A Quantitative Analysis of the Impact of Data Imports on OpenStreetMaps (OSM) Contributors

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I. ABSTRACT

OpenStreetMap (OSM) has simultaneously established itself as one of the leading mapping services and one of the most prosperous crowdsourcing platforms to this day. As of November 2017, 4.3 million unpaid volunteers[5] were registered as contributors to the platform. These users are the essence of OSM. Mass data imports, often donated by external parties, help the platform grow quickly. An example of this is the import of the TIGER datasource that was uploaded to OSM all over the United States, and geographic information such as roads and boundaries were imported. However, it is not clear what impact they have on OSM users' engagement with the platform. The success of OSM is linked to its users' engagement, hence, studying the impact of imports will help us understand how they affect the success of OSM. Thus, gaining a good understanding of the impact of imports on the OSM user base is crucial. In this paper, we question change in user behavior following these events. We attempt to identify whether large contributions result in an increase or decrease in activity overall and whether the content and style of subsequent edits will vary or remain stable. By comparing experimental and control groups focusing on the variety of metrics, we observed an array of different consequences that imports have had on the OSM community. Notably, we observed long term impact on more active users and short term impacts on minor contributors.

II. INTRODUCTION

Crowd-sourcing is the outsourcing of an activity to the crowd. This phenomenon is strongly linked to the development of new technologies of information and communication. Crowd-sourcing uses the creativity, intelligence and expertise of the crowd to achieve tasks normally carried out by employees or entrepreneurs. OpenStreetMap or OSM is a crowd-sourcing platform that aims to constitute a free geographical database of the world. It is worth mentioning Wikipedia the free encyclopedia of knowledge, which is similar to OSM. Indeed, Wikipedia is also a user-based platform who's success is based on volunteers contributing data.

OSM contributors are volunteers and thus their engagement to the platform is due to intrinsic motivation. Crowdsourcing's success relies on the contributions of users. However, their individual contribution pales in comparison to the amount of data uploaded during a data import. Imports are the process of taking an external dataset and converting its data in order to use it in OSM. They are done by one or a team of contributors over the course of a day. These bulk imports are complements to the data collected by the contributors. Since the motivation of volunteers is intrinsic such as a sense of greater good, imports might strip them of this feeling. We are interested in grasping the impact of imports on the behavior and engagement of users. For this purpose, we will analyze the intensity of contribution of users before and after an import and the retention rate of users. We will also look at changes in the way users take part in OSM. For instance, the evolution in the different actions a user can make on the platform or a change in the nature of the data they contribute. In general, we want to understand whether users are discouraged, encouraged or unaffected by imports.

In this paper we aim to quantify the impact of imports on the contributors of user-generated content platforms. Research about users' motivation is mainly qualitative and conducted through interviews and surveys. However, in this study we propose a quantitative approach that focuses on users' engagement. A quantitative approach enables the study of a much larger cohort of individuals as opposed to qualitative studies which are constrained to a handful of people being surveyed or interviewed. An engaged user is one that is committed to the user-based platform. We measure the impact of imports across five groups of users. The groups are divided from the less active users to the most active users, because in OSM like on many crowdsourcing platform, users' commitment vary considerably, and we do not expect an import to have the same effect on all of them. We measure the impact over short and long period of times, by looking at the following metrics: how much editing activity contributors perform, what geographic element they edit, whether users create data or modify it and users' activity timespan. We apply our methodology to analyze the role of imports in OSM in the following metropolitan cities:

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London, Paris, Rome, Madrid, Berlin, Bruxelles, Kiev. We conclude with a discussion on the implications of our findings and on the future of OSM and imports.

III. RELATED WORK

In this section, we discuss the main published papers that relate to our work. In the context of crowd-sourcing, and OSM in particular, bulk uploads are data imports which establish a base line of geodata so that the project can evolve, especially in countries or regions with a less active OSM contributor community. This is precisely on this type of contribution that our study is going to focus, as they could heavily affect other contributors manual data collection and editing efforts. Interestingly enough, little research has so far been conducted for countries in which OSM relied on bulk data imports. However, more geographically focused studies have investigated the role of those imports on various aspects of user engagement. As a starting point, a very recent study (Levente Juhsz, and Hartwig H. Hochmair, 2018) [9] presents the results of a study that explored if and how an OpenStreetMap (OSM) data import task can contribute to OSM community growth. Results show that long-term engagement of newly registered OSM mappers did not succeed, whereas already established contributors continued to import and improve data. In general, they found that an OSM bulk data import can add valuable data to the map, but also that encouraging long-term engagement of new users proved to be challenging. However, within the OSM community, bulk imports have always been a point of friction. This is why a study (Zielstra D. Hochmair H. H. Neis P, 2013) [12] has tried to bring more elements to answer this debate by deciding whether the OSM road network should be updated through periodic data imports from public domain data, or whether the currency of OSM data should rather rely on more traditional data collection efforts by active contributors. This completeness analysis of imports has been completed by an OSM quality assessment based solely on the data's history. Since the quality of OSM data from a bulk import can vary strongly, different aspects have been investigated in order to come up with an investigation framework. This framework contains more than 25 methods and indicators allowing a better understanding of how the quality of the data imported could impact the accuracy of the map (Christopher Barron, Pascal Neis, Alexander Zipf, 2013) [6]. As we mentioned earlier, due to their magnitude, bulk data imports can negatively affect the quality of the map if the imported data is inaccurate or conflicting. One of the main caveats that is closely related to this popularity increase is different types of vandalism that occur in the projects database. Since the applicability and reliability of crowd-sourced geodata, as well as the success of the whole community, are heavily affected by such cases of vandalism, it is essential to counteract those occurrences. The developed vandalism-detection tool was able to detect vandalism types committed by new users, illegal imports and mass edits. However, it can be difficult to distinguish false positive vandalism types from actual cases committed by users with a high reputation level or by users who only delete one or two objects. Following the massive TIGER-import, micro-tasking was introduced, it is used by the LA and NY buildings imports. Micro-tasking is the process of splitting a large job into small tasks that can be distributed to many people, over the Internet. While these imports serve as great case studies of imports, they do not deal with complex datasets, or updates to the data, neither do they deal with partitioning of tasks. the study (Atle Frenvik Sveen, Anne Sofie Strand Erichsen, 2017) [10] examines how the Norwegian FKB-dataset can be imported to OSM using micro-tasking, and perform a user-test to determine the best partition of these micro-tasking tasks. The aim of this study is thus to improve the micro-tasking method to enable efficient and correct imports and updates of Open Governmental Geospatial Data to OSM. Enventually, bulk imports can also cause serious contribution inequality. The case study (Anran Yang, Hongchao Fan, Ning Jing, Yeran Sun and Alexander Zipf, 2016) [11] shows that in countries without significant imports, contributions become more unequal over time. This trend is consistent with the rapid expansion of the silent majority, even though other classes of contributors also grow at a slower pace. On the other hand, contribution inequality fluctuates a lot in countries with huge imports. There are many research on imports, however none deal with their impact on users' engagement. In this paper, we aim to study this impact using a quantitative method.

IV. OPENSTREETMAP

The OSM dataset is constituted of three fundamental elements: nodes, ways and relations. Nodes are key elements of the OSM system. They are used to define points- of-interests (POI) such as Pubs or Restaurants. Ways are sets of at least two connected nodes, characterizing lines or polygons such as roads and buildings, respectively. Relations are collections of nodes, ways, or even relations. Tags are optionally associated to these basic elements by using keys and values. The key attributes for the purpose of this study are the following for both nodes and ways: version ID that is increased at each modification of previously created entity, deleted attribute specifying whether the element was deleted or not, date of creation, username of the contributor and tags. For the nodes we also used their latitude and longitude to locate them on the map. We also have the list of all the nodes that constitute a way. Users contribute to the OSM database by adding or creating elements. They can also maintain already existing information by updating or deleting nodes, ways or relations. Whenever a user edits, their name is recorded with the modification. Thanks to that, we were able to track and analyze individual users behavior. For our analysis we used the full data history dump of 14 cities, that contains all versions of all OSM objects that ever existed; including deleted objects. Each contribution done is also associated with a username, which allowed us to track the collaboration of each user. The full history dump of OSM is of 1 TB. However, for the purpose of reducing our dataset and since imports mostly focus on nodes or ways, we chose to disregard relations as well as focusing on just 14 cities: Paris, London, Madrid, Berlin, Rome, Brussels, Kiev, Marseilles, Manchester, Barcelona, Munich, Milan, Gand and Kharkiv. The data for each city was downloaded from geofabrik.com, which provides precut data, at different scales, of the cities we are interested in.

V. HYPOTHESIS AND METRICS

The purpose of imports is to upload a large amount of data to the OSM database at once. We want to quantify the impact of such imports on OSMs contributors in order to understand the effect this type of action has on the crowd. We put forward the following hypotheses:

Hypothesis 1: The quantity of user contributions will decrease after an import.

We put forward this hypothesis since studies have shown that users mainly contribute to OSM because they believe that their efforts are for the greater good of the community. An import may cause their efforts to be felt as no longer needed.

Hypothesis 2: The amount of deletes and updates will increase, while the amount of creations will decrease following an import.

Previous studies demonstrated that imports create conflicts between the data imported and the data provided by existing users. For this reason, users might be more likely to make an integration effort by maintaining the imported data instead of creating new elements.

Hypothesis 3: Users will contribute less on the objects affected by the imported.

Imports usually focus on one type of object, hence after an import users will change their focus from the imported objects to other objects.

To test the first hypothesis, we observe the evolution of the average number of contributions per week for each user. We particularly focus on whether or not imports lead to a change in the intensity of contribution of OSM volunteers.

To test the second hypothesis, we look at the evolution of maintenance to creation ratio per user per week. The ratio is specific to analyzing how the users' type of action changes over time after an import. Maintenance corresponds to updates and deletion of an existing OSM entity.

To test the third hypothesis, for each user we calculate the ratio of edits made on the amenity edited in the import to the total edits per user. For example, for an import X of type "tree", the ratio of each user will be equal to the number of contributions of trees he has done compared to the total number of contributions.

VI. METHODOLOGY

In order to analyze the impact of imports on users, we need to identify imports as well as who are the users contributing to the OSM database.

Imports. In order for an import to be accepted by OSM, some guidelines must be followed [3]. The community has to approve the import, the license of the data to be imported needs to be compatible with OSM's license and the import must be documented and reviewed before the upload can happen. Additionally, a new dedicated user account must be used for an import. However, these guidelines changed over time and were not always enforced, which made us design our method for finding an import. In our method, we considered imports as user contributions typically done in a single day within a geographically constrained region. We determined imports automatically by looking at the magnitude of the daily contributions of all users. We are interested in the biggest daily contribution made by a single user. A threshold was set through trial and error (with a value typically contained between 15 and 20 times the daily average contribution), and all contributions greater than this threshold were considered as imports.

In order to validate our import identification method, we applied it on the whole data history of London. For each of the five imports detected, we found OSM Wiki pages[4], blog articles [7] or forum discussions describing the imports.

We also tried to identify imports by focusing on contributions made by new users only since the import guidelines state that imports have to be made by a new dedicated user. However, the results were not as good. We believe the reason is that all imports identified in London were done before 2014, the new user per import guideline was probably set up after the imports were made.

Abnormal Returns. Abnormal return is a term used in finance that represents the difference between the actual return and the expected return. Usually, events such as mergers, interest rate increases or lawsuits trigger abnormal returns. In our case, the events are imports to the OSM database. We will use abnormal returns to measure the impact of imports by looking at the following metrics: the average number of contribution per week for each user, the ratio of maintenance to creation per user per week, the ratio of edits made on the amenity edited in the import to the total edits per user. Whenever an import takes place, for each user i and time period τ after the import, we measured the actual returns R_i as the average of the computed metric per unit of time t made by user i during period τ. We also computed the expected returns E_i as the average of the computed metric made by the same user i per unit of time t during a period prior to the event. We then calculated the abnormal returns $AR_i^{\delta^\tau}$ per unit of time t of each user i as:

$$AR_i^{\delta^\tau} = R_i^\tau - E_i^\delta \tag{1}$$

The higher the AR, the higher the impact of the event we are analyzing. In our case, a higher AR means that imports have a higher impact on the users intensity of contributions, ratio of maintenance to creation and ratio of edits on the amenity edited in the import to the total edits per user. In this study, we chose to compute our expected returns based on $\delta = 6$ months prior to the event, and to compute our actual returns based on $\tau =$ 1 week, 1 month and 3 months after the event. Thus, if for instance $AR_i^{\delta^\tau} = 100$ and Δt = 1 month then it means that in the month following the import, user i is performing on average 100 actions of contributions - edits, creation or deletion - more per week than in the six months preceding the event.

Contributors Grouping. In a previous study of OSM (D. Hristova, G. Quattrone, A. Mashhadi and L. Capra) [8], researchers looked into the impact of OSM mapping parties on editor's activity. In doing so, they divided users into 5 groups of contributors who greatly differ in terms of amount of contributions they make. The authors of this paper decided to group users based on their number of contributions. We decided to adopt a similar approach to quantify the impact of imports on OSM contributors, and spread users into five groups depending on their number of contributions during the 6 months prior to each import. Because the cities we studied vary a lot in size and in number of contributions, we could not use fixed limits for number of contributions for each group. In the paper (D. Hristova, G. Quattrone, A. Mashhadi and L. Capra) [8], the researchers used logarithmic binning to group users; we computed the percentage of the total contribution done by each group in the paper. Because of complexity and time constraints, we used the same values to create groups for each of the cities studied. This method created groups that are close to those created using logarithmic binning. Thus, we used the following groups: *Group 1(Less active users, responsible for 1% of total contribution); Group 2 (Users with low activity, responsible for 2% of total contribution); Group 3 (Users with medium activity, responsible for 7% of the total contribution); Group 4 (Very active users responsible for 30% of total contribution); Group 5 (Most active users, responsible for 60% of total contribution).* Users that contributed for the first time in the 6 months preceding an import do not have a sufficient editing history to be confidently placed in the above groups. Thus, we did not consider them in our analysis.

Control Groups. Control groups are groups of individuals that seek to demographically resemble the study group as much as possible. The difference between the two groups is that the latter is subject to some form of scientific research, while the control is used as a benchmark for normal behavior. We made use of control groups to allow the identification of unusual behavior before, during and after imports. If the same changes can be observed in both the study group and the control group then the changes are not caused by imports. To choose our control groups, we researched the second most populated city from the country of our inspected target. We chose different cities from the study group to ensure that there are no impacts resulting from imports. Also, we chose control groups from the same country as the study groups to avoid cultural differences. This should give enough demographic similarities between the two in order to make a well informed comparison.

VII. DATASET

Our study focuses on the datasets of the following cities: Paris, London, Madrid, Berlin, Rome, Brussels and Kiev. We also identified control groups for each city, respectively: Marseilles, Manchester, Barcelona, Munich, Milan, Gand, Kharkiv. These cities are all metropolitan cities where we can observe a considerable amount of OSM contributors. The dataset for each city spans from the date of the creation of OSM up until January 2018. Information about the data imported from the cities mentioned above are represented in the table above. To reduce the size of our dataset and since imports mostly focus on nodes or ways, we chose to disregard relations from the OSM dataset we downloaded.

VIII. RESULTS

Import Analysis. Prior to being able to test our hypotheses, we find the data imports in the seven cities that we are analyzing. Figure 1 below shows the result of import detection in the city of London. Five spikes can clearly be identified, that each corresponds to an import. Imports we found in the 7 cities studied are very different on several aspect: size, objects of interest or time frame. Table I, offers a summary of all imports identified in each cities. To test the hypothesis correctly, we look at the impact on the short, medium and long term. For each of these, we aggregate the results from all the imports in the cities that we are studying. We then present the qualitative results for each of the cities in a table, used to conclude on the impact of a data import.

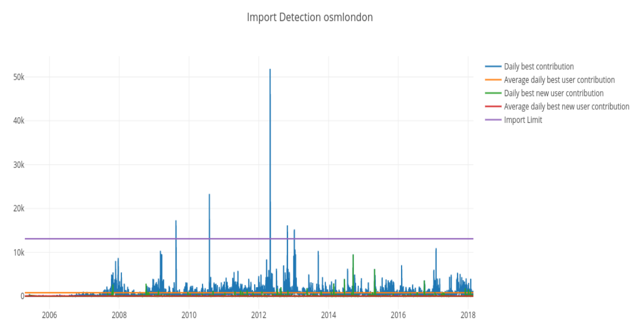

FIG. 1. Result of Import Detection in London

In addition to the validation of import detection we did for London, we searched for more information about each of the biggest imports detected in each of the studied cities. For most of the imports, we didn't find OSM Wiki pages, but we found topics on the forum of OSM in which the imports were planned and explained. For instance, we found that a Ukrainian OSM contributor took the decision, almost by himself, to import a part of Kiev [1], while a few contributors of the map of Berlin planned the import of house numbers and postcodes [2].

FIG. 2. Visualization of a bus stop import in London

Finally, we also made sure of the consistency of the imports detected with their specific object of interest by plotting imports on maps. Hence, we can see that on Figure 2 above for instance, nodes imported are indeed, as supposed to be, very likely to be bus stops.

Hypothesis 1: The first hypothesis we test is that users contribute less after an import. By having a look at the compiled result table (TABLE II) of the computed AR for the 5 groups, we can draw a set of conclusions that represent global trends shared among all cities and epochs. In order to produce this table, we analyzed the results of each city and compared it to their respective control group, and replicated this methodology for short, medium and long term. For this hypothesis, even though the three tables, for short, medium and long term, each present slightly different dynamics and specificities for each group of users and each city, we decided to include only the long term results table. In fact, all the tables allow us to uncover the same phenomena, and the variation of results between the different time periods is negligible, so picking the long term analysis allows us to capture with a greater confidence all the possible impacts of the imports on the groups of contributors.

First of all in table II, a noticeable result is that the first 2 groups are almost not impacted by the import in terms of intensity of contribution in comparison with their control group, with a median of number of edits rarely fluctuating, being close to 0 most of the time. To be more accurate, we can witness that this fluctuation is null for all cities expect for Kiev in Group 2 with one box increase comparing to Kharkiv. Concerning the median it only fluctuates in Kiev and London in group 2. This is understandable in the sense that these groups represent the weakest users, which mean that their involvement is very volatile and not constant in time. In the context of our analysis where we are looking the contribution intensity, groups 1 and 2 represent the users who tend to contribute once and then disappear for a long period of time. Indeed, a striking result is that for Paris, Rome, Madrid, Berlin and Brussels, theres is absolutely no evolution for groups 1 and 2. Hence, witnessing a lack of involvement from those users regarding an import is not a surprising result.

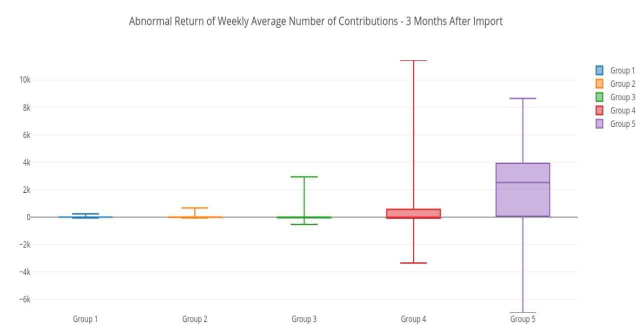

FIG. 3. Abnormal return of the contribution in the long term (3 months) for Brussels and its control group, Gand

For the other groups, we noticed some changes regarding the number of contributions. For group 3, the median of each city compared to their respective control group has a tendency to slightly go up except for madrid and Kiev, but this is very subtle and does not allow us to detect a shift in their editing strategy (median fluctuation ¡100 edits). For groups 4, the shift becomes a bit more noticeable, whereas group 5 experiences a massive shift.

City	# Imports	Avg. Import Size	Max Import Size	Min Import Size	Major Amenity Type	Import Limit	Time Frame
London	5	24 787	51 855	15 265	"tree", "bus_stop"	13 000 contrib.	2009 - 2013
Paris	9	52879	92302	36753	"building"	35000 contrib.	2010 - 2015
Rome	9	14424	24274	10001	"residential","highway"	9800 contrib.	2008 - 2017
Madrid	6	23536	83734	8929	"highway","housenumber"	8800 contrib.	2008 - 2016
Berlin	9	17700	31796	11241	"housenumber","tree"	10800 contrib.	2010 - 2015
Brussels	5	22137	27225	18690	"tree","housenumber"	18000 contrib.	2013 - 2014
Kiev	3	40529	81214	15204	"building","housenumber"	10000 contrib.	2011-2016

TABLE I: Summary of detected imports *(All sizes are number of contribution of nodes and ways)*

In fact, median differences can get over 2k edits for a single city like Brussels (FIG 3) compared to Gand, with a tendency to increase the editing intensity after the import, to the exception of Kiev, which is a city where OSM is not very popular (so not noteworthy) and London.

Cities	Group 1	Group 2	Group 3	Group 4	Group 5
London	ΔBox: None ΔMedian: None (Control: 0)	ΔBox: None ΔMedian: None (Control: 0)	ΔBox: None ΔMedian: +4 (Control: -4)	ΔBox: None ΔMedian: None (Control: -6)	ΔBox: Up ΔMedian: -78 (Control: -184)
Paris	ΔBox: None ΔMedian: None (Control: 0)	ΔBox: None ΔMedian: None (Control: 0)	ΔBox: Down ΔMedian: -17 (Control: -4)	ΔBox: Down ΔMedian: None (Control: -3)	ΔBox: Down ΔMedian: -26 (Control: -13)
Rome	ΔBox: None ΔMedian: None (Control: 0)	ΔBox: None ΔMedian: None (Control: 0)	ΔBox: Up ΔMedian: +10 (Control: -10)	ΔBox: Down ΔMedian: -100 (Control: 0)	ΔBox: Down ΔMedian: -270 (Control: -30)
Madrid	ΔBox: None ΔMedian: None (Control: 0)	ΔBox: None ΔMedian: None (Control: 0)	ΔBox: Up ΔMedian: None (Control: -2)	ΔBox: Down ΔMedian: -21 (Control: -4)	ΔBox: Down ΔMedian: +10 (Control: -17)
Berlin	ΔBox: None ΔMedian: None (Control: 0)	ΔBox: None ΔMedian: None (Control: 0)	ΔBox: Up ΔMedian: +3 (Control: -3)	ΔBox: None ΔMedian: None (Control: -6)	ΔBox: Up ΔMedian: -80 (Control: -20)
Brussels	ΔBox: None ΔMedian: None (Control: 0)	ΔBox: None ΔMedian: None (Control: 0)	ΔBox: Up ΔMedian: +2 (Control: -2)	ΔBox: Up ΔMedian: +5 (Control: -5)	ΔBox: Up ΔMedian: +2542 (Control: -213)
Kiev	ΔBox: None ΔMedian: None (Control: 0)	ΔBox: None ΔMedian: None (Control: 0)	ΔBox: None ΔMedian: None (Control: -1)	ΔBox: Down ΔMedian: -16 (Control: -6)	ΔBox: Up ΔMedian: +123 (Control: -236)

ΔBox: Position of the box compared to the control group.
ΔMedian: Difference in the median of the maintenance ratio compared to the control group.
Control: Value of the median of the maintenance ratio of control group.

TABLE II: **Summary of comparison of AR of contribution** of the studied cities vs. abnormal return of control groups in the long term (3 months)

We decided to go a step further into our analysis of hypothesis 1. In order to do so we used Survival Analysis. Survival analysis is a statistical method used to analyze the expected duration of time until one or more events happen. In our case, survival analysis is used to calculate how long after the import people stop contributing to the platform. To do this, we found the date of last contribution for each users in our groups. In this way, we were able to calculate the daily number of users still alive over a time period ranging from 6 months before the import to the current date. We proceeded to represent this information with a line graph.

Table III depicts a qualitative representation of the rates of death of OSM users following an import. To gain a better understanding of the data, we ran a survival analysis on groups of users who were active at least 6 months prior the the import. For each analysis on a targeted city, we ran the same exact model on its control group in order to create a benchmark for comparison. For each import date and for each group, we then observed the pair of graphs created, obtained by the city and its control group, and recorded our findings. Once all the results were gathered, we observed which were the most popular trends and reported them on the table above.

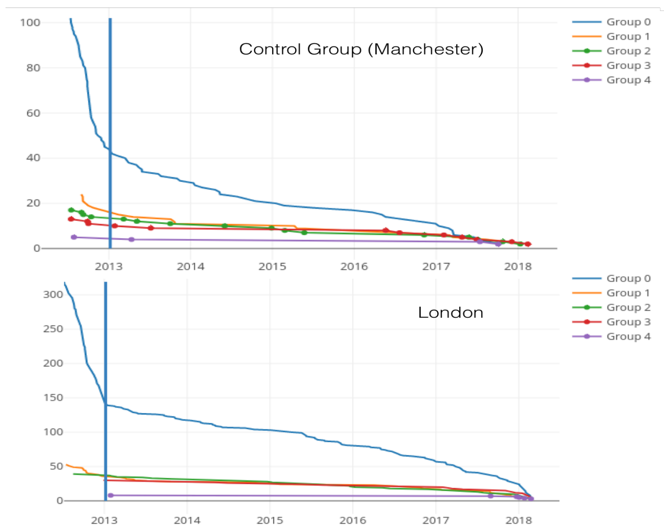

FIG. 4. Survival Analysis London (below) vs. its Control Group (Manchester)

Our findings suggest that imports do not seem to affect the Groups 2-5 survival rate. The most relevant impact was found on the users belonging to Group 1. Amongst these individuals, we have noticed a tendency to remain active contributors of the platform, with death rate curves displaying a clear decrease in steepness in our graphs. On the other hand, control groups, have often displayed more constant ratios, with no sudden changes in gradient. An example of this can be seen in FIG.4. Thus, we are pushed to believe that this is caused by the imports. At the same time, we know that users with lower contribution rates are also incline towards higher rates of volatility and randomness in behavior. Thus, it is difficult to define our findings as a trend with absolute certainty.

Cities	Group 1	Group 2	Group 3	Group 4	Group 5
London	1	0	0	0	0
Paris	1	0	0	0	0
Rome	0	0	0	0	0
Madrid	0	0	0	0	0
Berlin	1	0	0	0	0
Brussels	0	0	0	0	0
Kiev	1	0	0	0	0

1 = A decrease in the rate of death of users following an import relative to the pertinent control group.
0 = No noticeable change in rate of death relative to the pertinent control group.

TABLE III: Summary of Survival Analysis Results

Hypothesis 2: For the second hypothesis we analyze the users edits type behavior after an import, we want to test whether users perform more maintenance actions than create actions. To reiterate, we are looking at: the impact of a data import on how users modify/delete (maintenance) or create. We are testing the hypothesis that users maintenance edits increase after an import while create actions decrease. The graph and tables used in this results sections are TABLE IV/V and FIG. 5. The tables are a summary of analysis we did between a city and its control group.

For instance, the comparison between Madrid and Barcelona (FIG. 5) is summarized in the TABLE IV, where all the Δ Box and Δ Median show the changes between the study group and its control group. For the Group 5, in TABLE IV it shows Δ Box: Up, it means the box of Madrid has shifted up compared to that of its control group, Barcelona (Noticeable in FIG. 5). The Δ Median follows the same logic. The meaning of a shift up is that the users are doing more creates overall than they are expected to compared to the 6 month before an import and compared to the control group. A shift down is the opposite and means users are doing less creates than expected. This type of analysis used to complete the tables was repeated for all groups, for all cities, in the short, medium and long term.

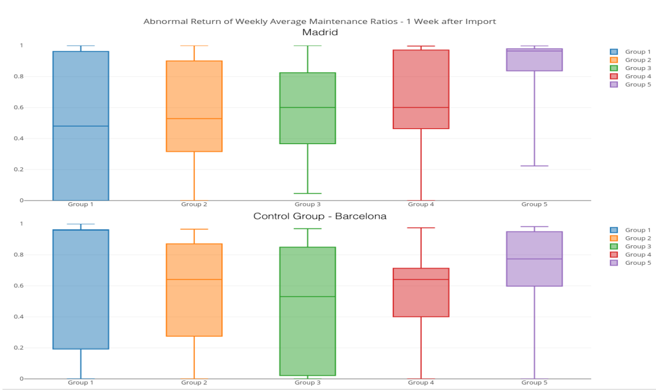

FIG. 5. Abnormal return of the maintenance ratio in the short term (1 week) for Madrid and its control group, Barcelona

In this paragraph, we look closer at the impact of data import in the short term summarized in TABLE IV (NOTE: The data for Brussels was corrupted for the short term). In general, it seems that Group 3, 4 and 5 are the most impacted by data imports in the short term. Most of these groups have seen an increase in creates 1 week after an import. Noticeably, in Group 5, Madrid, Paris and London are the cities which seems to have the greatest shifts in boxes up with regards to their control group and Kiev being the least significant city. In Group 3 and 4, the boxes and median of Rome, London, Berlin, Madrid and Paris have all shifted up compared to that of their control group. The only exceptions are for Group 4 in Rome and Group 3 in London which show no change, and only two downs changes in Kiev. Now looking at the impact on Group 1 and 2, most of the cities show no change in their boxes with the boxes being spread out similarly to the Group 1 box in figure 5. The difference in median relative to their control group is also random and insignificant. It shows that there is no real pattern for the behavior of weak contributors. To summarize the imports' impact on the short term, users in the most active groups of each cities create more nodes than they delete or modify in the week following an import .

Cities	Group 1	Group 2	Group 3	Group 4	Group 5
London	ΔBox: None ΔMedian: +0.1 (Control: 0.2)	ΔBox: None ΔMedian: 0.0 (Control: 0.55)	ΔBox: None ΔMedian: +0.1 (Control: 0.65)	ΔBox: Up ΔMedian: 0.0 (Control: 0.65)	ΔBox: Up ΔMedian: +0.15 (Control: 0.65)
Paris	ΔBox: None ΔMedian: -0.5 (Control: 0.9)	ΔBox: None ΔMedian: 0.0 (Control: 0.65)	ΔBox: Up ΔMedian: +0.2 (Control: 0.5)	ΔBox: Up ΔMedian: +0.08 (Control: 0.65)	ΔBox: Up Up ΔMedian: +0.15 (Control: 0.75)
Rome	ΔBox: None ΔMedian:+0,025 (Control: 0.65)	ΔBox: Up ΔMedian: -0.05 (Control: 0.7)	ΔBox: Up ΔMedian: -0.15 (Control: 0.7)	ΔBox: None ΔMedian:-0.05 (Control: 0.85)	ΔBox: None ΔMedian: -0,05 (Control: 0.95)
Madrid	ΔBox: None ΔMedian: -0.4 (Control: 0.9)	ΔBox: None ΔMedian: -0.15 (Control: 0.65)	ΔBox: Up ΔMedian: +0.05 (Control: 0.5)	ΔBox: Up Up ΔMedian: -0.05 (Control: 0.65)	ΔBox: Up Up ΔMedian: +0.2 (Control: 0.75)
Berlin	ΔBox: Down ΔMedian: 0,7 (Control: 0.95)	ΔBox: Down ΔMedian: 0,3 (Control: 0.65)	ΔBox: Up ΔMedian: 0,05 (Control: 0.55)	ΔBox: Up ΔMedian: -0.05 (Control: 0.65)	ΔBox: None ΔMedian: -0.2 (Control: 0.75)
Brussels	No Data	No Data	No Data	No Data	No Data
Kiev	ΔBox: None ΔMedian: -0,07 (Control: 0.55)	ΔBox: Down ΔMedian: 0,05 (Control: 0.8)	ΔBox: Down ΔMedian: 0,02 (Control: 0.82)	ΔBox: Down ΔMedian: 0,15 (Control: 0.95)	ΔBox: None ΔMedian: -0,05 (Control: 0.9)

ΔBox: Position of the box compared to the control group.
ΔMedian: Difference in the median of the maintenance ratio compared to the control group.
Control: Value of the median of the maintenance ratio of control group.

TABLE IV: **Summary of comparison of AR for the maintenance ratio** of the studied cities vs. abnormal return of control groups in the short term (1 week)

In the medium term, the general finding were not really significant. A similar table to table V was generated and no results of any significance featured on it. Precisely, the results are mostly spread out, with boxes not shifting much but also shifting with no real tendency compared to the short term. There are no differences between the stronger contributing groups and the lower contributing ones. The changes in boxes for each group of each city relative to that of its control group are in no case constant. The only relevant point is that there is no trend in the date in the medium term.

Cities	Group 1	Group 2	Group 3	Group 4	Group 5
London	**ΔBox**: Up **ΔMedian**:-0,005 (Control: 0.015)	**ΔBox**: Up **ΔMedian**: 0 (Control: 0,03)	**ΔBox**: Down **ΔMedian**: -0,015 (Control: 0.035)	**ΔBox**: Up **ΔMedian**:-0,0125 (Control: 0.0375)	**ΔBox**: None **ΔMedian**:-0,005 (Control: 0.0425)
Paris	**ΔBox**: None **ΔMedian**: -0.01 (Control: 0.045)	**ΔBox**: None **ΔMedian**: 0.0 (Control: 0.04)	**ΔBox**: Up **ΔMedian**: + 0.01 (Control: 0.03)	**ΔBox**: None **ΔMedian**: +0.01 (Control: 0.03)	**ΔBox**: Shrink **ΔMedian**: -0.01 (Control: 0.05)
Rome	**ΔBox**: Down **ΔMedian**: -0.005 (Control: 0,0375)	**ΔBox**: Up **ΔMedian**: -0.075 (Control: 0.0275)	**ΔBox**: None **ΔMedian**: -0.075 (Control: 0.045)	**ΔBox**: Down **ΔMedian**: 0.01 (Control: 0.05)	**ΔBox**: None **ΔMedian**: 0.025 (Control: 0.0525)
Madrid	**ΔBox**: None **ΔMedian**: -0.005 (Control: 0.045)	**ΔBox**: None **ΔMedian**: 0.0 (Control: 0.04)	**ΔBox**: Up **ΔMedian**: + 0.02 (Control: 0.03)	**ΔBox**: None **ΔMedian**: +0.02 (Control: 0.03)	**ΔBox**: None **ΔMedian**: 0.0 (Control: 0.05)
Berlin	**ΔBox**: Down **ΔMedian**: 0,025 (Control: 0.045)	**ΔBox**: Down **ΔMedian**: 0,01 (Control: 0.04)	**ΔBox**: None **ΔMedian**: -0.028 (Control: 0.032)	**ΔBox**: None **ΔMedian**: -0.027 (Control: 0.033)	**ΔBox**: Down **ΔMedian**: -0.011 (Control: 0.049)
Brussels	**ΔBox**: None **ΔMedian**: -0.01 (Control: 0.045)	**ΔBox**: None **ΔMedian**: 0.0 (Control: 0.04)	**ΔBox**: None **ΔMedian**: + 0.02 (Control: 0.03)	**ΔBox**: None **ΔMedian**: +0.02 (Control: 0.03)	**ΔBox**: None **ΔMedian**: 0.0 (Control: 0.05)
Kiev	**ΔBox**: Down **ΔMedian**: 0,001 (Control: 0.036)	**ΔBox**: Down **ΔMedian**: -0.006 (Control: 0.032)	**ΔBox**: Down **ΔMedian**: -0.006 (Control: 0.04)	**ΔBox**: Down **ΔMedian**: 0 (Control: 0.049)	**ΔBox**: Down **ΔMedian**: -0.009 (Control: 0.042)

ΔBox: Position of the box compared to the control group.
ΔMedian: Difference in the median of the maintenance ratio compared to the control group.
Control: Value of the median of the maintenance ratio of control group.

TABLE V: **Summary of comparison of AR for the maintenance ratio** of the studied cities vs. abnormal return of control groups in the long term (3 months)

In the long term, the results are entirely different to that of the short term and medium term for the stronger contributing groups. The number of creates to maintenance edits of edits is back to a normal behavior 3 month after an import because there is no difference with their control groups. More precisely, looking at table V, the boxes seem to change slightly compared to that of their control groups for the strong user contributing groups. In Group 3, Paris and Madrid have shifts up compared to their control groups while the rest are none for the exception of Kiev. In Group 4, only London shifts up compared to its control group with the others showing no shifts except for Kiev and Rome shifting down. Finally in Group 5, no shift upwards, two shifts down for Berlin and Kiev while the others seem to show no change. This can be resumes as the activity of the strong contributing groups (3,4,5) in the long term returns to normal with only three groups in groups (3,4,5) out of the 7 cities being impacted negatively. Again, similar to our short term table X, no apparent change in the behavior of weakly contributing groups.

Hypothesis 3: The third hypothesis aims to quantify the impact of imports on the contributions made on the imported objects after the import was made. As before we do so by computing the AR for the 5 groups. Control groups could not be used, as we are looking at the contribution of users on the amenity edited in the import. To quantify both short and long term effects of imports, we computed AR on three non-overlapping periods, $\tau=$ 1 week, 1 month and 3 months after the import. We used a weekly average of the ratio of edits made on the amenity edited in the import to the total edits per user. We also used box-and-whisker plots. The results for the long term period can be found in Table VI. We notice that the actual return is slightly lower than the expected returns for Group 5 in each city and for the three periods: short term, medium term and long term and for London, Rome and Brussels, the median is equal to zero on the long term. This group is constituted of the heavier contributors, they seem to be less impacted by imports than the other groups. Indeed the average of the medians for the 7 cities is equal to -0.02 on the short term, -0.036 on the medium term and -0.069 on the long term. Even though the average is increasing, it is very slight.

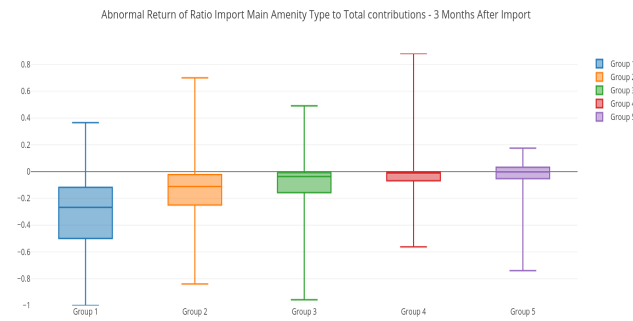

FIG. 6. Abnormal return of the ratio of contribution to the imported elements (same amenity) in the long term (3 months) for London

Cities	Group 1	Group 2	Group 3	Group 4	Group 5
London	**Q1**: -0,5 **Median**: -0,25 **Q3**: -0,1	**Q1**: -0,225 **Median**: -0,1 **Q3**: -0,015	**Q1**: -0,15 **Median**: -0,015 **Q3**: 0	**Q1**: -0,025 **Median**: 0 **Q3**: 0	**Q1**: -0,05 **Median**: 0 **Q3**: 0,03
Paris	**Q1**: -0,45 **Median**: -0,2 **Q3**: -0,015	**Q1**: -0,45 **Median**: -0,2 **Q3**: -0,03	**Q1**:-0,45 **Median**: -0,025 **Q3**: 0	**Q1**: -0,55 **Median**: -0,01 **Q3**: 0	**Q1**: -0,4 **Median**: 0,01 **Q3**: 0,15
Rome	**Q1**: -1 **Median**: -0,45 **Q3**: -0,225	**Q1**: -0,7 **Median**: -0,15 **Q3**: -0,1	**Q1**: -0,85 **Median**: -0,625 **Q3**: 0	**Q1**: -0,15 **Median**: 0 **Q3**: 0,15	**Q1**: 0 **Median**: 0 **Q3**: 0,1
Madrid	**Q1**: -0,5 **Median**: -0,35 **Q3**: -0,2	**Q1**: -0,5 **Median**: -0,35 **Q3**: -0,15	**Q1**: -0,45 **Median**: -0,35 **Q3**: -0,02	**Q1**: -0,1 **Median**: 0,015 **Q3**: 0,15	**Q1**: -0,4 **Median**: -0,2 **Q3**: -0,02
Berlin	**Q1**: -0,45 **Median**: -0,35 **Q3**: -0,15	**Q1**: -0,35 **Median**: -0,2 **Q3**: -0,1	**Q1**: -0,2 **Median**: -0,1 **Q3**: 0	**Q1**: -0,2 **Median**: -0,025 **Q3**: 0	**Q1**: -0,25 **Median**: -0,15 **Q3**: 0
Brussels	**Q1**: -0,35 **Median**: -0,2 **Q3**: -0,1	**Q1**: -0,35 **Median**: -0,02 **Q3**: -0,015	**Q1**: -0,25 **Median**: -0,015 **Q3**: 0,015	**Q1**: -0,35 **Median**: -0,1 **Q3**: 0,05	**Q1**: -0,1 **Median**: 0 **Q3**: 0,2
Kiev	**Q1**: -0,5 **Median**: -0,225 **Q3**: -0,1	**Q1**: -0,15 **Median**: -0,05 **Q3**: -0,025	**Q1**: -0,1 **Median**: -0,05 **Q3**: 0	**Q1**: -0,2 **Median**: -0,05 **Q3**: -0,025	**Q1**: -0,025 **Median**: -0,02 **Q3**:0

Q1: Difference in the Q1 compared to the control group.
Median: Difference in the median compared to the control group.
Q3: Difference in the Q3 compared to the control group.

TABLE VI: **Summary of AR results for the ratio of contribution to the imported elements (same amenity)** in the long term (3 months)

In parallel, 1 week after the import, we notice that the weaker contributors, Groups 1-2, focus less on the imported elements than expected, this observation is persistent over the medium and long terms. Indeed, the average of the medians for the 7 cities for Group 1 is equal to -0.33 in the short term, -0.29 in the medium term, -0.289 in the long term. For all the groups, comparing across the different time periods shows that the impact is stronger 1 week after the import is done and the results are mostly the same for the medium and long term. This group contributes less on the amenities edited in the import compared to Group 5. Group 2 also contributes less than Group 5, but is less affected than Group 1. The average of the medians for the 7 cities for Group 2 is equal to -0.15 in the short term, -0.145 in the medium term and -0.15 in the long term. These numbers are representative of the the box-and-whisker graph (FIG.6), which shows the results in the long term in London. In the graph we can see that Group 1's median is the lowest while Group 5's median is equal to 0. Thus, no change is witnessed in Group 5. The less a group contributes the more they seem to be affected by an import.

IX. CONCLUSION AND FUTURE WORK

Summary of Contributions.

In this work we analyze the impact of imports on the engagement of users in Paris, London, Madrid, Berlin, Kiev, Rome and Brussels. First, the results of the abnormal Return of contributions computed on the 5 groups show us that the stronger a contributor is, the more likely he is to be impacted by the import. This would seem paradoxical as they are supposed to be the most involved users. In fact, that is in the 5th group that we experience the widest gap in median, which proves that not all strong contributors react the same way to an import: some positively and some negatively (with a tendency to go up). At the opposite, the weaker a contributor is, the less likely they are to be affected (positively or negatively) by an import, across all epochs. Another interesting aspect of those results is that across the panel of studied cities, not all strong contributors behaved the same way regarding an import, sometime even oppositely. This could come from the fact that not all frequent users have the same consideration for imports and have contradicting views regarding their impact on OSM platform. Cultural differences could also explain this, but this is not something on which we could draw meaningful conclusions. This partially contradicts with our initial hypothesis as the decrease did not occur in the weak contributors' groups, and then occur in a very sparse way for the strong contributors (some extreme in positive and negative).

Second, for our analysis of maintenance to creation ratios, our results disagree with our hypothesis. It seems that data imports have an impact in the behavior of the strong contributing groups in the short term (1 week following an import) while no significant import on weak contributing groups. From the data, strong contributing groups do more create edits than deletes or modified with regards to the total amount of edits they carry out on the platform. However, in the long term, these behavior of these strong contributing groups tend to come back to normal (similar to that of their control group). Thus, it seems that data imports push strong contributors to do more creates just after an import, perhaps to complete these imports, but in the long term have no real significant impact.

Lastly, results we obtained working on our third hypothesis, show that the weaker contributors' focus is volatile compared to the heavier contributors; weak contributors are not as engaged and thus change the objects they edits. For example, this would mean that after an import of "tree", weak contributors are less likely to edit trees on the platform. Thus, a small change in the environment seems to disturb the focus of the weaker contributors. Concerning Group 5, they are used to contribute to the platform in a certain way and they contribute massively, thus one import is unlikely to disturb their strong habits of contribution. However, we were not able to compare these results to control groups, which leaves room for interpretation. Indeed, the change of focus of the weaker groups can be explained by their lack of engagement to the platform and not because of the imports.

Future work.

For the purpose of this study, only 14 cities were considered. In order to generalize our findings, more data have to be analyzed. We also chose to exclude OSM relations entities from our dataset to keep our data at a manageable size. However, in future works, it would be interesting to include relations in the analysis of the impact of imports on users' engagement. Concerning the control groups, we used large cities from the same country to avoid cultural differences. Because of that, chosen control groups tend to smaller both in number of contributions and number of contributors compared to studied cities. Yet, other control groups could have been considered such as the same city at a different time when no imports were made. Finally we grouped imports per city. Another option could have been to group imports in different cities by time periods.

Implications.

Imports aim to contribute a massive amount of data to the OSM platform. However, the OSM's success relies on the engagement of its users who, based on previous studies, are motivated by a sense of greater good towards their community. Do imports have an impact of the engagement of the contributors? In this paper, we propose a quantitative methodology to understand the impact of imports on the behavior of users in 7 cities: London, Paris, Rome, Madrid, Berlin, Kiev, Brussels. Our findings suggest that imports mostly affect negatively the contribution of heavy users while changing the focus of the edited entities of the weaker users. Also, imports seem to push heavy contributors to perform create actions in the short term period after an import, yet in the medium and long term they tend to perform more maintenance actions (updates and deletions).

Our research is quantitative and thus does not answer causality, we do not know the reason behind the results, we can only assume. User-based platforms such as OSM deeply rely on their communities. We believe that these platforms should measure the impacts of their activities on their contributors in order to engage new users and keep the most active ones. The methodology proposed in this paper goes one step in this direction by allowing a quantitative analysis of the impact of such events on the sustainability of the crowdsourcing community.

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