Deterring the New, Motivating the Established—
The Divergent Effect of Platform Competition on Member Contributions in Digital Mapping Communities

Abhishek Nagaraj
UC Berkeley-Haas
nagaraj@berkeley.edu

Henning Piezunka
INSEAD
henning.piezunka@insead.edu

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Abstract

While popular platforms developed by knowledge-producing communities such as Wikipedia and Linux co-exist and compete with alternatives such as Encyclopedia Britannica and Microsoft Windows, we understand little about how such competition affects those communities. We develop a theory where competition has a divergent effect on community members’ contribution—it deters potential new members from joining the community and contributing, but motivates established members to increase their contributions. To test this theory, we examine how community members’ contributions to OpenStreetMap (a widely-used digital mapping platform) changed following the competitive entry of Google Maps. We exploit the phased entry of Google Maps in different countries over time to isolate the effect of competition and our findings support our theory on the divergent effects of competition. We also find that social interaction among community members attenuates the deterrent effect of competition on potential new members, but strengthens the motivating effect of competition on established members. We discuss the implications for research on contributions to knowledge-producing communities, platform competition, and the effect of competition on organizations.

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Platforms that rely on contributions from community members such as Linux, Firefox and Wikipedia produce impressive bodies of knowledge and provide significant value to firms and society (Greenstein and Nagle, 2014; Jeppesen and Lakhani, 2010; Nagle, 2017). Yet such community-based platforms do not exist in isolation: Linux faces competition from Microsoft Windows, Firefox from Google Chrome, and Wikipedia from Encyclopedia Britannica.\(^1\) However, very little is known about the way community members respond when the community they contribute to faces competition. While prior research has uncovered what motivates them to volunteer and contribute their knowledge (e.g. Boudreau and Jeppesen (2015); Jeppesen and Frederiksen (2006); Lakhani and Wolf (2005); Ren et al. (2012); Shah (2006); Zhang and Zhu (2011)), the effect of competition on members’ contributions has been largely overlooked.

Past research provides arguments that would support both an increase or a decrease of contributions when the community faces competition. On the one hand, community members’ contributions may decrease their contributions. Community members often contribute when they use the platform and see opportunities to improve it. Contributing improves the platform they use and lets them gain social recognition (Boudreau and Jeppesen, 2015; Zhang and Zhu, 2011). Ceteris paribus, competition reduces platform usage and provides less opportunities to contribute and gain social recognition. Community members may thus reduce their contributions. On the other hand, community members may increase their contributions. Community members often identify with the community: they value being embedded in it (Ren et al., 2007, 2012; Zhang and Zhu, 2011) and appreciate its underlying ideology (Shah, 2006). Community members also benefit from prior contributions they made (e.g., they may have adjusted the platform to fit their personal needs or they may enjoy social recognition within the community). Competition is likely to motivate community members because it strengthens identification (Sherif et al., 1961), and endangers endowed benefits that community members derive from their prior efforts. Community members may thus contribute more.

While these arguments may seem to be in conflict as they render both, a decrease and an increase of contributions plausible, we develop a coherent theory integrating these seemingly incompatible arguments. We suggest competition to have a divergent effect. We hypothesize that potential new members will be de-

\(^1\) We define community-based platforms as a volunteer-led (non-profit) initiative where members self-select to join a community and to create a body of openly available knowledge.
tered by competition and hence decrease their contributions, whereas *established community members* will identify more strongly with the community and be motivated to increase their contributions.

We test our theory of the the divergent effect of competition by analyzing the effect of competitive entry by Google Maps on contributions to the community-based mapping platform OpenStreetMap, one of the largest community-based platforms on the web, with about half the number of active members as Wikipedia (Maher, 2016). To assess the impact of competition we exploit the fact that while OpenStreetMap had a global scope from the beginning (2004), Google Maps started in a handful of countries and expanded on a country-by-country basis after its inception in 2005. This phased roll-out, while not explicitly random, can reliably be exploited to evaluate the impact of competitive entry on member contributions to OpenStreetMap (cp. Seamans and Zhu (2014, 2017)). To capture the impact of this expansion, we develop a novel quantitative sample capturing over 2.4 million contributions between 2004 and 2015 made by 89,000 members of OpenStreetMap communities in the 87 countries that saw the entry of Google Maps as per our data. Further, we also personally familiarized ourselves with the OpenStreetMap platform by attending and presenting at multiple OpenStreetMap events. We joined OpenStreetMap mailing lists, contributed to the platform, and had numerous conversations with other community members.

We find that competition has indeed a divergent effect. *Competition deters potential new members* from joining and contributing to the community, resulting in a *decrease* in contributions from new members. At the same time *competition motivates established community members*, prompting an *increase* in contributions. However, the effects of competition are not uniform: in communities with *social interactions* among members, the deterrent effect on potential new members is attenuated, while the positive effect on established members’ contributions is strengthened.

Our study contributes to research on *knowledge-producing communities*. We advance this research by illustrating how (micro) factors underlying the motivation of community members (Boudreau and Jeppesen, 2015; Jeppesen and Frederiksen, 2006; Ren et al., 2012; Shah, 2006; Zhang and Zhu, 2011) interact with the community’s (macro) environment, allowing us to develop a theory of the effect of competition on knowledge-producing communities. By examining competition between communities and commercial alternatives we also add to prior research that tends to focus on the potential for collaboration between commercial firms and communities (Dahlander and Wallin, 2006; Nagle, 2017). Our study also contributes to research on *platform competition*. Prior research has examined how platforms are affected by and respond to com-
petition from other platforms (Lee, 2013; Seamans and Zhu, 2014, 2017; Zhu and Iansiti, 2012), as well as competition among complementors or competition between the platform and its complementors (Boudreau, 2012; Boudreau et al., 2011, 2016; Cantillon and Yin, 2008; Gawer and Henderson, 2007; Huang et al., 2013; Kapoor and Agarwal, 2017; Zhu and Liu, 2016) Our study indicates how complementors may respond if the platform to which they contribute faces competition. More broadly, our study contributes to research on the effect of competition on organizations. While prior research has illustrated how (members of) organizations faced with competition adjust and intensify their efforts (Polidoro and Toh, 2011; Zhou and Ethiraj, 2018), our theory suggests that organizations that face competition may benefit from increased efforts from current members, they struggle to recruit new members, and thus have difficulty renewing themselves.

**Theoretical Background**

Despite the fact that most community-based platforms face competition, research on the effects of competition is scarce. Seamans and Zhu (2014, 2017) examine how competition from community-based platforms affects commercial platforms, notably how the geographical expansion of the community-based Craigslist affected local newspapers. Their research design—ours is similar to theirs—enables them to examine the negative effect of competition from community-based platforms on commercial alternatives. However, it sheds no light on the reverse question of how competition affects community-based platforms. Examining this reverse effect is important since knowledge-producing communities are radically different from commercially-driven platforms (since they have no formal contracts and largely volunteer contributors) and play an increasingly important role in terms of their contribution to the economy (Greenstein and Nagle, 2014). A formal model by Athey and Ellison (2014) examines the effect of competition on knowledge-producing communities, illustrating how different assumptions about the response of members affects competition between commercial and community-based platforms. The ‘missing link’ is to develop and test a theory to explain how community members adjust their contributions when a platform they contribute to faces competition.
Motivation to contribute to community-based knowledge production

To understand how competition may affect community members’ contributions, we review the research on what motivates community members to contribute to community-based knowledge platforms. Starting from the puzzle of why community members contribute without being compensated (Lerner and Tirole, 2002), research has identified a variety of motivating factors (for an overview, see Von Krogh et al. (2012)). Various disciplines have contributed to this body of knowledge (Raasch et al., 2013), including scholars in economics (Boudreau and Jeppesen, 2015; Zhang and Zhu, 2011), information systems (Bagozzi and Dholakia, 2006; Fershtman and Gandal, 2007; Kane and Ransbotham, 2016; Kraut et al., 2012; Ren et al., 2012; Stewart and Gosain, 2006) and organizational theory (Alexy et al., 2013; Gallus, 2016; Jeppesen and Frederiksen, 2006; Lakhani and Wolf, 2005; Shah, 2006). They draw upon different motivational theories, e.g., of self-determination (Ryan and Deci, 2000), social identity (Tajfel et al., 1971), self-concept (Leonard et al., 1999), and norms (Alexy and Leitner, 2011)) to explain why individuals contribute to different forms of community-based knowledge production (e.g., knowledge platforms (Nagaraj, 2017a; Nov, 2007), ideation initiatives (Bayus, 2013; Dahlander and Piezunka, 2014), free and open-source software (Greenstein and Zhu, 2012; Lerner and Tirole, 2002)). Our focus is on research that examines why people start contributing as well as on research that examines why people continue to contribute.2

Research on why people start contributing has examined where new community members come from and why they start contributing. Community members often start out as users of a community-created platform (Gorbatai, 2014; Johnson, 2002). For example, people often start out as users of the Linux operating system before becoming contributing community members. When using the platform, they spot opportunities to improve it (Kane and Ransbotham, 2016), such as a bug they can fix or a feature they can add – and hence they become contributing community members.3 They may be willing to contribute in part because they themselves have already benefited from the platform and now want to give back (reciprocity) (Franke and Shah, 2003); or because as users of the platform they too will benefit from the improvement,4 or because

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2 Note that in other types of community-based knowledge production, other types of motivational factors play a role. For example, scholars studying the motivation underlying contributions to free and open-source software have pointed to the role of career concerns or the potential to leverage complementarities with commercial applications (Lerner et al., 2006; Lerner and Tirole, 2002; Nagle, 2017).

3 Their trajectory can be compared to the one of accidental entrepreneurs who become entrepreneurs while searching for a solution for their own problem (Shah and Tripsas, 2007).

4 As noted by The Economist in an article about Linus Torvalds’ contributions to Linux: “In writing his program, Mr Torvalds was just scratching his own itch: he simply needed what later became Linux for his own PC” (Economist, 2016)
doing so allows them to gain social recognition (Boudreau and Jeppesen, 2015; Fershtman and Gandal, 2011; Gallus, 2016; Jeppesen and Frederiksen, 2006; Zhang and Zhu, 2011).

Research on why people continue contributing once they become established community members has found that their reasons to continue contributing evolve (from those that got them started) (Shah, 2006): they begin to identify with the community (Ren et al., 2012); part of their identification with the community is anchored in their relationships with other community members with whom they share a “consciousness of kind” (Bagozzi and Dholakia, 2006) (p. 1099) (see also Ouchi (1980)) and maintaining these relationships is an important part of their motivation to contribute (Ren et al., 2007, 2012; Zhang and Zhu, 2011). Established community members also identify with the ideology underlying the community, e.g., free distribution of the knowledge and openness for anyone to participate (Alexy et al., 2013; Bagozzi and Dholakia, 2006; Belenzon and Schankerman, 2015; Lakhani and Wolf, 2005; Shah, 2006; Stallman, 1999; Stewart and Gosain, 2006). The relationships with other community members and their belief in the community’s ideology lets established community members identify with their community and motivates them to contribute.

Established community members may continue contributing because they also derive benefits from their own prior contributions. Their own contributions increase the value that the platform generates for them (Lakhani and Wolf, 2005), e.g., a group of wheelchair users developed a map-layer for OpenStreetMap specifically fulfilling their needs from which they continued to benefit. It is in part due to such benefits (which originated from their prior contributions) that they continue to use and to contribute to the community-based platform. Similarly, prior contributions may have also allowed established community members to develop a reputation and to accumulate status (Johnson, 2002). For example, within OpenStreetMap, certain users who performed tasks like adding all the major highways in the region have gained a reputation as a “super mapper” within the community. By continuing to contribute, members maintain the benefits they derive from their prior contributions.

**Hypotheses**

We develop a theory on the effect of competition on contributions by community members where competition has a *divergent* effect: we suggest that competition *deters* new community members from joining the collaboration. 

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5Similarly, in crowd science (Franzoni and Sauermann, 2014), contributors are motivated by the desire to provide open scientific knowledge to enable breakthrough discoveries.
community, resulting in a decrease of contributions from them, but *motivates* established members prompting an increase in their contributions.

We hypothesize that competition has a negative effect on contributions from new community members because it diminishes the pool of potential new community members, and reduces the share of potential new community members who actually become community members. Competition *is likely to diminish the pool* because, ceteris paribus, it results in less people using the platform. For example, the entry of Google Maps would result in less people using OpenStreetMap, and since users constitute the main pool of potential new community members, a reduction in users will negatively affect the number who actually become new community members.

Competition is also likely to reduce the *share* of users who become community members. In part, community members’ contributions are motivated by the potential to improve the platform – addressing an issue that concerned their own usage (Kane and Ransbotham, 2016). In the presence of a competitor, users may first check whether the competing platform has already resolved the issue – and if so switch to the competing platform rather than contributing and becoming a community member.\(^6\) The share of users who become community members may also be reduced because of the smaller audience they can reach and lower social recognition to be gained (Boudreau and Jeppesen, 2015; Fershtman and Gandal, 2011; Gallus, 2016; Jeppesen and Frederiksen, 2006; Zhang and Zhu, 2011). The competition-induced reduction of the number of users thus makes it less attractive for them to join the community and start contributing. Shah (2006) cites a programmer: “Why work on something that no one will use? There’s no satisfaction there.” Finally, potential community members may be unwilling to join a community ‘under siege’, whose survival is in doubt. They may be worried that any contribution they make will ultimately be in vain, and be unwilling to engage in a competitive battle that is not theirs.

**Hypothesis 1 (H1):** Competition decreases contributions by new community members.

In contrast, we hypothesize that competition has a positive effect on contributions by established community members. Competition tends to increase people’s identification with the group they belong to, and the

\(^6\) An incident in the history of OpenStreetMap is illustrative: After the Haiti earthquake in 2010, available maps of the country were outdated, but the emergency relief forces were in dire need of accurate maps. In response, the emergency forces became members of the OpenStreetMap community and updated the map of Haiti to reflect changes to the landscape (Coast, 2015). If, however, a competitor such as Google Maps could have provided an up-to-date map of Haiti, emergency teams would not have bothered to update the map on OpenStreetMap.
cohesion within the group (Hogg and Terry, 2000; Sherif et al., 1961; Tajfel et al., 1971). Hence established community members are likely to identify even more with their community, if a competitor enters and are more likely to “fight back”. Their motivation to help the community survive may further increase if the competitive entrant operates according to an alternative ideology. In such cases, they aspire to succeed despite the competition as well as to defeat the competition. Developers contributing to free and open source software sometimes consider it immoral to be employed by a private software company and to foster the diffusion of such software (Stewart and Gosain, 2006), further adding to their motivation to contribute to free and open software. The importance of ideological differences was exemplified by the response of OpenStreetMap community members when Google Maps started to become the dominant platform. They publicly emphasized the difference between the respective ideologies, how that difference was consequential, and why it was important for society that OpenStreetMap thrived. One prominent member of the community wrote an editorial in The Guardian entitled “Why the world needs OpenStreetMap” (Wroclawski, 2014).

Another illustration of how a competitor who operates according to a different ideology can motivate community members is provided by Dupont’s competitive entry into genetic research, which was seen as in an attempt to establish a commercial logic (e.g., patenting genes). The scientific community fought back with a vengeance (Murray, 2010) and refused to build on top of Dupont’s commercial knowledge (Murray et al., 2016). Similarly, in response to the efforts of Craig Venter’s private firm Celera to sequence and license the human genome, the scientific community – orchestrated by the U.S. National Human Genome Research Institute – sped up efforts to sequence and publish the human genome to ensure that the basic knowledge would be freely available (Marshall and Pennisi, 1998; Williams, 2013). We would expect that competition strengthens the degree to which community members’ identify with the community leading to an increase of contributions.

Established community members may also intensify their contributions out of concern for the benefits that they derive from their prior contributions. Established community members benefit from the platform-specific skills – which they have accumulated and which may become obsolete if a competitor goes on to dominate the market. For example, established members of the Linux community may be concerned about Microsoft gaining dominance as it would render their skills obsolete. They may also be concerned about the benefits they derive from having adjusted the platform to their personal needs, as in the case of the wheelchair users mentioned above, who would not benefit from their wheelchair-specific contribution to
OpenStreetMap if Google Maps squeezed OpenStreetMap out of the market. Similarly, benefits related to a member’s status and reputation derived from prior contributions (Boudreau and Jeppesen, 2015; Fershtman and Gandal, 2011; Gallus, 2016; Jeppesen and Frederiksen, 2006; Zhang and Zhu, 2011) would diminish if the competition squeezed the community-based platform out of the market. Established members are concerned about losing the benefits that they derive from their prior contributions, and they will increase their contributions to help the community succeed, thereby preserving their benefits.

_Hypothesis 2 (H2): Competition increases contributions by established community members._

**Attenuating the deterring effect of competition, strengthening its motivating effect: the role of social interaction**

In H1 we hypothesized about the negative effect of competition on contributions from new community members, and in H2 about the positive effect of competition on contributions from established community members. In Hypothesis 3 we posit that social interaction among community members attenuates the negative effect of competition on contributions from new members, but strengthens the positive effect of competition on contribution from established members, implying that the impact of competition is not uniform across communities. We focus on social interaction between members to examine heterogeneity in how communities are affected by competition, as this is a defining aspect of communities (in the absence of social interaction it would be a crowd rather than a community) and communities differ in the degree of social interaction among their members.

With respect to contributions from new members, we hypothesize that social interaction among community members attenuates the negative effect of competition had by diminishing the pool of potential new community members (i.e., users of the platform). Social interaction allows members to coordinate their contributions (Srikanth and Puranam, 2011), rendering the community more effective in responding to the competitive entrant. As a result, members produce knowledge that differentiates the community-based platform from the competitive entrant so that it continues to attract users (despite the competition). Social interaction thus helps to attenuate the decrease in the pool of users from which new community members originate.

Social interaction also attenuates the negative effect of competition on the share of potential new community members (i.e., users of the platform) that actually become community members. Social interactions, for
example through “meetups” (or social gatherings), help to convince new members to join and get them started (Coast, 2015). For example, we observed how potential new members often attended events organized by the local OpenStreetMap community to learn about the activity and the community, even before they had made their first contribution or knew exactly how OpenStreetMap worked. Established members introduced them to the community and educated them about why and how to best contribute. Only afterwards did they join the community and contribute to it.

Hypothesis 3a (H3a): The negative effect of competition on contributions from new community members as hypothesized in H1 is attenuated if the community is characterized by social interaction among members.

With respect to contributions from established community members we hypothesize that social interaction among community members strengthens the positive effect of competition on contributions by established community members. One reason is that competition has a multiplier effect on their identification with the community (cf. H2). The stronger the identification to begin with, the stronger the effect of competition. Social interaction strengthens the degree to which established members identify with the community by fostering relationships among them: the more they interact, the more they appreciate one another (Zajonc, 1968). Social interaction also intensifies their identification with the underlying ideology, e.g., when community members interact socially they are likely to learn about others ideological motivations strengthening their own belief in the community’s ideology. In brief, because identification and competition interact positively with respect to contributions from established community members (see H2 above) and because, social interaction has a positive effect on identification, it strengthens the positive effect of competition on contributions by established members.

Another reason why communities that are characterized by social interaction are likely to experience an increase of contributions by their established community members, is that it increases the benefits that established community members derive from their prior contributions. Social interaction allows status to emerge (Dahlander and O’Mahony, 2010; O’Mahony and Bechky, 2008) and allows status to translate into social benefits. For example, we observed at OpenStreetMap community events and conferences how community members would often cede authority to senior community members when discussing controversial topics such as intellectual property or the role of computer-assisted editing. Similarly, we noticed that at the an-

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7For example, the Guardian article mentioned above on why OpenStreetMap is necessary despite Google Maps was widely shared on OpenStreetMap mailing lists.
nual elections for OpenStreetMap’s board (which administers a budget of tens of thousands of pounds), members lacking in contributions and status would often have their authority questioned, making it harder for them to get elected. Faced with a competitor entering the market, established community members may be concerned about losing such benefits and thus contribute more to help the community in order to defend such benefits.

Hypothesis 3b (H3b): The positive effect of competition on contributions from established community members as hypothesized in H2 is strengthened if the community is characterized by social interaction among its members.

Setting, Data and Research Design

OpenStreetMap and Google Maps

Our empirical phenomenon in based in the multi-billion dollar mapping industry which produces one of the most primitive and basic forms of knowledge, having shaped the course of human development over many centuries (Harley et al., 1987; Nagaraj, 2017b). Specifically, we test our theory in the context of web-enabled digital mapping, specifically the response of members of country-based OpenStreetMap communities to the competitive entry of Google Maps in a variety of different countries around the world. An ideal experiment to test our theory would randomly assign some communities (from a group of comparable ones) to competition and examine the effects on contributions by new and established members. While such an experiment is difficult to conduct in practice, we exploit an analogous natural experiment by exploiting dozens of different country-based communities within OpenStreetMap that vary in their exposure to a single competitor (Google Maps). We argue that the variance in the exposure to competition we document is likely to be unrelated to the strength of communities in different countries—making it possible to tease out the effect of competition on contributions from community members over and above other factors.

OpenStreetMap was launched in 2004. Inspired by Wikipedia, it aims to create an openly provide a digital, web-map for the entire globe (Coast, 2015). At its core, OpenStreetMap is a database of geographic information that can be openly modified by any community member, after a free and simple registration process (Coast, 2015). Figure 1 provides an overview of the editing process, showing how a member may

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add a building or a street to an existing map. To collect this information, community members often survey neighborhoods with GPS devices to gather data about a region, or trace features from satellite images. As of November 2016, OpenStreetMap had over 3.2 million registered community members (Haklay, 2010). While most of these members are based in the developed world (countries like the UK, the USA and Germany), guided by our research design that is restricted to countries where Google Maps competition is plausibly exogenous and is covered in our data, we focus on 89,000 members from 87 countries, largely in the developing world.

We focus on the competition from Google Maps, a rival web-based mapping service launched in 2005. In contrast to OpenStreetMap, which is an openly-licensed and community-provided mapping database, Google Maps is a proprietary mapping platform that is not freely licensed, cannot be openly modified, and is available for downstream applications with numerous restrictions. While OpenStreetMap relies purely on community-contributed knowledge and freely licensed third-party sources, Google Maps sources its data from a variety of proprietary sources. This includes self-funded, proprietary data collection through surveys and via licensing contracts with third-party data providers in addition to public domain data sources as well as contributions from end users. Google Maps, however, does not use data from OpenStreetMap in its maps, because the latter is protected by a “copyleft” license – follow-on users are permitted to use the information as long as their adaptations are also licensed openly and released under a copyleft license. This legal proviso makes OpenStreetMap data unusable for Google Maps. While both Google Maps and OpenStreetMap both serve downstream users looking for a mapping application for physical navigation, they differ in that knowledge production and reuse within the OpenStreetMap system is entirely open and free, while Google Maps relies on licensing contracts and other forms of restrictions to both source and distribute its maps. Downstream users have the choice to use Google Maps or OpenStreetMap, and it is this competition for users’ interest that we focus on.9

9Note that OpenStreetMap might also compete with other community-based projects for member contributions, but our empirical focus is on its competition with Google Maps.
Google Maps’ Global Expansion

Our research design relies on the difference in global expansion timing between Google Maps and OpenStreetMap. Given OpenStreetMap’s reliance on the community to map the entire planet, it was able to launch in every country around the world at the same time with a blank map. In other words, all parts of the globe were available to be edited and there were no externally imposed limits on when a user could start contributing. Google Maps, in contrast, relies on proprietary data and was not able to launch across the globe at the same time. In fact, when Google Maps was first launched, it covered just the US and the UK (McClendon, 2012). It expanded its coverage gradually to different countries by acquiring data from third parties or governments, collecting its own mapping data and in some cases relying on users for information. Third-party data came from relatively expensive B2B providers who work with automobile companies and governments on larger engagements and did not typically have a web or mobile service that was part of the competition for online consumers. Therefore these companies did not directly compete with OpenStreetMap before Google Maps entered their respective markets.

While Google Maps’ expansion was gradual and strategic in the initial years after launch, focusing mostly on the developed world with lucrative markets, after 2009 it expanded rapidly in the developing world. (Figure 2 outlines Google Maps’ expansion to over 87 countries over 5 waves in a 2-year period, according to our data). Google entered a large number of countries in a short period of time, and cohorts often grouped a large number of countries in each wave. We focus on five waves of Google Maps’ expansion in our empirical analysis. In particular, we highlight how OpenStreetMap in some countries faced competition from Google Maps significantly sooner, because they happened to be in the earliest wave of Google Maps’ expansion, while in other countries the competition arrived much later.

[Insert Figure 2 About Here]

The timing variation presented in Figure 2 is exploited to identify the impact of Google Maps’ entry on country-level OpenStreetMap communities, over and above secular changes in contributions on the platform over time and across space. We include country and quarter fixed effects in all our specifications to

\[10\] In practice, there was some variation in when active communities developed in different regions, but these delays were not a function of externally-imposed restrictions from the global OpenStreetMap leadership.

\[11\] Google does not release systematic data on third-party providers. Anecdotally, it sources maps on many African countries from a company called AfriGIS Pvt. Ltd, and in the Middle East from a company called Orion Middle East.
control for all time-invariant covariates at the country level (like its size or geography) or country-invariant characteristics at the quarter level (like the launch of smartphones or OpenStreetMaps’ global popularity). Accordingly, concerns about static, time-invariant differences between country cohorts are less problematic in our context. The main concern that remains with the research design is the following: if Google Maps specifically targeted countries where contributions from new members were decreasing or established member contributions were increasing when making entry decisions, then our estimates may not pick up the effects of competition on OpenStreetMap, and we might incorrectly attribute pre-existing trends to the isolated effect of Google Maps competition. Our identifying assumption is this scenario is likely to be valid, i.e. Google Maps’ entry while not random, is unrelated to pre-existing trends in contributions within OpenStreetMap. This identifying assumption is likely to be valid in our context because we quantitatively test the idea that Google Maps’ entry was systematically related to country-level trends within OpenStreetMap. This evidence (discussed in the robustness checks) suggests that Google Maps’ entry into a given country was unrelated to the evolution of the OpenStreetMap community in that country.

In addition to the formal pre-trend analysis we present later, it is also useful to evaluate contextual information to justify this key assumption. First, evidence from publicly-available sources suggests that Google’s decision to enter different markets was based on their ability to collect and obtain third-party data in a given country, rather than focused on the strength of the local OpenStreetMap community. For example, press releases from Google executives mention that even though Google Maps’ ambition was to map every corner of the globe from the very beginning, 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 press release, June 2012). Accordingly, when it started expanding in the developing world, Google launched the Maps product in different countries at different points in time. The publicly-available material makes no mention of OpenStreetMap communities as being the driver of Google Maps’ decision to enter any given region, perhaps because of the relatively small size of OpenStreetMap at the time of Google’s expansion. Further, if Google Maps was explicitly targeting specific OpenStreetMap communities, then we would expect small, targeted launches in specific regions. For example, if South America represented a strategically important market, we might have expected Google to enter countries such as Ecuador, Venezuela and Colombia at around the same time. Instead, as Figure 2 indicates, Google Maps’ entered in waves of about 10 or 20 countries at a time, with one wave comprising of countries in many different regions. For example, unrelated countries such as Ecuador,
Afghanistan, Honduras and Saudi Arabia were all included in the fifth wave of Google Maps’ expansion, while Venezuela and Colombia were a part of the fourth wave. This is reassuring because it suggests that Google Maps did not target specific global regions at particular points in time, but launched in different countries as and when it was possible to do so. The quantitative tests that we performed along with this background makes us feel confident in using Google Maps’ entry as an exogenous shock to competition for OpenStreetMap to estimate the quantitative impact of competition on community members’ contributions.

Data

To estimate the impact of Google Maps’ entry on OpenStreetMap, we collect data on (a) contributions to OpenStreetMap by new and established members, (b) the timing of Google Maps entry (c) moderating variables measuring social interaction and (d) control variables (such as population or internet penetration) for the 87 countries in our sample. We focus on this set of countries that will sooner or later face Google Maps competition within a similar period of global expansion (although results are stable if we include a set of comparable countries as additional controls).

Our primary dataset is derived from the openly-available, OpenStreetMap “changeset” file,\textsuperscript{12} which contains the entire history of all contributions made to the OpenStreetMap database. Second, we manually, collect data on Google Maps’ entry in different markets from the Google Maps blog.\textsuperscript{13} Third, we collect data on the extent of social interaction in country-based OpenStreetMap communities by manually collecting information on the presence of mailing lists or social events as of the end of our time period. Finally, we rely on demographic and economic indicator data from World Bank data to collect control variables as well as help us perform robustness checks.

We organize this data into two different samples with different units of analysis. In the first sample (which we use to test H1 and H3a), we organize the dataset at the level of the country-quarter and calculate outcome and dependent variables at this level. In the second sample, we focus on 2127 pre-existing community members who were active before Google Maps started expanding (i.e. before 2009) and we record observations at the member-quarter level between 2006 and 2015.\textsuperscript{14} This group represents the population of all members.

\textsuperscript{12}from \url{http://planet.openstreetmap.org/}
\textsuperscript{13}In practice, we code Google’s Lat-Long blog announcements detailing Google’s entry into different markets.
\textsuperscript{14}Even though OpenStreetMap began operating in 2004, our sample begins in 2006 because no contributions were made in the countries in our sample before this year.
who made contributions before Google Maps’ expansion in early 2009 in the 87 countries in our sample. Here, we record contributions at the member-quarter level and employ this sample to test H2 and H3b. This section describes the variables we use in our analysis in more detail.

**Dependent Variable:** Our main outcome of interest is contributions by new and established members. In order to make a contribution, every OpenStreetMap member must create an account with a username (anonymous edits are not permitted), make a series of new additions or changes to a map in a given area and then upload this set of changes using a specialized program or the web editing interface. Every time a set of new or modified information is uploaded to OpenStreetMap, we infer that a new contribution has been made.\(^{15}\) The OpenStreetMap changeset file contains information on millions of contributions made to the database, of which 2.4 million contributions were made in the 87 countries we study. For each contribution, the file provides the username of the community member, the date and time the change was submitted, as well as the average latitude and longitude of all objects added or modified in a given contribution. Using the latitude and longitude, we wrote scripts that matched each edit to within a given country’s borders, allowing us to identify the location of each contribution and the country in question.\(^{16}\)

Armed with this raw data, we build our measure of contributions for new and established members. Contributions for new members in a given country-quarter is the sum of all contributions made by members who have never made a contribution before. For the contributions by established members, we focus on 2127 established community members who had made at least one contribution before 2009, i.e. the year in which Google Maps’ expansion begins. Using this data, we build a member-quarter sample, and measure total contributions made by every established member in every given quarter before and after Google Maps entry. The reason that we focus on 2127 pre-existing members before 2009 for all communities, rather than the year in which Google Maps’ enters a specific country, is to avoid any possible concerns of selection bias. Specifically, if different types of members join OpenStreetMap in 2010 or 2011 (which is possible given the large increase in OpenStreetMap’s popularity during this time), members who join at a later point in time might differ in their behavior, which might confound our estimates. To be sure, we also tried versions of our analysis using an alternative sample where we include all members who made contributions before Google Maps entered their respective country, and our results are largely consistent. Given the skewed distributions

\(^{15}\)In OpenStreetMap parlance, we focus on changesets rather than edits as our measure of contributions.

\(^{16}\)Some community members make contributions in more than one country. In such cases, we treat each member-country combination as a unique member for the purposes of our analysis. Our results are robust to excluding members who make contributions to more than one country.
of our dependent variables, we use logged versions of these measures in our specifications.

**Independent Variable:** We are interested in variation in competition to a country-level OpenStreetMap community via its exposure to Google Maps. Accordingly, our main independent variable is *Post Google Entry*, an indicator (binary) variable that equals one after Google Maps has formally entered a given country in a given quarter, or zero otherwise. In other words, the variable *Post Google Entry* captures whether the OpenStreetMap community in a given country is currently in competition with Google Maps as a digital mapping platform or whether it is yet to see commercial competition.

**Moderating Variable:** We are interested in the differential effect of competition within communities that are characterized by social interaction among its members. To evaluate this hypothesis, we rely on data on two channels (one online and one offline) which foster social interaction within the OpenStreetMap community: mailing lists and community events. Using two measures helps us to robustly test the role of social interaction using different yet conceptually similar variables. According to the OpenStreetMap help pages, “mailing lists are the traditional communication channel of the OpenStreetMap project”\(^ {17}\) and have been the typical way in which community members can communicate with each other and organize contributions. While mailing lists do exist at the global level (discussing general or technical topics), a significant share of discussions take place via the country-specific mailing lists. For example, the list *talk-is* was set up in August 2008 for discussions on mapping in Iceland. However, the existence of a mailing list for every country is not automatic. Typically, a community member will request for a new list to be created for a given country, after which it is created and then popularized. We collected data on the presence of mailing lists in the OpenStreetMap ecosystem.\(^ {18}\) We then matched our list of countries with this list to code whether a country has ever launched a mailing list that allows for online social interaction among community members.

In addition to mailing lists, we also relied on a second measure of social interaction within the OpenStreetMap communities at the country level. Specifically, OpenStreetMap has a long tradition of hosting community events called “mapping parties” to “get together to do some mapping, socialise, and chat about making a free map of the world!”.\(^ {19}\) These events are organized by members in a region who are interested in building community or to work on a specific project. Sometimes, leaders of the global OpenStreetMap community (including the founder), would also travel to other parts of the world where the OpenStreetMap movement

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\(^ {17}\) [http://wiki.openstreetmap.org/wiki/Mailing_lists](http://wiki.openstreetmap.org/wiki/Mailing_lists)

\(^ {18}\) [https://lists.openstreetmap.org/listinfo](https://lists.openstreetmap.org/listinfo)

\(^ {19}\) [http://wiki.openstreetmap.org/wiki/Mapping_parties](http://wiki.openstreetmap.org/wiki/Mapping_parties)
was still nascent in order to host mapping events and popularize and disseminate information about the project. A significant portion of these events are documented in a global database\textsuperscript{20} that we use to code whether a country has ever hosted community events. Collectively, our data on the presence of a mailing list and the existence of community events help us code two indicator variables that equal zero or one depending on whether local communities are characterized by online and offline social interaction among their members. We employ these two variables to estimate differential effects of Google Maps’ entry in countries with or without mailing lists or events.

**Control Variables:** We also collect a number of country-year specific variables that might help us control for unobserved variation across countries over time. While nonparametric country-fixed effects and quarter fixed effects control for most unobserved variation between countries in our context, it is possible that Google Maps’ entry is determined by local economic conditions. For example, if Google Maps enters a country when it is becoming more prosperous or more technologically advanced, and if such countries are also less likely to contribute to OpenStreetMap, then we might confound the effect of competition with the effect of economic or technology changes at the country level. Fortunately we can employ detailed, county-year level data on economic indicators as well as technology adoption to control for these factors directly.

In particular, at the country-year level we measure the *Population, GDP per capita, Internet Penetration, Mobile Penetration* and *Income Class*. For these data we rely on the World Bank World Development Indicators (WDI) database. *Population* is measured in millions, while *GDP per capita* is adjusted for purchasing-power-parity (PPP) and is indicated in 100s of US dollars. *Internet Penetration* and *Mobile Penetration* are measured in terms of internet users per 100 inhabitants, and mobile cellular subscriptions per 100 inhabitants. We also rely on the World Bank for our *Income Class* classification, which ranks countries as belonging to a higher or a lower category in terms of income.

Further, for the analysis around the differential effects of competition depending on the level of social interaction, we are cognizant of the concern that the presence of mailing lists or events is likely non-random. Specifically, it is likely that larger communities (with more members) are more likely to have mailing lists or events, and are also more likely to withstand commercial competition. While this is an important concern that is hard to completely eliminate, we collect data on community size before the entry of Google Maps that is helpful in helping address this challenge to some extent. Specifically, we construct *Small, Mid-size* and

\textsuperscript{20}http://wiki.openstreetmap.org/wiki/Current_events
Large variables that classify countries into three equal groups (small, mid-size or large) based on the total number of members at the country level before Google Maps’ entry. We employ these variables to test the additional impact of mailing lists or events beyond simple differences in community size between countries.

**Estimation Specification**

**Testing the Impact of Competition on New (H1) and Established Community Members (H2)**

To test H1 and H2, we utilize a differences-in-differences approach according to the following specification:

\[ \ln(Y_{it} + 1) = \alpha + \beta \times Post \, Google \, Entry_{it} + \gamma_i + \delta_t + X_{it} + \epsilon_{it} \]

Here, \( Y_{it} \) represents contributions by new members in a country \( i \) in quarter \( t \) (country-quarter sample) or contributions by established member \( i \) in quarter \( t \) (member-quarter sample). \( Post \, Google \, Entry_{it} \) is an indicator variable that equals one after Google Maps has entered a country in a given quarter, zero otherwise.

There are a few alternative factors that might be correlated with Google Maps entry in a given country making it difficult to identify the effect of competition. Countries and members are likely to vary significantly in terms of their propensity to contribute. For example, a country’s size, terrain or climate might make it more or less easy to perform mapping tasks, influencing OpenStreetMap contributions. Similarly, different members are likely to be of different ages and incomes with more or less free time to make contributions to OpenStreetMap. If Google Maps competition is correlated with these factors that influence contributions, we might incorrectly attribute a negative or positive relationship between Google Maps’ entry and contributions to the role of competition, when in fact this relationship is confounded by omitted variables bias. In order to address this important concern, we include time-invariant fixed effects \( \gamma_i \) in our specifications, which represents either country or member-level fixed effects depending on the sample being used. Similarly, during the time-period of study, OpenStreetMap is growing rapidly across the globe. These changes are driven by improvements in the OpenStreetMap interface, editing tools and other related technology, in addition to increasing awareness of the OpenStreetMap project. We control for this global trend towards increasing contribution activity using country-invariant quarterly trends, \( \delta_t \). Therefore our specification exploits purely within-country variation in contribution activity over and above any differences between geographies and over time in the propensity to contribute to OpenStreetMap. Given the skewed nature of the dependent variable, we employ log-OLS regressions with standard errors clustered at the country level. We inflate
the dependent variable by one before employing logs. We present robustness of these estimates to an alternate Poisson quasi-MLE specification (Azoulay et al., 2010) to test the sensitivity of our analysis to specific assumptions about the functional form.

Our main specification controls for time-invariant country effects, and a common quarterly time trend that does not change over countries. However, this specification does not control for variables that change both over time and within a given country, such as a country’s population or its income. In particular, it’s possible that, despite our qualitative evidence, Google Maps’ entry is correlated with changing population or changing economic status of a country, which could be driving contributions to OpenStreetMap and confounding the isolated effect of competition on contributions. We therefore include controls for population and GDP per-capita at the country-year level. Similarly, internet and mobile penetration is growing rapidly around the world during the period of study and it is important to have access to these technologies to contribute to OpenStreetMap. Accordingly, we also include $X_{it}$ which represent time-varying country-level controls for internet and mobile phone penetration. In other words, while our specification represents a within country-comparison, these controls allow us to account for changing within-country trends in demographics, the economy and technology adoption which might be important confounds in our analysis. In our preferred specification, the coefficient of interest, $\beta$ estimates the isolated impact of Google Maps competition after controlling for general time-trends in contributions as well as varying levels of income, population, mobile and internet penetration over time.

In addition to testing H1 and H2, we also estimate an additional specification where we evaluate the net effect of competition on OpenStreetMap. For this specification, we use the country-quarter sample, and specify $Y_{it}$ to be the total contributions made in a given country $i$ in quarter $t$. The estimate of $\beta$ from this regression estimates whether the overall effect of competition on OpenStreetMap is to reduce or increase contributions on OpenStreetMap.

**Testing the Role of Social Interaction (H3)**

Finally, in order to test H3, we modify the specification testing H1 and H2 as follows: $\text{Ln}(\text{Contributions}_{it} + 1) = \alpha + \beta_1 \times \text{Post Google Entry}_{it} + \beta_2 \times \text{Post Google Entry}_{it} \times \text{Interaction}_{i} + X_{it} + \delta_t + \varepsilon_{it}$

Note that we now include interaction terms $\text{Post Google Entry}_{it} \times \text{Interaction}_{i}$, where the variable $\text{Interaction}_{i}$ is equal to zero or one depending on whether a country has a mailing list or has hosted events. The coefficient of interest, $\beta_2$ measures the differential impact of competition on contributions in countries with a mailing
list or events as compared to countries without. Further, we also include Post Google Entry_{it} \times \text{Mid} - \text{Size}_{i} + \text{Post Google Entry}_{it} \times \text{Large}_{i} terms which capture the differential effects of competition by community size in order to isolate the role of social interaction above and beyond community size. We employ this specification to test whether social interaction attenuates the negative impact of competition for new members (H3a) using the country-quarter sample or whether it strengthens the positive effect of competition on established members (H3b) using the member-quarter sample.

Testing the Parallel Trends Assumption

A key test for the validity of our quasi-experimental design is the assumption that communities in countries that experienced entry from Google Maps early were on a similar trend, in terms of contributions for new and established members, as compared to countries that experienced entry later on. While our qualitative groundwork suggests that this assumption is likely to hold up in practice, we also test it quantitatively. Intuitively, we estimate difference-in-difference regressions (similar to the baseline analysis), except we estimate the effect of competition separately for every quarter before or after Google Maps’ entry separately, rather than simply one average estimate for the Post Google Entry variable. Specifically, we estimate regressions of the form: $Y_{it} = f(\alpha + \Sigma \beta_t \times 1(z) + \gamma_i + \delta_t + X_{it} + \epsilon_{it})$

where, $f$ represents the negative-binomial or Log-OLS functional form, $\gamma_i$ and $\delta_t$ represent country or member fixed effects and time fixed effects respectively. $X_{it}$ represent a series of controls as before. $z$ represents the “lag”, or the quarters relative to a “zero quarter”, which marks the quarter when a country first faced competition from Google Maps. The variable $z$ is therefore equal to minus one, a quarter before Google Maps enters a country and is equal to plus one the quarter after which Google Maps has entered. If the parallel trends assumption is justified, we should find estimates of $\beta_t$ where $t < 0$ to be relatively similar, suggesting no overall trends in contribution activity before Google Maps enters a given country. We test this proposition graphically in Figure 3 separately for new members and established members. Further, in addition to testing the pre-trends assumption, this figure provides us with a compelling, visual test of the divergent effect of competition on contributions. Note that for all the graphical results, we employ the negative binomial functional form (because these offer greater power), but present our tabular results using Log-OLS estimates for consistency.

Robustness Checks

In addition to our main regressions, we also evaluate the robustness of our specification to alternate modeling
assumptions. First, we employ a poisson quasi-maximum likelihood specification for the count dependent variable, i.e. 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 countries as compared to poorer ones. Finally, we implement a “placebo” regression to identify whether our results are driven purely by the structure of our setup or data rather than the specific timing of Google Maps’ entry. Specifically, 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 variable that we employ in the regression testing H1. For example, if a country experiences 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) and assign a country from the fifth wave to the second wave, et cetera. If estimates for this regression remain significant then our results are likely to be mechanical artifacts of our setup, while a non-significant and small estimate will indicate otherwise. Together, these robustness tests allow us to control and test for a number of different confounding stories that could muddle the interpretation of our baseline estimates.

Results

Summary statistics for our variables in the country-quarter level can be found in Table 1. The mean value of new member contributions is 297.9 in a given country-quarter and the median is 33. The mean value of our main independent variable Post Google Entry is 0.6, indicating that 40% of our country-quarter observations are pre-entry, while the rest are post-entry. We also computed summary statistics for our member-quarter sample used to estimate H2 and H3b, which shows that established members can make as many as 2600 edits per quarter (results are available from the authors).

Table 2 reports results from our baseline estimation for H1. The first model presents estimates with country and quarter fixed effects, the second model adds controls for GDP and population, while the final model also adds controls for internet and mobile penetration. The coefficients on all three models are negative and statistically significant. Given that these coefficients are obtained from Log-OLS models, they express the
percent change in the outcome variable for one unit change in the independent variable. For example, in the third model, the coefficient of -0.55 represents a decrease in contributions by new members of about 55% in a country after it has experienced entry from Google Maps, after controlling for country and year fixed effects, in addition to GDP, population and internet and mobile penetration. These results validate Hypothesis 1 that competition lowers contributions by new members.

Table 3 reports results from our estimation for H2. This specification tests the impact of competition on contributions at the individual community member level, for the set of established community members (i.e. those who were active before Google Maps expansion begins). Similar to Table 2, the coefficients are reported from Log-OLS models and the first model includes country and quarter fixed effects, while subsequent models add controls for population and GDP, and mobile and internet penetration. In each of the three models the coefficients are positive, and significant. Note that the main coefficients remain significant even though these specifications include over 2000 fixed effects (one for each established member) which tends to increase the size of the standard errors and decrease significance. Overall, the estimates indicate about a 1.8-2% increase in contributions from established community members after the entry of Google Maps validating H2. Collectively, across all established members in a region, this translates into a sizeable increase in the number of contributions.

In addition to testing H1 and H2, we estimate the overall effect of competition on total contributions using the country-quarter sample. Note that total contributions includes contributions from new members, established members (i.e. those active before 2009) as well as a third category of members: those who joined after 2009, but are not necessarily making their first contribution in the focal quarter. Table 4 presents results from this analysis. As this table shows, the overall effect of competition on total contributions is negative and significant. This fact shows that Google Maps competition considerably weakened OpenStreetMap contributions in the period that we study. This may be because we studied OpenStreetMap during a phase in its lifecycle when new and recent members significantly dominated the number of established members.

\[\text{Note that since we include fixed effects for each member, we are also controlling for any larger country level differences between countries.}\]
in the community and this overall effect might change considerably in other settings depending on the mix of new and established members.

Next, Table 5 reports results testing H3a and H3b, i.e. the impact of competition on new and established members’ contributions in country-level communities that foster social interaction through mailing lists and events. Models (1) and (3) test the impact of mailing list presence, while Models (2) and (4) test the impact of events. Models (1) and (2) are estimated for new users using the country-quarter sample (H3a), while Models (3) and (4) are estimated for established users using the member-quarter sample (H3b). In order to evaluate the marginal value of mailing lists and events over and above community size, all models include fixed effects for mid-size and large communities (small is the omitted category). For each of the two measures we employ, we find support for H3a and H3b; these results persist and remain stable even after including interaction variables for community size. As the estimates show, while the effect of competition for new members is negative, the coefficient on the Post X Mailing-List variable in Model (1) is 0.56 which nearly equals the main, negative effect of -0.68 in the Post variable, indicating the strong effect of mailing list presence on reducing the contribution-reducing effects of competitive entry by a competitor for new members. It also seems like the positive effects of mailing lists are slightly stronger than those of events (0.56 as compared to 0.41), although these are not statistically significantly different from one another. Similarly, for established members, while the overall effect of competition on contributions is positive, this increase is strengthened in countries with mailing list presence or events. For example, as shown in Model 3, the positive effect of competition almost doubles in countries with mailing-lists as compared to those without. Note however that this effect is less precisely estimated (the interaction coefficient in Model (3) is not significant at a 90-percent level).22

Overall, the estimates from Table 5 therefore strongly confirm H3a and H3b showing that countries that enable social interaction are able to attenuate the negative impact of competition on new member contributions and strengthen the positive effect for established members.

22These effects are similar but significant at the 99-percent level when considering country-level fixed effects (rather than over 2000 member level fixed effects) in unreported analysis.
It is important to note that while social interaction weakens the contribution-reducing effect for new members and strengthens the contribution-increasing effect for established members, it is possible that this result is driven by related differences across countries that is correlated with the presence of a mailing list. Reassuringly, community size, which we believe to be the main alternative explanation in this context, is unlikely to diminish the importance of social interaction given how the coefficients in all our models are positive despite the addition of these strong controls. It is, however, possible that communities with measurable social interaction are also characterized by perhaps better governance, more motivated communities or communities with stronger identities. Having said that, while our analysis strongly suggests that social interaction through mailing lists or events could moderate the influence of competition, our evidence should not be interpreted as strictly causal in this context.

Next, we test an important assumption for the validity of the difference-in-difference research design, namely the parallel trends assumption. Specifically, if Google Maps systematically entered early in countries where contributions from new members are already decreasing and contributions from established members are already increasing, then we might be biased in our estimates of the impact of competition on contributions. We test this idea using Figure 3. Panel A presents this chart for contributions by new members while Panel B depicts a similar figure for established members. As this evidence shows, before Google Maps enters a given country, the level of contributions from both new and established members is very similar to countries where Google Maps is yet to enter. The difference changes dramatically after Google Maps’ entry—we start to see an immediate difference between countries facing competition and countries where Google Maps is yet to arrive. Contributions decrease for new members and they increase for established members. This figure starkly outlines the core message of this paper—competition is likely to have a divergent effect on contributions within a knowledge-producing community. Note that, as in common in these specifications, estimates just before or after Google Maps entry are not significant at the 95-percent level, but the differences become large and significant over time. These time-varying estimates, estimated now using Log-OLS models, are presented in a table format in Table 6. These results are reassuring because they demonstrate that countries facing early and late competition do not seem to be systematically different in terms of their contributions, and the estimates from the regressions are likely to represent credible effects of competition on contributions in online communities.

[Insert Figure 3 and Table 6 About Here]
Finally, having found support for Hypotheses 1-3, we now turn to Table 7 which reports results from robustness tests specified before. Each of the six models tests the robustness to alternate specifications and finds the results for H1 (Models 1-3) and H2 (Models 4-6) to be quite robust. The results indicate that when Poisson models (Models 1 and 4) are used to estimate the impact of competition on new and established member contributions, the divergent impact of competition is evident. Further, the coefficient for H1 remains significant and negative and that for H2 remains positive and significant when region specific time trends (Models 3 and 5) are added to the estimation. Finally, Models (3) and (6) report results from a placebo exercise where countries are assigned to a randomly chosen wave in terms of Google Maps competition. Reassuringly, the coefficients from this regression are close to zero and insignificant in both cases, suggesting that the results are driven by meaningful information contained the specific Google Maps entry dates rather than mechanically driven through the setup of the estimation or the data. Overall the robustness checks in Table 7 provide confidence in our theory of the divergent effect of competition on member contributions in knowledge-producing communities.

[Insert Table 7 About Here]

Discussion

The divergent effect of competition

Our primary contribution lies in developing and testing the theory of the divergent effect of competition. We found competition to result in a decrease of contributions from new community members but an increase of contributions from established community members. We suspect this divergent effect to hold across a variety of contexts, but recognize that the micro-mechanisms underlying it may differ.\textsuperscript{23} Broadly speaking, competition reduces the number of new members that an organization attracts, but strengthens the motivation of current members. Our finding points to a novel, hitherto neglected mechanism to explain how competition affects organizations. Prior research on the impact of competition has focused on its effect on established

\textsuperscript{23}With respect to communities, we suggest that competition reduces contributions from new members because they are less likely to use the community’s platform, but that it increases contributions from established community members because they are more likely to identify with the community. Scholars of classical organization may find that competition deters new employees due lack of job security in joining a company under siege, but incentivizes existing employees to work harder to secure their jobs which are threatened by the competition. Scholars of multi-sided platforms may find that platforms facing competition struggle to attract new complementors, but that current complementors develop more and better complements to protect their platform-specific investments that are threatened by the competition.
members who engaged prior to the emergence of a competitive threat (e.g., Sherif et al. (1961)), yet has overlooked the notion that competition makes it less likely to attract new members.

One important implication of the divergent effect is that competition on the outside changes the composition of organizations on the inside (i.e., the distribution of tenure of an organization’s members)—the share of established members increases, whereas the share of new members decreases. Another (related) implication is that it may help to explain why organizations become more exploitative when faced with competition (Toh and Polidoro, 2013) – because they fail to recruit new members who would foster exploration (March, 1991; Rosenkopf and Almeida, 2003). Our research on the divergent effect may thus inform research on the link between competition and innovation (Aghion et al., 2005; Greve and Taylor, 2000; Katila and Chen, 2008; Toh and Polidoro, 2013). Another implication of the divergent effect of competition is that it helps to understand which organizations are likely to decrease or to increase their output when faced with competition. In organizations that have a lot of established members, the positive effect from the increased contributions of established members may outweigh the reduced contributions from new members. By contrast, in organizations that do not have a lot of established members, the negative effect on contributions from new members may outweigh the increased contributions from established members. Beyond these broad theoretical implications our research also has implications specific to our understanding of knowledge-producing communities and platform-based markets.

**Knowledge-producing communities**

We contribute to research on knowledge-producing communities. Our research answers the call for studies that move beyond examining the direct link between motivation and contributions, to investigate conditions that enable and hinder motivation (Von Krogh et al., 2012). Recent research has begun to do so by studying how community members are embedded within the community (Ren et al., 2007, 2012; Zhang and Zhu, 2011), but has yet to study how environmental characteristics (such as competition) affect members’ willingness to contribute. Research has focused on the effect of competition among community members (Boudreau et al., 2011, 2016; Miric, 2017), not on the effect of competition to the community as a whole. We show how a community’s environment, specifically competition, impacts community members’ motivation.

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24To 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 in and out of the community. The divergent effect suggests that competition decreases the entry- and the exit-rate. This effect is somewhat counter-intuitive, as one would expect factors that deter new members to also foster the exit of established members.
In so doing, our research also helps to understand the dynamics underlying community members’ motivation. Prior research has found that the main drivers of community members’ motivation evolve with their increasing participation in the community (Shah, 2006). Our study supports these findings and points to the explanatory power of studying the events (such as competitive entry) experienced by community members during their tenure.

**Competition between platforms**

Research on platform competition has often compared and contrasted different types of platforms (Eisenmann, 2008; Gawer, 2011; Huang et al., 2013; Kapoor and Agarwal, 2017; Piezunka, 2011). However, a platform type that is viable in isolation may be less viable when competing against other types (Casadesus-Masanell and Zhu, 2010; Seamans and Zhu, 2014, 2017). While research on platform competition has focused on competition between platforms of the same type (Cennamo and Santaló, 2013; Lee, 2013, 2014; Zhu and Iansiti, 2012), recent research examines the competition between different types of platforms (Casadesus-Masanell and Zhu, 2010; Seamans and Zhu, 2014, 2017). In the setting we studied, a two-sided platform that relies for content on volunteer members (i.e., OpenStreetMap) competed against a one-sided platform that relies for content on contractors (i.e., Google Maps). While the one-sided platform did not explicitly compete for volunteering community members, it nevertheless hindered the other platform’s ability to attract new contributing members.

Our findings also illustrate what platforms are competing for. Research on platforms has often focused on how platforms compete for the same complementors (Bresnahan et al., 2014; Cantillon and Yin, 2008), and the conditions under which competition is able to lure complementors away. Our work suggests that competition might increase the likelihood of complementors to stay committed to their existing platform. Competition between platforms may thus become competition between two coalitions, each composed of a platform and the affiliated complementors. These coalitions would then compete to attract new consumers and new complementors.

This competition between platforms raises the broader question: what type of platform is likely to succeed? While the stellar success of community-based platforms (e.g., OpenStreetMap, Linux, Wikipedia) illustrates their vast potential (Greenstein and Nagle, 2014; Jeppesen and Lakhani, 2010; Nagle, 2017), we have seen remarkable perseverance by commercial alternatives (Economist, 2016). Scholars, managers, and policy
makers alike are interested in understanding the long-term evolution of industries (Agarwal and Gort, 1996). Platform-based markets tend to tip towards one dominant platform (Augereau et al., 2006). Understanding the conditions under which a community-based platform will be dominant is important because they provide open access to the underlying knowledge and stimulate follow-on innovation (Boudreau and Lakhani, 2015; Furman and Stern, 2011; Nagaraj, 2017a; Scotchmer, 1991). Our study shows that commercial platforms negatively affect platforms relying on community-based knowledge production. The perseverance of commercial alternatives is thus not necessarily an indicator of their superiority. If Google Maps had not entered the market at the nascent stage of the industry, OpenStreetMap could have continued to develop unhindered and could potentially be the superior platform that would also openly allow downstream reuse. While we cannot say whether community or commercial knowledge production is superior, our study shows that competition hinders platforms that rely on community-based knowledge production to fully realize their potential.

**Managerial Implications**

Managers must be wary of the divergent effect of competition. Interestingly, managers may observe the increased motivation of established members, but miss the impact on attracting new members because it is less immediate and less visible. Another implication is that managers may need to communicate differently with established members and potential new members when faced with competition. In communicating with established members, they may “play up” the competition to motivate them, whereas with potential new members managers may “play down” the competition, in order to not deter them. Our work also suggests that community managers can take steps to increase social interaction between members in an effort to buffer their communities against competitive pressures, using tactics such as promoting discussions on mailing-lists and organizing community events to help build such interactions between members.

**Limitations, Boundary Conditions, and Future Research**

Our research is subject to limitations. We are limited in our ability to disentangle specific sub-mechanisms at play. For example, while we show competition to have a different effect on established and potential new users, we cannot disentangle the underlying sub-mechanisms. In evaluating H3a and H3b, while the social interaction enabled by events and mailing lists seem to be an important determinant of helping communities
combat the negative effects of competition on contributions, we do not evaluate the specific mechanisms through which social interaction attenuates the negative impact of competition. Our main contribution is thus to illustrate the impact of competition on contributions by community members and to develop a theoretical and empirical framework in this regard, setting the stage for further study investigating the micro-mechanisms through which competition plays out in practice, and how it might be resisted.

Further, our measurement for established and new members, depends on the timing of when a member joined the community. However, it possible that even within these two groups there will be members who will be more “dedicated”. We propose that our theory compares not just members who have joined before competition arrives with those who join later, but applies to dedicated versus more casual members as well. In our empirical estimates, we are unable to draw these fine distinctions between member types given the data available; rather, we point to a broad difference between categories of members along one important dimension: the time at which they joined the platform and imply that similar effects are likely to be at play for members with a higher or lower level of dedication.

Our work has important implications and points to avenues for future research. While we study OpenStreetMap and Google Maps as competing platforms, they also compete in the sense that they enable a range of third-party applications (“apps”) for mobile devices. It would be interesting to focus on the differential impact of competition on OpenStreetMap in cases where it enables a host of follow-on applications (compared to when it does not). Further, a key insight is that when assessing the effect of competition, research may benefit from treating the focal organization not as a single entity, but instead examine how the effect of competition differs across current and potential members of the organization. For example, future research may further explore whether companies exposed to competition have more motivated employees but struggle to recruit new ones, or how, by motivating established members but deterring new recruits, competition may change the direction of organizations’ innovation.

References


Stallman, R. (1999). The GNU operating system and the free software movement.


1 Tables and Figures

FIGURE 1. OVERVIEW OF OPENSTREETMAP: MAKING A CONTRIBUTION

Note: Screenshot of a member making a contribution (adding a street) on OpenStreetMap in Port-au-Prince, Haiti.

FIGURE 2. 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 3. COMPARING THE EFFECT OF COMPETITION BETWEEN ESTABLISHED AND POTENTIAL NEW MEMBERS

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

Table 1. SUMMARY STATISTICS – COUNTRY QUARTER LEVEL

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Outcomes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>New Member Contributions</td>
<td>297.9</td>
<td>1224.3</td>
<td>33.0</td>
<td>0</td>
<td>27034</td>
</tr>
<tr>
<td>Overall Contributions</td>
<td>692.3</td>
<td>2098.2</td>
<td>79.0</td>
<td>0</td>
<td>44774</td>
</tr>
<tr>
<td>New Members</td>
<td>26.2</td>
<td>58.8</td>
<td>10.0</td>
<td>0</td>
<td>1373</td>
</tr>
<tr>
<td>Total Members</td>
<td>39.1</td>
<td>77.3</td>
<td>15.0</td>
<td>0</td>
<td>1557</td>
</tr>
<tr>
<td><strong>Timing Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Post</td>
<td>0.6</td>
<td>0.5</td>
<td>1.0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Year</td>
<td>2010.5</td>
<td>2.9</td>
<td>2010.5</td>
<td>2006</td>
<td>2015</td>
</tr>
<tr>
<td><strong>Social Interaction Vars</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mailing List</td>
<td>0.2</td>
<td>0.4</td>
<td>0.0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Any Event</td>
<td>0.3</td>
<td>0.5</td>
<td>0.0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>Controls</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population (millions)</td>
<td>0.2</td>
<td>0.3</td>
<td>0.1</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>GDP per capita (in 100s USD)</td>
<td>0.1</td>
<td>0.2</td>
<td>0.1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Mobile Penetration (per 100)</td>
<td>71.7</td>
<td>42.8</td>
<td>70.4</td>
<td>0</td>
<td>232</td>
</tr>
<tr>
<td>Internet Penetration (per 100)</td>
<td>20.0</td>
<td>21.1</td>
<td>11.6</td>
<td>0</td>
<td>98</td>
</tr>
</tbody>
</table>

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, while data for the social interaction variables are time invariant. GDP per capita is PPP adjusted.
Table 2. IMPACT OF COMPETITION OF POTENTIAL NEW MEMBERS’ CONTRIBUTIONS (H1)

<table>
<thead>
<tr>
<th></th>
<th>(1) Contributions</th>
<th>(2) Contributions</th>
<th>(3) Contributions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post Google Entry</td>
<td>-0.62***</td>
<td>-0.60***</td>
<td>-0.55***</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.15)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>Population (millions)</td>
<td>3.99**</td>
<td>4.16**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.85)</td>
<td>(1.79)</td>
<td></td>
</tr>
<tr>
<td>GDP per capita</td>
<td>-0.18</td>
<td>0.29</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.09)</td>
<td>(2.55)</td>
<td></td>
</tr>
<tr>
<td>Mobile Penetration</td>
<td></td>
<td>0.0065**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0028)</td>
<td></td>
</tr>
<tr>
<td>Internet Penetration</td>
<td></td>
<td>-0.0048</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0081)</td>
<td></td>
</tr>
<tr>
<td>Country FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>3480</td>
<td>3224</td>
<td>3192</td>
</tr>
<tr>
<td>Adj. R2</td>
<td>0.78</td>
<td>0.78</td>
<td>0.79</td>
</tr>
</tbody>
</table>

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 new OpenStreetMap members 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, inflated by one and is measured as the total number of edits by new members in country i in a given quarter t. Post Google Entry=1 after Google Maps has entered the country i in a given quarter. X represent time varying controls that are specific to country i. \( \gamma \) and \( \delta \) indicate fixed effects for country and quarter respectively. Clustered standard errors at the country level are reported.
Table 3. THE IMPACT OF COMPETITION ON ESTABLISHED MEMBERS’ CONTRIBUTIONS (H2)

<table>
<thead>
<tr>
<th></th>
<th>(1) Contributions</th>
<th>(2) Contributions</th>
<th>(3) Contributions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post Google Entry</td>
<td>0.018* (0.0094)</td>
<td>0.018* (0.0097)</td>
<td>0.020** (0.0099)</td>
</tr>
<tr>
<td>Population (millions)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.072 (0.078)</td>
<td>0.082 (0.076)</td>
<td></td>
</tr>
<tr>
<td>GDP per capita</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.087 (0.065)</td>
<td>-0.12 (0.092)</td>
<td></td>
</tr>
<tr>
<td>Mobile Penetration</td>
<td></td>
<td></td>
<td>0.00023 (0.00015)</td>
</tr>
<tr>
<td>Internet Penetration</td>
<td></td>
<td></td>
<td>-0.000053 (0.00032)</td>
</tr>
<tr>
<td>Community Member FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>85080</td>
<td>80800</td>
<td>80524</td>
</tr>
<tr>
<td>Adj. R2</td>
<td>0.056</td>
<td>0.057</td>
<td>0.057</td>
</tr>
</tbody>
</table>

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 established members on OpenStreetMap in a differences-in-differences framework. The unit of analysis is member-quarter. The specification is $\ln(\text{Contributions}_{it}) = \alpha + \beta \times \text{Post Google Entry}_{it} + X_{it} + \gamma_i + \delta_t + \epsilon_{it}$. This specification is estimated using logged OLS models. The outcome variable is logged $\text{Contributions}_{it}$ (inflated by one) and is measured as the total number of edits in a given country by an established member $i$ in a given quarter $t$. $\text{Post Google Entry}_{it}=1$ after Google Maps has entered a given country, in a given quarter. $\gamma_i$ and $\delta_t$ indicate fixed effects for member and quarter respectively. The control variables $X_{it}$ including Population, GDP, Internet and Mobile Penetration vary at the country-year level. Clustered standard errors at the country level are reported.
Table 4. THE IMPACT OF COMPETITION ON TOTAL CONTRIBUTIONS

<table>
<thead>
<tr>
<th></th>
<th>(1) Contribution</th>
<th>(2) Contribution</th>
<th>(3) Contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post Google Entry</td>
<td>-0.58***</td>
<td>-0.58***</td>
<td>-0.51***</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.17)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>Population (millions)</td>
<td>2.61</td>
<td>2.86*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.65)</td>
<td>(1.59)</td>
<td></td>
</tr>
<tr>
<td>GDP per capita</td>
<td>2.56</td>
<td>2.85</td>
<td></td>
</tr>
<tr>
<td>GDP per capita</td>
<td>(1.73)</td>
<td>(2.37)</td>
<td></td>
</tr>
<tr>
<td>Mobile Penetration</td>
<td></td>
<td></td>
<td>0.0081***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0031)</td>
</tr>
<tr>
<td>Internet Penetration</td>
<td>-0.0030</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0085)</td>
</tr>
<tr>
<td>Country FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>3480</td>
<td>3224</td>
<td>3192</td>
</tr>
<tr>
<td>Adj. R2</td>
<td>0.84</td>
<td>0.84</td>
<td>0.84</td>
</tr>
</tbody>
</table>

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 contributions on OpenStreetMap in a differences-in-differences framework. The unit of analysis is country-quarter. The specification is \( \ln(\text{Contributions}_{it} + 1) = \alpha + \beta \times \text{Post Google Entry}_{it} + \gamma_i + \delta_t + \varepsilon_{it} \). 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 \( i \) in a given quarter \( t \). Post Google Entry\(_{it}\) is an indicator variable that equals one after Google Maps has entered a given country, in a given quarter. \( \gamma \) and \( \delta \) indicate fixed effects for country and quarter respectively. The control variables \( X_{it} \) including Population, GDP, Internet and Mobile Penetration vary at the country-year level. Clustered standard errors at the country level are reported.
Table 5. THE DIFFERENTIAL IMPACT OF COMPETITION ON CONTRIBUTIONS:
THE ROLE OF SOCIAL INTERACTION (H3)

<table>
<thead>
<tr>
<th></th>
<th>H3a. Country-Qtr Sample</th>
<th>H3b. User-Qtr Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Contributions</td>
<td>(2) Contributions</td>
</tr>
<tr>
<td>Post-Google-Entry</td>
<td>-0.68***</td>
<td>-0.74***</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>Post-Google-X-Mailing-List</td>
<td>0.56***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td></td>
</tr>
<tr>
<td>Post-Google-X-Event</td>
<td></td>
<td>0.41**</td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Post-Google-X-Mid-Size</td>
<td>0.098</td>
<td>0.081</td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>Post-Google-X-Large</td>
<td>0.015</td>
<td>0.077</td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(0.22)</td>
</tr>
</tbody>
</table>

Country FE                   | Yes                     | Yes                  | Yes                | Yes               |
Quarter FE                    | Yes                     | Yes                  | Yes                | Yes               |
Controls                     | Yes                     | Yes                  | Yes                | Yes               |
N                             | 3192                    | 3192                 | 80524              | 80524             |
Adj. R2                       | 0.84                    | 0.84                 | 0.057              | 0.057             |

Standard errors in parentheses

Note: This regression estimates the differential impact of competition from Google Maps on contribution activity of new and established members on OpenStreetMap in a differences-in-differences framework. The specification is $\ln(Y_{it} + 1) = \alpha + \beta_1 \times \text{Post Google Entry}_{it} + \beta_2 \times \text{Post Google Entry}_{it} \times \text{SocialInteraction}_i + \chi_d + \delta_t + e_{it}$. This specification is estimated using Log-OLS models. $\text{SocialInteraction}_i$ is measured using either the MailingList or Event variable which are indicator variables that capture whether a country has a mailing list to interact with each other, or whether that country has hosted a physical event to foster community. Similar to the baseline specification, the outcome variable $Y_{it}$ measures the total quarterly contributions, either by new members in country $i$ or by established member $i$ in quarter $t$ depending on whether the country-quarter sample (Panel A), or member-quarter sample (Panel B) is used. Post Google Entry_{it}=1 after Google Maps has entered a given country, in a given quarter and $\gamma$ and $\delta$ indicate fixed effects for country and quarter respectively. Post Google Entry_{it} \times Mid – Size$_i$ and Post Google Entry_{it} \times Large$_i$ are terms which capture the differential effects of competition by community size. $X_d$ includes controls for Population, GDP, Internet and Mobile Penetration as before. Clustered standard errors at the country level are reported.
Table 6. ROBUSTNESS CHECK: COMPARING PRE-TRENDS BETWEEN TREATMENT AND CONTROL COMMUNITIES IN LOG-LINEAR MODELS

<table>
<thead>
<tr>
<th></th>
<th>New Members (Country-Qtr Sample)</th>
<th>Established Members (User-Qtr Sample)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>main</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Google-Entry(-4)</td>
<td>0.23 (0.18)</td>
<td>0.14 (0.18)</td>
</tr>
<tr>
<td>Google-Entry(-3)</td>
<td>0.21 (0.18)</td>
<td>0.16 (0.17)</td>
</tr>
<tr>
<td>Google-Entry(-2)</td>
<td>0.10 (0.18)</td>
<td>0.058 (0.17)</td>
</tr>
<tr>
<td>Google-Entry(-1)</td>
<td>0.26 (0.16)*</td>
<td>0.21 (0.16)</td>
</tr>
<tr>
<td>Google-Entry(1)</td>
<td>-0.14 (0.15)</td>
<td>-0.13 (0.15)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Google-Entry(2)</td>
<td>-0.28 (0.17)*</td>
<td>-0.24 (0.16)*</td>
</tr>
<tr>
<td>Google-Entry(3)</td>
<td>-0.34 (0.17)**</td>
<td>-0.32 (0.17)*</td>
</tr>
<tr>
<td>Google-Entry(4)</td>
<td>-0.36 (0.17)**</td>
<td>-0.30 (0.17)*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Google-Entry(5)</td>
<td>-0.34 (0.18)*</td>
<td>-0.29 (0.17)*</td>
</tr>
<tr>
<td>Google-Entry(6)</td>
<td>-0.35 (0.18)*</td>
<td>-0.29 (0.17)*</td>
</tr>
<tr>
<td>Google-Entry(7)</td>
<td>-0.44 (0.18)**</td>
<td>-0.36 (0.18)**</td>
</tr>
<tr>
<td>Google-Entry(8)</td>
<td>-0.45 (0.18)**</td>
<td>-0.35 (0.18)**</td>
</tr>
<tr>
<td>Google-Entry(9)</td>
<td>-0.46 (0.18)**</td>
<td>-0.29 (0.18)**</td>
</tr>
<tr>
<td>Google-Entry(10)</td>
<td>-0.46 (0.18)**</td>
<td>-0.32 (0.18)**</td>
</tr>
<tr>
<td>Google-Entry(11)</td>
<td>-0.58 (0.19)**</td>
<td>-0.42 (0.19)**</td>
</tr>
<tr>
<td>Google-Entry(12)</td>
<td>-0.73 (0.19)**</td>
<td>-0.56 (0.19)**</td>
</tr>
<tr>
<td>Population (millions)</td>
<td>0.43 (0.072)**</td>
<td>0.43 (0.071)**</td>
</tr>
<tr>
<td>GDP per capita</td>
<td>0.90 (0.12)**</td>
<td>-0.57 (0.18)**</td>
</tr>
<tr>
<td>Mobile Penetration</td>
<td>0.0048 (0.00071)**</td>
<td>0.0048 (0.00071)**</td>
</tr>
<tr>
<td>Internet Penetration</td>
<td>0.016 (0.0017)**</td>
<td>0.016 (0.0017)**</td>
</tr>
</tbody>
</table>

Country FE: Yes Yes Yes Yes  
Quarter FE: Yes Yes Yes Yes  
N: 3224 3192 80800 80524  
Log-likelihood: -15169.0 -15025.8 -16131.3 -16126.9

Standard errors in parentheses
* p < 0.15, ** p < 0.10, *** p < 0.05, **** p < 0.01

Note: This table provides estimates from Figure 3, using the time-varying, log-linear specification \( \ln(Y_{it} + 1) = \alpha + \sum \beta_k t \times I(z) + \gamma + \delta_t + \varepsilon_{ict} \) where \( \gamma \) and \( \delta \) represent country and region fixed effects respectively for country or member \( i \) 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. Separate estimates for New Members and Established Members from the respective samples are presented. Estimates from \( z > 5 \) and \( z < -5 \) are supressed for brevity.
### Table 7. EVALUATING ROBUSTNESS TO ALTERNATE SPECIFICATIONS

<table>
<thead>
<tr>
<th></th>
<th>New Member Contrib. (H1)</th>
<th></th>
<th>Established Members Contrib. (H2)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td>Poisson</td>
<td>Diff. Trends</td>
<td>Placebo</td>
<td>Poisson</td>
</tr>
<tr>
<td><strong>main</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post Google Entry</td>
<td>-0.19***</td>
<td>-0.53***</td>
<td>-0.026</td>
<td>0.78***</td>
</tr>
<tr>
<td></td>
<td>(0.0052)</td>
<td>(0.18)</td>
<td>(0.14)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>Population (millions)</td>
<td>2.91***</td>
<td>1.79</td>
<td>2.93*</td>
<td>4.23***</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(1.52)</td>
<td>(1.60)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>GDP per capita</td>
<td>-8.87***</td>
<td>3.23*</td>
<td>2.71</td>
<td>-2.43***</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(1.77)</td>
<td>(2.43)</td>
<td>(0.70)</td>
</tr>
<tr>
<td>Mobile Penetration</td>
<td>0.0098***</td>
<td>0.0064**</td>
<td>0.0086***</td>
<td>0.0067***</td>
</tr>
<tr>
<td></td>
<td>(0.000082)</td>
<td>(0.0025)</td>
<td>(0.0031)</td>
<td>(0.00055)</td>
</tr>
<tr>
<td>Internet Penetration</td>
<td>0.0014***</td>
<td>0.0073</td>
<td>-0.0030</td>
<td>0.044***</td>
</tr>
<tr>
<td></td>
<td>(0.000020)</td>
<td>(0.0064)</td>
<td>(0.0086)</td>
<td>(0.0011)</td>
</tr>
<tr>
<td><strong>Country FE</strong></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Time FE</strong></td>
<td>Quarter</td>
<td>Inc. X Quarter</td>
<td>Quarter</td>
<td>Quarter</td>
</tr>
<tr>
<td><strong>Age FE</strong></td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>3192</td>
<td>3192</td>
<td>3192</td>
<td>80524</td>
</tr>
<tr>
<td><strong>Adj. R2</strong></td>
<td>0.85</td>
<td>0.84</td>
<td></td>
<td>0.057</td>
</tr>
</tbody>
</table>

Note: This table evaluates the robustness of the baseline results to alternate specifications. The Country-Qtr Sample evaluates H1, while the member-quarter sample evaluates H2. In each analysis, column (1) estimates a specification similar to the baseline specification, using Poisson rather than Log-OLS models with the dependent variable being $\text{Contributions}_i$ and reports standard errors clustered at the country level. Column (2) estimates the log OLS models using the baseline specification, except these estimates include region-specific time-trends rather than 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 separate time trend as compared to the rest. Finally, Column (3) presents results from a placebo exercise where countries are randomly assigned to the five Google Maps entry cohorts, and the $\text{Post Google Entry}$ variable represents the period after this randomly assigned date.