How Competition Affects Contributions to Open Source Platforms: Evidence from OpenStreetMap and Google Maps

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Abstract

Knowledge platforms differ in how they source their knowledge; they can be categorized as *traditional* (e.g., Encyclopedia Britannica, Guide Michelin) or *crowdsourced* (e.g., Wikipedia, Yelp). While research has compared and contrasted the two, we examine how they compete with one another; specifically, how the presence of traditional competitors affects contributions to crowdsourced knowledge platforms. We suggest a *divergent* effect across contributors, depending on whether they joined before the entry of a competitor or are newly recruited to the platform. Contributions from pre-entry contributors increase due to increased attachment to the platform, but contributions from newly recruited contributors decrease; such contributors are less likely to join as competition decreases their awareness of the platform. In order to test our theory, we examine how the phased entry of Google Maps in different countries over time affects contributions to OpenStreetMap, a crowdsourced mapping platform. We find the hypothesized divergent effect and explore the mechanisms of increased attachment among *pre-entry contributors* and decreased awareness among *newly recruited contributors*. Our study's main contribution is to research on crowdsourcing; we explore the intersection of competitive strategy and crowdsourcing and inform research on willingness to contribute. We also shed light on platform competition and on the effect of competition on organizations more broadly.

Knowledge platforms wield enormous power in markets. For example, knowledge goods like the *Guide Michelin* and the *Encyclopedia Britannica* have long shaped which restaurants or individuals receive attention and how they are perceived. Traditionally, such organizations have sourced knowledge from hired professionals. But over the last 30 years, in contrast to such *traditionally sourced* knowledge goods, the internet and the forces of digitization have led to a new *crowdsourced* mode of knowledge production, with volunteers self-selecting to contribute knowledge to online platforms to be accumulated and organized. Crowdsourced platforms such as Wikipedia, Reddit, Yelp, and StackOverflow have amassed enormous bodies of knowledge and wield considerable influence.

Research has compared and contrasted these two modes of knowledge sourcing, finding that crowdsourcing can produce knowledge similar in quality to that of traditional approaches and can provide better or broader coverage (e.g., Giles 2005, Almirall and Casadesus-Masanell 2010, Greenstein and Zhu 2012, Mollick and Nanda 2016, Reimers and Waldfogel 2021). Such comparisons, while useful, overlook the fact that these two modes of knowledge sourcing often *compete*. For example, Yelp (crowdsourced) and the *Guide Michelin* (traditional) compete in providing restaurant reviews, Wikipedia (crowdsourced) and the *Encyclopedia Britannica* (traditional) compete in providing encyclopedia content, and Linux (crowdsourced) and Windows (traditional) compete in providing operating system software and applications. This raises the question, not just of how they compare, but of how they affect one another.

We focus on the effect of competition on the central input for crowdsourced platforms: *contributions from volunteers*. Beyond the practical importance of this question, our study is theoretically interesting as it examines how platform competition interacts with the complex and heterogeneous motivations of contributors (Lakhani and Wolf 2005, Kraut and Resnick 2012, Miric et al. 2019). Our research question is therefore: *How does competition affect contributors' tendency to contribute to crowdsourced platforms*?

We hypothesize that the effect of competition varies across contributors; specifically, it depends on whether contributors started contributing before or after the competitive entry. We suggest that competition *increases* the rate of contributions from *pre-entry contributors* because they are deeply attached to the platform and this attachment increases in the presence of a competitor. In contrast, competition *decreases* total contributions from the set of *newly recruited contributors*—first time contributors to the platform in each time period—because competition hinders recruitment. Thus, our theory suggests that there will be a *divergent effect* of competition on contributions from pre-entry and newly recruited contributors.

To test our predictions, we analyze how contributors to the crowdsourced mapping platform OpenStreetMap responded to the competitive entry of Google Maps. While OpenStreetMap launched globally in 2004, Google Maps started in only a handful of countries and expanded on a country-by-country basis after its inception in 2005. While not explicitly random, this phased roll-out has the potential to help us understand how competition affects contributions to OpenStreetMap across volunteers from different countries (cf. Seamans and Zhu 2014, 2017). To investigate our research question, we pair this variation in Google Maps coverage with a novel quantitative dataset capturing millions of contributions made between 2004 and 2015 by pre-entry and newly recruited contributors of the OpenStreetMap communities in 87 countries. We do indeed find a divergent effect: while pre-entry contributors increase their contributions, newly recruited contributors collectively decrease their contribution. We explore mechanisms driving these effects by looking at the roles of awareness and attachment.

Our primary contribution is to research on crowdsourcing, as we explore the intersection of *competitive strategy and crowdsourcing*. While crowdsourcing has been shown to be an often superior sourcing strategy (Mollick and Nanda 2016), research has yet to explore how performant it is when the organization faces competition. We help answer this macro-level question by addressing a so-far neglected micro-level question: how does platform-level competition affect volunteers' willingness to contribute? This allows us to inform research on contributors' tendency to contribute (Lakhani and Wolf 2005, Kraut and Resnick 2012, Miric et al. 2019), as we illustrate how macro-level factors—specifically, competition—interact with micro-level factors that underlie contributors' tendency to contribute. By studying how traditional and crowdsourced platforms compete with and affect one another, we also contribute to research on *platform* *competition* (Eisenmann et al. 2011, Rietveld et al. 2019), which has primarily focused on competition between platforms of the same type (for notable exceptions, see Casadesus-Masanell and Ghemawat (2006) and Casadesus-Masanell and Zhu (2010)). The divergent effect at the heart of our paper also speaks to research on the effect of competition on organizations more broadly: competition may motivate current employees but hinder recruitment.

THEORETICAL BACKGROUND

2.1 Crowdsourced and Traditional Knowledge Goods

Research has compared crowdsourced and traditional knowledge goods with respect to the knowledge they provide (see Appendix Table C1 for examples of such competition). While they are of similar quality in terms of *how* entities are covered,[1] there remain vast differences with respect to *what* entities are covered. Specifically, crowdsourced platforms tend to be more inclusive and cover a wider range of entities. For example, Wikipedia covers many more entities than *Britannica* (Giles 2005) and crowdsourced forms of evaluation fund projects that are more creative than those by funded professional evaluators (Mollick and Nanda 2016).[2] Such comparisons, though useful, overlook the possibility that these two modes of knowledge sourcing may not only coexist but also compete.

We are not the first to point out the need to study competition between crowdsourced and traditional knowledge goods. Lerner and Tirole (2005: 107) state: "While the relative merits of open source and proprietary software are discussed in a number of contributions, direct competition between the two

[1] Crowdsourced knowledge goods tend to be of high quality when compared to knowledge produced by professionals (Mollick and Nanda 2016). For example, Wikipedia compares quite favorably to *Britannica* (Giles 2005), and crowdsourced Yelp and traditionally sourced Michelin arrive at similar restaurant evaluations (Silver 2014). But there are also differences. Greenstein and Zhu (2018) find that political articles in Wikipedia tend to be more biased and more slanted toward Democratic views than those in *Britannica*.

[2] This could be for various reasons. For example, in crowdsourced production, the costs of coverage are shouldered by volunteers. Further, traditional knowledge goods were often provided in capacity-constrained formats (e.g., a book or a CD-ROM), whereas crowdsourced knowledge is distributed on the internet, where there are no such capacity constraints. Differences in coverage are also driven by differences in incentives, as traditional knowledge goods are often provided by commercial entities. Nagaraj and Stern (2020), comparing the maps produced by traditional (commercial) Google Maps and crowdsourced (nonprofit) OpenStreetMap, find that refugee settlements tend to be well mapped on OpenStreetMap but often ignored on Google Maps.

paradigms has received little attention." Following this call, the competition between crowdsourced and traditional-mode knowledge goods has been studied using formal models (Baake and Wichman 2003, Athey and Ellison 2014), in which a crucial contingency is whether and how voluntary contributions change if a platform faces competition. We address the current lack of theoretical and empirical research on this topic by asking: *how does platform competition affect contributors' tendency to contribute*.

While the linkage between competition and contribution has yet to be studied, there are burgeoning literatures on *platform competition* and on *people's tendency to contribute*. We review both briefly since our work sits at their intersection.

Platform Competition

Most research on platform competition concerns platforms of the same type. By taking the perspective of the platform, it examines strategies to compete, such as pricing (Parker and Van Alstyne 2005, Armstrong 2006, Rochet and Tirole 2006), market timing (Zhu and Iansiti 2012), expansion (Eisenman et al. 2011), sourcing (Lee 2013, Rietveld et al. 2019), certification (Rietveld and Schilling 2021), technology choices (Cennamo et al. 2018), and perception management (Boudreau et al. 2022).

Our focus differs; we examine the competition between different types of platform: crowdsourced and traditional. While research has examined collaboration between such types (Dahlander and Wallin 2006, Nagle 2018, Shah and Nagle 2019), there has been little on the competition between them. Notable exceptions do illustrate the potentially enormous impact of competitors using a different business model (Casadesus-Masanell and Ghemawat 2006, Casadesus-Masanell and Zhu 2010). In the research that comes closest to ours, Seamans and Zhu (2014, 2017) show how competition from crowdsourced Craigslist affects traditionally sourced local newspapers. Our study of the effect of competition from a traditionally sourced platform may thus be understood as the reversed case of that study.

Although research in this domain illustrates both the impact of competitors using a different business model and the incumbent's response, it has yet to examine how competition from a platform of a different type affects the tendency of a platform’s contributors to contribute.

Only a few studies on platform competition have taken the perspective of the actors contributing to the platform. Venkatraman and Lee (2004) show that video game developers tend to publish their games on newer, less-crowded, and more-popular platforms. Loh and Kretschmer (2022), comparing two game "wiki" platforms, found that a platform's stronger competitive position is associated with higher activity by contributors when that activity is triggered by an external event (such as a game update). While insightful, the authors do not look at the competition between crowdsourced platforms (nor between traditional and crowdsourced platforms) and do not examine the direct effect of competition.

In brief, despite a literature on platform competition, research has not examined how contributors’ tendency to contribute changes when the crowdsourced platform to which they contribute faces competition.

Contributors’ Tendency to Contribute

The literature on contributors’ tendency to contribute provides an overview of micro-level determinants of contribution (Butler 2001, Lakhani and Wolf 2005, Kraut and Resnick 2012, Gallus 2017). This research shows *how people become contributors*: They typically become *aware* of a crowdsourced platform and start out as consumers of the knowledge it provides. They start contributing when they see the potential to improve that knowledge (e.g., they encounter a bug or a gap) (Gorbatai 2014, Kane and Ransbotham 2016).[3] Research also illustrates the drivers of *contributors’ decision to continue* to contribute: they become *attached* to the platform (Bateman et al. 2011, Ren et al. 2012). They identify with it and feel a cognitive and emotional connection to it (Ashforth and Mael 1989, Pratt 1998, Paxton and Moody 2003, Hassan 2012). Research points to three types of attachment, anchored in (a) the ideology of crowdsourcing (Shah 2006, Stewart and Gosain 2006), (b) contributors’ social interaction with peers (Zhang and Zhu 2011,

[3] Their trajectory can be compared to that of accidental entrepreneurs—those who become entrepreneurs while searching for a solution for their own problem (Shah and Tripsas 2007).

Shriver et al. 2013), or (c) their standing in the community (Johnson 2002, Chen et al. 2010).

Yet this research has largely overlooked the fact that crowdsourced platforms do not exist in isolation. As Hill and Shaw (2019) note, "Established approaches to the comparative study of online community success have almost exclusively looked *inside* [emphasis added] communities." Thus, this literature has not studied how macro-factors such as competition might interact with the outlined micro-factors and thus with contributors' tendency to contribute.

HYPOTHESIS

We suggest that to understand the effect of competition on crowdsourced platforms, we must differentiate contributors. Specifically, it might be useful to separate contributors based on the *timing* of their contributions vis-a-vis competitive entry. Accordingly, we focus on contributions from (a) *pre-entry contributors*—those who contributed before the entry of a competitor—and *newly recruited contributors*—first time contributors to the platform in each time period. This differentiation is based on the two determinants of contributors' motivation outlined above: *awareness* and *attachment*. We suggest that competition affects the tendency to contribute via these two channels, thus having divergent effects on contributions by pre-entry and newly recruited contributors. Note that our discussion largely focuses on individual contributors. While corporations are increasingly active in open-source communities and on OpenStreetMap, their involvement was nonexistent in the time period we study (Anderson et al. 2019).

Effect of Competition on Pre-entry Contributors

We suggest that pre-entry contributors increase their contributions if a crowdsourced platform faces competition from a traditional knowledge-provider. They are already aware of the crowdsourced platform and attached to it. This sense of attachment increases when their platform faces competition (Ashforth and Mael 1989, Pratt 1998, Paxton and Moody 2003, Hassan 2012) and we therefore expect such contributors to contribute *more* in order to defend the platform and thus to protect what underlies their attachment.

Specifically, (a) the demise of crowdsourced platforms in general would lead to the dominance of closed traditional platforms which don't subscribe to the "open *ideology"* to which contributors are attached (Stewart and Gosain 2006, Murray 2010); (b) the demise of the particular crowdsourced platform to which they have been contributing would curtail or even end their *relationships* with peer contributors (Zhang and Zhu 2011, Shriver et al. 2013); and (c) their *standing* in the platform community would lose its meaning if the platform itself disappeared (Johnson 2002, Chen et al. 2010).[4] We thus expect pre-entry contributors to contribute at a higher rate to defend the crowdsourced platform against the competition.

This prediction echoes research suggesting that stakeholders attached to an organization increase their support when it is under threat (Zavyalova et al. 2016). Similarly, Lerner and Tirole (2002: 228) speculate that "open source projects gain momentum when facing a battle against a dominant firm," although they clarify that "this is an empirical fact, which remains to be established."

Effect of Competition on Potential Newly Recruited Contributors

While we suggest a competition-induced increase in contributions from pre-entry contributors, we suggest a decrease in the total contribution from newly recruited contributors. The competing (traditionally sourced) knowledge platform, being a substitute, reduces the number of consumers of the crowdsourced platform. Contributors typically start out as consumers and, in this capacity, constitute the pool of potential recruits. The competitive entry of an alternative (i.e., the traditional knowledge provider) would therefore, ceteris paribus, hinder the crowdsourced platform's recruitment of new contributors—potential contributors are less likely to even be *aware* of it. We would thus expect a reduction of the group of newly recruited contributors and, correspondingly, a reduction of the overall amount of contribution coming from that group.

Taken together, we hypothesize:

[4] Research suggests standing to be an important driver of behavior (e.g., Bothner et al. 2007, Katila et al. 2022).

Hypothesis: Competition has a divergent effect on crowdsourced knowledge platforms: it increases contributions from pre-entry contributors but decreases the total contribution from newly recruited contributors.

METHODS

We empirically study how pre-entry and newly recruited contributors to the crowdsourced map platform OpenStreetMap respond to the competitive entry of traditionally sourced Google Maps.

OpenStreetMap was launched in 2004. Inspired by Wikipedia, it aims to provide a crowdsourced, open-source, online map for the entire globe (Coast 2015). It is one of the largest crowdsourced platforms on the web, with about half the number of active contributors as Wikipedia (Maher 2016). At its core, OpenStreetMap is a database of geographic information that can be modified by any contributor after a free and simple registration process. Appendix Figure C1 summarizes the four steps of the editing process, showing how a contributor can add a street or building to an existing map. To collect information, contributors often survey neighborhoods with GPS devices or trace features from satellite images. As of September 2021, OpenStreetMap had 7.8 million registered contributors around the world (https://wiki.openstreetmap.org/wiki/Stats).[5] It has been empirically studied in management and information systems and operations (Nagaraj 2021, Urrea and Yoo 2022), but our study is the first we know of in the context of strategy research.

[Insert Figure 1 Here]

To study the effect of competition, we examine the impact on OpenStreetMap of Google Maps, its main competitor. Google Maps, launched in 2005, is a proprietary mapping platform. It sources its data in a traditional manner from a variety of proprietary sources and hires contractors and employees to collect

[5] We include only a sliver of these users because we focus on (a) a very early time in the platform's history when it was much smaller and (b) a set of countries which form a much smaller part of the global user base.

data,[6] although it cannot legally use OpenStreetMap data due to licensing restrictions.

Google Maps' Global Expansion

Our research design leverages the temporally staggered global expansion of Google Maps. While OpenStreetMap launched globally (i.e., simultaneously in all countries) with a blank map in August 2004,[7] Google Maps was launched in 2005 in the United States and the United Kingdom (McClendon 2012), as shown in Appendix Figure C2, then expanded from country to country in a staggered manner. Before launching in any country, Google collected data internally and only when the map was up to a certain standard did it launch, making the treatment relatively sharp around the dates we consider. Figure 1 outlines Google Maps' expansion to 87 countries in five distinct waves over a two-year period, according to our data. We focus on these five waves in our empirical analysis.

The advantage of this approach is that it allows us to compare contributions on OpenStreetMap from the same competitor in an empirically rigorous manner. In particular, even though OpenStreetMap is a single, global crowdsourced platform, it can be thought of as a collection of country-based platforms attracting contributions from local volunteers. This feature provides us with a population of distinct sets of comparable crowdsourced platforms within a single overarching platform, which means we can compare the effects of competition across different country-based communities that face competition at different times. Also, the differential timing means that we can include (a) time trends that control for OpenStreetMap's growing global popularity and (b) country fixed effects which control for fixed differences among regions in their tendency to contribute. We can then isolate the role of competition over and above these alternate explanations.

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[6] Google does not release systematic data on third-party providers. Anecdotally, it sources maps of Africa from a company called AfriGIS Pvt. Ltd and of the Middle East from a company called Orion Middle East.

[7] In practice, there was some variation in when active communities developed in different regions, but these delays were not a function of restrictions imposed by OpenStreetMap leadership.

Data and Variables

We rely on three data sources. First, we collect data on contributions to OpenStreetMap from its "changeset file," which contains metadata on every contribution ever made to the OpenStreetMap database.[8] Next, we collect the date of Google Maps' entry in each of the countries in our dataset from the Google Maps blog.[9] Finally, we rely on demographic and economic indicator data from the World Bank as control variables and for robustness checks. Our main analysis focuses on the 87 countries that faced Google Maps competition in five waves between 2009 and 2011.[10]

Contributions. Our two dependent variables measure the contribution activity of pre-entry and newly recruited OpenStreetMap contributors at the quarter level. We identify 2,127 pre-entry contributors who were active in our set of 87 countries before Google Maps started expanding (i.e., before 2009) and we record observations at the contributor-quarter level between 2006 and 2015. Thus, our main dependent variable, $Contributions_{ijt}$, captures the number of contributions made by contributor i in time t in country j contingent on contributor i having contributed before 2009. For newly recruited contributors, we analyze the dataset at the level of country-quarter (rather than contributor-quarter) because the set of contributors changes from quarter to quarter. For this analysis, the main dependent variable is $Contributions_{jt}$ which is the number of contributions in country j in quarter t from newly recruited contributors; that is, from those whose contributions before time t equal 0. The key question is whether these two variables respond differently to competition.

For both sets of contributors, it is useful to understand what contributions are (and how we measure them) in order to interpret our results. To contribute to OpenStreetMap, an individual must create an account or log in with a username (anonymous edits are not permitted), make an addition or change to the map, and

[8] Available at http://planet.openstreetmap.org/.
[9] In practice, we code Google's Lat-Long blog announcements announcing Google's entry into different markets.
[10] We do not include the entire globe because we cannot estimate Google Maps' entry dates in some locations and also because entry timing in some locations is likely driven by highly strategic considerations.

upload it. Every time new or modified information is uploaded, we infer that a contribution has been made.[11] There were 2.4 million contributions (by both pre-entry and newly recruited contributors) to maps of the 87 countries we study in our time period (2006–2014).[12] For each contribution, the changeset file provides the contributor's username, the date and time the change was submitted, and the average latitude and longitude of all objects added or modified in that contribution. We have no data on the nature of the contribution itself. Using the latitude and longitude, we wrote scripts that placed each edit within a country's borders.[13] Using this location and timing information, we can measure our key variables.

Post Google Entry. This indicator variable, equal to 1 for each quarter after Google Maps has formally entered a given country and 0 otherwise, captures whether the OpenStreetMap community in a given country is in competition with Google Maps.

Controls. We collect several country-year variables to control for unobserved variation across countries over time by measuring economic indicators and technology adoption, since these could affect both Google's entry and OpenStreetMap contributions. In particular, we use annual measures of a country's population, GDP per capita, internet penetration, mobile penetration, and income class. For this data, we rely on the World Bank's World Development Indicators database. Population is adjusted by 100 million, while GDP per capita is adjusted for purchasing-power parity and adjusted by hundreds of thousands of US dollars. Internet and mobile penetration are measured as internet users and mobile cellular subscriptions per 100 inhabitants, respectively. Income class categorizes countries as high, upper-middle, lower-middle, or low based on gross national income per person.

We identify 1,412 pre-entry contributors making 36,683 contributions in the contributor-quarter sample and 661,593 newly recruited contributors making 37,886,605 contributions in the country-quarter sample.

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[11] In OpenStreetMap parlance, we focus on changesets rather than edits as our measure of contributions.

[12] Even though OpenStreetMap began operating in 2004, our sample begins in 2006 because no contributions were made in the countries in our sample before that year.

[13] Some contributors make contributions in more than one country. In such cases, we treat each contributor-country combination as a unique contributor for the purposes of our analysis. Our results are robust to excluding such contributors instead.

Table 1 shows summary country-quarter statistics for our variables. The mean value of overall contributions for a given country-quarter is 692.3; the median is 79. The mean value of our main independent variable, *Post Google Entry*, is 0.6; that is, 40 percent of our country-quarter observations are pre-entry and 60 percent post-entry. Appendix Table C2 shows summary contributor-level statistics.

[Insert Table 1 Here]

Research Design

To examine the effect of Google Maps competition, we use a two-way fixed-effect research design with the following specification:

$$Ln(Y_{it} + 1) = \alpha + \beta \times Post\ Google\ Entry_{it} + \gamma_i + \delta_t + X_{it} + \epsilon_{it}.$$

The unit *i* corresponds to either contributor-level (for pre-entry analysis) or country-level (for newly-recruited analysis). In other words, depending on the sample, the subscript *i* denotes either a contributor or a country.[14] Y_{it} is the dependent variable in unit *i* in quarter *t*, γ_i are unit fixed effects, δ_t are time fixed effects, and X_{it} are time-varying country-level controls for internet and mobile phone penetration. Note that the raw data for our controls do not vary at the quarter level, only at the yearly level. To estimate the specification at the quarter level, we simply use the same value of each control for all quarters in a given year. Further, the key dependent variables represent flows, not stocks; that is, they are the total number of contributions in a focal country-quarter, not the cumulative sum up to that point.

The coefficient β estimates the impact of Google Maps competition. The key prediction of our divergent effect is that this coefficient should be positive for pre-entry contributors and negative for newly recruited contributors. We use fixed effects to control for unobserved variation that plausibly influences a population's propensity to contribute to OpenStreetMap. For example, a country's size, terrain, or climate

[14] If a contributor makes contributions to multiple countries, we treat each country-contributor combination as a unique contributor. Excluding these users (Appendix Table C17) only makes our results stronger.

might make mapping more or less easy. Similarly, the average age and income in different countries are likely to influence people's free time and thus their propensity to contribute to an online community. We include country or contributor fixed effects to account for these differences. We also recognize that during the study period, OpenStreetMap's popularity is growing rapidly across the globe, driven by improvements in its interface, editing tools, and other technology. Quarter-year fixed effects account for these temporal trends. By including fixed effects, our specification identifies within-unit variation in contribution activity separate from other differences over space and time in the propensity of populations to contribute to OpenStreetMap.

Because the dependent variable is skewed, we use log-OLS regressions with standard errors clustered at the country level, first inflating the dependent variable by 1. We also present the robustness of these estimates by (a) using an alternate Poisson quasi-MLE specification (Hausman et al. 1984) to test the sensitivity of our analysis to specific assumptions about the functional form and (b) dropping countries with particularly skewed outcomes.

Validity of the Research Design

While our empirical design is promising, the reliability of our estimates depends on the extent to which Google Maps' entry decisions can be treated as exogenous to OpenStreetMap contribution trends. Sources suggest that Google's decision to enter a country's market was based on its ability to obtain third-party data for that country. For example, even though Google Maps' ambition from the start was to map the entire globe, it was also committed to "launch early and often" when "we had licensed data from as many good providers as we could find" (Google Maps 2012). The publicly available material makes no mention of OpenStreetMap communities playing a role in Google Maps' decision to enter any market, perhaps because OpenStreetMap was fairly small at the time of Google's expansion. Further, if Google Maps was explicitly targeting specific OpenStreetMap communities, we would expect targeted launches in specific regions. For example, if South America was a strategically important market, we might have expected Google to enter various South American countries at around the same time. Instead, as Figure 1 indicates, it entered in waves of about 10 or 20 countries, with each wave including countries in different regions. This pattern suggests that Google Maps did not target specific regions at particular times, but launched in any given country as soon as it was possible.

We also conduct two quantitative tests by estimating a model of Google Maps' entry and examining whether we can predict entry based on OpenStreetMap contribution patterns. In particular, we build a country-level sample and regress the timing of Google Maps' entry on a variety of country characteristics (Bennett et al. 2015). Results are presented in Appendix Table C3. When considering both a cross-sectional model (Panel A) and a discrete-time probit model (Panel B), it seems that contribution growth is not statistically related to the timing of Google Maps' entry, which is reassuring, although Google's entry is tied to other factors for which we do need to control, such as internet and mobile penetration.

To address a second validity concern, we examine, as is standard in two-way fixed-effects analysis, the difference in trends between treated and yet-to-be-treated countries before Google Maps entry, using our baseline regression framework. If Google Maps enters where OpenStreetMap contributions are already increasing or decreasing, we would see a positive or negative pre-trend before the quarter of entry. We therefore estimate the effect of competition separately for every quarter before and after Google Maps entry, using regressions of the form:

$$Y_{it} = f\Big(\alpha + \Sigma_z\ \beta_t \times 1(z) + \gamma_i + \delta_t + X_{it} + \epsilon_{it}\Big),$$

where f is the functional form and z is the "lag"—the quarters relative to a "zero quarter"—which marks the quarter when a country first faced competition from Google Maps. In Figure 2, Panels A and B, we investigate these pre-trends separately for pre-entry contributors and newly recruited contributors. The inference is complicated by the short time for which pre-entry data is available and the possibility that there are indeed some (small) pre-trends in evidence. However, they do not seem severe and, as recent literature indicates, small pre-trends do not necessarily obviate results from a two-way fixed-effects analysis, although the magnitudes of the estimates likely need to be reduced (Rambachan and Roth 2023).

A third concern with our research design is that the entry of Google Maps could affect OpenStreetMap contributions by allowing contributors to directly copy data from the commercial map to the open map. While this is theoretically possible, we are not concerned about it for a few reasons. First, there are strong formal rules and informal norms against copying Google's data.[15] These norms are especially adhered to by pre-entry contributors, who are more attached to the platform and its rules. Second, there are no incentives (such as leaderboards) motivating people to take shortcuts to increase their rate of contribution. Third, it may be that people usually get into mapping for the enjoyable experience of being in the field collecting data; copying data would quite miss the point. All the same, we do check whether countries with higher Google Maps' popularity also have higher increases in pre-entry contributions, which would suggest copying. Further, if copying were an issue, we would expect average contribution size to increase significantly. We find no evidence for either of these two predictions (Appendix Figure C3 and Appendix Table C4).

RESULTS

Divergent Response of Pre-entry and Newly Recruited Contributors

Our analysis displays the hypothesized divergent effect of competition, with contributions from pre-entry contributors *increasing* and those from newly recruited contributors *decreasing*. We focus on this intensive margin and will explore the extensive margin (number of contributors) when unpacking the mechanisms. These results are presented in Tables 2 (pre-entry contributors) and 3 (newly recruited contributors). In both, Column 1 presents estimates without accounting for Google Maps' entry and the following columns add the key independent variable—*Post Google Entry*—and controls. All models include country and

[15] OpenStreetMap's website states: "[O]ther sources must not be used as the base of any data uploaded to OSM—whether maps, aerial imagery, or photographs such as Google Street View. This is because their licences and/or terms of use (contracts) forbid you to do so" https://wiki.openstreetmap.org/wiki/Legal_FAQ#Can_I_trace_data_from_Google_Maps/Nokia_Maps/.

quarter fixed effects.

Table 2 presents the results for pre-entry contributors. Interestingly, the coefficients on all three models (Columns 2–4) are positive and statistically significant. The main coefficients remain significant even when the specifications include over 2,000 fixed effects (one for each pre-entry contributor), which increases standard errors and so decreases significance.[16] Overall, the estimates indicate about a 1.8–2.0-percent[17] *increase* in contributions per quarter from pre-entry contributors after Google Maps entry. Across all pre-entry contributors, this is a sizable increase.

Table 3 presents the results from our analysis of newly recruited contributors, using the country-quarter sample. We find a negative response: fewer contributions from newly recruited contributors after competitive entry. Column 4, providing estimates with all controls, suggests an approximately 42-percent[18] reduction per quarter. Put another way, if the platform got 100 contributions from newly recruited contributors in the quarter before Google Maps entered, it got only 58 from such contributors on average in the period following entry.

[Insert Table 2 & Table 3 Here]

Figure 2 examines whether our differential treatment effects are robust to the pre-trends concerns typical of event studies. Figure 2 suggests that these effects are robust, since for both Panel A (pre-entry contributors) and Panel B (newly recruited contributors), we see no obvious evidence of severe pre-trends. In both panels, standard errors are imprecisely estimated. This does not completely rule out concerns about pre-trends (Rambachan and Roth 2023), but it is clear that the effect of competition is divergent across pre-entry and newly recruited contributors—our central hypothesis. In Panel A, contributions from pre-entry contributors remain stable until Google Maps enters, then increase each quarter. Panel B makes clear that

[16] Since we include fixed effects for each pre-entry contributor, we are also controlling for any country-level differences.

[17] When regressing a logarithmic dependent variable on a dummy, the corresponding percentage change is obtained via 100 * (exp(beta)-1). Therefore, 100*(exp(0.018) - 1) = 1.8 and 100*(exp(0.02) - 1) = 2.

[18] 100*(exp(-0.55) - 1) = -42.

contributions from newly recruited contributors decline each quarter after Google Maps enters, but not before. Quantitative estimates can be found in Appendix Table C5.

[Insert Figure 2 Here]

Mechanisms: Unpacking the Divergent Responses

We use the remainder of the paper to examine what underlies the observed differences in response to competitive entry and to further contribute to a theoretical understanding of this phenomenon.

Examination of the Mechanisms Underlying Increased Contribution from Pre-entry Contributors

We hypothesized that pre-entry contributors' *attachment* may lead to an increase in their contributions when the crowdsourced platform faces competition. We suggested that their attachment may stem from the (open) ideology of crowdsourcing, their social interaction with peers, or their community standing.

To explore each of these, we use various country- or individual-level proxy variables. To proxy for *attachment based on ideology*, we use, for each country, (a) the average number of contributions (or "pushes") per capita to GitHub (an open-source platform) and (b) the market share of the crowdsourced browser Mozilla Firefox, which may express the population's ideological commitment to crowdsourced platforms even when strong, traditional alternatives are available.[19] To proxy for *attachment based on social interaction*, we collect data on the presence of mailing lists—a type of online interaction—and of local social events—an offline interaction—as of 2014 at the country level within OpenStreetMap. Both types of data are collected from official OpenStreetMap sources; the list of country-level mailing lists and events can be found online.[20] To proxy for *attachment based on community standing*, we differentiate between pre-entry contributors according to whether they made a significant number of contributions (more than 10) or on their rank (top five contributors) before Google Maps entry.

[19] The GitHub measure is from 2018 and the browser market share measure is from 2009.
[20] https://lists.openstreetmap.org/listinfo and https://wiki.openstreetmap.org/wiki/Current_events

Table 5 displays the results. With respect to *attachment based on ideology*, Models 1 and 2 show that contributors in countries with above-median GitHub contributions and Firefox market share have a greater positive (statistically significant) response to competition. These results hold in the full Model 7, in which we account for the other sources of attachment. With respect to *attachment based on social interaction* (Models 3 and 4), contributors in countries with a mailing list or local social events have a greater positive—and significant—response to competition than those who are not. However, in the full Model 7, these estimates become smaller and no longer significant. With respect to *attachment based on standing*, we find little support for the role of high rank (Model 5) and significant prior contributions (Model 6). Thus, the role of attachment based on standing in shaping the positive response seems limited. Appendix Table C6 examines these results without controlling for community size but with similar results.

[Insert Table 5 Here]

Overall, the results support our attachment-based explanation of the positive effect of competition on contributions from pre-entry contributors and pinpoint the important role of attachment based on ideology, with modest support for the role of social interaction but none for the role of standing. The standing result is intriguing because it suggests that those who were most active were not more likely than others to respond. While we can only speculate, one reason could be regression to the mean, since these users were already very active before Google's entry. The findings that the entry of (commercial) competitors strengthened contributors' ideology-based attachment is in line with what we learnt through personal interaction with community members who emphasized the importance of an open model of data collection in the context of mapping. As one contributor said: "The point is that when you use any (traditional) map provider, you are handing them the controls—letting them determine what features get emphasised, or what features may not be displayed at all."[21]

Irrespective of the specific driver of attachment, the effect this mechanism should be to make active pre-

[21] https://www.theguardian.com/technology/2014/jan/14/why-the-world-needs-openstreetmap

entry contributors even more engaged rather than spurring non-contributors (pre-entry) to become engaged. In other words, the intensive margin (contributions from pre-entry contributors) should increase, but the extensive margin (number of pre-entry contributors who contribute) should not be much affected. We tested these two margins in Table 4, Models 1 and 2 and do find a positive coefficient on the intensive margin but no movement on the extensive margin. This contrast further supports the role of attachment in shaping the competitive response of pre-entry contributors.

While these results are in line with our theory and seem to follow a coherent logic, we find it notable that contributors who are not contractually bound or monetarily rewarded and whose audience is likely to shrink as a result of a competitor's entry nevertheless increase their contribution after such an entry.

Examination of the Mechanisms Underlying Decreased Contribution from Newly Recruited Contributors

We theorized that a crowdsourced platform could find itself with fewer consumers after the entry of a (traditional) competitor, which would reduce the pool of potential newly recruited contributors and therefore reduce contributions from that population.

Testing this idea is relatively straightforward as compared to testing the different sources of attachment. An awareness-based explanation would suggest that competitive entry itself reduces the entry of new contributors, after which the presence of competition should have a smaller effect. In other words, whereas the intensive margin was more affected than the extensive margin for pre-entry contributors, here the effects should be concentrated on the extensive rather than the intensive margin.

Models 3 and 4 of Table 4 test this distinction. We evaluate the impact of competition on the number of newly recruited contributors and on the extent of their contributions, but looking at average contributions per contributor. We find results in line with the awareness mechanism. Even though contributions per contributor does decreases after the entry, the effects are larger and more significant on the extensive margin; there is a 27-percent drop[22] in the number of new contributors, suggesting that fewer potential contributors are aware of its existence than were before the entry of Google Maps.

[Insert Table 4 Here]

Robustness Checks

Role of community size. While our hypothesized mechanisms concern the direct effect of competition on contributors, indirect effects are also likely. Since a contributor's tendency to contribute is shaped by how active other contributors are (Zhang and Zhu 2011), competition could have an indirect effect on a focal contributor by shaping how other contributors respond. Our results are an amalgamation of these direct and indirect effects. In Appendix Table C7, as in Table 5, we estimate baseline results while controlling for community size. The results are remarkably consistent. Appendix Table C8 examines heterogeneous effects by community size; pre-entry contributors' positive response does not depend on how active others are. However, newly recruited contributors' negative response is lower if they are embedded in larger communities. While we are not explicitly interested in separating the two channels (and our focus is on direct effects), these results suggest that indirect effects could matter for newly recruited contributors.

Definitions and skew. To add robustness to our baseline results, Appendix Table C9 uses alternate definitions of newly recruited contributors (depending on the time relative to competitive entry) and Appendix Table C10 examines robustness to alternate specifications, including country group X quarter fixed effects. See Appendix A for more detail on both tables. To deal with the skewness in our data, Appendix Table C11 drops countries at the right tail of the contribution distribution (shown in Appendix Figure C4). Our basic conclusion does not change with any of these alternate tests.

Accounting for exit. One might worry that the positive effect on pre-entry contributors is driven by increased contributions from a smaller group and we are not accounting for exit. While we lack a perfectly balanced

[22] 100*(exp(-0.32) - 1) = -27.

panel, we do capture exit because we impute zeroes for contributors who are no longer active, so that our results do not imply a greater number of contributions from a smaller group of pre-entry contributors. This is best seen in Appendix Figure C5, which shows the total number of pre-entry contributors in our sample. Appendix Table C12 also shows that competitive entry does not affect that number.

Coarsened-exact-matching (CEM) sample. Our specifications so far have looked at the variation in Google Maps' entry within the 87 countries in our sample. As a further robustness check, we estimate our specification for newly recruited contributors on a parallel sample of 160 countries (79 that experience entry in our data and 81 control). These countries are chosen using a CEM procedure based on a coarsened matching of countries' GDP, population, income class, region, and internet and mobile phone penetration. Results, shown in Appendix Table C13, confirm our baseline results. For pre-entry contributors, we use a similar approach by matching 512 contributors in countries that rank above the median in terms of ideology (as measured by GitHub contributions) with 512 in countries that rank below the median, based on (a) total number of annual contributions in 2006, 2007, and 2008, (b) the quarter in which they were exposed to Google Maps entry, (c) income class, and (d) region. Results, shown in Appendix Table C14, are in line with our baseline findings about the mechanism driving pre-entry contributors' response.

Country-level heterogeneity. So far we have largely controlled for country characteristics, but have not examined whether results are driven by any one particular wave of countries or whether there is variation in response based on country characteristics. Appendix Figure C6 examines the variation in country characteristics by wave and finds no systematic differences. The fifth wave of countries seems most distinctive due to a gap in the timing of when they are added. Appendix Table C15 provides estimates dropping countries in this wave; results are even stronger. Appendix Table C16 examines heterogeneity in response based on country characteristics. We find no major differences for either hypothesis, except in Panel B, Column 1, where we find that newly recruited contributors respond less negatively in more-populous countries, suggesting an effect of community size.

Overall, our analysis suggests that competition from traditional knowledge goods has a divergent effect, significantly reducing contributions from newly recruited contributors, while increasing contributions from pre-entry contributors.

Aggregating the Divergent Effect of Competition across Contributors

Our main goal was to test our hypothesis about the divergent effect of competition, but it might still be interesting to understand how these two effects aggregate and thus co-determine the overall effect on the platform. We do so through (a) empirical examination of the overall country-level effects of competition and (b) a simulation.

Empirical Estimation of the Effect of Competitive Entry on Total Contribution

Given that the effects of competition on pre-entry and newly recruited contributors go in opposite directions, we expect enormous variation in the overall effect. As described in Appendix A and shown in Appendix Figure C7, we illustrate this effect at the country level, each dot representing the treatment effect for a pair of countries. The impact of competition ranges from a positive of 50 percent to a negative of almost 100 percent, depending on the country. This confirms our expectation that the overall effects of competition are likely to be context-specific. However, we do not have power to empirically disentangle the drivers of this variation. We investigate this using a simulation instead.

5.3.2 Simulation

Because our data represent a composite of the divergent effects on pre-entry and newly recruited contributors, it is important to understand what drives the heterogeneity in the overall effect. Because our data lack variation with respect to critical factors that could affect relative contributions from both types of contributor, we developed instead an agent-based simulation model in Appendix B. We consider hypothetical worlds in which simulated contributors decide whether and how much to contribute based on different levels of awareness and attachment and we trace the patterns of their contributions with and without competition.

We first examine contributions over time for pre-entry and newly recruited contributors and replicate our divergent effect in this setting (see Appendix Figure C8). We can then use the simulation to explore three factors that could shape the balance between the number of contributions from pre-entry and newly recruited contributors and thereby condition the overall effect of competition (see Appendix Figure C8 and C9). We base these factors on three observations. First, *timing of competitive entry* could matter. When a competitor enters later rather than sooner, the effect of competition will be more positive since this increases the number of active pre-entry contributors relative to newly recruited contributors. Second, *the natural growth rate* of the platform could be relevant. When a platform is growing more quickly, it will accumulate pre-entry contributors more quickly and the negative effect on newly recruited contributors will be muted. Finally, the *quality* of content on the traditional platform could be important. When the competitor is of lower quality, the awareness effect on newly recruited contributors is less prominent, leading to a more positive overall effect. The results of the simulation illustrate these expected effects. Overall, when pre-entry contributors rather than newly recruited contributors play a bigger part in shaping the competitive response, we expect the overall effect to be more positive, and vice versa. This result highlights the central importance of accounting for the divergent effect of competition in predicting its overall effect on contributions.

DISCUSSION

We examined the effect of competition from a traditional knowledge provider on contributions to a crowdsourced platform. We theorized a divergent effect, increasing contributions from pre-entry contributors but decreasing contributions from newly recruited contributors. Results support this divergent effect and provide suggestive evidence of the underlying mechanisms: attachment and awareness.

Figure 3, a stock-and-flow diagram, provides an overview of our findings and the various channels by which competition affects contributions to the crowdsourced platform. There are three important stocks of individuals to keep track of: *the number of pre-entry contributors, the number of newly recruited contributors*, and *untapped consumers*—those yet to contribute, a fraction of whom could contribute in the future. The *number of newly recruited contributors* is a function of *untapped consumers* who decide to contribute (i.e., *entry rate: newly recruited contributors*). Competition affects the entry rate at which *untapped consumers* convert into *the number of newly recruited contributors.* The stock of *pre-entry contributors* cannot, by definition, increase post-entry. The stocks of *pre-* and *newly recruited contributors* also depend on whether they continue to contribute (i.e., *exit rate: pre-entry* and *newly recruited contributors*). Our paper suggests that competition decreases the entry rate of newly recruited contributors, partly by affecting the pool of untapped customers.

These three stocks influence the number of *accumulated contributions* to the crowdsourced platform. Accumulated contributions depend on new contributions; we distinguish—in line with our empirical analysis—between *contributions from post-* and *pre-entry contributors*. Each of these flows naturally depends on the *number of pre-entry/newly recruited contributors*, but also on *contributions per pre-entry and newly recruited contributor,* themselves affected by competitive entry. Our results suggest that pre-entry contributors increase contributions through the intensive margin (contributions per contributor) while contributions from newly recruited contributors largely decrease through the extensive margin (number of contributors).

[Insert Figure 3 Here]

We outline below how our research informs various theoretical debates.

Competitive Strategy and Crowdsourcing

There has been an explosion of firms using crowds and of researchers studying them. Organizations rely on crowds to fund themselves (Mollick 2014), predict the future (Atanasov et al. 2017, Kapoor and Wilde 2023), make more accurate estimates (Csaszar and Eggers 2013, Mollick and Nanda 2016, source ideas (Bayus 2013, Park et al. 2023), solve problems (Jeppesen and Lakhani 2010, Lifshitz-Assaf 2018), and more. Such research has shown the potential of crowdsourcing, but has generally neglected the role of competition and, thus, the question of whether crowdsourcing is effective in the presence of competition. Reasons for this neglect may be epistemological—research often addresses the relevance of a phenomenon before establishing its antecedents and contingencies—or methodological—research on crowdsourcing typically leverages highly granular data on a single firm, depriving it of variation on ecological factors. Our paper addresses this gap and shows how crowdsourcing performs when the organization deploying it faces competition. Our findings show that it is crucial for managers and researchers to take competition into account when considering crowdsourcing. Competition shapes the degree to which organizations can rely on crowdsourcing and the population of contributors on whom they can rely.

Platform Competition: Traditional Sourcing vs. Crowdsourcing Platforms

We contribute by making a foray into understanding the competition between traditionally sourced and crowdsourced platforms. Research has compared and contrasted the two (e.g., Giles 2005, Almirall and Casadesus-Masanell 2010, Greenstein and Zhu 2012). We answer the call for more research on competition between these two paradigms (Lerner and Tirole 2002, 2005). Despite some theoretical work (Baake and Wichmann 2003, Casadesus-Masanell and Ghemawat 2006, Gaudeul 2007, Athey and Ellison 2014), there is little systematic quantitative evidence. Our evidence shows that competition from a traditional platform does affect contributions to crowdsourced platforms. It is, therefore, insufficient just to compare and contrast these two modes of knowledge production[23] without understanding how they affect one another.

Our examination also reveals *how* competing platforms affect one another. Interestingly, the traditional platform reduces the crowdsourced platform's access to volunteers' contributions, an input the two do not directly contest. While the two platforms compete downstream for consumers, the traditional platform does

[23] Research has examined whether crowdsourced or traditional platforms are superior (e.g., Giles 2005, Mollick and Nanda 2016). Our study cautions against oversimplified answers to that question. Even if traditionally sourced platforms are found to be superior, that may result in part from how they affect crowdsourced platforms. In the presence of traditionally sourced competition, crowdsourced platforms may not be able to reach their full potential, which raises the question of whether a crowdsourced platform would actually be superior in the absence of traditional competition.

not directly compete for volunteers and their contributions. It is thus remarkable that the traditional platform deprives the crowdsourced platform of a key input that the former does not itself need.

We also contribute to research on competition between types of platform (or of business model). While research has typically focused on competition between platforms of the same type (Zhu and Iansiti 2012, Cennamo and Santaló 2013, Lee 2013, 2014), there is by now a literature on competition between business models (Casadesus-Masanell and Ghemawat 2006, Casadesus-Masanell and Zhu 2010, Seamans and Zhu 2014, 2017, Loh and Kretschmer 2022). We show how potentially disruptive a competitor with a different business model can be. While scholars and practitioners have generally focused on how new business models can disrupt traditional business models, we show that the reverse is also true: the traditionally sourced Google Maps can undermine the novel crowdsourced OpenStreetMap.

Our paper also raises the question of the conditions under which crowdsourced or more traditional forms of knowledge production will dominate a market (Augereau et al. 2006). While crowdsourced platforms (e.g., OpenStreetMap, Linux, Wikipedia) have had stellar success (Jeppesen and Lakhani 2010, Greenstein and Nagle 2014, Nagle 2017), there has been remarkable perseverance by commercial alternatives (Economist 2016). Our study shows that competition hinders platforms that rely on crowdsourced knowledge production and therefore points to the role of strategic entry in shaping the dominant mode of knowledge production in a given market.

Our study also complements work on platform strategies. Research has examined how platforms can compete more effectively, showing the importance of strategic decisions on technological compatibility (Kretschmer and Claussen 2016), impression management (Boudreau 2021), complementor control (Boudreau 2010), expansion (Eisenmann et al. 2011), vertical integration (Lee 2013), complementor exclusivity (Cennamo and Santalo 2013), acquisitions (Miric et al. 2021), and prices (Parker and van Alstyne 2005).

Tendency to Contribute: Competition as a Key Contingency

Research has examined what underlies the tendency to volunteer and contribute (Ren et al. 2007, 2012, Zhang and Zhu 2011). Our study answers the call to move beyond examining the direct link between motivation and contribution and to investigate contextual factors that affect tendency to contribute (Von Krogh et al. 2012). We show how a crowdsourced platform's environment—specifically, its competition—affects contributors' motivation.

We are not the first to ask how competition affects willingness to contribute. Research has raised—but not studied—this question and has made contradictory assumptions about the effect of competition. Casadesus-Masanell and Ghemawat (2006) and Athey and Ellison (2014) assume a negative effect; Lerner and Tirole (2002, 2005) and Gaudeul (2007) suggest a positive effect. This work tends to *assume* a general contributor response to competition, but does not provide systematic evidence. We complement this work by providing empirical patterns and showing the need to differentiate types of contributor.

Our study on the linkage between competition and contributors' efforts also complements work at the intersection of competition and contributing. While prior work examined how contributors respond when facing competition from other contributors (Boudreau et al. 2011, 2016, Miric 2017), our study examines how they respond when the platform they contribute to faces competition.

We also explore mechanisms by which competitive entry affects (pre-entry) contributor motivation. Our findings suggest that the link between competitive entry and pre-entry contributors' responses can be traced to their ideological concerns about a traditional competitor. Contributors are not simply interested in seeing their platform prevail, but also want a crowdsourced platform to prevail over a commercial one. Our finding is consistent with research on competition and ideology. Murray's (2010) detailed account shows how it may take the entrance of a competitor operating according to an alternative logic to make people understand the importance of the ideological difference. This finding is also consistent with public statements by members of the open-source community. In an article in *The Guardian*, "Why the world needs OpenStreetMap," Serge Wroclawski (2014), a contributor, points out:

> Every time I tell someone about OpenStreetMap, they inevitably ask "Why not use Google Maps?" From a practical standpoint, it's a reasonable question, but ultimately this is not just a matter of practicality, but of what kind of society we want to live in. . . . [N]o one company should have a monopoly on place.

6.5 The Effect of Competition on an Organization: Motivation Up, Recruitment Down

Our study illustrates more broadly how organizations may be affected by competition (Polidoro and Toh 2011, Ethiraj and Zhou 2019). Our key contribution is to conceptualize competition as *multi-touch*, as it affects different kinds of organizational member in different ways. Organizations facing competition may benefit from the increased motivation of current contributors but may struggle to recruit new ones.

External competition changes an organization's internal composition: the share of old members increases while the share of new members decreases.[24] This competition-induced change informs research on the link between competition and innovation (Greve and Taylor 2000, Aghion et al. 2005, Katila and Chen 2008, Toh and Polidoro 2013); organizations facing competition may fail to recruit new members who would foster exploration and instead rely more on established members who focus on exploitation.

6.3 Limitations and Boundary Conditions

It is plausible that in other empirical settings, the effect of competition on pre-entry and newly recruited contributors may be differential without being, as we observe, divergent. A strong enough competitor may decrease contributions even from pre-entry contributors.[25] Further, while our research design provides a natural experiment to estimate the effect of competition on contributions, we lack a similar design for the mechanisms we study. For example, we do not have a quasi-random assignment of ideology-based

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[24] To understand the effect of competition on the demography of members in the community, the analogy of a stock-and-flow diagram is illustrative: Two valves regulate the in- and outflow of community members. The observed divergent effect suggests that competition decreases the rates of entry and of exit. This effect is somewhat counterintuitive, as one would expect factors that deter new members to also foster the exit of established members.

[25] If the competitive entry greatly reduces the number of consumers, even pre-entry contributors, may—despite feeling more attached—contribute less, as they see their contributions having less impact (Lerner and Tirole 2002, Jeppesen and Frederiksen 2006, Fershtman and Gandal 2007, Zhang and Zhu 2011, Boudreau and Jeppesen 2015, Gallus 2017, Blasco et al. 2019). Shah (2006) cites a programmer: "Why work on something that no one will use? There's no satisfaction there."

attachment. Also, our measures are only proxies (e.g., GitHub and Firefox adoption as an operationalization of ideology-based attachment to crowdsourced platforms). It is possible that a contributor in a place with low GitHub/Firefox adoption has *higher* rather than lower ideological attachment. Our proxy variable makes it difficult to measure this concept conclusively. Further, while our simulation outlines contingencies in our effect, future work should test them empirically. Finally, contributors in our setting do not directly copy from the traditional platform, but in other settings this might be possible. Our setting does not shed light on how the effects we document would differ in settings where copying would be possible.

6.4 Implications for Managers and Policymakers

Our study has practical implications for four types of stakeholder in platform-based ecosystems:

Knowledge providers. We provide guidance on how traditionally sourced platforms could attack crowdsourced platforms by entering a market early.[26] Crowdsourced platforms can protect themselves by increasing usage and building up the ranks of motivated pre-entry contributors.

Featured entities. We illustrate the dynamism of inter-platform competition. Such competition may affect the entities featured on these platforms. Entities featured prominently on traditional platforms (e.g., Michelin-star restaurants) might welcome platform competition if it undermines crowdsourced platforms that increase the set of entities against which they must compete. Entities featured prominently on crowdsourced platforms, however, may suffer from more competition.

Individual knowledge contributors. Our study illustrates that there are probably many people who would have become contributors but never did, due to competition from traditional platforms. Such people may want to foster crowdsourced knowledge platforms to preserve the opportunity to contribute to them.

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[26] Our research is also informative for managers of traditionally sourced platforms that consider leveraging crowdsourcing to act on their value chain. For example, Gambardella and von Hippel (2019; see also Baake and Wichmann 2003) develop a formal model of downstream firms co-developing a crowdsourced platform for upstream inputs that would foster upstream competition and lower their dependence on the proprietary upstream supplier on which they currently rely. Our study illustrates that such downstream crowdsourced platforms are likely to struggle to recruit voluntary contributors, given the presence of traditional competititors.

Businesses and consumers reliant on knowledge gathered by crowdsourced platforms. Many businesses and consumers rely on knowledge gathered by crowdsourced platforms; for example, Apple Maps, Facebook, and Uber source much of their map data from OpenStreetMap. Our study helps them assess when a crowdsourced platform is likely to be robust against competition.

Beyond these general contributions, we want to highlight the importance of the phenomenon in the context we study. Maps (and knowledge-based platforms more generally) have long been recognized as a powerful tool to shape the fortunes both of those they describe and those they leave out (Harley et al. 1987, Nagaraj and Stern 2020, Nagaraj 2022). Our work points to the role of competition in shaping these tools. As long as knowledge-based platforms play an outsized role in guiding market participants, understanding how they are shaped by their ecological environment will be an important topic of study.

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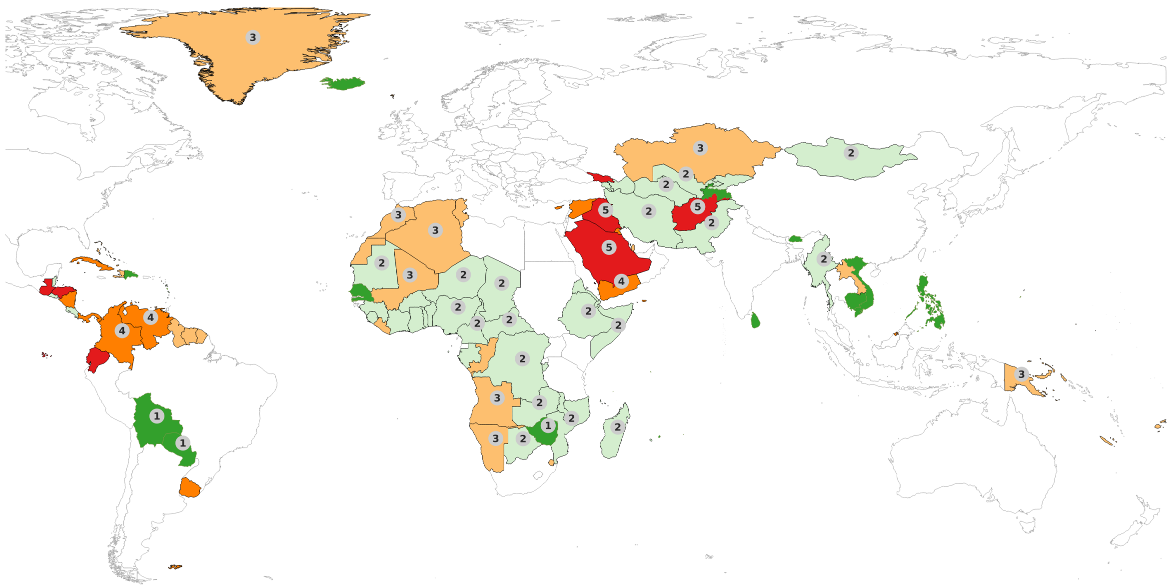
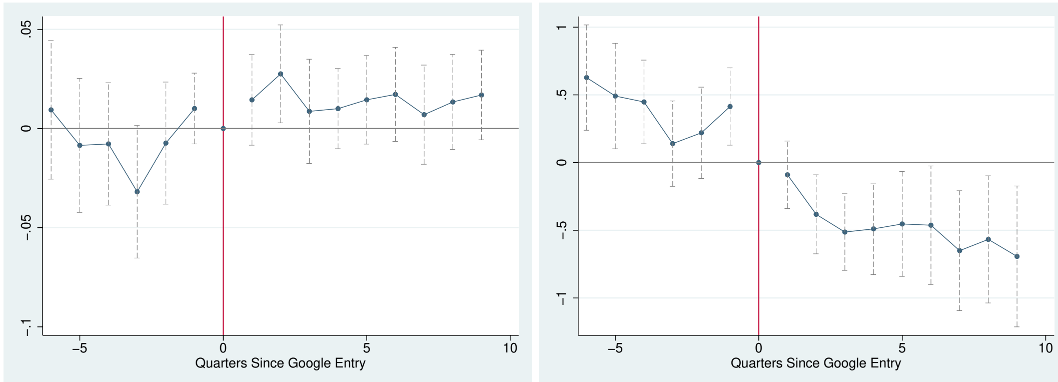
FIGURE 1. Google Maps Launch Cohorts in Different Countries Over Time



Note: This figure provides an overview of Google Maps' entry in different countries at different points in time, as per our data. The five entry periods (labeled 1-5 chronologically) are 2009q1, 2009q2, 2009q3, 2010q2 and 2011q4.

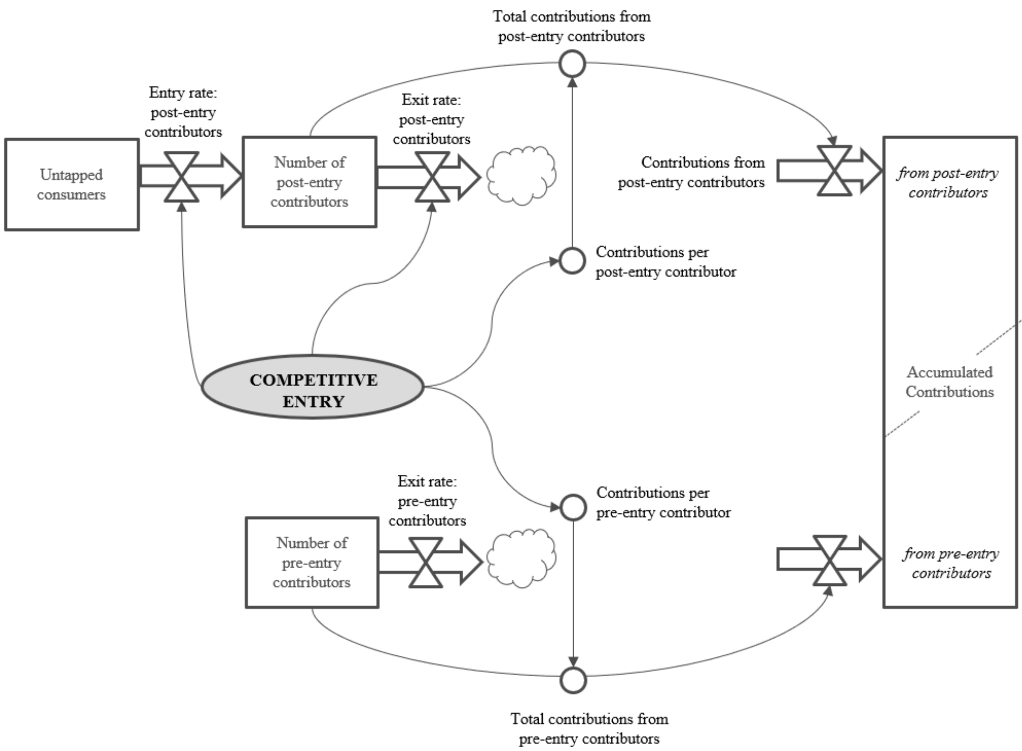
FIGURE 2. Comparing the Effect of Competition between Pre and Newly-Recruited Contributors

A. Pre-Entry Contributors B. Newly-Recruited Contributors



Note: This figure plots estimates (and confidence intervals) of β_t from the event study specification described in the paper. On the x axis is quarter. Panel A is based on member-quarter observations and Panel B is based on country-quarter observations and the outcome variable on the y-axis is $Contributions$ for both panels. Coefficients are estimates from log-ols models.

FIGURE 3. Stylized Representation of Theoretical Framework



Note: This figure is a stylized representation of the theoretical framework we develop for the effect of competitive entry on crowd-sourced platforms based on a stock and flow logic. A solid box (☐) represents a stock (of contributors or contributions), and large block arrows (⇒) indicate flows which are regulated by valves (shown by ⋈). Thin arrows (→) illustrate influence relationships between stocks. Small circles (◯) represent parameters which then affects the stocks. The cloud symbol () represents an exit from the system. This figure provides a decomposition of the various channels through which the total number of contributions is determined and can be used to illustrate the predicted effects of competitive entry at various points along this process.

Table 1. Summary Statistics (Country-Quarter Level)

	N	Mean	SD	Median	Min	Max
Outcomes						
Contributions from Newly Recruited Contributors	3480	297.9	1224.3	33	0	27034
Overall Contributions	3480	692.3	2098.2	79	0	44774
Newly-Recruited Contributors	3480	26.2	58.8	10	0	1373
Total Contributors	3480	39.1	77.3	15	0	1557
Timing Variables						
Post	3480	0.6	0.5	1	0	1
Year	3480	2010.5	2.9	2010.5	2006	2015
Controls						
Population (100 millions)	3464	0.2	0.3	.0978477	0	2
GDP per capita, PPP (in 100k USD)	3224	0.1	0.2	.0562283	0	1
Mobile Penetration (per 100)	3472	71.7	42.8	70.35506	0	232
Internet Penetration (per 100)	3452	20.0	21.1	11.6	0	98

Note: Observations at the country-quarter level. N=3480 for 87 countries over 40 quarters from 2006-2015. Data on controls is at the country-year level. GDP per capita is PPP adjusted.

Table 2. The Impact of Competition on Contributions from Pre-Entry Contributors

	(1) Contributions	(2) Contributions	(3) Contributions	(4) Contributions
Post Google Entry		0.018^{*}	0.018^{*}	0.020^{**}
		(0.0094)	(0.0097)	(0.0099)
Population (millions)	0.079		0.072	0.082
	(0.075)		(0.078)	(0.076)
GDP per capita	-0.12		-0.087	-0.12
	(0.090)		(0.065)	(0.092)
Mobile Penetration	0.00020			0.00023
	(0.00015)			(0.00015)
Internet Penetration	-0.000045			-0.000053
	(0.00031)			(0.00032)
Community Member FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	80524	85080	80800	80524
Adj. R2	0.057	0.056	0.057	0.057

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This regression estimates the impact of competition from Google Maps on contribution activity of pre-entry contributors on OpenStreetMap in a differences-in-differences framework. The unit of analysis is contributor-quarter. The specification is $Ln(Contributions_{it}+1) = \alpha + \beta \times Post\ Google\ Entry_{it} + X_{it} + \gamma_i + \delta_t + \varepsilon_{it}$. This specification is estimated using logged OLS models. The outcome variable is logged $Contributions_{it}$ (inflated by one) and is measured as the total number of edits in a given country by a pre-entry contributor i in a given quarter t. $Post\ Google\ Entry_{it}$=1 after Google Maps has entered a given country in a given quarter. γ_i and δ_t indicate fixed effects for contributor and quarter respectively. The control variables X_{it} include population, GDP, internet penetration, and mobile penetration, and they vary at the country-year level. Clustered standard errors at the country level are reported.

Table 3. Impact of Competition of Contributions from Newly-Recruited Contributors

	(1) Contributions	(2) Contributions	(3) Contributions	(4) Contributions
Post Google Entry		-0.62***	-0.60***	-0.55***
		(0.14)	(0.15)	(0.15)
Population (millions)	4.23**		3.99**	4.16**
	(1.80)		(1.85)	(1.79)
GDP per capita	0.12		-0.18	0.29
	(2.57)		(2.09)	(2.55)
Mobile Penetration	0.0070**			0.0065**
	(0.0028)			(0.0028)
Internet Penetration	-0.0047			-0.0048
	(0.0082)			(0.0081)
Country FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	3192	3480	3224	3192
Adj. R2	0.78	0.78	0.78	0.79

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Estimates the impact of competition from Google Maps on the contributions by newly-recruited OpenStreetMap contributors in a differences-in-differences framework. The unit of analysis is country-quarter. This specification is estimated using logged OLS models. The outcome variable is logged $Contributions_{it}$ (inflated by one) and is measured as the total number of edits by newly-recruited contributors in country i in a given quarter t. *Post Google Entry*$_{it}$=1 after Google Maps has entered the country i in a given quarter. The control variables X_{it} include population, GDP, internet penetration, and mobile penetration, and they vary at the country-year level. γ_i and δ_t indicate fixed effects for country and quarter respectively. Clustered standard errors at the country level are reported.

Table 4. Evaluating the Effect of Competition on Number of Contributors (Extensive Margin) vs. Contributions per Contributor (Intensive Margin)

	Pre-Entry		Newly-Recruited	
	(1) Active(0/1)	(2) Contributions	(3) Contributors	(4) Avg. Contributions
Post Goog. Entry	0.0024	0.020**	-0.32***	-0.16**
	(0.0042)	(0.0099)	(0.089)	(0.076)
Population	0.010	0.082	2.57*	0.47
	(0.020)	(0.076)	(1.30)	(0.48)
GDP/cap.	-0.032	-0.12	0.32	-0.33
	(0.034)	(0.092)	(1.78)	(0.62)
Mobile Users	0.000051	0.00023	0.0041**	0.0019*
	(0.000049)	(0.00015)	(0.0020)	(0.0011)
Internet Users	-0.000069	-0.000053	-0.0013	-0.0028
	(0.00011)	(0.00032)	(0.0056)	(0.0029)
FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	80524	80524	3192	3192
Adj. R2	0.13	0.057	0.84	0.54

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: We estimate the effect of competition on the number of active contributors (the extensive margin) and the number of contributions per contributor (intensive margin). The first column in each analysis estimates the effect on the extensive margin, while the second estimates the effect on the intensive margin. For pre-entry users, the intensive margin is a dummy variable for a given contributor as to whether she is active, and the extensive margin is the total number of contributions by that contributor. For newly-recruited contributors and the full sample, the extensive margin is the number of first-time and total contributors respectively and the intensive margin is the number of contributions per active newly-recruited and total contributors.

Table 5. Evaluating the Heterogenous Effect of Competition on Pre-Entry Contributors

	Ideology		Social		Standing		All
	(1) Github	(2) Firefox Share	(3) Maillist	(4) Events	(5) Rank	(6) Contribs	(7) —
Post Google Entry	0.0099	0.0060	0.011	0.0087	0.038**	0.024**	0.031*
	(0.011)	(0.012)	(0.010)	(0.0098)	(0.015)	(0.0092)	(0.016)
Post X High-Ideology	0.022**	0.015*					0.022**
	(0.010)	(0.0084)					(0.010)
Post X High-Social			0.015	0.017*			0.0075
			(0.011)	(0.0099)			(0.011)
Post X High-Standing					-0.044	-0.079**	-0.045*
					(0.027)	(0.033)	(0.027)
Post X Mid-Size	0.0047	0.0056	0.0055	0.0078	-0.010	0.0055	-0.011
	(0.0093)	(0.0095)	(0.0094)	(0.0093)	(0.012)	(0.0097)	(0.012)
Post X Large-Size	0.0046	0.0040	0.0039	0.0076	-0.012	0.0072	-0.017
	(0.010)	(0.012)	(0.012)	(0.011)	(0.019)	(0.012)	(0.016)
N	80524	80524	80524	80524	80524	80524	80524
adj. R^2	0.056	0.056	0.056	0.056	0.057	0.057	0.057

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: We present estimates decomposing the positive effect of pre-entry users depending on different drivers of attachment for this group of contributors. In three different analyses, we evaluate the role of ideological environment, opportunities for social interaction and the standing of the contributor, along with a model that includes all three factors. For each analysis, we classify a contributor as belonging to a group that ranks highly on each dimension and provide a heterogenous response to the effect of competitive entry. High-Ideology equals one if the contributor belongs to a country with above-median github contributions or firefox market share, High-Social equals one if a contributor belongs to a community with a mailing-list or has hosted a mapping event and High-Standing equals one if a contributor ranks in the top 5 by contributions or has more than 10 contributions in her community. All models include interactions by community size as well as an additional control. Please see text for more details.

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APPENDIX A: Additional Details on Robustness Checks

Alternate specifications

In addition to our main regressions, the entry model, and the graphical analysis, we evaluate the robustness of our specification to alternate modeling assumptions in Appendix Table C10. In the first model, we use a Poisson quasi-maximum likelihood specification for the count dependent variable—the number of contributions. Second, we estimate our regressions with region-specific time trends. Specifically, we classify countries depending on the World Bank Income Classification (high income or low/middle income) and then include separate quarterly time-trends for each of these two income categories. This specification allows us to control for the possibility that OpenStreetMap is evolving differently in richer and poorer countries. Finally, we implement a "placebo" regression to identify whether our results are driven purely by the structure of our setup or data rather than by the specific timing of Google Maps entry. In the spirit of Bertrand et al. (2004), we randomly assign each country to one of the five quarters in which Google Maps entered and use this entry time to estimate a new $Post\ Google\ Entry_{it}$ variable that we use in the regression testing the baseline specification.[1] For example, if a country experiences a Google Maps entry in the first quarter of 2009 (the first wave), we might randomly assign it to the fourth quarter of 2010 (the fifth wave), assign a country from the fifth wave to the second wave, and so on.

The results from all three tests for the pre-entry and post-entry contributions variables are presented in Appendix Table C10; the results are not sensitive to these alternate specifications. In particular, as Columns 3 and 6 show, the estimates from our baseline regression are not significantly different from zero, suggesting that our results are not driven by mechanical artifacts of our setup or by the definitions of variables, but are indeed driven by the specific timing of Google Maps entry. Further, our results for post-entry contributions are based on the number of contributors making their first contribution in a given quarter. This definition of a post-entry user is admittedly arbitrary and so, in Appendix Table C9, we examine alternate definitions

[1] We do not implement many permutations of the placebo inference, just one of the many possible combinations using a randomly chosen seed.

of post-entry users (those who have been active in the previous two quarters or the previous six quarters) and find the negative effect on contributions robust. In other words, it does not matter if we measure post-entry contributors as those making their first contribution in a given quarter or those who are “relatively new” (having contributed in the last few quarters for the first time); the effect of competition on contributions from this group is still negative. Combined with the event study figures, these results are especially helpful in building confidence in the result that pre-entry and post-entry contributors have a differential response to competition.

DID Decomposition

In staggered Difference-in-Difference, the general estimator from the TWFE approach is actually a "weighted average of all possible two-group/two-period DiD estimators in the data.” When the treatment effect varies across time, some of these 2x2 estimates enter the average with negative weights because already-treated units act as controls: more weights will be given to units treated towards the middle of the panel, so if the treatment effects during that period differ materially from other treatment effects, the coefficient could be biased (Goodman-Bacon 2021).

Appendix Figure C7 shows results based on DiD decomposition theorem from Goodman-Bacon (2021) for the total number of contributions. The plot shows each 2x2 DiD with its weight and calculates the average effect (shown by the red line). The weights are determined by the absolute size of the subsample, the relative size of the treatment and control groups in the subsample, and the timing of the treatment in the subsample (variance). We can see that the groups treated earlier in the period (light cross) and the groups treated later in the period (dark cross) distribute evenly and the majority of the TWFE estimates are negative. The few positive coefficients are lightly-weighted as the relative sample size is very small and the treatment is toward the beginning or ending of the sampling period.

APPENDIX B: Simulation

We provide a simple simulation framework to explain how competition could shape the long-term contribution patterns of a crowdsourced community.

Setup

To fix ideas, consider a world with population N. In each time period t, a random subset N_s of the population considers contributing to the crowdsourced community. Each potential user i at a time t has benefit defined by:

$$Benefit_{it} = f(Attachment_{it}, TotalContrib_t)$$

Here, $Attachment_{it}$ is a parameter that defines the attachment of an agent to the crowdsourcing platform potentially due to factors such as ideology. $dBenefit_{it}/dAttachment_{it} > 0$, i.e. the greater the attachment, the higher the benefit to the agent from contributing. TotalContrib_t is a parameter which tracks the overall quality level of the platform which is a function of the sum of contributions and quality in the previous time period, multiplied by a depreciation factor. Communities that naturally grow fast, could be thought of as having a small depreciation factor, while communities with a slower growth rate could be modeled as having a larger depreciation factor.

If there is no competitor, then the user contributes an amount $Cpre_{it} = (Benefit_{it} - AwarenessCost_{it})$ if $C > 0$, otherwise she contributes 0. Here, awareness_{it} is a parameter to keep a track of the agent's awareness on the contribution to crowdsourcing platforms and attachment. A lack of awareness can be thought of as higher costs for agents to know about and contribute to the platform. Hence we have the assumption that the greater the awareness costs, the lower the resulting contribution.

Further, we assume that the total population of agents is N, of which a fraction N_s consider contributing at any point in time. Further, if an agent makes a contribution in time period t, she does not contribute again till time period t+p, where p is a "pause" parameter that captures the natural breaks users take between contributions.

Competition

In this setup, consider the entry of a competitor of quality Q_c. Rather than contributing if $Cpre_{it} > 0$, users contribute if $Cpost_{it} > 0$, where $Cpost_{it} = (Benefit_{it} - AwarenessCost_{it} - Q_c)$ and zero otherwise. In other words, rather than contributing if their benefits are greater than barriers from awareness, agents will only contribute if the potential benefit is larger than the potential quality of a competitor. Q_c captures both the performance differences between products, but also ideological and other differences that might create gaps in attachment from a competitor.

Further, a competitor chooses a time T_c to enter the market, at which point agents switch their decision criteria from $Cpre_{it}$ to $Cpost_{it}$. There is only one competitor that remains in the market till the end of time after $t > T_c$.

Further, agents update their $Attachment_{it}$ and $AwarenessCost_{it}$ post the entry of competition. Our empirical results suggest that pre-existing users increase contributions post competitive entry, likely for reasons of attachment. Accordingly, we model that agents' Attachment_{it} increases substantially only if they have already contributed to the platform. Else, it remains the same.

Further, our results suggest that competition also affects the awareness of the platform among post-entry users. Accordingly, we model that $AwarenessCost_{it}$ increases for users as long as they have not already contributed to the platform. For pre-existing users it remains the same.

Results

We now present some results from simulations that operationalize the above framework with specific parameter values. For example, we consider a world with 10,000 agents (of which 100 are at risk of contributing in every time period). Agents attachment and awareness costs are drawn from uniform distributions lying between [0,1] and [0,2] respectively. We consider the evolution of the platform over T=500 time periods with competition entering at different points in time.

Result #1: Competition increases contributions from pre-entry users but decreases from post-entry users

In Appendix Figure C8, panel A, we explore how contributions change in the presence of competition. We consider a competitor with Qc=5 entering at T=100. As is clear from this chart, competition decreases total contributions to the platform, especially in the near term right after entry. Contributions from post-entry users drop dramatically while contributions from pre-existing users drop for a period, after which it increases and becomes larger than before.

Result #2: The later the competitive entry, the higher the steady state level of total contributions

In Appendix Figure C8 panel B, we have a competitor enter with Quality (Q_c=5), we plot how the contributions change with different times of entry of competition, T=50, 100 and 250. It is evident that early competition(T=50/100) reduces the overall contribution compared to no-competition, whereas late entry of competition(T=250) increases the overall contribution, and even crosses above the no-competition level of about 2800.

Result #3: The higher the natural growth rate of the platform, lower the impact of competition -- although timing of competitive entry is more important

In Appendix Figure C9, panel A, we have the same case as in Appendix Figure C8 Panel B, we however vary the natural growth rate, i.e. the depreciation factor of Quality. In the left panel, we consider a low level, a factor of O_q=0.95 in this case and in the right panel the growth rate factor is much higher, with O_q =0.65. In the left panel, we note that the overall contributions now settle with a steady state contribution around 500, significantly lower than in the case with the higher growth rate. We can observe the factor of difference between steady state levels for the three different cases of competition entry has reduced in this case, which means the competition timing also matters more when the growth is higher.

Result #4: Higher the quality of competition, greater the impact on overall contributions, and timing of entry is less important.

In Appendix Figure C9, Panel B, we plot the overall contribution when the competitor with a varying Competition quality (Q_C= 1, 5, 10) enters at different time periods.

The left panel has the competition quality very low at 1, the effect of the competition increases the overall contribution even at early entry of competition and there is no significant difference in the steady state value of contribution for different times of entry. The right panel has much higher quality with 10, the effect on all the cases is that the overall contributions are lowered. The difference between the varied competition entry time is much lower in proportion which makes the time of entry less significant.

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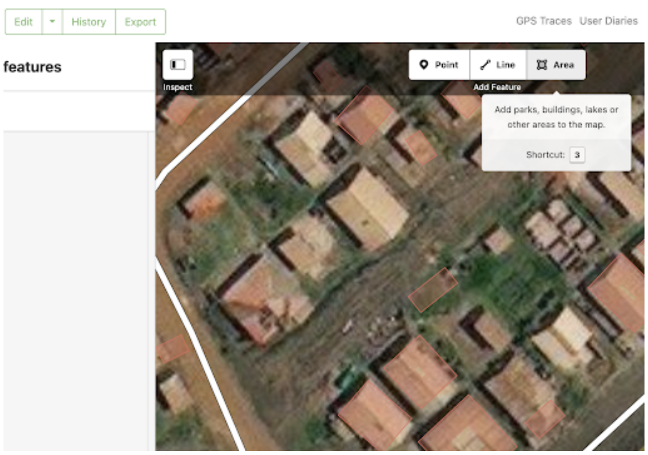
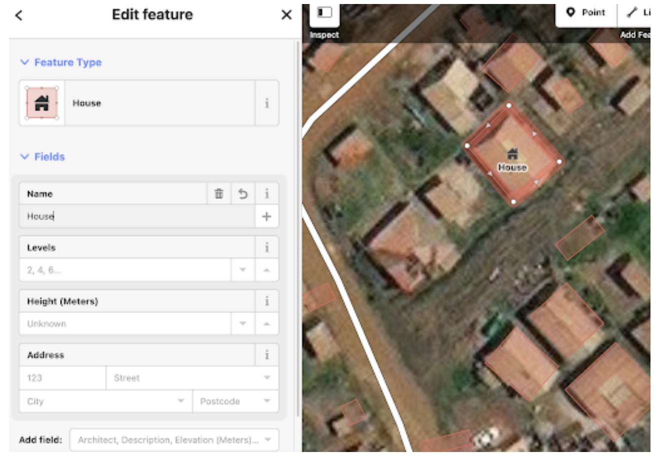
FIGURE C.1. Overview of Making a Contribution on OpenStreetMap

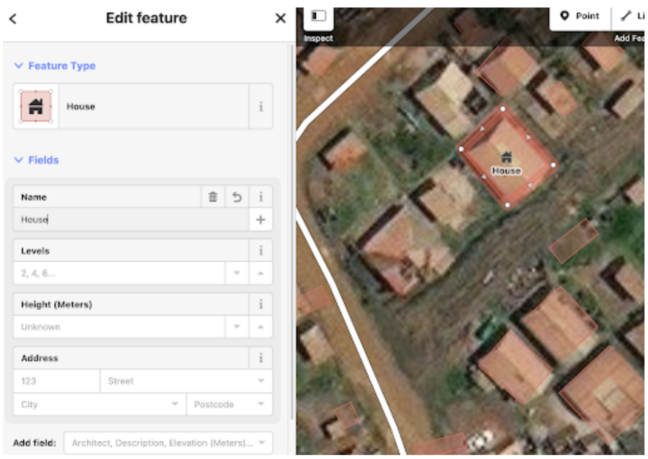
(i) Locate



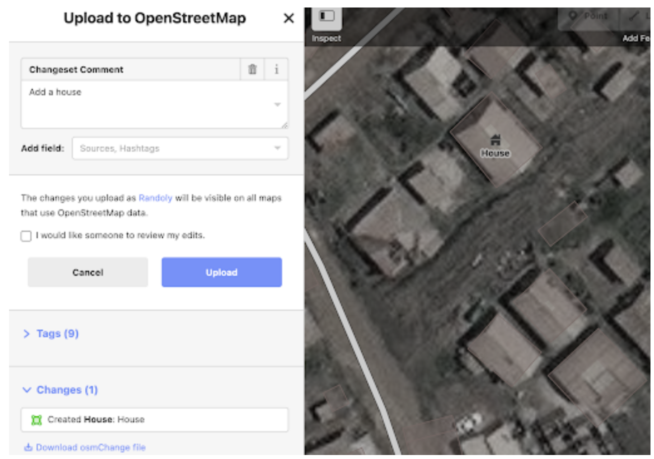
(ii) Portray



(iii) Describe

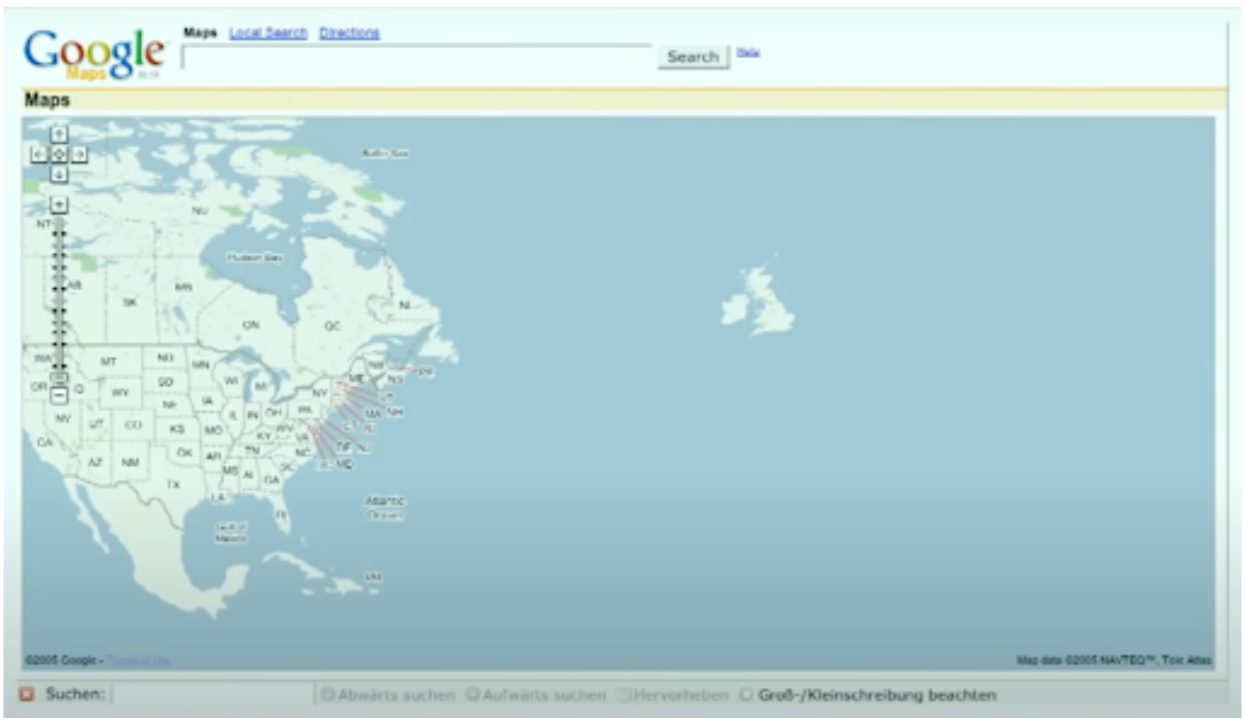


(iv) Save



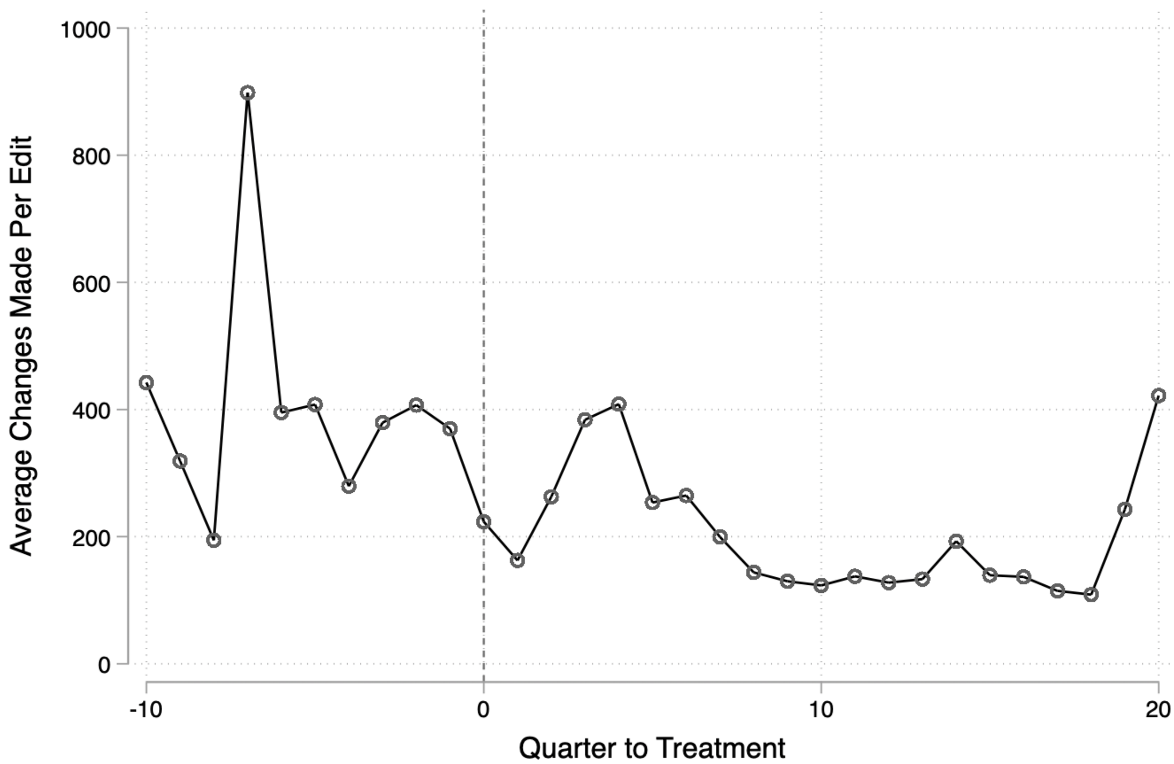
Note: This graph shows the steps for a member to make a contribution (adding a building) on OpenStreetMap.

FIGURE C.2. Google Map Launched Globally with a "Blank Map"



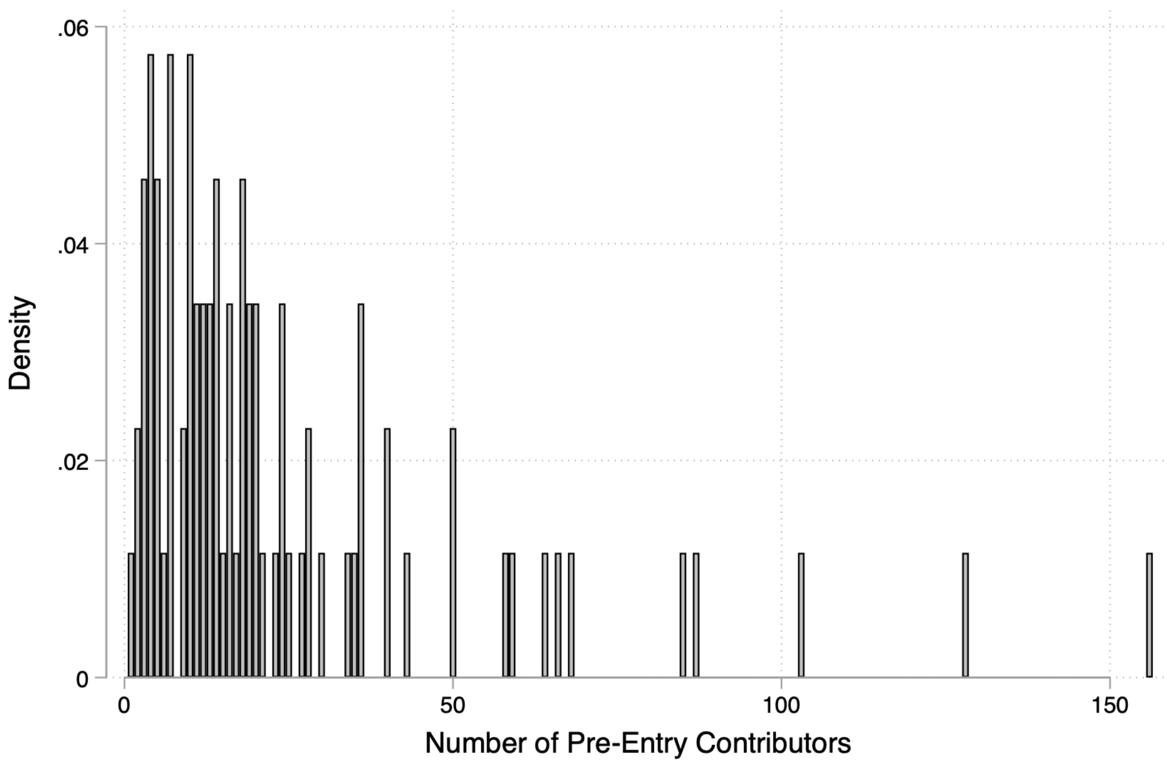
Note: This graph shows how Google Map launched globally with a "blank map".

FIGURE C.3. Average Number of Changes Made Each Edit



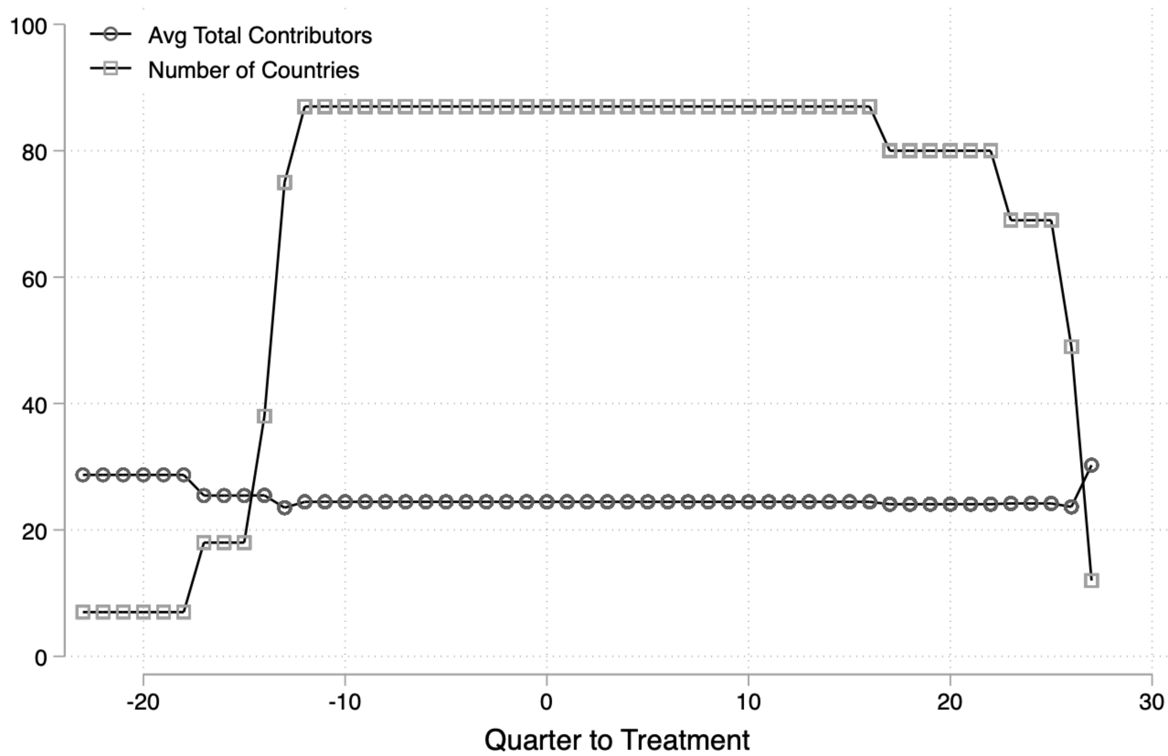
Note: This graph shows the trend in the average number of changes made in each edit over time.

FIGURE C.4. Distribution of the Number of Pre-Entry Contributors



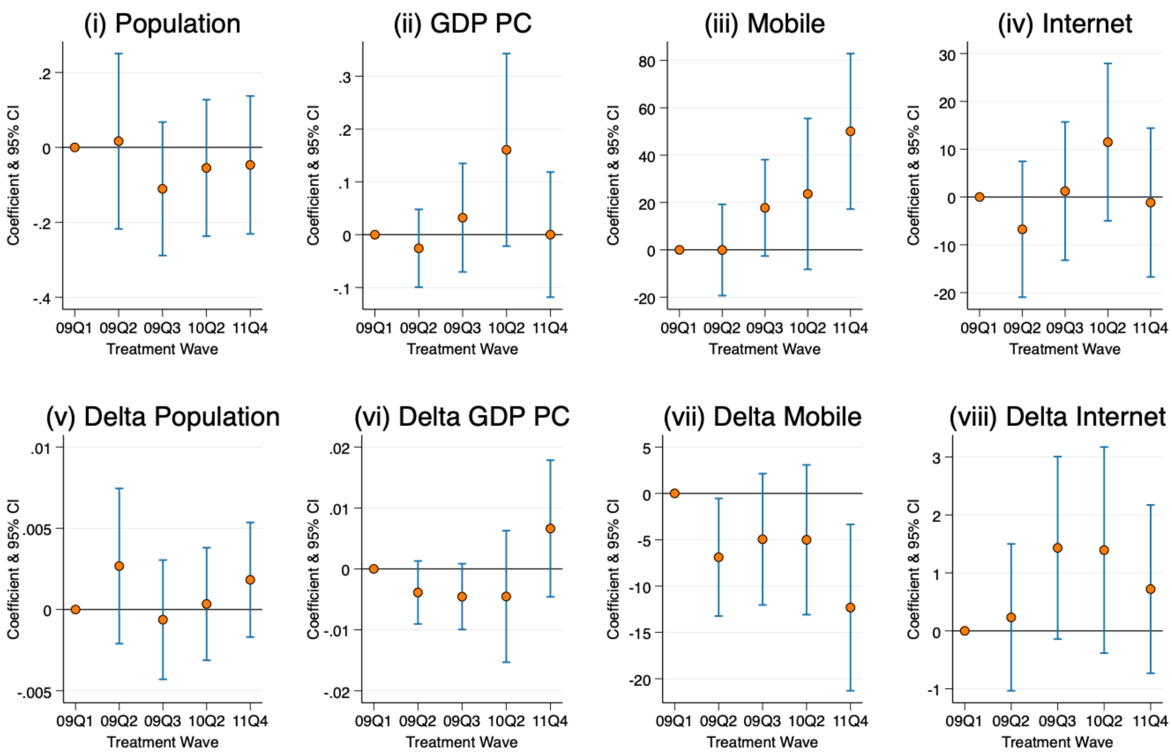
Note: This graph shows the distribution of the number of pre-entry contributors by country.

FIGURE C.5. Size of Pre-entry Sample



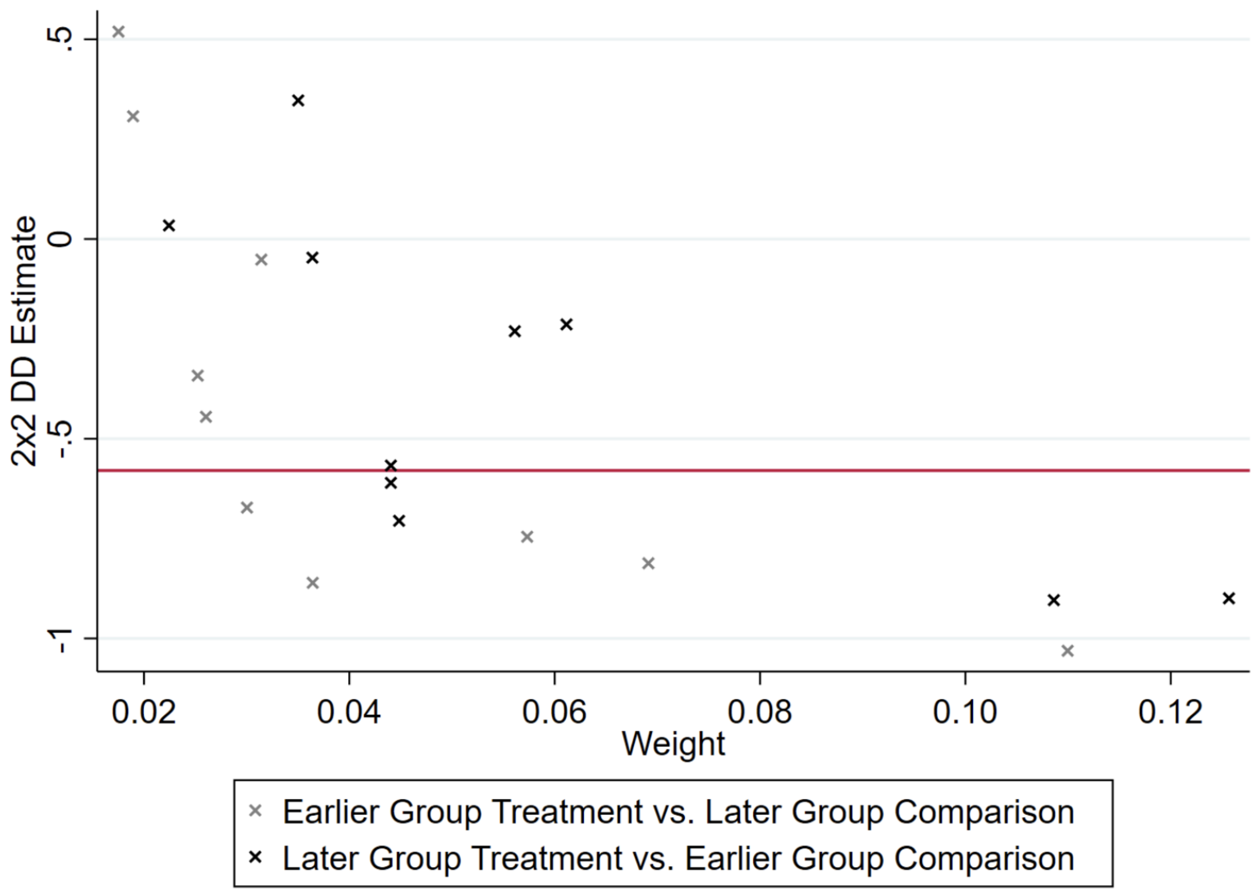
Note: This graph shows the number of countries and the average number of total contributors in the pre-entry sample.

FIGURE C.6. Compare Countries by Wave



Note: This figure compares all the countries depending on the year in which they were treated. Each panel presents coefficients on the years of treatment from cross-sectional regressions of different country-level covariates. The dependent variables in the first row are (i) population, (ii) GDP per capita, (iii) mobile penetration and (iv) internet penetration. Variables in the second row provide a measure of pre-treatment trends, which are (v) change in population, (vi) change in GDP per capita, (vii) change in mobile penetration, and (viii) change in internet penetration. We plot coefficients for each year of digitization, including 95% confidence intervals. The omitted category is the group of countries that were first treated (2009 Q1).

FIGURE C.7. DID Estimate Decomposition

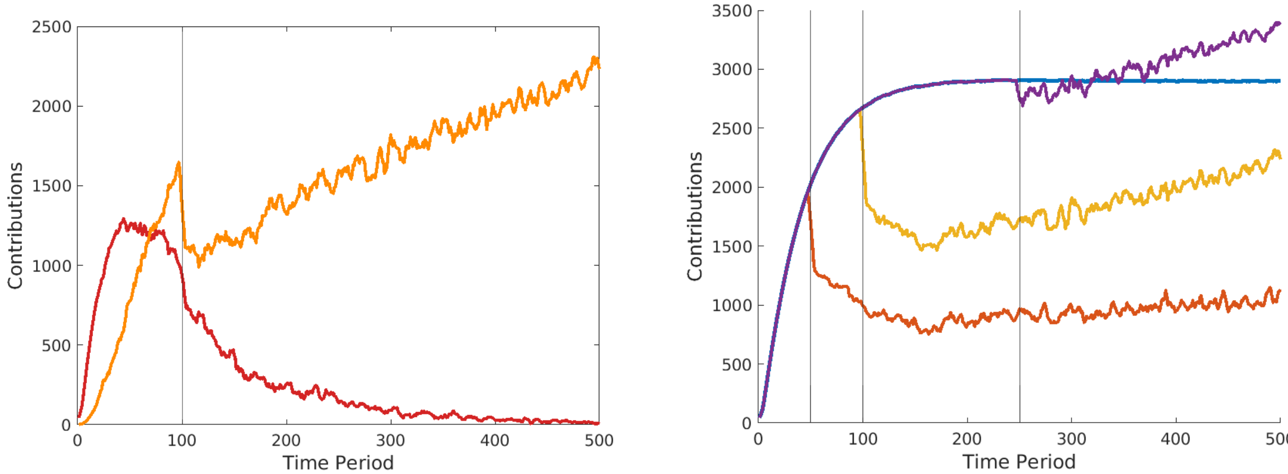


Note: This figure provides the decomposition of DID estimates for the total number of contributions based on Goldman-Bacon (2021). See text for more details.

FIGURE C.8. Simulation Results: Effect of Competition

A. Effect of Competition

B. Timing of Entry

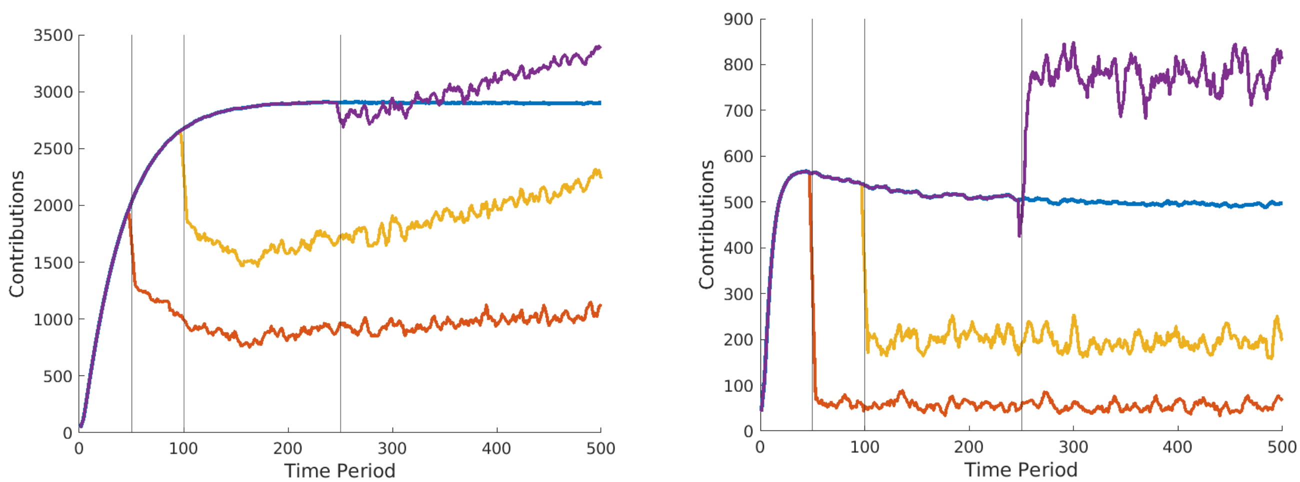


Note: These figures present results from our simulation model. In Panel A, the orange line represents contributions from pre-entry contributors while the red line represents contributions from post-entry contributors. The vertical line represents the time when a competitor enters the market. In Panel B, we present the effects of competition on total contributions. The three vertical lines represent three different scenarios for comepetitive entry, and the three lines (red, yellow and purple) represent the effect on total contributions for early, middle and late entry. The blue line represents the counterfactual with no competitive entry. Please see text for more details and parameter assumptions.

FIGURE C.9. Simulation Results: Exploring Contigencies

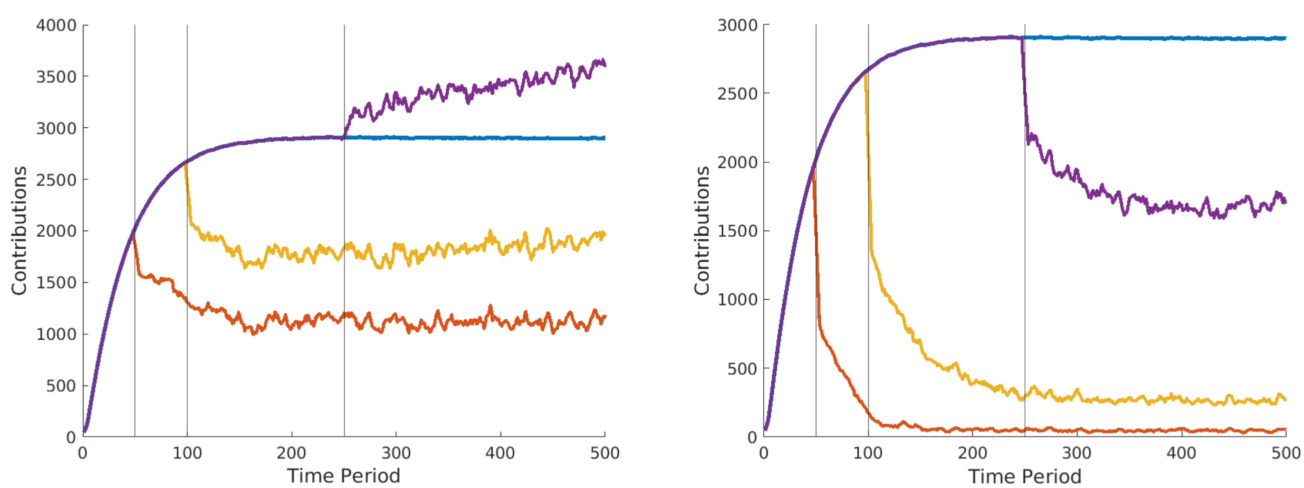
A. Growth Rate

Low High



B. Strength of Competition

Low High



Note: These figures present results from our simulation model. Panel A shows a version of Figure C2, Panel B under different assumptions of natural growth rates for the platform (low on the left, and high on the right). Panel B shows the results of a similar exercise, by varying the strength of the competitor (low on the left, and high on the right).

Table C.1. Examples of Competition between Traditional and Crowdsourced Knowledge Platforms

Category	**Traditional** Professionally sourced, closed	**Crowdsourced** Volunteer, Open
Reference guides		
Online Maps	Google Maps	OpenStreetMap
Encyclopedic Reference	Encyclopaedia Brittanica	Wikipedia
Coding Guides	O'Reilly	Stackoverflow
Reviews/Evaluations		
Restaurant Reviews	Guide Michelin	Yelp
Product Reviews	Consumer Reports	Amazon Reviews
Book Reviews	NY Times	Goodreads
Theater/Arts	National Endowment for Arts	Kickstarter
Startups	TechCrunch, Venture Capital	Angellist
Software		
Mapping Software	ESRI Arc GIS	QGIS
Image Editing Software	Adobe Photoshop	GNU Image Manipulation Pro
Relational Databases	Oracle9i	MySQL
Desktop Publishing	Microsoft Word	OpenOffice
Media & Publishing		
News	Newspapers	Blogs
Financial Analysis	CNBC, Wall Street Journal	Reddit WallStreetBets
Classifieds	Newspapers	Craigslist
Stock Photography	Getty (pre 2005), Corbis	Flickr, iStockPhoto
Video Entertainment	Netflix / Traditional TV	YouTube

Note: This table illustrates a few examples where traditional and crowdsourced platforms compete with each other in different categories. These examples are only illustrative of the diversity in the type of competition we study and are not a comprehensive list of all such types of competition, or even of all the relevant platforms in any given category.

Table C.2. Summary Statistics (Contributor-Quarter Level)

	N	Mean	SD	Median	Min	Max
Outcomes						
Overall Contributions	85080	0.4	14.5	0	0	2649
Total Active Members	85080	0.1	0.2	0	0	1
Timing Variables						
Post	85080	0.6	0.5	1	0	1
Year	85080	2010.5	2.9	2010.5	2006	2015
Controls						
Population (100 millions)	85016	0.4	0.4	.207206	0	2
GDP per capita, PPP (in 100k USD)	80800	0.1	0.1	.0720666	0	1
Mobile Penetration (per 100)	85012	76.6	41.5	76.67284	0	232
Internet Penetration (per 100)	84808	22.6	22.1	14.33	0	98

Note: Observations at the user-quarter level. Data on controls is at the country-year level. GDP per capita is PPP adjusted.

Table C.3. Entry Model

Panel A. Cross-Sectional

	(1) Entry Quarter	(2) Entry Quarter	(3) Entry Quarter
Population (millions)		-0.54	-1.16
		(0.79)	(0.96)
GDP per capita		1.54	2.17
		(2.69)	(2.66)
Mobile Penetration	0.028	0.024	0.016
	(0.019)	(0.019)	(0.019)
Internet Penetration	-0.045	-0.056*	-0.048
	(0.030)	(0.031)	(0.032)
User Contribution Growth			0.019
			(0.014)
N	81	76	76
R2	0.21	0.21	0.24

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B. Discrete Time Hazard Model

	(1) Entry Quarter	(2) Entry Quarter	(3) Entry Quarter	(4) Entry Quarter	(5) Entry Quarter
Population (millions)		0.10	0.10	0.10	0.10
		(0.087)	(0.086)	(0.089)	(0.088)
GDP per capita		-0.31	-0.30	-0.30	-0.31
		(0.28)	(0.26)	(0.29)	(0.29)
Mobile Penetration	-0.0023**	-0.0024**	-0.0023**	-0.0024**	-0.0024**
	(0.00093)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Internet Penetration	0.000070	0.0027	0.0027	0.0026	0.0026
	(0.0033)	(0.0038)	(0.0038)	(0.0039)	(0.0039)
Change Ratio (last quarter)			0.000015		
			(0.000032)		
Change Ratio (last 2 quarters)				-0.000022	
				(0.000044)	
Change Ratio (last 3 quarters)					-0.0000092
					(0.000037)
N	218	204	204	204	204
Quarter FE	Yes	Yes	Yes	Yes	Yes

*p<0.10; **p<0.05; ***p<0.01

Reported coefficients represent marginal effects with quarter fixed effects. Standard errors clustered at the country level.

Note: This table provides estimates of a model predicting the timing of Google Maps entry based on country and openstreet-map characteristics. The key dependent variable is the quarter in which Google Maps enters. Panel A uses a cross-sectional panel of countries, while Panel B presents results from a discrete time probit model.

Table C.4. Impact of Competition on Contributions Interacted with Google Popularity

	(1) Pre-Entry Contributions	(2) Newly Recruited Contributions
Post Google Entry	0.021^{**}	-0.48^{***}
	(0.0096)	(0.17)
Post Google $\times$ High Competition	-0.0020	-0.13
	(0.0096)	(0.14)
Population (millions)	0.081	4.00^{**}
	(0.076)	(1.77)
GDP per capita	-0.13	0.44
	(0.089)	(2.61)
Mobile Penetration	0.00022	0.0063^{**}
	(0.00016)	(0.0028)
Internet Penetration	-0.000035	-0.0037
	(0.00030)	(0.0081)
Community Member FE	Yes	Yes
Quarter FE	Yes	Yes
N	80524	3192
Adj. R2	0.056	0.78

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Estimates the impact of competition from Google Maps on the number of pre-entry and newly-recruited contributions in a differences-in-differences framework and interacts the Post dummy with an indicator of whether the country is of high competition.

Table C.5. Robustness Check: Comparing Pre-trends between Treatment and Control Communities in Log-Linear Models

	Pre-Entry		Newly-Recruited	
	(1)	(2)	(3)	(4)
Google-Entry(-6)	0.012	0.0094	0.72***	0.63***
	(0.021)	(0.021)	(0.23)	(0.23)
Google-Entry(-5)	-0.0072	-0.0085	0.54**	0.49**
	(0.020)	(0.020)	(0.23)	(0.23)
Google-Entry(-4)	-0.0067	-0.0078	0.49**	0.45**
	(0.018)	(0.019)	(0.19)	(0.19)
Google-Entry(-3)	-0.031	-0.032	0.17	0.14
	(0.020)	(0.020)	(0.19)	(0.19)
Google-Entry(-2)	-0.0067	-0.0073	0.24	0.22
	(0.018)	(0.018)	(0.20)	(0.20)
Google-Entry(-1)	0.010	0.010	0.42**	0.41**
	(0.011)	(0.011)	(0.17)	(0.17)
Google-Entry(1)	0.014	0.014	-0.10	-0.090
	(0.014)	(0.014)	(0.15)	(0.15)
Google-Entry(2)	0.027*	0.028*	-0.41**	-0.38**
	(0.015)	(0.015)	(0.17)	(0.18)
Google-Entry(3)	0.0078	0.0087	-0.54***	-0.51***
	(0.016)	(0.016)	(0.17)	(0.17)
Google-Entry(4)	0.0089	0.010	-0.52***	-0.49**
	(0.012)	(0.012)	(0.20)	(0.20)
Google-Entry(5)	0.013	0.014	-0.50**	-0.45*
	(0.013)	(0.013)	(0.22)	(0.23)
Google-Entry(6)	0.016	0.017	-0.52**	-0.46*
	(0.014)	(0.014)	(0.26)	(0.26)
Google-Entry(7)	0.0057	0.0070	-0.70***	-0.65**
	(0.015)	(0.015)	(0.26)	(0.27)
Google-Entry(8)	0.012	0.013	-0.62**	-0.57**
	(0.014)	(0.014)	(0.28)	(0.28)
Google-Entry(9)	0.015	0.017	-0.76**	-0.69**
	(0.014)	(0.014)	(0.30)	(0.31)
Google-Entry(10)	0.012	0.013	-0.83**	-0.77**
	(0.013)	(0.013)	(0.35)	(0.35)
Population (millions)	0.068	0.078	3.90**	4.07**
	(0.076)	(0.074)	(1.84)	(1.78)
GDP per capita	-0.080	-0.11	-0.24	0.21
	(0.064)	(0.091)	(2.02)	(2.46)
Mobile Penetration		0.00021		0.0061**
		(0.00015)		(0.0029)
Internet Penetration		-0.000041		-0.0047
		(0.00031)		(0.0081)
Country FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	80800	80524	3224	3192
Log-likelihood	-18773.1	-18825.5	-4535.8	-4482.8

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table provides estimates from Figure 2 Panel A and B, using the time-varying, log-linear specification $Ln(Y_{it}+1) = \alpha + \Sigma_z \beta_t \times 1(z) + \gamma_i + \delta_c t + \varepsilon_{ict}$ where γ_i and δ_t represent country and region fixed effects respectively for country or contributor i and quarter t. z represents the "lag", or the quarters relative to a "zero quarter", which marks the quarter when a country first faced competition from Google Maps except for $z > 10$ and $z < -6$ where z equals 10 and -6 respectively.

Table C.6. Heterogenous Effect of Competition on Pre-Entry Contributors without Control Community Size

	Ideology		Social		Standing		All
	(1) Github	(2) Firefox Share	(3) Maillist	(4) Events	(5) Rank	(6) Contribs	(7) —
Post Google Entry	0.013	0.0094	0.015	0.014	0.029^{***}	0.028^{***}	0.021^{*}
	(0.0097)	(0.010)	(0.0094)	(0.0097)	(0.010)	(0.0092)	(0.011)
Post X High-Ideology	0.023^{**}	0.015^{*}					0.021^{**}
	(0.011)	(0.0080)					(0.010)
Post X High-Social			0.016	0.016			0.0063
			(0.011)	(0.010)			(0.011)
Post X High-Standing					-0.039^{*}	-0.079^{**}	-0.039^{*}
					(0.022)	(0.033)	(0.023)
N	80524	80524	80524	80524	80524	80524	80524
adj. R^2	0.056	0.056	0.056	0.056	0.057	0.057	0.057

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: We present estimates decomposing the positive effect of pre-entry users depending on different drivers of attachment for this group of contributors. In three different analyses, we evaluate the role of ideological environment, opportunities for social interaction and the standing of the contributor, along with a model that includes all three factors. For each analysis, we classify a contributor as belonging to a group that ranks highly on each dimension and provide a heterogenous response to the effect of competitive entry. High-Ideology equals one if the contributor belongs to a country with above-median github contributions or firefox market share, High-Social equals one if a contributor belongs to a community with a mailing-list or has hosted a mapping event and High-Standing equals one if a contributor ranks in the top 5 by contributions or has more than 10 contributions in her community. All models include interactions by community size as well as an additional control. Please see text for more details.

Table C.7. Impact of Competition of Contributions Controlling for Community Size

(a) Pre-Entry Contributors

	(1) Contributions	(2) Contributions	(3) Contributions	(4) Contributions
Post Google Entry		0.018**	0.018**	0.019**
		(0.0085)	(0.0088)	(0.0089)
Population (millions)	0.12		0.11	0.12
	(0.075)		(0.077)	(0.076)
GDP per capita	-0.11		-0.057	-0.12
	(0.094)		(0.069)	(0.095)
Mobile Penetration	0.00012			0.00014
	(0.00015)			(0.00015)
Internet Penetration	0.00019			0.00018
	(0.00039)			(0.00040)
Lag Community Size	0.0039**	0.0039**	0.0039**	0.0039**
	(0.0016)	(0.0015)	(0.0015)	(0.0016)
Community Member FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	80448	84993	80718	80448
Adj. R2	0.058	0.058	0.059	0.058

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Newly Recruited Contributors

	(1) Contributions	(2) Contributions	(3) Contributions	(4) Contributions
Post Google Entry		-0.58***	-0.56***	-0.52***
		(0.14)	(0.14)	(0.15)
Population (millions)	1.76*		1.59	1.71
	(1.03)		(1.09)	(1.03)
GDP per capita	0.016		-0.67	0.18
	(1.89)		(1.56)	(1.86)
Mobile Penetration	0.0064***			0.0059**
	(0.0023)			(0.0023)
Internet Penetration	-0.0086			-0.0085
	(0.0070)			(0.0069)
Lag Community Size	0.0040***	0.0043***	0.0040***	0.0040***
	(0.0011)	(0.0012)	(0.0011)	(0.0011)
Country FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	3116	3393	3142	3116
Adj. R2	0.78	0.78	0.78	0.78

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table replicates the baseline specification with an additional co-variate controlling for lagged community size.

Table C.8. Impact of Competition on Contributions Interacted with Community Size

(a) Pre-Entry Contributors

	(1) Contributions	(2) Contributions	(3) Contributions	(4) Contributions
Post Google Entry		0.021**	0.024**	0.024**
		(0.0096)	(0.010)	(0.0100)
Post × Mid-Size		-0.0029	-0.0073	-0.0055
		(0.0086)	(0.0090)	(0.0089)
Post × High-Size		-0.0034	-0.0084	-0.0066
		(0.012)	(0.011)	(0.011)
Population (millions)	0.079		0.093	0.098
	(0.075)		(0.071)	(0.068)
GDP per capita	-0.12		-0.074	-0.12
	(0.090)		(0.069)	(0.091)
Mobile Penetration	0.00020			0.00021
	(0.00015)			(0.00014)
Internet Penetration	-0.000045			0.0000059
	(0.00031)			(0.00031)
Community Member FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	80524	85080	80800	80524
Adj. R2	0.056	0.056	0.056	0.056

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Newly Recruited Contributors

	(1) Contributions	(2) Contributions	(3) Contributions	(4) Contributions
Post Google Entry		-0.89***	-0.83***	-0.77***
		(0.17)	(0.17)	(0.18)
Post × Mid-Size		0.28***	0.24***	0.22***
		(0.077)	(0.080)	(0.077)
Post × High-Size		0.48***	0.41***	0.41***
		(0.11)	(0.11)	(0.11)
Population (millions)	4.23**		3.01*	3.23*
	(1.80)		(1.72)	(1.64)
GDP per capita	0.12		-0.29	0.27
	(2.57)		(1.90)	(2.36)
Mobile Penetration	0.0070**			0.0067**
	(0.0028)			(0.0028)
Internet Penetration	-0.0047			-0.0056
	(0.0082)			(0.0078)
Country FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	3192	3480	3224	3192
Adj. R2	0.78	0.78	0.78	0.78

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.9. Alternate Definitions of Newly-Recruited Contributions

Panel A: 2 Quarters

	(1) Contributions	(2) Contributions	(3) Contributions	(4) Contributions
Post Google Entry		-0.56***	-0.54***	-0.50***
		(0.14)	(0.15)	(0.15)
Population (millions)	2.55		2.29	2.48
	(1.65)		(1.75)	(1.66)
GDP per capita	-1.30		-2.37	-1.04
	(2.64)		(2.23)	(2.56)
Mobile Penetration	0.0068**			0.0062*
	(0.0031)			(0.0031)
Internet Penetration	-0.012			-0.012
	(0.0094)			(0.0093)
Country FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	2692	2922	2700	2692
Adj. R2	0.66	0.66	0.66	0.67

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: 6 Quarters

	(1) Contributions	(2) Contributions	(3) Contributions	(4) Contributions
Post Google Entry		-0.54***	-0.53***	-0.48***
		(0.16)	(0.17)	(0.17)
Population (millions)	2.15		1.86	2.08
	(1.57)		(1.69)	(1.58)
GDP per capita	0.19		-1.08	0.43
	(2.78)		(2.33)	(2.70)
Mobile Penetration	0.0078**			0.0072**
	(0.0034)			(0.0034)
Internet Penetration	-0.014			-0.013
	(0.010)			(0.010)
Country FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	2692	2922	2700	2692
Adj. R2	0.69	0.68	0.69	0.69

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Contributors are considered “post-entry” if they made their first contribution in the focal quarter of the quarter before (Panel A) or upto six quarters preceeding the focal quarter (Panel B).

Table C.10. Evaluating Robustness to Alternate Specifications

	Pre-Entry			Newly-Recruited		
	(1) Poisson	(2) Diff. Trends	(3) Placebo	(4) Poisson	(5) Diff. Trends	(6) Placebo
Post Google Entry	0.78***	0.021*	0.00053	-0.27***	-0.54***	-0.091
	(0.037)	(0.012)	(0.0090)	(0.0084)	(0.16)	(0.11)
Population (millions)	4.23***	0.069	0.079	3.66***	3.16*	4.24**
	(0.22)	(0.073)	(0.075)	(0.076)	(1.73)	(1.79)
GDP per capita	-2.43***	-0.11	-0.12	-6.94***	0.88	0.14
	(0.70)	(0.083)	(0.090)	(0.16)	(1.17)	(2.61)
Mobile Penetration	0.0067***	0.00019	0.00020	0.0074***	0.0051**	0.0070**
	(0.00055)	(0.00016)	(0.00015)	(0.00012)	(0.0021)	(0.0028)
Internet Penetration	0.044***	-0.000013	-0.000045	-0.017***	0.0040	-0.0048
	(0.0011)	(0.00032)	(0.00031)	(0.00031)	(0.0060)	(0.0082)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Quarter	Inc. X Quarter	Quarter	Quarter	Inc. X Quarter	Quarter
Age FE	No	No	No	No	No	No
N	80524	80524	80524	3192	3192	3192
Adj. R2		0.057	0.057		0.79	0.78

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table evaluates the robustness of the baseline results to alternate specifications for contributions by pre-entry and post-entry contributors in two sets of analyses. In each analysis, the first column estimates a specification similar to the baseline specification, using Poisson rather than Log-OLS models with the dependent variable being $Contributions_{it}$ and reports standard errors clustered at the country level. The second model estimates the log OLS models using the baseline specification, except these estimates include region-specific time-trends rather that common quarter fixed effects across regions. Specifically, this model includes, IncomeClass X Quarter fixed effects, where countries in the High income category (based on the World Bank Income Classification) have a spearate time trend as compared to the rest. Finally, the third model presents results from a placebo exercise where countries are randomly assigned to the five Google Maps entry cohorts, and the *Post Google Entry* variable represents the period after this randomly assigned date.

Table C.11. Impact of Competition of Contributions Removing Outliers

(a) Pre-Entry Contributors

	(1) Contributions	(2) Contributions	(3) Contributions	(4) Contributions
Post Google Entry		0.017^{*}	0.016	0.018^{*}
		(0.0096)	(0.0098)	(0.010)
Population (millions)	0.031		0.028	0.033
	(0.049)		(0.051)	(0.050)
GDP per capita	-0.066		-0.077	-0.067
	(0.077)		(0.060)	(0.077)
Mobile Penetration	0.00026^{*}			0.00028^{*}
	(0.00015)			(0.00014)
Internet Penetration	-0.00033			-0.00036^{*}
	(0.00021)			(0.00021)
Community Member FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	65456	69600	65732	65456
Adj. R2	0.058	0.058	0.058	0.058

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Newly Recruited Contributors

	(1) Contributions	(2) Contributions	(3) Contributions	(4) Contributions
Post Google Entry		-0.63^{***}	-0.61^{***}	-0.56^{***}
		(0.14)	(0.15)	(0.16)
Population (millions)	3.84^{**}		3.64^{**}	3.78^{**}
	(1.66)		(1.76)	(1.66)
GDP per capita	0.14		-0.26	0.29
	(2.53)		(2.06)	(2.51)
Mobile Penetration	0.0072^{**}			0.0067^{**}
	(0.0028)			(0.0028)
Internet Penetration	-0.0055			-0.0055
	(0.0085)			(0.0084)
Country FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	3076	3360	3108	3076
Adj. R2	0.78	0.78	0.78	0.78

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table replicates the baseline specification. For contributors who contribute to multiple countries, only the country with the highest number of contributions counts.

Table C.12. The Impact of Competition on the number of Pre-Entry Contributors

	(1) Contributors	(2) Contributors	(3) Contributors	(4) Contributors
Post Google Entry		-0.032	-0.032	-0.027
		(0.053)	(0.056)	(0.057)
Population (millions)	-0.44		-0.38	-0.45
	(0.39)		(0.39)	(0.39)
GDP per capita	-0.11		-0.35	-0.098
	(0.64)		(0.55)	(0.64)
Mobile Penetration	0.00068			0.00065
	(0.00086)			(0.00086)
Internet Penetration	-0.0034*			-0.0034**
	(0.0017)			(0.0017)
Country FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	3192	3480	3224	3192
Adj. R2	0.66	0.65	0.66	0.66

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Estimates the impact of competition from Google Maps on the number of pre-entry OpenStreetMap contributors in a differences-in-differences framework. The unit of analysis is country-quarter. The outcome variable is $Contributor_{it}$ and is measured as the total number of pre-entry contributors in country i in a given quarter t. $Post\ Google\ Entry_{it}$=1 after Google Maps has entered the country i in a given quarter. The control variables X_{it} include population, GDP, internet penetration, and mobile penetration, and they vary at the country-year level. γ_i and δ_t indicate fixed effects for country and quarter respectively. Clustered standard errors at the country level are reported.

Table C.13. CEM and Time-Varying Trends

	New Recruits Contributions	
	(1)	(2)
Post Google Entry	-0.42*	-0.42*
	(0.23)	(0.23)
Cntry-Pair FE	Yes	Yes
Time FE	Quarter	Income X Q
Sample	CEM	CEM
N	6400	6380
Adj. R2	0.75	0.76

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This model provides additional robustness checks on the baseline models with a larger sample of countries matched using CEM. Cols 2 and 4 using time-varying income-group times quarter fixed effects while Cols 1 and 3 include quarter fixed effects only

Table C.14. Testing Ideology Using 512 Matched Users

	(1) Github	(2) Firefox Share	(3) Combined
Post Google Entry	0.0079	0.0083	0.014
	(0.014)	(0.015)	(0.021)
Post X High-Ideology	0.034***	0.023*	0.027***
	(0.0100)	(0.013)	(0.0088)
Post X High-Standing			-0.036
			(0.041)
Post X High-Social			0.018
			(0.014)
N	37156	37156	37156
adj. R^2	0.055	0.054	0.055

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents robustness to the regression examining the mechanisms underlying the positive response of pre-entry contributors. We match 512 "high ideology" pre-entry users with a similar number of control users based on the quarter of Google Maps entry, income and region category and with a similar pattern of contributions prior to Google Maps entry. In the final column, high-ideology is measured based on Github contributions, standing based on rank in terms of contributions and social in terms of whether the community has a mailing list. See text for more details.

Table C.15. Impact of Competition of Contributions Dropping the 5^{th} Wave

(a) Pre-Entry Contributors

	(1) Contributions	(2) Contributions	(3) Contributions	(4) Contributions
Post Google Entry		0.040***	0.043***	0.043***
		(0.012)	(0.013)	(0.013)
Population (millions)	0.079		0.074	0.085
	(0.076)		(0.081)	(0.078)
GDP per capita	-0.097		-0.061	-0.092
	(0.11)		(0.099)	(0.12)
Mobile Penetration	0.00025			0.00024
	(0.00016)			(0.00016)
Internet Penetration	-0.000089			-0.000081
	(0.00033)			(0.00035)
Community Member FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	72484	77040	72760	72484
Adj. R2	0.056	0.056	0.056	0.056

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Newly Recruited Contributors

	(1) Contributions	(2) Contributions	(3) Contributions	(4) Contributions
Post Google Entry		-0.57***	-0.49***	-0.48***
		(0.14)	(0.15)	(0.15)
Population (millions)	4.64**		4.34**	4.59**
	(1.91)		(1.99)	(1.90)
GDP per capita	0.61		-0.11	0.76
	(2.58)		(2.28)	(2.61)
Mobile Penetration	0.0074**			0.0074**
	(0.0029)			(0.0029)
Internet Penetration	-0.0072			-0.0074
	(0.0083)			(0.0083)
Country FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	2912	3200	2944	2912
Adj. R2	0.78	0.77	0.78	0.78

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table replicates the baseline specification with only the first 4 waves of treatment.

Table C.16. Country-level Heterogeneous Impact of Competition on Contributions

(a) Pre-Entry Contributors

	(1) Population	(2) GDP PC	(3) Mobile	(4) Internet
Post Google Entry	0.019	0.012	0.019^{*}	0.010
	(0.013)	(0.011)	(0.011)	(0.010)
Post × High	0.0014	0.012	0.0017	0.016
	(0.0096)	(0.0096)	(0.011)	(0.0098)
Population (millions)	0.078	0.094	0.086	0.095
	(0.075)	(0.072)	(0.088)	(0.071)
GDP per capita	-0.12	-0.15	-0.12	-0.13
	(0.092)	(0.10)	(0.094)	(0.097)
Mobile Penetration	0.00023	0.00026	0.00023	0.00028^{*}
	(0.00015)	(0.00016)	(0.00015)	(0.00016)
Internet Penetration	-0.000055	-0.00025	-0.000078	-0.00039
	(0.00032)	(0.00030)	(0.00030)	(0.00032)
Country FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	80524	80524	80524	80524
Adj. R2	0.056	0.056	0.056	0.056

Standard errors in parentheses

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

(b) Newly Recruited Contributors

	(1) Population	(2) GDP PC	(3) Mobile	(4) Internet
Post Google Entry	-0.85^{***}	-0.36^{*}	-0.48^{**}	-0.64^{***}
	(0.20)	(0.21)	(0.21)	(0.20)
Post × High	0.63^{***}	-0.26	-0.052	0.22
	(0.16)	(0.19)	(0.20)	(0.19)
Population (millions)	-0.029	2.26	2.74^{*}	3.06^{*}
	(1.03)	(1.58)	(1.62)	(1.65)
GDP per capita	2.94	3.26	2.91	2.81
	(1.99)	(2.36)	(2.39)	(2.37)
Mobile Penetration	0.0082^{***}	0.0080^{***}	0.0083^{**}	0.0086^{***}
	(0.0028)	(0.0030)	(0.0032)	(0.0030)
Internet Penetration	-0.0024	0.0018	-0.0023	-0.0084
	(0.0078)	(0.0085)	(0.0086)	(0.0096)
Country FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	3192	3192	3192	3192
Adj. R2	0.84	0.84	0.84	0.84

Standard errors in parentheses

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

Note: This table replicates the baseline specification and interacts the Post dummy with indicators of country-level heterogeneity. Column (1) interacts with an indicator of high population, column (2) interacts with an indicator of high GDP per capita, column (3) interacts with an indicator of high mobile penetration, and column (4) interacts with an indicator of high internet penetration.

Table C.17. Impact of Competition on Contributions Dropping Multi-country Contributors

(a) Pre-Entry Contributors

	(1) Contributions	(2) Contributions	(3) Contributions	(4) Contributions
Post Google Entry		0.045^{**}	0.044^{**}	0.046^{**}
		(0.019)	(0.019)	(0.019)
Population (millions)	0.14		0.13	0.15
	(0.14)		(0.14)	(0.15)
GDP per capita	-0.14		-0.31	-0.15
	(0.17)		(0.21)	(0.18)
Mobile Penetration	0.00056^{**}			0.00060^{***}
	(0.00023)			(0.00021)
Internet Penetration	-0.0014^{***}			-0.0014^{***}
	(0.00050)			(0.00051)
Community Member FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	108852	114720	109344	108852
Adj. R2	0.013	0.012	0.013	0.013

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Newly Recruited Contributors

	(1) Contributions	(2) Contributions	(3) Contributions	(4) Contributions
Post Google Entry		-1.14^{***}	-1.10^{***}	-1.04^{***}
		(0.18)	(0.19)	(0.20)
Population (millions)	7.53^{***}		7.02^{**}	7.41^{***}
	(2.80)		(2.72)	(2.79)
GDP per capita	0.95		1.73	1.25
	(3.77)		(3.05)	(3.75)
Mobile Penetration	0.0091^{**}			0.0082^{*}
	(0.0042)			(0.0042)
Internet Penetration	0.0047			0.0046
	(0.011)			(0.011)
Country FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	3192	3480	3224	3192
Adj. R2	0.63	0.61	0.63	0.63

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table replicates the baseline specification. For contributors who contribute to multiple countries, only the country with the highest number of contributions counts.