Productivity or Equity? Tradeoffs in Volunteer Microtasking in Humanitarian OpenStreetMap

YAXUAN YIN, The Information School, University of Wisconsin–Madison, USA
LONGJIE GUO*, University of Washington, USA
JACOB THEBAULT-SPIEKER, The Information School, University of Wisconsin–Madison, USA

Microtasking, the decomposition of tasks into small units of work, is prolific in human computation and crowdsourcing. Some peer production systems are beginning to leverage this same technique in volunteer contribution-based settings. While early research suggests that focusing volunteer work in this way using microtasking may be fruitful, the effects of microtasking on contributor behavior in volunteer peer production settings, like OpenStreetMap, remain unclear. This paper takes advantage of a natural experiment facilitated by the Humanitarian OpenStreetMap's Tasking Manager microtasking system and employs causal inference analysis to evaluate the effects of a microtasking intervention on contributor dynamics. Our study systematically leverages a global dataset to analyze peer production dynamics, building on prior research to address a gap in peer production literature and informing the design of the microtasking interfaces. We causally show that, indeed, microtasking can be an effective intervention in peer production settings, but it may exacerbate power-law patterns that are common in such settings. By further analyzing project design decisions and characteristics, we develop implications for platform practitioners, with a focus on addressing engagement and contribution inequity issues prevalent in settings like OpenStreetMap.

CCS Concepts: • **Human-centered computing → Empirical studies in collaborative and social computing**; *Wikis.*

Additional Key Words and Phrases: Crowdsourcing, OpenStreetMap, Peer Production, Causal Inference

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1 INTRODUCTION

OpenStreetMap is one of the largest collaborative geographic datasets in the world [37]. To date, there are over 1.5 million active contributors who have helped to edit over 1 billion features [34], and it has been called "the Wikipedia of Maps". With the growth of active users, OpenStreetMap has deployed a series of strategies and collaborations to support a wider range of uses, such as cooperating with private sector organizations like Microsoft Bing and Foursquare to achieve business and economic value [41]; interacting with governments to address social issues [18]; and initiating humanitarian mapping projects aiming for disaster relief and international development [22], which is the focus of our paper here.

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Authors' addresses: Yaxuan Yin, yaxuan.yin@wisc.edu, The Information School, University of Wisconsin–Madison, 600 N Park St, Madison, Wisconsin, USA, 53706-1403; Longjie Guo, University of Washington, Washington, USA; Jacob Thebault-Spieker, The Information School, University of Wisconsin–Madison, Wisconsin, USA.

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Geospatial data, like that produced in OpenStreetMap, plays an important role in facilitating effective humanitarian aid and informed decision-making processes [51]. However, OpenStreetMap has known coverage gaps [9, 16, 53], and governmental spatial data is often unavailable or out of date [2]. This lack of available spatial data undermines the ability of countries to implement efficient disaster response strategies, which is one aspect of the UN Sustainable Development Goals [2]. The Humanitarian OpenStreetMap Team (HOT) was formed in 2010 to help fill this spatial information gap [22]. This effort has since expanded to include organized humanitarian mapping activities facilitated by HOT, which have become integral in filling information gaps and improving data accessibility on the ground [55]. For instance, during the 2015 earthquake in Nepal, a remarkable response from approximately 9,000 volunteers worldwide through OpenStreetMap rapidly addressed spatial information gaps that had been left by the official mapping agency, within just three days. The resulting map emerged as a critical resource guiding the allocation of essential supplies and medicine during subsequent disaster relief operations [18].

Indeed, Humanitarian OpenStreetMap's successes may indicate a promising path forward to addressing information gaps in OpenStreetMap more broadly. Prior work has shown that information coverage in OpenStreetMap tends to be more limited and of lower quality in economically disadvantaged areas compared to wealthier regions [9, 16, 53]. Moreover, globally, the regions most prone to natural disasters and facing development challenges also tend to suffer from economic, social, and infrastructure vulnerabilities [1]. Humanitarian OpenStreetMap's high-profile success at addressing humanitarian information gaps in these vulnerable regions, may suggest a strategy for mitigating more generalized disparities and information gaps in map coverage.

Importantly, as the HOT community has grown, using computational tools to facilitate and manage mapping activities has become essential. The HOT "Tasking Manager" (https://tasks.hotosm.org/) was developed as a tool to coordinate volunteers and organize groups to map on OpenStreetMap collaboratively. The Tasking Manager adopts concepts from crowdsourcing for geographic data production in OpenStreetMap, structuring work through microtasking, decomposing work into smaller, focused tasks, helping focus individuals' work without requiring people to commit lengthy blocks of time [56]. The Humanitarian OpenStreetMap Team (HOT) — with partner organizations such as Doctors Without Borders (Médecins Sans Frontières), the Red Cross, and others [38] — uses the Tasking Manager to launch projects that focus and structure mapping activities of thousands of volunteers [40], and has shown repeated success [9], echoing findings in other peer production systems [6, 43].

However, it remains unclear how microtasking tools like the HOT Tasking Manager interact with known peer production dynamics that are common in these kinds of systems. For instance, power-law distributions in peer production — wherein a small group of contributors produce the majority of the contributions and account for the most proportion of efforts — are common in peer production systems like OpenStreetMap [24, 27, 50], and some preliminary findings suggest that they may contribute to information gaps and disparities in peer production settings [52].

Moreover, peer production communities notably do not prioritize efficient contributions above all else: Wikipedia has had thorough community discussions and formalized policies around paid contributors [60] and automated editing [59]; OpenStreetMap is currently engaged in similar debates and has, since its inception, suggested that local on-the-ground GPS traces are better than 'armchair mapping' [39].

Our work here sits at the center of these two ideas: microtasking interfaces seem to be broadly effective for driving contribution, but may undermine valuable contribution and community dynamics in peer production settings. Specifically, relying on a natural experiment enabled by the HOT Tasking Manager, we causally study how microtasking influences contribution and community dynamics in OpenStreetMap, and explore how project design decisions and characteristics of the Tasking Manager's interface influence its effectiveness. Our work makes three primary contributions:

- We causally replicate prior work indicating that microtasking increases contribution and contributor rates, while complicating and adding nuance to these findings — microtasking also worsens power-law dynamics, by concentrating contribution effort into the hands of relatively fewer contributors.
- Moreover, we explore how project and organizational differences predict changes in contribution dynamics and find mixed results. In some cases, task difficulty and being affiliated with specific organizations predict increases in contributors' participation and a higher concentration of contributions among fewer contributors. In other cases, we find the opposite — task difficulty and organizational affiliation predict lower rates of contributors, but contributions are more evenly distributed.
- Overall, our work identifies a tension between increased productivity versus the concentration of effort and output within a project. Given prior work, this tension may generalize to other peer production settings and highlights important design implications for organizations running Humanitarian OpenStreetMap projects, as well as peer production communities and practitioners. For instance, urgent disaster-response projects may entail the risk of biases or low data quality due to contribution inequity.

2 RELATED WORK

Prior work has focused extensively on contributor and community dynamics in peer production settings, and our work here extends that line of work. Specifically, we focus on the effect of microtasking tools like the HOT Tasking Manager, with a particular eye towards its impact on both contributor and community dynamics, as well as how it may influence known data coverage issues in OpenStreetMap. As such, our work builds upon and extends three primary bodies of prior research: (1) Peer Production for Humanitarian Goals, (2) Contributor Activities and Events in Humanitarian OpenStreetMap, and (3) Geographic Variations in Effectiveness of Peer Production.

2.1 Peer Production for Humanitarian Goals

The information production work and online community efforts to support humanitarian and disaster relief efforts, even beyond OpenStreetMap, are often done, at least in part, remotely [5, 16, 24, 47–49]. For instance, Keegan et al. [24] showed that when breaking news occurs, it can increase focused group collaboration on articles about the breaking news topics. Moreover, in the early stages, the groups of contributors are fairly diverse: some may have participated in previous events, whereas others could be new contributors. Beyond breaking news, studies in the crisis informatics literature have shown the potential for remote volunteers to help disseminate information [48] or otherwise provide support for crisis and disaster events [40]. Indeed, some research in this space echoes Keegan et al. [24]'s findings, and shows that participating in these activities to support disaster relief may help motivate participation again [5, 48].

Within peer production communities, Esworthy [14] worked to characterize the patterns of contributions across both OpenStreetMap and Wikipedia during major disaster events like earthquakes and hurricanes. On both platforms, contributor activity spikes shortly after the disaster, and then that participation decays over time. Moreover, Palen et al. [40] focused on the potential for quality work and recognized that user contributions after a HOT project is created follow a similar power-law to the area before a project was created, in some specific regions.

More specifically, some research has also focused on evaluating the outcomes of HOT itself, generally studying larger and more well-known campaigns like earthquakes in Haiti [40] and Nepal

[42], or typhoon Haiyan/Yolanda[8]. These studies found that while first-time contributors map at lower rates than experienced mappers, the contributions made by first-time mappers are essential for completing data collection. Dittus et al. [8] compared HOT contributor participation and found that meaningfully fewer new users continue participating during event-centric campaigns than during mission-based campaigns. They suggest different recruiting practices and community-building practices between the campaigns might cause contributors to self-select, and could cause differences in engagement. A further study [8] investigated the outcomes of 26 campaigns and pointed out that event-centric campaigns can meaningfully support recruitment and reactivation of contributors, but that newcomers produce lower quality content during event-centric campaigns.

Overall, prior work suggests that peer production systems and Humanitarian OpenStreetMap *do* effectively contribute, remotely, to humanitarian and disaster relief efforts. Moreover, there is some early evidence to suggest that *how recruitment occurs*, plays an important role in how people participate and how effective these remote humanitarian response efforts are.

2.2 Contributor Activities and Events in Humanitarian OpenStreetMap

Distinguishing itself from general OpenStreetMap, Humanitarian OpenStreetMap grew out of a more informal process of mapping, for the purposes of disaster relief [21]. A primary goal of HOT is to support community growth and humanitarian efforts in OpenStreetMap. The earthquake in Haiti arguably catalyzed the growth of numerous "volunteer technology communities" with the intention of providing aid or supporting aid workers during disasters and other humanitarian events [47]. Since then, HOT has provided disaster relief to a number of major disaster events [9].

In addition to its initial emphasis on disaster event-centric initiatives, Humanitarian OpenStreetMap's Tasking Manager has come to be used for a wide range of activities [10]. For instance, a number of initiatives are working towards helping strengthen the OpenStreetMap map data *before* disaster hits, or to help build out the map for other humanitarian goals [21]. These efforts are frequently longer-term and more mission-focused campaigns, with larger areas to map. In other cases, Humanitarian OpenStreetMap partners with organizations whose goals align with building out map data, including the Peace Corps, MapGive, and Missing Maps [4, 31]. In one example, what started as a localized emergency response campaign for Ebola grew larger and longer, stretching far beyond its initial urgent disease response. Prompted by the disease response, a series of mission-focused projects was created to help augment the map in a number of different regions that were affected by Ebola [29].

Users who choose to participate in Humanitarian OpenStreetMap projects may initially go about it in several different ways. In some cases, HOT projects may occasionally be discussed publicly in the media, on social media, and through other external promotion methods, which can help generate interest and attract mapping labor to the Tasking Manager for project completion [4, 29, 45, 46]. Particularly high-profile catastrophic events draw attention to the need for volunteers. In addition to the influential role of news and social media, organizers may also recruit contributors through their own social networks (e.g. organizations and campaigns) [32]. Campaigns and organizations are the two primary approaches commonly employed to encourage mapping efforts, foster relationships with contributors, and facilitate community development. In particular, recruiting methods and strategies have been identified as crucial for community-building efforts and have been shown to impact the success of tasks [11, 58]. Importantly, public recruitment in the media or via organizations does not preclude anyone from working on projects independently, after all, the HOT Tasking Manager system is available publicly.

The nuances of participation and recruitment strategies suggest, therefore, that specific characteristics of outreach campaigns and organizations may affect contribution and community dynamics as well. Some prior work has studied metrics like retention rate and labor hours [8, 40, 42], which we discuss in more detail below.

2.3 Geographic Variations in Effectiveness

One key mechanism leveraged by this humanitarian peer production work is the potential for anyone, located anywhere, to contribute information about any location. However, research has consistently shown that significant disparities exist in both the quality and quantity of content on OpenStreetMap, despite the opportunities for remote contribution. In general, regions with relatively high Human Development Indexes are greatly favored in OpenStreetMap's mapping efforts [21], whereas areas with low and medium levels of human development, where the majority of the population resides, do not receive enough attention. In actuality, only a small portion of the roads and buildings in these regions are mapped in OpenStreetMap [21]. Haklay [16] demonstrated that the number of contributions is meaningfully lower in areas of low socioeconomic status, with the number of contributors directly correlating to the volume of contributions. These findings have been echoed by Dittus et al. [9] and Thebault-Spieker et al. [53]. The latter found that these trends seem to follow "born, not made" processes — namely, that the individuals who contribute the most content to OpenStreetMap tend to overlook rural and low socioeconomic areas, and this pattern is evident from the moment they join the platform.

With regard to Humanitarian OpenStreetMap more specifically, prior work does not present a clear story on how HOT might influence community and contributor dynamics. Herfort et al. [21] found that humanitarian mapping efforts, such as post-disaster mapping campaigns, broadly help improve the coverage of existing open geographic data and maps in places that are disadvantaged by these general socioeconomic trends in geographic coverage. Of course, they also note the need to address the remaining stark data inequalities, which vary significantly across countries — While Humanitarian OpenStreetMap mapping efforts may not directly tackle the underlying data inequalities, they could be aiding in mitigating them over time. Complicating this matter further is work by Nagaraj [35], which suggests that once data is imported to the map, volunteers are less likely to return and "clean up" the map. Taken together, while humanitarian mapping does seem to help improve coverage, such a rapid influx of data may then produce a chilling effect on more sustained maintenance and improvement.

3 METHODOLOGY

Prior work suggests a combination of findings that present an unclear picture: microtasking efforts, like the HOT Tasking Manager, are effective for producing content in places where map data is needed, at least in prominent cases. However, it is unclear if and how these microtasking tools may create other consequences for community dynamics. It is also uncertain how the specifics of the microtasking projects influence both contributions and the dynamics within the community. This is the focus of our study here, and we formalize two research questions as guiding directions for our work:

RQ1 How does project creation in the HOT Tasking Manager influence the contribution and community dynamics of peer production?

RQ2 How do project attributes (e.g. affiliation with an organization, task difficulty, etc.) influence the effectiveness of project creation?

Our work here takes a systematic view, using a causal inference approach to understand the impact of the HOT Tasking Manager's microtasking intervention on contribution and community dynamics. We augment this analysis by also characterizing how the attributes of Humanitarian OpenStreetMap projects might vary the impact of these causal outcomes.

The HOT Tasking Manager is the platform through which Humanitarian OpenStreetMap projects are built and deployed. HOT strategically focuses contributor efforts on regions that need better coverage in map data, in order to support humanitarian goals. The Tasking Manager interface, depicted in Figure 3, facilitates these coordinating mapping activities. Specifically, people or organizations launching a new project specify regions, and the Tasking Manager subdivides those regions and helps to coordinate the micro-task specification. In our work here, we treat this project creation process as a natural experiment — an opportunity to causally study the influence that creating a Humanitarian OpenStreetMap project has on contribution and community dynamics in the specified region, compared to a nearby, similar region. A key mechanism that facilitates this type of natural experiment (e.g. [35]) relies on insight from the First Law of Geography [54], which states "everything is related, but nearby things are more closely related". In other words, when a HOT project is created, we can likely identify a second, nearby region that is very similar, and the only difference will be that a HOT project was created in one of the two regions.

More formally, we adopted a quasi-experimental, difference-in-differences (DID) approach common in social sciences, in order to make causal inferences about the effects of microtasking intervention, while controlling confounding effects including geographic region and time of project creation, among others. The difference-in-differences approach compares the trends in variables — before and after the creation of a HOT project — between two different regions: one where a HOT project was created, and a nearby region that is otherwise similar but no HOT project was created. This natural experiment structure allows comparison between an "experimental treatment" group, and a paired "experimental control" group, where the former experienced the creation of a HOT project while the latter did not.

3.1 Data Collection

3.1.1 Constructing the Natural Experiment.

To specify our "treatment" group consisting of HOT projects, we queried the Tasking Manager API for all 8396 published projects, through January 2022. However, during the data collection process, we encountered 552 projects that did not return data from the API, indicating that they had been deleted or removed from public access. As a result, we were left with a total of 7874 projects, which form the basis of our dataset.

For each project, we gathered data on several project-specific attributes, including the geographic region of creation. To address our second research question, we also collected data on project priority, difficulty level, mapping type, organization name, campaign name, and country name. These project attributes are visible in the Tasking Manager interface, allowing contributors to filter, search, and select projects that align with their skill sets or preferences, as shown in Figure 3. The "experimental treatment" group in our dataset, therefore, consists of 7874 HOT project regions, and the associated project metadata.

To conduct a difference-in-differences analysis, we also needed to establish the "experimental control" portion of our dataset, for comparison. It is a common practice in this type of analysis to establish "experimental pairs" [61], with one member belonging to the "control" group and the other having received the "treatment". Regions that are near one another tend to be geographically similar [15, 20], helping to facilitate similarity between "control" and "treatment" groups. However, prior work has shown that OpenStreetMap contribution dynamics are heavily connected to the human populations living in the region [17, 53], suggesting that physical proximity may not sufficiently characterize similarity between regions for our purposes. Therefore, in addition to proximity, we also incorporated population as an additional criterion to further refine the selection process, ensuring that our selected "experimental pairs" are similar both due to geographic proximity, and have similar populations as well.

Concretely, for each "treatment" region, we first computed the diameter of that region. We then identified a set of nearby regions with that range, allowing for rotation of the orientation of the region. This created a set of possible "control" regions. We computed the population of both our "treatment" region and all of the possible "control" regions, based on the global Gridded Population of the World, Version 4 (GPWv4) dataset from NASA's Socioeconomic Data and Applications Center (SEDAC). Based on these population density values, we then selected a single corresponding "control" region for each of our "treatment" regions. The median difference in population between our "treatment" and "'control" regions is 444 people — in other words, our "experimental pairs" are similar both geographically, and in terms of the number of people living in the region.

3.1.2 *Observation Period.*

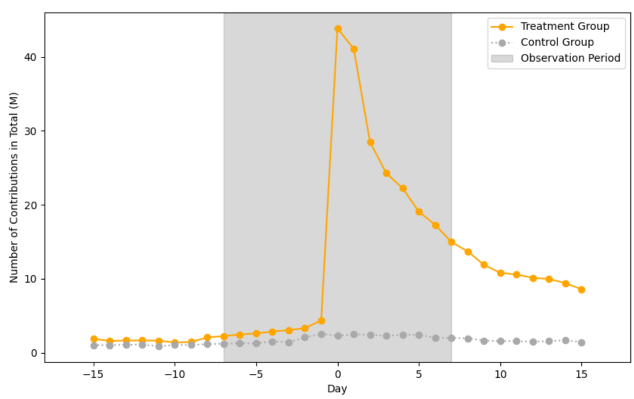

Fig. 1. Total Number of Contributions in Project Regions and Control Regions Over Time.

With our "treatment" and "control" regions identified, the next step was to collect the relevant OpenStreetMap data within each region to determine the observation period. We extracted the complete history of our "treatment" and "control" regions from an OpenStreetMap "history" planet dump and computed the average number of daily contributions in both the "treatment" and "control" regions, starting with a 30-day period (15 days before project creation and 15 days after project creation). On further inspection, and as shown in Figure 1, we narrowed our analysis window to a two-week period, 7 days before and after project creation. In making these decisions, we follow best practices [35], to both ensure we had a sufficiently wide observation window to capture the causal effect, while also ensuring the observation window is narrow enough to be confident that our results are not due to external, spurious correlations.

Notably, prior to the creation of a HOT project, the "treatment" and "control" regions demonstrate a generally similar level of daily contributions, but show slight variations as the date approaches project creation. To ensure the credibility of our findings, we explore this in more detail with a time-relative analysis technique, to assess if the trends of "treatment" and "control" regions are parallel before project creation, in line with the assumptions of a difference-in-differences analysis. We discuss this in more detail in Section 3.2.1.

3.1.3 *Dependent Variables.*

In order to build the necessary models for our difference-in-differences analysis, described below, we computed three dependent variables (for three separate models): the number of contributors, the average number of contributions per person, and the Gini coefficient. Each of these variables are intended to evaluate different aspects of contributor and community dynamics in OpenStreetMap. The first two metrics, number of contributors and average number of contributions per person, focus on contributor activity and productivity dynamics. The third metric, Gini coefficient, is a metric of distributional skew commonly used in economics, and allows our analysis to explore how project creation affects how evenly distributed mapping work is across the contributors involved in a given HOT project. When the Gini coefficient is near 0, the number of contributions is nearly equal among all contributors. When the Gini coefficient is near 1, the majority of contributions are highly concentrated among a few very active contributors [13].

Using the same OSM history data as we did to identify our observation window, we also computed our dependent variables in both our "treatment" and our "control" regions. Specifically, for each project region — and its paired control region — we then computed the daily number of contributors working in both our "treatment" and our "control" regions, the average daily number of changesets per contributor, and the daily Gini coefficient of contributions for each region. The resulting dataset was 14 values for each of our three dependent variables, for each pair of "treatment" and "control" regions. These variables serve as our dependent variables in our difference-in-differences modeling, which we return to below.

3.1.4 *Independent Variables.*

Projects in the HOT Tasking Manager each have their own project page, which is visible to contributors looking for projects to work on. We provide an example of one such page in Figure 2, and note specific aspects of the interface. Each project page provides contributors with project attributes information, including priority, difficulty, types of mapping, campaign name, organization name, and country name. These variables also function as filters on the homepage to help contributors choose what to work on, as in Figure 3. In other words, these attributes provide additional information that contributors use to make decisions about their participation in a given project.

We rely on these attributes as independent variables in our analysis for our second research question. The project-specific attributes that are visible to contributors and serve as our independent variables include:

- **Priority Level:** HOT projects can be at one of four priority levels: Low (in our data: 4,735 projects were assigned "low"), Medium (2,761 were assigned "medium"), High (293 were assigned "high"), or Urgent (85 were assigned "urgent"). In our models, we consider projects with "Low" urgency as the baseline for comparison in the DDD model, below.
- **Difficulty Level:** The difficulty level of each project is a self-reported estimation of the necessary experience level for a contributor, though it is not formal requirement. These levels are: "Beginner Mapper" (7,005 projects), "Intermediate Mapper" (783 projects), and "Advanced Mapper" (86 projects). In our models, we consider projects with "Beginner Mapper" level difficulty as the baseline for comparison, below.
- **Variability in Mapping Type:** Projects can specify any combination of, or none of, the following mapping types: Roads, Waterways, Buildings, Landuse and Other. Based on these mapping types, we construct a "variability" metric, which is a sum of the number of mapping types required, ranging from 0 to 5. In our data, there were 2309, 2763, 1932, 454, 222, and 194 projects in each of our computed variability tiers (0 – 5, respectively).
- **Campaign Name:** Projects can also optionally be affiliated with a specific campaign, for the purposes of recruitment or affiliation. In our data, 48% (3,818) of projects are unaffiliated, and the rest are distributed across 308 different campaigns. Among these, we identified the top 10 most popular campaigns, which account for 28.18% of all projects, as shown in Table 1. We

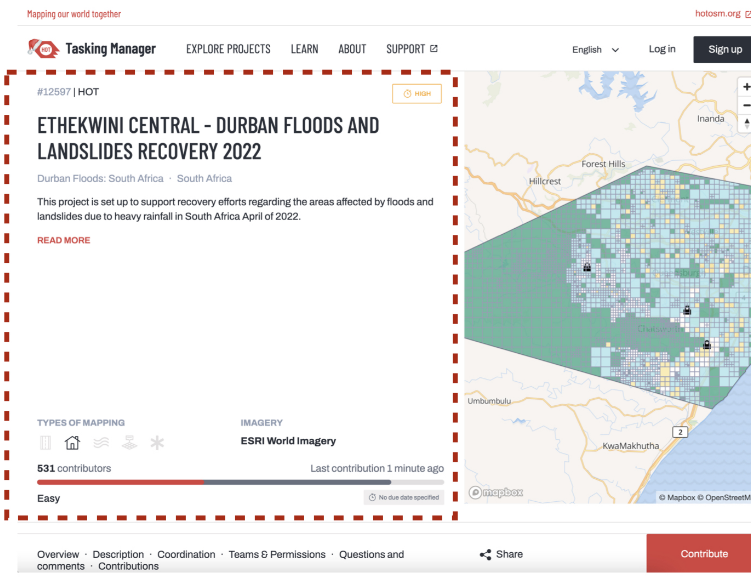

Fig. 2. Screenshot of the Tasking Manager Interface's Project Page. The contextual project attributes are highlighted.

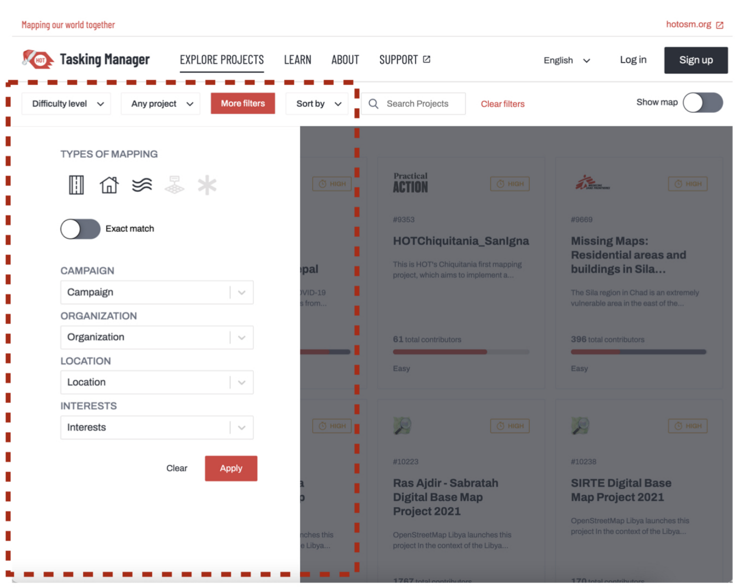

Fig. 3. Screenshot of Tasking Manager Homepage. The project attributes function as filters as highlighted.

labeled projects in these top-10 campaigns accordingly, and grouped the remaining 298 less prominent campaigns under the category of "Others Campaign Types". Despite some visual similarities, we kept campaigns distinct according to their numeric campaign IDs. Projects

Table 1. The Distribution of Campaign Types Among 7874 Projects

Campaign ID	Campaign Name	Number of Projects	Percentage
	No Campaign Affiliated	3818	48.56%
288	Missing Maps	764	9.71%
161	Malaria Elimination	416	5.29%
237	COVID-19	302	3.84%
230	Disaster Response	139	1.77%
334	OpenCities LAC	128	1.63%
276	Road Network Improvement x Kaart	109	1.39%
177	Tanzania Mini-Grids	101	1.28%
81	#missingmaps	98	1.24%
168	Ebola2018	96	1.22%
315	Local Impact Governance Activity	64	0.81%
	Others Campaign Types	1839	23.35%

Table 2. The Distribution of Organization Types Among 7874 Projects

Organization ID	Organization Name	Number of Projects	Percentage
	No Organization Affiliated	2323	29.51%
88	INTEGRATION Consulting Group	917	11.64%
73	HOT	826	10.49%
34	Médecins Sans Frontières (MSF)	467	5.93%
17	American Red Cross	374	4.75%
22	OpenMap Development Tanzania	213	2.70%
7	OSM RDC	203	2.58%
1	Other	189	2.40%
33	CartONG	144	1.83%
10	Kaart	141	1.79%
	Other Organization Types	875	11.11%

that did not have campaign information available were used as the baseline comparison point in our models, below.

Organization Name: We also identified the projects associated with the top-10 most common affiliated organizations, which together account for almost 60% of all projects, as shown in Figure 2. For organizations not among these top-10, we classified them under "Other Organization Types". This classification is distinct from the "Other" organization affiliation category that was pre-existing in the dataset, which we have retained for consistency. Projects that did not have organization names available were considered as a baseline for comparison in our models, as described below.

Country Name: Projects can also specify which country they operate in, however, the distribution is heavily skewed — more than half of the countries in the dataset have fewer than 15 projects associated with them. This distributional skew creates statistical concerns. Therefore, we instead labeled each project according to which continent that project is located within, relying on the reported country names to place the projects. The distribution of projects by continent is shown in Figure 4 — most projects are concentrated in Africa and Asia.

Projects without country names were considered the baseline for comparison in our models, as discussed below.

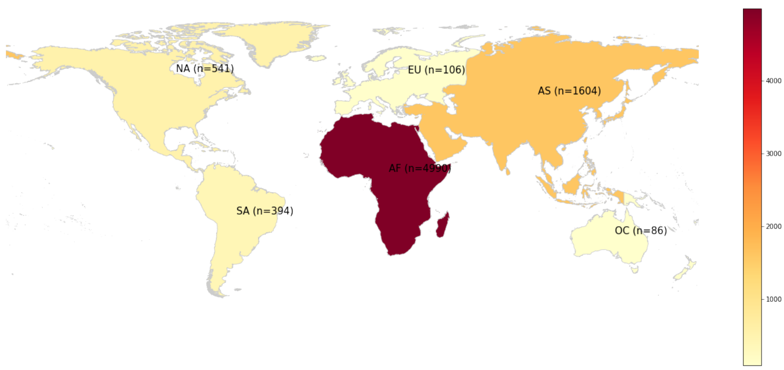

Fig. 4. Distribution of Projects by Continent

3.2 Analytical Approach

Above, we describe both the intuition behind our analysis and how we constructed our dataset to enable this analysis. Prior to moving into discussing results, we follow standard practice when presenting quasi-experimental methods, and discuss the formal construction of our models. Formally, to study our first research question, we conduct a difference-in-differences analysis (DID), defined as:

$$\widehat{\beta}^{DD}_{\text{project region}} \equiv \overbrace{\left(\bar{y}^{\text{Post}}_{\text{project region}} - \bar{y}^{\text{Pre}}_{\text{project region}}\right)}^{\Delta\,\bar{y}_{\text{project region}}} - \overbrace{\left(\bar{y}^{\text{Post}}_{\text{control region}} - \bar{y}^{\text{Pre}}_{\text{control region}}\right)}^{\Delta\,\bar{y}_{\text{control region}}}$$

We consider the seven days prior to project creation as the pre-treatment period (PRE), and the seven days following project creation as the post-treatment period (POST).

To address our second research question, we also extend our analysis by constructing a third-order Difference-in-Difference-in-Differences (DDD) model. The DDD model builds on the causal analysis of the DID model and incorporates HOT project-specific attributes as interaction terms. This enables us to examine the correlational interaction effects of these attributes in addition to the two-way causal effects. By incorporating these additional variables, we can extend our study to understand the factors that are correlated to contribution and community dynamics in peer production. Formally, our DDD model is defined as:

$$\begin{aligned} Y_{it} &\sim \alpha_i + \beta_t + \boxed{X_{it}} \Rightarrow \text{causal effect} \\ &+ Z_t + \alpha_i * Z_t + \beta_t * Z_t + \boxed{X_{it} * Z_t} \Rightarrow \text{interaction effects} \end{aligned}$$

Y_{it} is equal to each metric in turn: number of contributors, individual productivity, and Gini coefficient. α_i is the indicator of time i, and β_t represents whether the region in question is in the "treatment" group. The coefficient of X_{it} describes the effect of a Tasking Manager project being created in a given region, by comparison to its paired nearby region without a Tasking Manager project. If project creation creates a positive change in our metrics, then we would expect the coefficient of X_{it} should be significant and positive, but if it has a negative effect on these metrics, then the estimates for X_{it} coefficient should be less than zero.

To investigate the influence of HOT project attributes on the effectiveness of project creation, our DDD model extends the standard difference-in-differences (DID) approach by incorporating an additional control group, which allows us to consider statistical interactions between independent variables specific to each project and our temporal variable. By doing so, we account for potential effects that may not be captured by the DID method alone and effectively control for the causal effect of project creation. Here, Z_t represents our independent variables, which encompass a range of project attributes associated with each project. If the corresponding attributes have a positive influence on our dependent variable, then the $X_{it} * Z_t$ coefficient in this model should be positive and significant; if such project attributes have a negative effect on our dependent variable metrics, then the estimate of our $X_{it} * Z_i$ coefficients should be a negative number, and show statistical significance as well.

3.2.1 *Supporting the Parallel Trends Assumption.*

As noted above, a key analytical assumption in difference-in-differences analyses is the "parallel trends" [44, 54]. In short, the assumption of "parallel trends" poses a counterfactual — if the treatment had never occurred, both the treatment group and the control group should exhibit parallel trends over time. In our case, if a HOT project did not get created in a treatment region, "parallel trends" would predict no differences in our dependent variables, between the treatment and the control regions. Because this assumption is counterfactual, it cannot be tested, but it is common [25, 44] to provide evidence supporting its plausibility.

The first approach is the test of prior trends, which examines whether the treated and untreated groups show divergent trends leading up to the point of HOT project creation (in our case). One common way to assess this is by visually inspecting the average outcomes over time in the pre-treatment period, as depicted in Figure 8. The trends in the average volumes of contributors, average contribution rates, and average Gini coefficients appear to be parallel before the creation of projects, indicating similarities in dynamics between the treatment and control group before project creation.

The second approach to evaluating the plausibility of the parallel trends assumption involves conducting a statistical test to assess the differences in trends between the groups and quantify the magnitude of these differences [25]. The simplest form of this test involves using a regression model, as shown in the following equation:

$$Y_{it} = \alpha + \beta_1 * \text{Day} + \beta_2 * \text{Day} * \text{Treated}$$

This model relies on data exclusively from the pre-treatment period — the time before project creation. In this context, Day represents the number of days before project creation. Therefore, in the control group (where Treated is 0), a one-unit increase in time (Day) approaching the project creation is associated with a β_1 increase in the outcome. For the treatment group, the time trend increases by β_1 plus β_2 for every one unit increase in time. The parameter β_2 captures the additional effect on the outcome specifically for the treatment group. Specifically, the coefficient β_2 measures the significance of the difference in trends between the treatment and control groups. If β_2 is close to zero, it suggests that the treatment and control groups had similar trends before the project creation and are unlikely to differ significantly.

Based on our regression analysis, the coefficient β_2 in the regression for the number of contributors, contribution rates, and Gini coefficients was found to be close to zero. This indicates that the trends in the treatment and control groups were similar before HOT projects were created.

Overall, both techniques that are commonly used to evaluate a key validity assumption for a difference-in-differences method — the "parallel trends" assumption — provide substantive evidence that this assumption holds, in our case. In short, the "parallel trends" assumption does hold for our data, lending statistical confidence to our findings described below.

3.3 Methodological Limitations

As with many quasi-experimental approaches, our findings are constrained to a relatively short window of time around the creation of a Tasking Manager Project. Future work should consider a more observational, longitudinal study to evaluate the longer-term impacts of this kind of intervention. In addition, the strategy we used to identify a "control" group of regions is based on the proximity of population density and distance to project regions. While theory from the field of geography and evidence within the field of Computer-Supported Cooperative Work (CSCW) suggest that population and proximity are intuitive operationalizations of similarity, there may be other geographic factors that would provide further nuance to our findings. Future work might consider variables such as landuse and economic indices as well. Third, our difference-in-difference-in-differences analysis does not enable us to draw causal conclusions from the interaction effects we examine regarding project attributes. This limitation arises from the absence of a comparable "control" group with the same project attributes, as the "control" regions do not have Tasking Manager projects at all. Future work might consider alternative operationalizations of this natural experiment to incorporate statistical controls that allow for that comparison, but our data precludes such an analysis.

4 FINDINGS

Our research questions focus on understanding how the HOT Tasking Manager, as an instance of microtasking, affects contribution and community dynamics in OpenStreetMap more broadly. We organize the results section accordingly, with our findings for RQ1 in Section 4.1, and our findings pertaining to RQ2 from Section 4.2 to 4.4. Due to the large number of interaction terms in our model, we present the full model in Appendix 16, and highlight specific model terms and coefficients throughout this section.

4.1 Causal Effects of Micro-task Creation

As Table 3 shows, we see significant, causal increases in the number of contributors (4.19 contributors), and the individual contribution rate (225.87 contributions) for the "treated * time" term. These findings causally confirm prior results by Dittus et al. [8]. Indeed, in general, creating a HOT Tasking Manager project causes an influx of contributors and increases the rate of individual contributor productivity.

Importantly, creating a new project through the HOT Tasking Manager *also* causes the contributions to be more concentrated around relatively few contributors in the region. Our results show an increase in the Gini coefficient by 0.11. In other words, this means that creating a HOT Project through the HOT Tasking Manager leads to more contributors and higher rates of contribution, but it intensifies the inequity in who produces the content — a smaller group of contributors becomes responsible for a larger share of the content generated within the project regions. Overall, our RQ1 findings suggest that creating microtasking projects through the HOT Tasking Manager *creates a tension between contribution productivity and community equity in OpenStreetMap.* We return to this point in more detail below.

[t]0.4

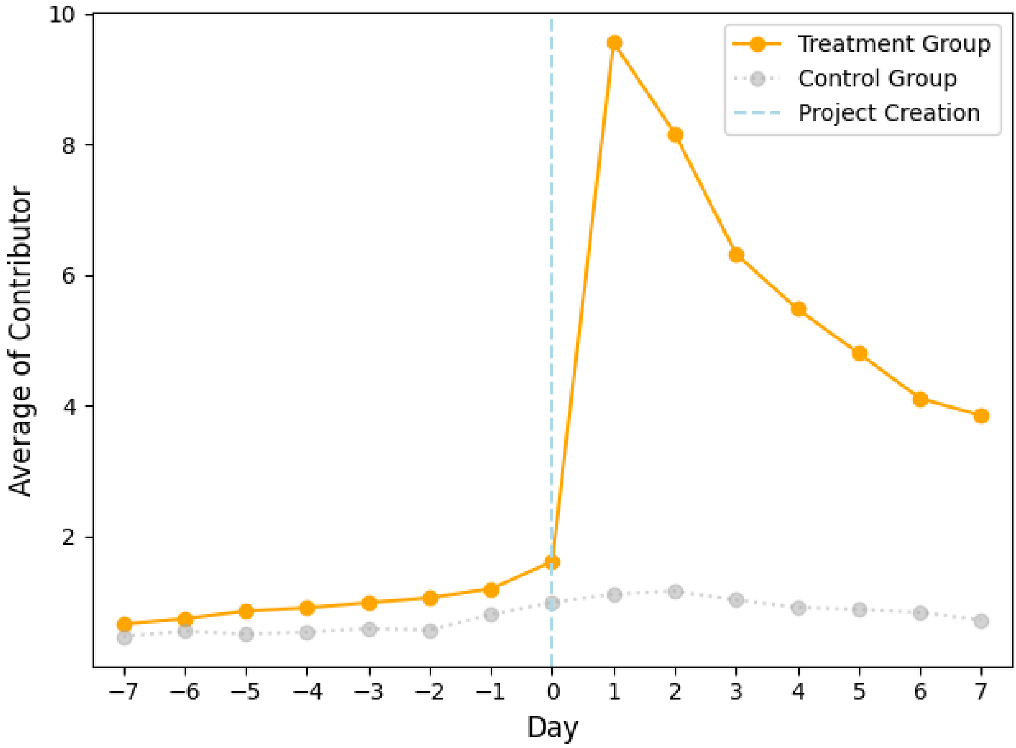

Fig. 5. Average Number of Contributors in Project Regions and Control Regions Over Time

[t]0.4

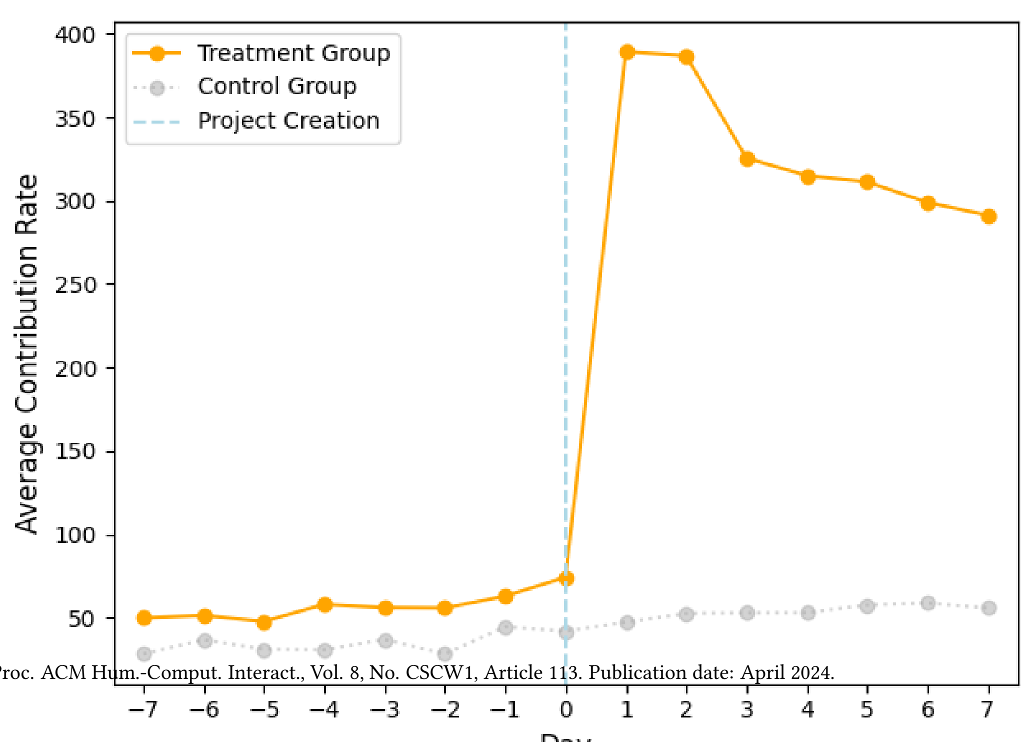

Table 3. Impact of Project Creation on Metrics. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Predictors	**Number of Contributors**	**Productivity**	**Gini Coefficient**
(Intercept)	0.08	35.08	0.02**
treated*time	4.19***	225.87***	0.11***
treated	0.34**	20.74***	0.01***
time	0.91**	-13.19*	0.02***

4.2 Interaction Effects of Project-Specific Attributes on Contributor Growth

Our findings in Section 4.1 present a clear story: creating a project through the HOT Tasking Manager increases both contributors and contributions in that region, but also increases the Gini coefficient, worsening known power-law dynamics in peer production communities. Of course, there are a wide plethora of different types of humanitarian goals in Humanitarian OpenStreetMap: some projects are reacting to natural disasters that already occurred, and others are trying to preempt future natural disasters, others are focused on relevant mapping needs for addressing COVID-19. Moreover, some projects are affiliated with humanitarian organizations that bring recruitment and visibility, and others are more grassroots in nature. The specifics of how these variations in HOT Tasking Manager projects may influence issues of contribution and community dynamics are not captured through our difference-in-differences analysis above, but are the focus of our second research question.

Turning our attention to Table 4, we see mixed results regarding the impact of different project attributes on the effectiveness of HOT project creation in number of engaged contributors. A comparison with the baseline priority level of “Low” reveals that projects labeled as “High” or “Urgent” tend to attract a greater number of contributors (4.79 and 2.13 contributors, respectively) than projects with “Low” priority. In particular, “Urgent” projects draw even more attention than “High” projects, which aligns with the notion that “Urgent” projects face greater time constraints. On the other hand, projects classified as “Medium” priority have significantly fewer (-1.33) contributors compared to “Low” priority projects, which is somewhat surprising. This trend can be visualized in Figure 9. It appears that “Medium” priority projects do not exhibit the same ability to attract contributors as higher priority projects. This discrepancy may be attributed to the fact that “Medium” priority projects lacks the same level of urgency as higher priority projects but is perceived as having higher stakes than lower priority projects.

Overall, project urgency seems to be a significant motivating factor for a project. While there are clearly opportunities for practitioners and organizers to leverage this strategically by creating a false sense of urgency, if that were to become widespread, it may not continue to be an effective strategy.

Further, according to our DDD estimation in Table 4, the projects corresponding to “Intermediate Mapper” level attract 0.87 more users than projects with the “Beginner Mapper” level as the baseline. However, this positive effect does not persist in projects with “Advanced Mapper” level specifications, as the observed difference is not statistically significant. This suggests that while creating a Tasking Manager project does increase the rate of contributors, as seen above, projects that do not require advanced skills may stand to benefit more. In other words, there seems to be a cap on the potential for more difficult projects to attract contributors.

Similarly, we find a negative correlation between variability of mapping types and contributor participation. Our results in Table 4 show that with each higher level of variability (more variable types of mapping), the number of contributors significantly decreases by 0.64 contributors on

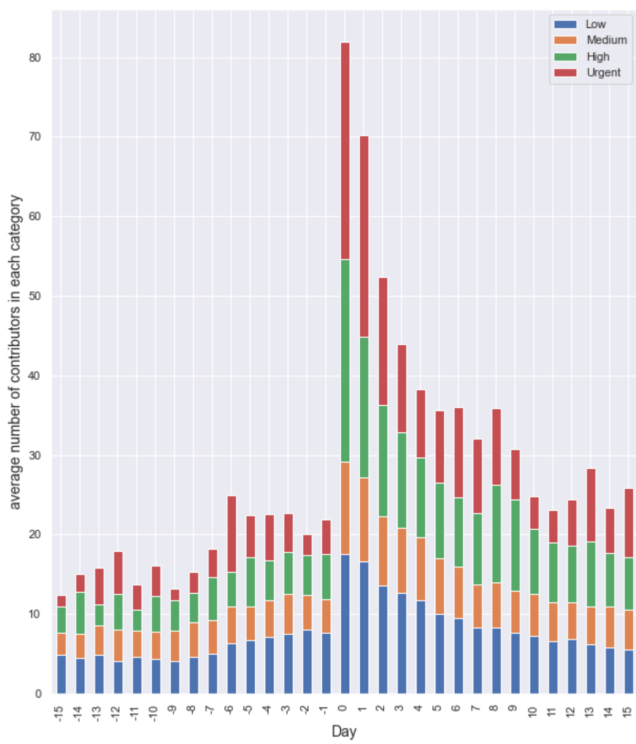

Fig. 9. Average Number of Contributors per Project in Each Level of Urgency

Table 4. Impacts of Attributes (Priority, Difficulty Level, Variability of Mapping Types) on Number of Contributors. *p<0.05, **p<0.01, ***p<0.001

Predictors	**Number of Contributors**
(treated*time)* Priority [Urgent]	4.79***
(treated*time)* Priority [High]	2.13***
(treated*time)* Priority [Medium]	-1.33***
(treated*time)* Difficulty [Advanced Mapper]	-0.36
(treated*time)* Difficulty [Intermediate Mapper]	0.87*
(treated*time)* Variability [Mapping Types]	-0.64***

average. This suggests that projects requesting more variable types of mapping seem to be less effective in drawing contributors, which might point to the mismatch between the expectations of contributors within the HOT Tasking Manager and the diverse mapping goals. While contributing to Humanitarian OpenStreetMap projects provides the flexibility of an open-ended mapping process,

Table 5. Impacts of Campaign Attributes on Number of Contributors. *p<0.05, **p<0.01, ***p<0.001

Predictors	**Number of Contributors**
(treated*time) * Campaign [Disaster Response]	12.03***
(treated*time) * Campaign [Tanzania Mini-Grids]	3.63***
(treated*time) * Campaign [Missing Maps]	1.48**
(treated*time) * Campaign [Road Network Improvement with Kaart]	1.55
(treated*time) * Campaign [#missingmaps]	1.25
(treated*time) * Campaign [Ebola2018]	0.70
(treated*time) * Campaign [Malaria Elimination]	-1.57***
(treated*time) * Campaign [COVID-19]	-3.74***
(treated*time) * Campaign [Local Impact Governance Activity]	-4.58***
(treated*time) * Campaign [OpenCities LAC]	-5.62***

where contributors can focus on specific aspects or engage in various mapping projects, the Tasking Manager interface's emphasis on specifying multiple mapping types may create the perception of more rigidly defined mapping tasks and a heavier workload. Our results suggest that contributors lean towards engaging in simpler projects with fewer mapping types, and broader projects with more variable types of mapping may deter participation. HOT Tasking Manager projects may find it fruitful to strike the right balance of difficulty ("Mapping Level") and variability ("Mapping Types"); mishandling these aspects may risk undermining contributors' willingness to help.

Unlike the project attributes we discussed above, which exist in every single project, there are additional optional attributes, such as campaign names, organization names, and country names. To investigate the interaction effects related to these optional attributes, we consider the projects without these attributes as the baseline.

We first looked at how campaign names are associated with differential effects of project creation. Even though these are the ten campaigns with the most affiliated projects, we do not see significant effects for all of them. As Table 5 shows, among the top 10 popular campaigns that have the most projects, only Disaster Response, Tanzania Mini-Grids, and Missing Maps have significantly more contributors separately than baseline projects that have no campaign names (12.03, 3.63, and 1.48 contributors, respectively). COVID19, Malaria Elimination, Local Impact Governance Activity and OpenCities LAC have a significant decrease in the volume of contributors compared to the reference baseline (3.74, 1.57, 4.58, and 5.62 contributors, respectively). These results suggest that the goals of the HOT Tasking Manager projects, insofar as they are aligned with a broader campaign, may influence contributor interest.

These results also show an interesting pattern: among the top 10 popular campaigns, post-disaster urgent mapping campaigns, like Disaster Response, succeed in attracting more contributors to meet their quick-response requirements. On the other hand, infrastructure-focused campaigns and disaster preparedness campaigns that are preemptive — like Local Impact Governance Activity and OpenCities LAC — either have fewer contributors involved than projects without campaign affiliations or are not statistically distinguishable from projects without campaign affiliations.

According to the coefficients in Table 6, the projects that are associated with nine of the top ten organizations have significantly fewer contributors than projects without any organizational affiliation. These results may indicate that organizational affiliation does not seem to help, but instead hinders, the growth of projects in HOT Tasking Manager. These results may indicate a disconnect between the goals of the Humanitarian OpenStreetMap community and the goals of

Table 6. Impacts of Organization Attributes on Number of Contributors. *p<0.05, **p<0.01, ***p<0.001

Predictors	Number of Contributors
(treated*time) * Organization [HOT]	0.39
(treated*time) * Organization [OpenMap Development Tanzania]	-2.70***
(treated*time) * Organization [CartONG]	-3.11***
(treated*time) * Organization [Other]	-3.12***
(treated*time) * Organization [Médecins Sans Frontières]	-2.97***
(treated*time) * Organization [INTEGRATION Consulting Group]	-4.60***
(treated*time) * Organization [OSM RDC]	-4.76***
(treated*time) * Organization [American Red Cross]	-5.09***
(treated*time) * Organization [HOT Uganda]	-6.28*
(treated*time) * Organization [Kaart]	-7.51***

Table 7. Impacts of Country Attributes on Number of Contributors. *p<0.05, **p<0.01, ***p<0.001

Predictors	Number of Contributors
(treated*time) * Country [North America]	2.18***
(treated*time) * Country [Asia]	0.93
(treated*time) * Country [South America]	0.96
(treated*time) * Country [Europe]	-0.58
(treated*time) * Country [Africa]	-0.90
(treated*time) * Country [Oceania]	-1.91

external organizational affiliates, and we see exploring this organization-community relationship as an important direction of future work.

The coefficients in Table 7 suggest that, in general, the geographic region on which a project focuses does not have a significant impact on the number of contributors involved in these projects. One exception is projects in North America, which shows a positive, significant effect on the number of contributors. This may be a reflection of a self-focus bias [19] of the people primarily contributing to Humanitarian OpenStreetMap, though further exploration is necessary to be confident.

4.3 Interaction Effects of Project Attributes on Individual Productivity

We now turn our analysis to focus on how these same project attributes influence individual contribution rates within projects. According to Table 8, there is an increase of approximately 90.03 contributions per person in the projects with “Medium” priority. Notably, projects with “Urgent” priority have no significant effect on individual contribution rates, which differs from the trend we saw when considering number of contributors, above. Even though “High” and “Urgent” projects seem to engage more contributors, we do not see a similar pattern in terms of individual contribution productivity. On the contrary, even though the “Medium” prioritized projects engage fewer contributors, they do seem to have generally higher individual contribution rates.

Moreover, comparing to the participants in “Beginner” level projects, the coefficients in Table 8 suggest that each volunteer makes 213.53 more contributions in the projects with “Intermediate Mapper” level than the baseline. The projects with “Intermediate Mapper” labels not only recruit more contributors, but also seem to have higher individual contribution productivity. It may be that these higher contribution rates occur because the project difficulty is more engaging, or that

Table 8. Impacts of Attributes (Priority, Difficulty Level, Variability of Mapping Types) on Productivity. *p<0.05, **p<0.01, ***p<0.001

Predictors	**Individual Productivity**
(treated*time)* Priority [Urgent]	68.38
(treated*time)* Priority [High]	-26.38
(treated*time)* Priority [Medium]	90.03***
(treated*time)* Difficulty [Advanced Mapper]	84.62
(treated*time)* Difficulty [Intermediate Mapper]	213.53***
(treated*time)* Variability [Mapping Types]	31.03***

people who identify as "Intermediate Mappers" are a different group of people than beginners, our analysis here is not able to disentangle these interpretations. We also find that this pattern does not hold for more advanced level projects.

Our results above suggested that increasing mapping type variability seems to decrease the average number of contributors, but we see the opposite trend for individual contribution productivity. As shown in Table 8, an increase in the mapping variability level of projects corresponds to an average growth of 31.03 contributions per person. This suggests that while projects with higher variability in mapping type have fewer contributors, those contributors exhibit higher productivity due to the diverse range of mapping tasks.

In Table 9, we again see variable effects of projects being associated with campaigns. The projects operated by #missingmaps and Malaria Elimination see increases in individual productivity (366.71 and 112.10 contributions per person, respectively). In some cases, such as Local Impact Governance Activity, COVID-19 and Missing Maps, the projects see significantly lower individual productivity (-420.83, -253.22 and -93.66 contributions per person, respectively).

In Table 10, we find that contributors to the projects running by INTEGRATION Consulting Group and Other are pretty productive. Compared to the projects without organizational affiliation information, each volunteer makes about 62.24 and 111.64 more contributions, respectively. To re-emphasize, in our data, "Other" is an organization name specified in the HOT data, not a grouping we applied, and it accounts for over 8% of projects with an organization name, which distinguishes it from the baseline projects without an organization name. Further, American Red Cross, Médecins Sans Frontières, OpenMap Development Tanzania, OSM RDC, and HOT Uganda have a significant decrease of -77.58, -97.48, -167.00, -296.28 and -587.51 contributions per person, respectively. While most of these top 10 organizations seem to draw higher numbers of contributors, the rates of individual contributions tend to decrease compared to the baseline.

Similarly, while projects located in North America saw higher numbers of contributors, the coefficients in Table 11 suggest that projects located in Africa are the only ones to show a statistically significant trend in terms of the rate of contributions — 97.52 more contributions per person on average.

4.4 Interaction Effects of Project Attributes on the Gini Coefficient

As described above, we use the Gini coefficient to understand how evenly distributed contributions are across all contributors. While projects prioritized as "High" and "Urgent" attract more contributors, we see in Table 12, that that the Gini coefficients in "High" and "Urgent" projects increase by 0.10 and 0.06 separately. In other words, projects with "High" and "Urgent" priority levels see their power-law dynamics worsen — more contributions are being made by fewer contributors. When considered alongside the rate of contributor increase in "High" and "Urgent" priority projects, these

Table 9. Impacts of Campaign Attributes on Productivity. *p<0.05, **p<0.01, ***p<0.001

Predictors	**Individual Productivity**
(treated*time) * Campaign [#missingmaps]	366.71**
(treated*time) * Campaign [Malaria Elimination]	112.10***
(treated*time) * Campaign [Tanzania Mini-Grids]	64.24
(treated*time) * Campaign [Ebola2018]	6.37
(treated*time) * Campaign [Road Network Improvement with Kaart]	-27.42
(treated*time) * Campaign [Disaster Response]	-47.56
(treated*time) * Campaign [OpenCities LAC]	-51.44
(treated*time) * Campaign [Missing Maps]	-93.66***
(treated*time) * Campaign [COVID-19]	-253.22***
(treated*time) * Campaign [Local Impact Governance Activity]	-420.83***

Table 10. Impacts of Organization Attributes on Productivity. *p<0.05, **p<0.01, ***p<0.001

Predictors	**Individual Productivity**
(treated*time) * Organization [Other]	111.64**
(treated*time) * Organization [INTEGRATION Consulting Group]	62.24**
(treated*time) * Organization [HOT]	39.36
(treated*time) * Organization [CartONG]	9.16
(treated*time) * Organization [Kaart]	-137.19
(treated*time) * Organization [American Red Cross]	-77.58*
(treated*time) * Organization [Médecins Sans Frontières]	-97.48***
(treated*time) * Organization [OpenMap Development Tanzania]	-167.00***
(treated*time) * Organization [OSM RDC]	-296.28***
(treated*time) * Organization [HOT Uganda]	-587.51***

Table 11. Impacts of Country Attributes on Productivity. *p<0.05, **p<0.01, ***p<0.001

Predictors	**Individual Productivity**
(treated*time) * Country [Africa]	97.52**
(treated*time) * Country [South America]	39.22
(treated*time) * Country [Oceania]	15.11
(treated*time) * Country [Asia]	7.01
(treated*time) * Country [Europe]	5.77
(treated*time) * Country [North America]	-35.74

increases in the Gini coefficient suggest that the concentration of contributions with a relatively few numbers of people may be more severe in “High” priority projects compared to “Urgent” priority projects.

Notably, while projects with “Intermediate” mapping level seem to draw higher numbers of contributors and increase individual contribution rates, we do not find a significant effect on the Gini coefficient for this mapping level. The increase in individual contribution rates seems to be evenly distributed across the population of contributors, even while those numbers of contributors grow

Table 12. Impacts of Attributes (Priority, Difficulty Level, Variability of Mapping Types) on Gini Coefficient. *p<0.05, **p<0.01, ***p<0.001

Predictors	Gini Coefficient
(treated*time)* Priority [Urgent]	0.06***
(treated*time)* Priority [High]	0.10***
(treated*time)* Priority [Medium]	0.01*
(treated*time)* Difficulty [Advanced Mapper]	-0.00
(treated*time)* Difficulty [Intermediate Mapper]	-0.00
(treated*time)* Variability [Mapping Types]	0.00

Table 13. Impacts of Campaign Attributes on Gini Coefficient. *p<0.05, **p<0.01, ***p<0.001

Predictors	Gini Coefficient
(treated*time) * Campaign [Disaster Response]	0.10***
(treated*time) * Campaign [Missing Maps]	0.02**
(treated*time) * Campaign [Ebola2018]	0.02
(treated*time) * Campaign [Road Network Improvement x Kaart]	-0.01
(treated*time) * Campaign [Tanzania Mini-Grids]	-0.02
(treated*time) * Campaign [OpenCities LAC]	-0.03*
(treated*time) * Campaign [Malaria Elimination]	-0.03***
(treated*time) * Campaign [#missingmaps]	-0.10**
(treated*time) * Campaign [COVID19]	-0.11***
(treated*time) * Campaign [Local Impact Governance Activity]	-0.12***

in intermediate level projects. We also do not see higher variability of mapping types significantly impacting the Gini coefficient, as shown in Table 12.

While the Disaster Response and Missing Maps campaigns seem to attract more volunteers, these campaigns also see an increase in their Gini coefficient, indicating a worsening of their power-law dynamics. In Table 13, Disaster Response and Missing Maps projects see an increase of 0.1 and 0.02 on Gini coefficient, respectively. Notably, projects associated with the COVID-19, Malaria Elimination, Local Impact Governance Activity, and OpenCities LAC campaigns showed statistically significant decreases in their Gini coefficients (-0.11, -0.03, -0.12, and -0.03, respectively). Earlier, we saw that the projects affiliated with these campaigns tended to draw fewer contributors, our findings of Gini coefficient suggest that the distribution of contributions is more uniformly distributed across contributors.

Our results earlier suggested that projects with an organizational affiliation seem to attract fewer overall contributors, our results in Table 14 also show that contributions seem to be more evenly distributed across all contributors. Additionally, according to Table 15, Gini coefficients for projects in Oceania, North America, and Africa see an increase of 0.05, 0.03, and 0.02 respectively. Thus, we might expect that power-law dynamics worsen in these areas of the world, by comparison to projects without region labels.

5 DISCUSSION

Taken holistically, our results here present a number of tensions and trade-offs in the role that microtasking tools, like the HOT Tasking Manager, play in peer production settings. In some cases,

Table 14. Impacts of Organization Attributes on Gini Coefficient. *p<0.05, **p<0.01, ***p<0.001

Predictors	**Gini Coefficient**
(treated*time) * Organization [HOT]	0.01
(treated*time) * Organization [CartONG]	-0.02
(treated*time) * Organization [HOT Uganda]	-0.04
(treated*time) * Organization [Other]	-0.03**
(treated*time) * Organization [Médecins Sans Frontières]	-0.05***
(treated*time) * Organization [OpenMap Development Tanzania]	-0.08***
(treated*time) * Organization [American Red Cross]	-0.08***
(treated*time) * Organization [OSM RDC]	-0.10***
(treated*time) * Organization [Kaart]	-0.11***
(treated*time) * Organization [INTEGRATION Consulting Group]	-0.14***

Table 15. Impacts of Country Attributes on Gini Coefficient. *p<0.05, **p<0.01, ***p<0.001

Predictors	**Gini Coefficient**
(treated*time) * Country [Oceania]	0.05**
(treated*time) * Country [Africa]	0.03**
(treated*time) * Country [North America]	0.02*
(treated*time) * Country [South America]	0.02
(treated*time) * Country [Europe]	0.02
(treated*time) * Country [Asia]	0.00

these tensions suggest critical directions for future research and design, and in others, there are practical trade-offs that humanitarian mapping project organizers may want to consider. We discuss each of these in more detail below.

5.1 Gini Coefficient and Inequity in Peer Production

First, while our causal results in Section 4.1 do confirm and replicate findings by others [8], we also find that the HOT Tasking Manager makes well-known power-law dynamics (e.g. [19]) *worse*. That is, the Tasking Manager facilitates a concentration of mapping effort, with fewer people making more contributions. A fundamental goal of Humanitarian OpenStreetMap, and by extension, the Tasking Manager, is to address humanitarian needs by leveraging local knowledge, a value deeply embedded in the OpenStreetMap ethos. Our results suggest that while the Tasking Manager does help fill important spatial information gaps in OpenStreetMap, it also amplifies the disparities in contribution patterns that naturally occur in peer production settings [16, 19].

The consequences of these power-law dynamics in peer production contexts are a subject of ongoing debate within the research community [16]. One such consequence is what power-law dynamics means for data production, and prior work suggests mixed outcomes. For instance, Haklay [17] have argued that there may be risks to data quality when contributor pools become too homogeneous. Thebault-Spieker et al. [53] further showed that such power-law dynamics may contribute, overall, to the creation of geographic disparities in coverage. Conversely, Warncke-Wang et al. [58] suggest that frequent and active contributors, who have gained proficiency through prior experience, are more likely to contribute larger amounts of, and perhaps higher quality, data.

However, centralizing contribution efforts in the hands of a relatively small group of contributors may also have implications for community development. Top contributors may establish community norms that enforce their own standards or viewpoints, creating barriers to entry for newcomers [17]. Moreover, if taken to the extreme, the centralization of data production and maintenance could pose challenges if the leading contributors disengage from participation. Recent research [28] has explored the economic value of labor produced in online communities like OpenStreetMap, which could ensure that contributors receive economic compensation for their work. However, if this approach were to be implemented, the trends observed above would shift the Gini coefficient from describing the concentration of contribution amounts to describing the concentration of economic value in peer production systems. In other words, in a scenario where contributors are compensated for their contributions, systems like the Tasking Manager that we study here could potentially facilitate the "rich get richer" dynamics in peer production systems, further exacerbating geographic biases in these systems [53].

Our findings underscore the presence of power-law dynamics within Humanitarian OpenStreetMap and the exacerbating role of microtasking tools like the Tasking Manager on these dynamics, alongside a *fundamental tension* between the benefits of efficiency and productivity in data production, and the potential downsides for peer production communities themselves. We view further exploration of this tension as a critical research trajectory moving forward. We encourage researchers to continue developing deeper understandings of how power-law dynamics shape the sustainability of volunteer communities in these peer production settings, with a particular focus on issues of contributor participation, interest, and engagement, as well as overall community issues like growth, diversity of perspectives, and representation. Microtasking tools, and the benefits of power-law processes can be effective. However, comprehending how and when to effectively design and leverage microtasking techniques without potentially undermining the fundamentals of a peer production community as critical next steps.

5.2 Balancing Success Metrics: Examining Tensions in Peer Production

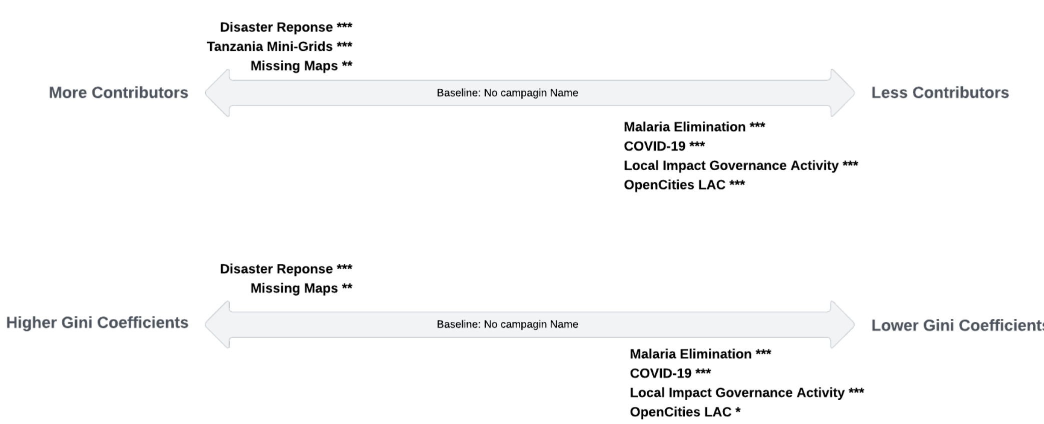

Fig. 10. Impact of Campaigns on Number of Contributions (Upper) and Gini Coefficients (Lower).

From our results, Figure 10 illustrates the distribution of campaign affiliations in comparison to the baseline, focusing on the number of contributors and the Gini coefficient. As described above, campaigns such as Disaster Response and Missing Maps exhibit a higher number of contributors compared to projects without campaign affiliations. However, these campaigns also demonstrate an increase in their Gini coefficients, indicating a greater concentration of contributions among a smaller group of individuals. In contrast, campaigns such as Local Impact Governance Activity, OpenCities LAC, and COVID-19 have a lower number of contributors than the baseline but show lower Gini coefficients, suggesting a more equitable distribution of contributions. Notably, projects labeled as “High” or “Urgent” attract a larger number of participants but exhibit higher Gini coefficients, indicating a more pronounced concentration of contribution rates within a select few individuals.

We see opportunities to perhaps ameliorate the unintended consequences of microtasking in urgent disaster-response style settings, namely – data validation and maintenance work. In projects associated with time-sensitive campaigns, it may be the right decision to prioritize high rates of contributors and coverage in a time-sensitive way. After all, the goal is to support the spatial data needs of humanitarian responders on the ground. However, because the concentration of contributions from a small group of individuals increases the risk of errors or biases in the data, it is likely fruitful to explore tools and techniques to help ensure robust validation of the data creation as well.

Moreover, these findings highlight a key nuance in our discussion of power-law processes: exclusively focusing on mobilizing contributors may inadvertently lead to a less balanced distribution of work. Focusing on a single metric (rate of contributions, number of contributors, or degree of contribution concentration) limits our understanding of these community dynamics. Prior studies have highlighted that the Missing Maps campaign exhibits lower retention rates in both the short-term and long-term compared to campaigns like Typhoon Yolanda and Ebola Response [8, 30]. These findings, along with the findings of our own research, emphasize the importance of evaluating projects from multiple dimensions.

5.3 Promoting Equitable Contribution Distribution: The Impact of Organized Mapping Activities and Collaborative Organizations

In a related vein, Herfort et al. [21] and others have argued that an inclusive map should have the capability to generate, maintain, and improve geographic data that authentically represents local perspectives in the long term. In other words, developing a sustainable community is an important part of inclusivity. Indeed, the Humanitarian OpenStreetMap community started from this perspective — some areas of the world are “left out” of the map, and this harms then when disaster strikes.

Our findings suggest that organized mapping activities, like some that currently exist in Humanitarian OpenStreetMap today, may serve as a meaningful intervention to distribute the work more evenly. Contributors associated with the top 10 organizations or campaigns tend to contribute at more equitable rates across the entire contributor pool, as evidenced by lower Gini coefficients. Notably, the impact and generalizability of these findings are more pronounced and widespread across the top 10 organizations compared to the campaigns. This suggests that the values and mission inherent to these organizations and campaigns may foster a strong sense of affinity among contributors towards the task and project, leading to increased levels of engagement and contributions.

Campaigns within peer production settings are often initiated and promoted through various channels, including news outlets and social media platforms. These campaigns aim to raise awareness and attract a wider audience to contribute to the project [4, 29, 45, 46]. On the other hand, organizations involved in peer production tend to focus on local operations and collaborate with external resources to expand their contributor base [4, 31]. They actively seek partnerships and leverage external networks to recruit and engage more individuals in the project. Additionally, these organizations prioritize regular maintenance activities to ensure the cohesiveness and effectiveness of their initiatives over time [8, 40, 42].

Based on our results, both the use of campaigns and the involvement of community organizations, seem to help "flatten" the power-law concentration of contributions that pervade peer production systems. Campaigns leverage news outlets and social media platforms to reach a larger audience and attract diverse contributors, thereby promoting a more equitable distribution of contributions. On the other hand, organizations adopt a localized approach, collaborating with external resources and conducting regular maintenance activities to ensure cohesiveness and engagement among contributors. These strategies collectively contribute to reducing the concentration of contributions among a few individuals and fostering a more inclusive and participatory peer production environment.

Prior work has highlighted the value of community maintenance activities, such as effectively communicating the mission and values, in facilitating strong identification among new participants, leading to improved engagement and retention [7]. Moreover, social support mechanisms, such as mentorship, have been shown to be effective in enhancing newcomer inclusion and engagement within online communities like Wikipedia [33]. Indeed, it may be that these social support mechanisms may help ease or mitigate the potential risks to the community from microtasking described above. In addition, external organizations leading organized mapping activities and conducting recruitment campaigns could help expand the pool of contributors and promote a more diverse set of individuals participating in peer production [3]. We see opportunities to develop strategies and tools that foster sustained, distributed, and equitable rates of contributions, through community organizations and partnerships. For instance, rural representation (e.g. [53]) may not be a *humanitarian* concern, but organizations focused on rurality may be able to leverage similar microtasking techniques coupled with rural community outreach (e.g. through map-a-thons or equivalent) to help include local needs and knowledge in OpenStreetMap in a sustainable, equitable way.

5.4 Variability and Difficulty of Mapping as Barriers to Entry

In Section 4.2, we show how project attributes seem to influence the number of contributors that participate. We found that project difficulty and variability in mapping types were two distinct project attributes that seemed to follow similar trends in our data. Specifically, compared to the baseline "Beginner Mapper" projects, the "Intermediate Mapper" projects tended to see an increase in both the number of contributors and individual productivity. In addition, increases in both number of contributors and individual contribution rates would not suggest that these mapping levels increase the concentration of mapping effort, and indeed our Gini coefficient results bear that out, as indicated by the insignificance and value of 0 for the Gini coefficient. However, for the "Advanced Mapper" level, we do not see this same trend holding continuously.

As mapping gets more difficult and more variable, there seems to be a threshold beyond which project creation may not actually help. In other words, regardless of contributors prior mapping experience, projects with high difficulty and mapping variability may discourage contributors from participating. Contributors with sufficient motivation might still take on these projects, but there is a risk that contributors who are less confident may get involved with easier projects, or even leave entirely [52]. A similar phenomenon also exists among Mechanical Turk crowd workers, Khanna et al. [26] found that project variability of mapping types can signal a need for more sophisticated understanding, which may create participation barriers. Psychological theory would suggest that people may be more motivated to participate in collective activities if their unique expertise or abilities are recognized, their personal value of the group's outcome is emphasized, and the cost of participation is decreased [1]. In other words, our findings indicate that the design of project difficulty and mapping types filters in the interface may hinder volunteer participation, irrespective of their prior mapping experience. These filters could potentially act as barriers to entry, deterring volunteers from engaging in projects that are perceived as more challenging or with more variable mapping types. While these projects may have noble purposes and visions associated with humanitarian mapping, simply having meaningful goals may not be sufficient to overcome the barriers created by the high mapping difficulty and variability.

Therefore, our results suggest that the design of mapping types and difficulty filter may hold for less difficult and less variable mapping types projects, but as volunteers move forward to more mature practices, motivational cues beyond the project itself are amplified, like projects' ideology and needs [23]. Therefore, project organizers and platform administrators might consider strategies that aim to reduce barriers and enhance motivation among volunteers. This could involve implementing interface design strategies that provide clear tutorials and intuitive workflows to ensure pre-education before entering the mapping task to help contributors feel confident in their knowledge and skills for harder mapping tasks. Moreover, the concept of "fun" or enjoyment has been consistently identified as a significant motivation that positively influences engagement in various online settings [12, 36, 57]. Hence, incorporating gamification elements into the design of humanitarian mapping projects may encourage contributors to take on more variable mapping types and challenging mapping projects. While research on motivating new user participation in crowdsourcing and citizen science has been ongoing for some time [1, 23], further exploration of how interface design, such as the Tasking Manager and other microtasking systems, influences new user engagement over time is an important area of future work.

6 CONCLUSION

In this study, we conducted a causal investigation within the context of Humanitarian OpenStreetMap to examine the impact of microtasking and project attributes on volunteer contributions and the development of personal capacity. Our findings reveal tensions between contributor productivity enabled and facilitated through microtasking tools like the HOT Tasking Manager, and worsening the power-law dynamics that are common in peer production systems. We further explore how project attributes may strengthen or worsen these dynamics, adding nuance to our causal study. We conclude by identifying a number of tensions and trade-offs in the use of microtasking tools in peer production settings and highlighting community and tool design opportunities to support sustainable community growth while also reaping the speed and efficiency benefits of microtasking tools.

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Table 16. Triple Difference-in-Differences model. *p<0.05, **p<0.01, ***p<0.001

Predictors	**Number of Contributors**	**Productivity**	**Gini Coefficient**
(Intercept)	0.08	35.08	0.02**
treated*time	4.19***	225.87***	0.11***
treated	0.34**	20.74***	0.01***
time	0.91**	-13.19*	0.02***
Priority[Medium]	-0.11	-1.18	0.00
Priority[High]	0.03	-11.25	0.00
Priority[Urgent]	0.32	-52.28	-0.01***
Difficulty[Intermediate Mapper]	1.07	42.19***	0.02**
Difficulty[Advanced Mapper]	0.75*	21.64	0.01
Variability[Mapping Types]	-0.12	-4.27	-0.00**
Campaign[Malaria Elimination]	0.16	-31.00*	0.00
Campaign[Ebola2018]	0.86	-29.12	0.04***
Campaign[Tanzania Mini-Grids]	0.18	-2.05	0.02
Campaign[Disaster Response]	2.83***	-10.80	0.04***
Campaign[COVID19]	-0.00	4.53	0.01
Campaign[Road Network Improvement with Kaart]	0.10	3.33	-0.02
Campaign[Missing Maps]	0.60	-19.85	0.00
Campaign[Local Impact Governance Activity]	-0.69	-57.26	-0.01
Campaign[OpenCities LAC]	-0.56	-6.75	0.00
Campaign[#missingmaps]	0.06	3.35	0.01
Campaign[Other Campaign Types]	0.40	-15.27	-0.02*
Organization[American Red Cross]	-0.84	-4.07	-0.02*
Organization[CartONG]	-0.89	-20.73	-0.02*
Organization[HOT]	-0.12	0.34	-0.02**
Organization[HOT Uganda]	-0.64	-2.57	-0.03
Organization[INTEGRATION Consulting Group]	-0.51	-29.28*	-0.03***
Organization[Kaart]	-0.65	-20.35	-0.02
Organization[Médecins Sans Frontières]	-1.01*	-7.85	-0.03***
Organization[OpenMap Development Tanzania]	-0.35	8.78	-0.01
Organization[OSM RDC]	-0.70	91.90***	-0.01
Organization[Other]	-0.91	-8.66	-0.03**
Organization[Other Organizations Types]	-0.62	1.34	-0.02***
Country[Africa]	0.40	28.62	0.02*
Country[Asia]	0.77	34.97	0.03***
Country[Europe]	0.31	2.04	0.03
Country[North America]	0.87	20.68	-0.02*
Country[Oceania]	-0.10	8.40	0.02
Country[South America]	7.02***	20.69	0.02

Table 17. Triple Difference-in-Differences model. *p<0.05, **p<0.01, ***p<0.001

Predictors	Number of Contributors	Productivity	Gini Coefficient
treated*Priority[Medium]	-0.55**	-0.21	-0.00
treated*Priority[High]	-0.51	19.33	0.01**
treated*Priority[Urgent]	0.82	-27.34	0.06***
treated*Difficulty[Intermediate Mapper]	0.42	6.29	-0.01*
treated*Difficulty[Advanced Mapper]	0.16	-44.43	-0.02*
treated*Variability[Mapping Types]	-0.06	-5.60	-0.00
treated*Campaign[Malaria Elimination]	-1.99***	-40.95*	-0.05***
treated*Campaign[Ebola2018]	1.25	12.02	0.02*
treated*Campaign[Tanzania Mini-Grids]	0.11	-29.55	-0.02*
treated*Campaign[Disaster Response]	-1.91***	13.31	0.00
treated*Campaign[COVID19]	0.13	-46.02	0.03***
treated*Campaign[Road Network Improvement with Kaart]	-0.57	-154.60*	-0.07***
treated*Campaign[Missing Maps]	0.16	-17.50	0.00
treated*Campaign[Local Impact Governance Activity]	0.39	0.97	-0.02
treated*Campaign[OpenCities LAC]	0.52	-35.21	-0.02
treated*Campaign[#missingmaps]	-0.65	-490.27***	-0.04
treated*Campaign[Other Campaigns Types]	-0.23	-7.15	-0.00
treated*Organization[American Red Cross]	-2.05***	-7.29	-0.04***
treated*Organization[CartONG]	-1.32*	0.98	-0.01
treated*Organization[HOT]	-1.45***	-25.11	-0.01*
treated*Organization[HOT Uganda]	-0.67	437.28***	0.01
treated*Organization[INTEGRATION Consulting Group]	-1.22***	-16.84	-0.03***
treated*Organization[Kaart]	-1.36	96.13	0.04*
treated*Organization[Médecins Sans Frontières]	-0.79	16.14	-0.02***
treated*Organization[OpenMap Development Tanzania]	-0.82	-19.37	-0.03***
treated*Organization[OSM RDC]	-1.19*	-91.57**	-0.05***
treated*Organization[Other]	-1.15*	-2.97**	-0.01
treated*Organization[Other Organization Types]	-1.07***	4.45	-0.02***

Table 18. Triple Difference-in-Differences model. *p<0.05, **p<0.01, ***p<0.001

Predictors	**Number of Contributors**	**Productivity**	**Gini Coefficient**
treated*Country[Africa]	0.06	-4.66	-0.01
treated*Country[Asia]	1.29*	-7.92	0.00
treated*Country[Europe]	0.93	37.77	0.02
treated*Country[North America]	-0.64	-1.09	-0.02*
treated*Country[Oceania]	-0.11	-23.95	-0.03**
treated*Country[South America]	0.49	-22.59	-0.00
time*Priority[High]	0.63	19.33	0.01**
time*Priority[Medium]	-0.16	-0.21	-0.00
time*Priority[Urgent]	0.56	-27.34	0.06***
time*Difficulty[Intermediate Mapper]	-0.38	6.29	-0.01*
time*Difficulty[Advanced Mapper]	-0.93	-44.43	-0.02*
time*Variability[Mapping Types]	-0.00	-1.91	-0.00
time*Campaign [Malaria Elimination]	1.43***	16.77	0.04***
time*Campaign[Ebola2018]	0.63	-36.45	0.03*
time*Campaign[Tanzania Mini-Grids]	1.14	-3.72	0.02**
time*Campaign[Disaster Response]	-0.63	3.43	-0.00
time*Campaign [COVID19]	0.60	38.75	0.03***
time*Campaign [Road Network Improvement with Kaart]	-0.33	8.21	-0.00
time*Campaign [Missing Maps]	-0.41	2.84	0.00
time*Campaign [Local Impact Governance Activity]	0.59	-15.34	0.01
time*Campaign [OpenCities LAC]	1.47*	-7.91	0.04***
time*Campaign [#missingmaps]	0.53	-14.13	0.03
time*Campaign [Other Campaign Types]	0.10	22.22	0.00
time*Organization[American Red Cross]	0.26***	-15.96	-0.02**
time*Organization[CartONG]	-0.35	-16.26	-0.03***
time*Organization[HOT]	-0.56	1.66	-0.02***
time*Organization[HOT Uganda]	-0.94	91.18	-0.04***
time*Organization[INTEGRATION Consulting Group]	-0.51	-13.37	-0.02***
time*Organization[INTEGRATION Consulting Group]	-0.51	-13.37	-0.02***
time*Organization[Kaart]	-0.40	-27.20	-0.03*
time*Organization[Médecins Sans Frontières]	-0.34	-39.20	-0.02**
time*Organization[OpenMap Development Tanzania]	-0.30	-21.83	-0.01

Table 19. Triple Difference-in-Differences model. *p<0.05, **p<0.01, ***p<0.001

Predictors	Number of Contributors	Productivity	Gini Coefficient
time*Organization[OSM RDC]	-0.33	91.28**	-0.03***
time*Organization[Other]	-0.37	-28.24	-0.02**
time*Organization[Other Organizations]	-0.34	-4.88	-0.01**
time*Country[Africa]	-0.25	-4.43	-0.01
time*Country[Asia]	-0.20*	-4.04	-0.01
time*Country[Europe]	-0.10	1.45	-0.00
time*Country[North America]	-0.08	-18.65	-0.01
time*Country[Oceania]	-0.13	-16.24	-0.02**
time*Country[South America]	0.14	-21.00	0.00
(treated*time)*Priority[High]	2.13***	-26.38	0.10***
(treated*time)*Priority[Medium]	-1.33***	90.03***	0.01*
(treated*time)*Priority[Urgent]	4.79***	68.38	0.06***
(treated*time)*Difficulty[Advanced Mapper]	-0.36	84.62	-0.00
(treated*time)*Difficulty[Intermediate Mapper]	0.87*	213.53***	-0.00
(treated*time)*Variability[Mapping Types]	-0.64***	31.03***	0.00
(treated*time)*Campaign[Malaria Elimination]	-1.57***	112.10***	-0.03***
(treated*time)*Campaign[Ebola2018]	0.07	6.37	0.02
(treated*time)*Campaign[Tanzania Mini-Grids]	3.63***	64.24	-0.02
(treated*time)*Campaign[Disaster Response]	12.03***	-47.56	0.10***
(treated*time)*Campaign[COVID19]	-3.74***	-253.22***	-0.11***
(treated*time)*Campaign[Road Network Improvement x Kaart]	1.55	-27.42	-0.01
(treated*time)*Campaign[Missing Maps]	1.48**	-93.66***	0.02**
(treated*time)*Campaign[Local Impact Governance Activity]	-4.58**	-420.83***	-0.12***
(treated*time)*Campaign[OpenCities LAC]	-5.62***	-51.44	-0.03*
(treated*time)*Campaign[#missingmaps]	1.25	366.71**	-0.10**
(treated*time)*Campaign[Other Campaign Types]	1.12**	-73.87***	0.01

Table 20. Triple Difference-in-Differences model. *p<0.05, **p<0.01, ***p<0.001

Predictors	**Number of Contributors**	**Productivity**	**Gini Coefficient**
(treated*time)*Organization[American Red Cross]	-5.09***	-77.58*	-0.08***
(treated*time)*Organization[CartONG]	-3.11***	9.16	-0.02
(treated*time)*Organization[HOT]	0.39	39.36	0.01
(treated*time)*Organization[HOT Uganda]	-6.28*	-587.51***	-0.04
(treated*time)*Organization [INTEGRATION Consulting Group]	-4.60***	62.24**	-0.14***
(treated*time)*Organization[Kaart]	-7.51***	-137.19	-0.11***
(treated*time)*Organization[Médecins Sans Frontières]	-2.97***	-97.48**	-0.05***
(treated*time)*Organization[OpenMap Development Tanzania]	-2.70***	-167.00***	-0.08***
(treated*time)*Organization[OSM RDC]	-4.76***	-296.28***	-0.10***
(treated*time)*Organization[Other]	-3.12***	111.64**	-0.03**
(treated*time)*Organization[Other Organization Types]	-1.92***	37.94	-0.00
(treated*time)*Country[Africa]	-0.90	97.52**	0.03**
(treated*time)*Country[Asia]	0.93	7.01	0.00
(treated*time)*Country[Europe]	-0.58	5.77	0.02
(treated*time)*Country[North America]	2.18**	-35.74	0.02*
(treated*time)*Country[Oceania]	-1.91	15.11	0.05**
(treated*time)*Country[South America]	0.96	39.22	0.02