations rather than through the number of donors.

6. Concluding comments

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Tables

Table 1: Baseline results. Limburg vs. rest of Flanders

	(1.1)	(1.2)	(1.3)
Length of the window	Two week	Four weeks	Six weeks
Limburg * After	5.270	5.270	6.236
	(2.109)**	(2.797)***	(3.637)***
Constant	35.34	27.12	50.73
	(16.63)***	(10.93)***	(23.79)***
Municipality fixed effect	yes	Yes	yes
Day fixed effect	yes	Yes	yes
Observations	8,010	15,486	21,894
R-squared	0.186	0.172	0.154
Adjusted R-squared	0.157	0.150	0.173
Number of municipalities	534	534	534

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Concentric circles around the disaster.

	(2.1)	(2.2)	(2.3)
Length of the window	Two weeks	Four weeks	Six weeks
Circle 2 * After	-2.986	-5.464	-4.796
	(-0.819)	(-1.903)*	(-2.011)**
Circle 3 * After	-2.869	-4.448	-5.645
	(-0.882)	(-1.685)*	(-2.609)***
Circle 4 * After	-2.897	-5.374	-3.676
	(-0.901)	(-2.036)**	(-1.695)*
Constant	38.34	46.95	46.95
	(11.39)***	(22.41)***	(22.24)***
Municipality fixed effect	yes	yes	yes
Day fixed effect	yes	yes	yes
Observations	7,725	14,935	21,115
R-squared	0.192	0.178	0.179
Adjusted R-squared	0.166	0.159	0.160
Number of municipalities	515	515	515

Robust t-statistics in parentheses

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

Table 3: Non-linear effect over time.

	(3.1)	(3.2)	(3.3)
Length of the window	Two weeks	Four weeks	Six weeks
Limburg * 1st week-end after	1.507	1.522	2.321
	(0.675)	(0.705)	(1.094)
Limburg * 1st week after	8.091	6.119	6.918
	(2.206)**	(2.550)**	(2.888)***
Limburg * After the 1st week		6.595	6.932
		(1.730)*	(2.975)***
Constant	34.96	26.94	26.89
	(16.38)***	(10.76)***	(10.74)***
Municipality fixed effect	yes	yes	yes
Day fixed effect	yes	yes	yes
Observations	8,010	15,486	21,894
R-squared	0.158	0.172	0.154
Adjusted R-squared	0.186	0.150	0.173
Number of municipalities	534	534	534

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Placebo tests.

	(1)	(2)	(3)	(4)
	-15 days	-10 days	+10 days	+15 days
2 weeks window				
Limburg * After	2.582	1.446	-0.203	0.702
	(1.158)	(0.759)	(-0.0745)	(0.187)
Observations	8,010	8,010	8,010	8,010
R-squared	0.146	0.230	0.124	0.079
Adjusted R-squared	0.121	0.196	0.107	0.0682
4 weeks window				
Limburg * After	-0.186	2.398	2.358	-0.495
	(-0.111)	(1.322)	(1.099)	(-0.202)
Observations	15,486	15,486	15,486	15,486
R-squared	0.265	0.188	0.146	0.092
Adjusted R-squared	0.237	0.163	0.132	0.0822
6 weeks window				
Limburg * After	-0.494	2.368	2.479	1.673
	(-0.285)	(1.577)	(1.405)	(0.751)
Observations	21,894	21,894	21,894	21,894
R-squared	0.301	0.241	0.153	0.106
Adjusted R-squared	0.276	0.217	0.138	0.116
Municipality fixed effect	yes	yes	yes	yes
Day fixed effect	yes	yes	yes	yes
Number of post2	534	534	534	534

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Dependent variables: median donation. Limburg vs. rest of Flanders

	(1)	(2)	(3)
Length of the window	Two weeks	Four weeks	Six weeks
Limburg * After	5.638	5.058	6.052
	(2.443)**	(2.739)***	(3.711)***
Constant	32.83	26.02	44.86
	(16.01)***	(10.59)***	(22.41)***
Municipality fixed effect	yes	yes	yes
Day fixed effect	yes	yes	yes
Observations	8,010	15,486	21,894
R-squared	0.152	0.118	0.134
Adjusted R-squared	0.131	0.132	0.121
Number of post2	534	534	534

Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Dependent variables: number of donations. Limburg vs. rest of Flanders

	(1)	(2)	(3)
Length of the window	Two weeks	Four weeks	Six weeks
Limburg * After	0.0624	0.425	0.404
	(0.203)	(0.826)	(0.791)
Constant	1.278	0.615	2.436
	(14.20)***	(4.239)***	(29.55)***
Municipality fixed effect	yes	yes	yes
Day fixed effect	yes	yes	yes
Observations	8,010	15,486	21,894
R-squared	0.369	0.274	0.375
Adjusted R-squared	0.241	0.383	0.273
Number of post2	534	534	534

Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A1: Testing for a common trend in donations before the disaster

	(1) One week	(2) Two weeks	(3) Three weeks
Trend	0.571	-1.056	-0.445
	(1.675)*	(-9.979)***	(-6.182)***
Limburg * trend	0.173	0.0529	0.251
	(0.256)	(0.204)	(1.577)
Constant	6.090	85.14	57.04
	(0.424)	(20.18)***	(21.61)***
Observations	3,738	7,476	10,680
R-squared	0.001	0.012	0.003
R-squared	0.000344	0.00849	3.38e-09
Number of post2	534	534	534
F test	2.218	58.75	20.04

Robust t-statistics in parentheses