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

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Abstract

Open source platforms often face competition from commercial alternatives and yet we lack an understanding of whether and how commercial competition affects contributions to open source platforms. We study how contributions to OpenStreetMap, a widely-used open source 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. We find that the entry of Google Maps has a negative effect on contributions to OpenStreetMap, illustrating that commercial competition plays an important role in shaping open source contributions. We then examine if different contributors react differently to competitive entry, finding that new contributors (those who are contributing for the first time) decrease their contributions while pre-existing contributors (those who contributed before competitive entry) increase their contributions. We find that the reduction in new contributors seems to be driven by a reduction in consumption of the open source platform. The increase in contributions by pre-existing contributors seems to be associated with their attachment to the platform, which is anchored in their ideological inclination towards open source and to a lesser extent, the social interaction it offers with their fellow contributors.

Over the last thirty years, individual contributions to open source platforms have produced impressive results, from Wikipedia's vast encyclopedia to Linux's operating system (Greenstein and Nagle 2014; Jeppesen and Lakhani 2010; Nagle 2017). A voluminous literature has examined why individuals voluntarily contribute to these projects, identifying individual and group level factors that are associated with such contributions (Butler 2001; Lakhani and Wolf 2005; Gallus 2017; Kraut and Resnick 2012). While this work has significantly enriched our understanding of the determinants of volunteer contributions, it has largely overlooked the fact that open source platforms do not exist in isolation. Rather, they often face external competition from commercial alternatives. Wikipedia, for example, competes with Encyclopedia Britannica online, and Linux competes with Microsoft Windows. While open source platforms and commercial alternatives differ in the way they organize, they often offer largely similar products and features, thereby competing for the same consumers. While a large body of research has examined how open source and commercial platforms compare and contrast (e.g., Almirall and Casadesus-Masanell 2010; Greenstein and Zhu 2014; Giles 2005), our knowledge of whether and how they affect one another is limited.

Given the emphasis in the literature on internal factors that affect contributions, no empirical research has looked at the topic of competition. We thus do not know whether competition has any meaningful role to play in shaping contributions. Even if competition shapes contributions, we do not know whether its effect is negative or positive. For example, commercial competition has the potential to reduce the pool of contributors as well as their motivation, thereby reducing contributions. On the other, contributors might have a sense of attachment to the open source platform and might increase contributions in order to preserve it. Given the lack of research on this topic, we do not yet know which mechanisms are at play, and to what degree and to whom they apply. Motivated by this gap, we examine *whether and how commercial competition affects voluntary contributions to open source platforms.*

Our interest in this question is echoed by prior work which has pointed out the potentially important theoretical and practical implications of studying the role of competition in shaping contributions to open source platforms and has called for more research in this area (Lerner and Tirole 2002). Understanding the effect of commercial competition is important because competition may substantially affect the viability of open source platforms. Investigating this question is methodologically challenging, however, as it requires a comparable set of open source communities where only some are exposed to competition. Further, competition can arise endogenously since a commercial competitor is likely to enter against those communities that are easiest to compete with. It is empirically challenging to tease apart the effect of competition from these endogenous factors.

We develop a research design that addresses these challenges. We analyze the effect of the competitive entry of Google Maps on contributions to OpenStreetMap, one of the largest open source platforms on the web with about half the number of active members as Wikipedia (Maher 2016). Even though OpenStreetMap is a single, global open source project, it is maintained by distinct country-based communities, providing us with a population of distinct but comparable communities within a single overarching platform. While OpenStreetMap launched globally in 2004, Google Maps started in only a handful of countries and expanded on a country-by-country basis after its inception in 2005. We suggest that this phased roll-out, while not explicitly random, can reliably be exploited to evaluate whether and how commercial competition affects contributions to OpenStreetMap across the distinct country-based communities (cf. Seamans and Zhu 2014, 2017).[1] We pair this variation in Google Maps with a novel quantitative dataset capturing over 2.4 million contributions between 2004 and 2015 made by 89,000 members of the OpenStreetMap communities in 87 countries in order to investigate our research question.

[1] Note that it might seem like we are lumping unrelated countries in one group and examining the effect of competition among them. However, in this research design, we include country fixed effects and so essentially we are examining how contributions in a country changes as compared to itself after competitive entry. The differential timing is helpful in allowing us to include time fixed effects to control for platform-wide dynamics.

We also consider a specification that relies on a sample of 160 countries (79 in our main sample for which we found a match to a set of 81 control countries).

In the absence of clear theoretical predictions on the effect of commercial competition on contributions, we present empirical estimates of the effect of competition by Google Maps on contributions to OpenStreetMap. We analyze detailed information at the level of the individual, the country-level community, and the community's broader national context to explore various mechanisms through which commercial competition could affect contributions. Accordingly, our goal in this paper is to provide the first systematic and large-scale evidence of the possible role of competition in shaping contributions to open source platforms and to rule in potential mechanisms that will guide future theoretical work in this area.

Our results suggest that commercial competition has a substantial effect on contributions to open source platforms. Specifically, we find that the entry of Google Maps in a country *decreases* contributions to OpenStreetMap by 51% in the average quarter after entry. This finding illustrates how detrimental commercial competition can be to open source platforms. More broadly, the finding that competition does have an effect on contributions reinforces our motivation that it is not enough to compare and contrast open source and commercial alternatives; rather, we must examine the effect that they have on one another.

Having established the important role of competition in shaping contributions, we then examine heterogeneity in the overall response to commercial competition within and across communities. To do this, we analyze separately contributions from pre-existing contributors (contributors who joined prior to the market entry of Google Maps) and contributions from new contributors (those who start contributing for the first time in a particular quarter). In other words, for a country j in quarter t, contributions from pre-existing contributors are defined as the total number of contributions made by all contributors i who made their first contribution before the competitive entry of Google Maps. Contributions from new contributors are defined as total contributions made by all contributors *i* whose contributions before the focal quarter *t* equal zero. Therefore, we contrast the effect of competition on the fixed set of pre-existing contributors with its effect on first time contributors in every country-quarter. We find that total contributions per quarter from pre-existing contributors *increases* after the entry of Google Maps. However, the total contributions per quarter from new contributors *decreases* after the entry of Google Maps. While prior work points out that contributors differ in their motivations, and that the key drivers underlying their motivations change over time (e.g., Shah 2006), we present what is, to the best of our knowledge, the first evidence that distinct groups of contributors respond very differently to commercial competition.

Further, we provide an exploratory examination of what underlies the different responses by new and pre-existing users. Because new contributors are not a fixed group but are defined relative to the quarter under study, the finding that the total number of contributions per quarter from new contributors goes down could be because there are fewer new contributors, because each new contributor makes fewer contributions on average, or both. Our findings suggest that the first effect might be stronger than the second. Contributions from new contributors decrease largely because the commercial competitor acts as a substitute, reducing the number of consumers of the open platform. Because consumption often precedes contributions (Kane and Ransbotham 2016), this reduction in consumption results in fewer new contributors. Competition also appears to reduce the motivation of new users: the average number of contributions each new contributor makes in their first quarter of contributing is higher before Google Maps enters than the average number of contributions each new contributor makes in their first quarter of contributing after Google Maps enters. However, this effect is small compared to the decline in the number of new contributors. In contrast, pre-existing contributors increase their average number of contributions in the face of competition due to their attachment to the open source platform. By attachment, we refer to the extent to which contributors identify with the organization and feel a cognitive and emotional connection to it (Paxton and Moody 2003; Hassan 2012; Ashforth and Mael 1989). We consider two possible drivers of attachment that have been theorized in the context of open source contributions (Ren et al. 2012), finding that attachment driven by ideological inclinations seems to drive this positive response, although attachment driven by the social interaction among contributors matters to a smaller extent.

Taken together, these results indicate that the key mechanisms at play when an open source platform is faced with competition is that it attracts fewer new contributors than before but it receives more contributions from pre-existing contributors who are driven by their ideological attachment to the platform to increase their contributions in order to preserve it. In the context of OpenStreetMap, the increase of contributions by pre-existing contributors does not compensate for the decrease in new contributors and their average contributions, resulting in an overall negative effect.

We add to the research on what motivates individuals to contribute to open source platforms by looking beyond intra-community determinants of contributions, focusing instead on the role of ecological factors. Our findings illustrate the substantial effect of competition, perhaps the most prominent ecological factor, on people's tendency to become contributors and to contribute. Further, by studying competition and the mechanisms through which it affects contributions, we also answer the call to look beyond the micro-factors that shape individual motivation and start examining how individual motivation is enhanced or dampened by macro-factors (von Krogh et al. 2012). Our finding that competition has a heterogeneous effect—reducing the number of new contributors and their contributions while increasing contributions from pre-existing contributors—points to the intricate relationship between the macro-environment and people's motivation to contribute to open source.

We also contribute by helping to develop a better understanding of the competition between open source platforms and commercial competition following the call by Lerner and Tirole (2002, 2005). While prior work has provided a rich qualitative account (Gaudeul 2007) and developed formal theory

(Baake and Wichman 2003; Bitzer and Schröder 2006; Casadesus-Masanell and Ghemawat 2006; Athey and Ellison 2014), our study is to the best of our knowledge the first that provides systematic large-scale empirical evidence on the effect of commercial competition on open source alternatives. Our findings demonstrate that commercial competition can have a substantial negative effect on open source platforms, rendering them less viable. The difference in response by new and pre-existing contributors illustrates that external competition can change the internal composition of the open source community as engagement from pre-existing contributors increases while engagement from new contributors decreases.

Theoretical Background

Contributions from unpaid volunteers are the lifeblood of open source platforms. Research into what motivates people to contribute focuses largely on individual- and community-level factors (Butler 2001; Lakhani and Wolf 2005, Gallus 2017; von Hippel 2017). This research largely focuses on the level of the contributing individuals and their peers. Given the breadth of that literature, rather than summarize the entirety of this work, we focus on aspects we consider to be directly relevant to understand the effect competition may have. Research in this domain examines the process of how people *start to contribute*. Kane and Ransbotham (2016) and Gorbatai (2014) find that the process typically begins with people who use the open source platform themselves and then contribute when they identify a need or potential to improve the platform (e.g., they encounter a bug or missing information). Subsequent research finds that people continue to contribute because they become attached to the platform (Ren et al. 2012; Bateman, Gray, and Butler 2011). Contributors form bonds with their peers and enjoy interacting with them (Zhang and Zhu 2010; Shriver, Nair, and Hofstetter 2013). They also tend to adopt the ideology of open source—that knowledge should be freely distributed and accessible to everyone—and this becomes an important motivator (Shah 2006). That ideology is fundamentally distinct from commercial platforms, and the difference between them is a source of contributors' motivation to contribute to open source (Stewart and Gosain, 2006).

While this rich body of research has examined in great detail individual-level factors and individuals' immediate environment, there has been little research on how ecological factors affect people’s motivation to contribute. As Hill and Shaw (2019) state, “Established approaches to the comparative study of online community success have almost exclusively looked *inside* communities” (emphasis added). As a result, we know little about whether and how macro-factors enable or constrain these micro-factors (von Krogh et al. 2012). We address this lacuna by focusing on perhaps one of the most salient of environmental factors that affects organizations, namely whether it exists in isolation or whether it faces competition from a similar alternative. Specifically, we focus on whether an open source platform faces competition from a *commercial* alternative. While there has been a wide-ranging debate on how open source and commercial platforms compare to one another (e.g., Almirall and Casadesus-Masanell 2010; Greenstein and Zhu 2014; Giles 2005), there has been little research on how the two types of platforms affect one another. Understanding the effect of commercial competition on contributions is important because it allows us to better understand how ecological factors shape the development of open source platforms and thus helps us to predict and to understand when open source platforms are likely to thrive, prevail, or fail.

We are not the first to point out the need to study competition. Lerner and Tirole (2005, 107) write, “While the relative merits of open source and proprietary software are discussed in a number of contributions, direct competition between the two paradigms has received little attention.” The few studies in this area are largely theoretical, do not focus directly on competition and even when they do, how competition affects contributions is an assumption of the model, not a result. For instance, Baake and Wichman (2003) model the competition between two commercial software firms when one firm makes part of the software open source. They assume that open sourcing a part of the commercial software will reduce development costs by attracting volunteers while competition raises coding expenditures due to increased demand for coders. They assume competition has no effect on encouraging or discouraging volunteers. Athey and Ellison (2014) use a formal model to examine the dynamics of an open source project, assuming that a commercial competitor offers an "outside option" and lowers the supply of volunteers to the open source project. Gaudeul (2007) qualitatively studies the dynamics of the open source software (LA)TEX, focusing on how competition changes the internal dynamics of contributor activity and the type of contribution. Taken together, the few theoretical attempts in this area rely on different and sometimes contradictory assumptions about how competition shifts contribution activity. An empirical examination of whether and how competition affects contributions has the potential to discipline existing theory and inspire an integrated and generalizable theoretical framework for the role of competition in shaping open source contributions.

The lack of prior research makes it difficult to deduct clear hypotheses on the effect of commercial competition on open source contributions. The literature studying the motivation to contribute to open source has not studied the effect of commercial competition, and the literature on paradigmatic competition has not studied the effect of competition on the motivation of voluntary contributors. In other words, the linkage between macro-competition and micro-motivation has been neglected. While prior research does not allow for a clear theoretical prediction on the effect of competition, it does allow us to *speculate* about the effect that commercial competition may have on contributions to open source platforms. We build on the rich body of work on the motivation to contribute (Butler 2001, Lakhani and Wolf, 2005, Gallus 2017), and focus on theoretical mechanisms we consider to be directly relevant to understand the effect competition may have.

It seems plausible that commercial competition results in a *decrease* of contributions. Commercial competition provides a substitute for the open source platform and so can be expected, ceteris paribus, to reduce the *consumption* of the open source platform. Reduced consumption can be expected to decrease contributions via two mechanisms. First, prior research suggests that consumption often precedes contributions (Kane and Ransbotham 2016). A competition-induced reduction of consumption would thus reduce the number of potential new contributors by reducing the number of consumers; consumers may simply not become aware of the open source platform and the opportunity to contribute. Second, consumption matters because contributors care about the impact their contributions have (Lerner and Tirole 2002; Boudreau and Jeppesen 2015; Fershtman and Gandal 2007; Blasco et al. 2019). Contributors may be less motivated when a commercial competitor achieves substantial market share because their contributions now benefit fewer people. Taken together, competition might reduce both the pool of potential contributors and the number of contributions made by each contributor.

It is, however, also plausible that competition results in *an increase* in contributions. Lerner and Tirole (2002, 228) speculate that "open source projects gain momentum when facing a battle against a dominant firm," although they clarify that this proposition assumes that "this is an empirical fact, which remains to be established." A potential mechanism why commercial competition may lead contributors to increase their contributions is contributors' *attachment* to the open source platform, that is, the degree to which contributors identify with the organization and feel a cognitive and emotional connection to it (Paxton and Moody 2003; Hassan 2012; Ashforth and Mael 1989; Pratt 1998). Prior research suggests that attached stakeholders increase their support when the organization to which they are attached is under threat (Zavyavola et al. 2016). Attachment is a generally an important driver of people's motivation to contribute to open source (Ren et al. 2012; Bateman, Gray, and Butler 2011). It may be particularly important after competitive entry because attached contributors are likely to be concerned that competition may ultimately lead to the open source platform's demise. Contributors may wish to prevent this outcome given their attachment for two different reasons. One, they might miss the social interactions with fellow contributors that are meaningful to them (Zhang and Zhu 2010; Shriver, Nair, and Hofstetter 2013). Two, they might be concerned that dominance of a commercial platform will overshadow the open source ideology that they subscribe to (Stewart and Gosain 2006; Murray 2010). In addition to attachment, contributors might also increase the number of contributions they make to preserve their standing within the community (Johnson 2002; Chen et al. 2010). Regardless of which of these factors is at play, contributors might be concerned about the demise of their platform and may thus increase their contributions in order to help the open source platform thrive.

Finally, while we have outlined the reasons for a competition-induced increase or decrease, it is of course also plausible that competition has no effect on contributions. Research has long documented that contributors to open source projects are intrinsically motivated through factors such as enjoyment and intellectual satisfaction (Lakhani and Wolf 2005). For example, in a survey of contributors to user innovation projects, von Hippel (2017, p.29) documents that more than 55% of participants are motivated to contribute for "fun and learning." Contributors might therefore be largely unaware or unconcerned about the external competitive environment, which would lead to the finding that competition has a limited role to play in explaining contributions to open source projects.

Given that a decrease, an increase, or no effect on contributions all seem equally plausible a priori, it is difficult to speculate from prior theory about the potential effect of commercial competition on contributions. Therefore, to make progress on this question, we adopt an empirical approach, providing the first quantitative examination of the impact of commercial competition on open source contributions. This examination helps us uncover if commercial competition does indeed influence contributions and if so, in what direction. Our data also help us shed light on the specific mechanisms through which commercial competition affects contributors and their contributions, setting the stage for future theory in this area. Accordingly, we now turn to describing our setting, research design, and data.

Setting and Data

There exist hundreds of open source projects that offer alternatives to commercial counterparts in areas as diverse as online encyclopedias, operating systems, gaming, graphic applications, networking tools, web development tools, databases, and servers. For example, Octave is an open-source alternative to the commercial mathematical computing platform MATLAB; MySQL provides an open-source database alternative to Oracle9i; OpenOffice is an open-source word processing platforms that rivals Microsoft Word; and GNU Image Manipulation Program (GIMP) provides an alternative to commercial image editing programs such as Adobe Photoshop. In each of these examples, the open source platform and its commercial competitor offer very similar products and therefore address the needs of a similar customer segment. We are interested in the effects of this type of direct commercial competition on contributions to open source platforms.

Despite the plethora of examples and significant theoretical interest in the question of competition between commercial and open source platforms, quantitative empirical work has yet to examine this topic. An ideal experiment would consider a set of comparable open source communities and identify random variation in competitive entry to examine the causal impact of competition on open source contributions. However, in reality open source platforms are not directly comparable; there are too many variables to make such a comparison valid. One cannot compare contributions to OpenOffice after Microsoft Word enters to contributions on Wikipedia after Encyclopedia Britannica enters given the stark differences in the nature of contributions and the types of contributors to these two communities. Furthermore, competition may be endogenous: commercial providers might enter precisely where open source communities have few contributions, and therefore it is unclear if lower contributions are caused by competition or whether competitive pressures are realized in the face of lower contributions.

We devise a research design that tackles these challenges. Our key insight is to consider relatively distinct contributor communities within a single open source project and then examine the effects of exogenous variation in competition *within* a project but *across* communities. Specifically, we examine the response of contributors to country-based OpenStreetMap open source communities to the competitive entry of Google Maps in countries around the world. The entry of Google Maps provides a valid construct for examining the role of competition given that Google Maps and OpenStreetMap offer virtually the same functionality and target the same set of use cases, i.e. looking up directions and places on a global web map. Before Google Maps' entry, OpenStreetMap was usually the only online map provider in a country. After Google Maps entered, OpenStreetMap faced direct competition from a stronger and better-known rival. Importantly, as we will show, the variation in the exposure to competition is likely to be unrelated to the strength of contributor communities in different countries, making this a useful research design to tease out the effect of competition on contributions. Finally, this case is of substantial interest in itself, given that OpenStreetMap and Google Maps represent the two leading platforms in the web-based mapping industry and since maps have long been recognized as one of the most valuable forms of knowledge (Harley et al. 1987; Nagaraj 2018; Nagaraj and Stern 2020). In what follows, we provide a brief overview of the two mapping platforms and describe our research design and data.

The Open Source and Commercial Competitors

OpenStreetMap was launched in 2004. Inspired by Wikipedia, it aims to provide an open source, online map for the entire globe (Coast 2015). At its core, OpenStreetMap is a database of geographic information that can be modified by any community member after a free and simple registration process (Coast 2015). Even though it is a non-commercial project, it is steeped in its own forms of legal restrictions and contracts—such as the requirement to publish openly any derivative work. Figure 1 provides an overview of the editing process, showing how a member can add a building or a street to an existing map. To collect information, community members often survey neighborhoods with GPS devices or trace features from satellite images. As of February 2020, OpenStreetMap had over six million registered community members around the world.[2] To focus our research on countries where Google Maps competition is plausibly exogenous, our main analysis uses 89,000 contributors in 87 countries mainly from the developing world. In some robustness analyses we do include data from a wider set of 160 countries.

[Insert Figure 1 Here]

OpenStreetMap's main competitor is Google Maps, a rival web-based mapping service launched

[2] https://wiki.openstreetmap.org/wiki/Stats

in 2005. Google Maps is a proprietary mapping platform that is not freely licensed, cannot be openly modified, and is available for downstream applications only with numerous restrictions. While OpenStreetMap relies 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 licensing contracts with third-party data providers in addition to public domain data sources and contributions from users.[3] Google Maps, however, does not use data from OpenStreetMap in its maps because the latter is protected by a "copyleft" license that means it can be used only by applications that are also licensed openly and released under a copyleft license.[4]

Google Maps' Global Expansion

Our research design relies on the difference in the timing of global expansion of Google Maps and OpenStreetMap. Because OpenStreetMap relies on local communities to provide map information, 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 when OpenStreetMap launched in August 2004.[5] Google Maps, in contrast, relied on proprietary data and was not able to launch maps for all countries at the same time. In fact, when Google Maps was first launched in 2005, it covered just the United States and the United Kingdom (McClendon 2012). It expanded its coverage first to the developed world with its lucrative markets. After 2009, it expanded rapidly in the developing world. Figure 2 outlines Google Maps' expansion to over 87 countries in five distinct waves over a two-year period, according to our data. We focus on these five waves of Google Maps' expansion in our empirical analysis. In particular, we

[3] 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.

[4] Note that OpenStreetMap might also compete with other community-based projects for member contributions, but our empirical focus is on its competition with Google Maps.

[5] 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 OpenStreetMap leadership.

highlight how OpenStreetMap faced competition from Google Maps sooner in some countries than in others based on the timing of Google Maps' expansion.

[Insert Figure 2 Here]

To proceed with our analysis, we assume that Google Maps does not make its expansion decisions based on contribution trends in OpenStreetMap. Because this assumption is critical, we seek both qualitative and quantitative evidence to support it. Because we include country and time fixed effects in our regressions, the main concern with the research design is the following: if Google Maps specifically targeted countries where contributions were decreasing or 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. We will discuss the quantitative evidence for this assumption before we discuss our empirical results.

From a qualitative perspective, evidence from publicly-available sources suggests that Google's decision to enter a country's market was based on its ability to obtain third-party data for that country. For example, 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" (McClendon, June 2012). The publicly available material makes no mention of OpenStreetMap communities as playing a role in Google Maps' decision to enter any market, 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 including 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 regions at particular points in time, but launched in different countries when it was possible to do so. The quantitative tests that we perform, which are reported in the Results section, along with this qualitative evidence make us feel confident in using Google Maps' entry as an exogenous shock to competition for OpenStreetMap, allowing us to estimate the quantitative impact of competition on community members' contributions.

Data

To estimate the impact of Google Maps' entry on OpenStreetMap, we use three primary data sources. First, we collect data on contributions to OpenStreetMap from its "changeset file," which contains metadata on every contribution ever made to the OpenStreetMap database.[6] Second, we collect the date of Google Maps' entry in each of the countries in our dataset from the Google Maps blog.[7] Finally, we rely on demographic and economic indicator data from the World Bank as control variables as well as to help us perform robustness checks. Our main analysis focuses on the set of 87 countries that faced Google Maps competition in five waves between 2009 and 2011. We also run our analyses with a larger set of 160 countries for robustness.

Our key dependent variable is the total number of contributions to OpenStreetMap at the country-quarter level. In other words, for country *i* in the quarter *t*, we count the total number of contributions and label this $\text{Total-Contributions}_{it}$ to form our main dependent variable. In order to make a contribution, an individual must create an account or login with their username (anonymous edits are not permitted), make an addition or a change to the map, and then upload this change. Every time a set of new or modified information is uploaded to OpenStreetMap, we infer that a contribution has been made.[8]

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[6] Available at http://planet.openstreetmap.org/

[7] In practice, we code Google's Lat-Long blog announcements announcing Google's entry into different markets.

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

There were 2.4 million contributions made to maps of the 87 countries we study in our time period of 2006 to 2014. [9] For each contribution, the file provides the username of the community member, the date and time the change was submitted, and the average latitude and longitude of all objects added or modified in a given contribution. We do not possess data on the nature of the contribution itself. Using the latitude and longitude, we wrote scripts that placed each edit within a country's borders to identify the location of each contribution.[10] Using this location and timing information, we are able to measure the total number of contributions in a given country-quarter between 2006 and 2014[11] and estimate the impact of Google Maps entry on this key variable. Note that the contribution is the final step in a process that might begin with a person casually browsing OpenStreetMap as a consumer, then registering for an account and then making her first edit. We are unable to collect data on this broader "risk set", but we measure contributions after an account has contributed at least once.

Next, we measure Post Google Entry, an indicator variable that equals 1 for each quarter after Google Maps has formally entered a given country and 0 otherwise. This variable captures whether the OpenStreetMap community in a given country is currently in competition with Google Maps. We also attempt to capture how strong the competition from Google Maps was in a given country based on the frequency with which people searched for Google Maps. Specifically, we collected data from Google Trends on the popularity of the term "google maps" in each country for each quarter after Google Maps was launched. Using this data, we ranked countries in terms of the relative popularity of Google Maps. Those in the top half of this ranking are considered to have a "high" degree of competition. These data help to evaluate whether the extent of penetration of Google Maps' (rather than a simple binary variable

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[9] 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.

[10] 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.

[11] 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.

for the presence of competition) in a given country is related to changes in contributions on OpenStreetMap.

We also collect a number of country-year specific variables to help us control for unobserved variation across countries over time. While nonparametric fixed effects control for most unobserved variation, 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 conditions also make people in those countries more or less likely to contribute to OpenStreetMap, then we might confound the effect of competition with the effect of economic or technology changes. 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 hundreds of US dollars. Internet penetration and mobile penetration are measured as internet users per 100 inhabitants and mobile cellular subscriptions per 100 inhabitants, respectively. The income class variable categorizes countries as high income, upper-middle income, lower-middle income, or low income based on the country's gross national income per person.

Armed with these data, on total contributions, Google Maps entry timing and a host of control variables we are able to estimate whether and how competition from a commercial competitor affects open source contributions. We now turn to discussing the empirical specification and resulting estimates.

Results

Summary statistics for our variables at the country-quarter level can be found in Table 1. The mean value of total contributions is 692.3 and the median is 79 for a given country-quarter. 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 and 60% are post-entry.

[Insert Table 1 Here]

Estimation Approach

To test the effect of competition on total contributions to OpenStreetMap, we utilize a differences-in-differences approach with the following specification:

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

where Y_{it} represents total contributions in a country *i* in quarter *t*, γ_i are country fixed effects, δ_t are time fixed effects, and X_{it} are time-varying country-level controls for internet and mobile phone penetration. The coefficient β estimates the impact of Google Maps competition on total contributions. We incorporate fixed effects to control for unobserved variation that plausibly influences a population's propensity to contribute to OpenStreetMap. For example, a country's size, terrain, or climate might make it more or less easy to perform mapping tasks. Similarly, the average age and income in different countries is likely to influence people's free time and thus their propensity to contribute. We include country fixed effects to account for these differences. We also recognize that during the period under study OpenStreetMap is expanding rapidly across the globe, driven by improvements in the OpenStreetMap interface, editing tools, and other related technology, in addition to increasing awareness of the OpenStreetMap project. Non-parametric quarter fixed effects, i.e. four fixed effects for every quarter of every year in our data (i.e. a total of 40 fixed effects) account for these differences. By including fixed effects, our specification identifies within-country variation in contribution activity separate from other differences in the propensity of populations to contribute to OpenStreetMap over space and time.

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 also present robustness of these estimates to an alternate Poisson quasi-MLE specification (Azoulay, Graff Zivin, and Wang 2010) to test the sensitivity of our analysis to specific assumptions about the functional form.

Testing the Validity of the Research Design

Before presenting the results, it is important to confirm the validity of our difference-in-difference research design. In particular, while we include country and quarter fixed effects, which helps to control for a vast number of alternate explanations, there is still the concern that the timing of Google Maps' entry is related to OpenStreetMap's evolution in a certain country. In particular, if Google Maps enters precisely in those countries where OpenStreetMap is struggling, then our results would be driven by reverse causality, i.e., decreased contributions are causing Google Maps to enter and not the other way around.

In addition to our qualitative discussion of this concern in the previous section, we provide here an additional empirical test of our assumption that Google Maps' entry is uncorrelated with contribution dynamics on OpenStreetMap. As is common in difference-in-difference studies, we estimate a model of Google Maps' entry and examine whether we can predict entry based on OpenStreetMap contribution patterns. In particular, we build a country-level sample and regress the timing of Google Maps' entry on a variety of country characteristics. Results from this specification are presented in Appendix Table A1. A negative coefficient implies that a higher value of a covariate leads to faster entry in a given country. As shown in Column (2) it seems that Google Maps tends to enter countries with higher population and higher internet penetration earlier and richer countries later, although only the coefficient on the internet penetration variable is statistically significant. We then add in the variable that captures the growth in contributions in a country before Google Maps' entry. In particular, we measure the change in the total number of contributions in the quarter of Google Maps' entry and the first quarter when a country was active on OpenStreetMap and divide this growth by the number of elapsed quarters to arrive at an estimate of average quarterly growth. Including this variable in the regression shows that contribution growth is not statistically related to the timing of Google Maps' entry, which is reassuring. It does not seem to be the case that Google Maps' is entering precisely in the countries where OpenStreetMap contributions are already declining.

Estimation Results

Table 2 reports results from our estimates. The first column presents a baseline specification examining the determinants of contributions on OpenStreetMap. The strongest predictors of contributions are country and time fixed effects, but time-varying measures of population and mobile penetration also seem to be associated with contribution activity.

We now add in our key independent variable for competition, first without controls (Column 2) and then with some or all controls (Columns 3 and 4). The coefficient on β in all three models is negative and statistically significant. Because these coefficients are obtained from log-OLS models, they express the percent change in the outcome variable for one unit of change in the independent variable. Thus in Column 3, the coefficient of -0.51 represents a decrease in contributions of about 51% in a country after it has experienced entry from Google Maps, a significant change, after controlling for country fixed effects, year fixed effects, GDP, population, and internet and mobile penetration.

In Column 5, we interact the Post Google Entry variable with an indicator variable for High-Competition. Our expectation is that competition matters not only by its mere presence, but also by the extent of penetration: i.e the degree to which Google Maps gains popularity in a given country. While the impact of competition on contributions is negative in all specifications, the effect seems to be even more negative when the competitive pressure from Google Maps is particularly high. However, this interaction variable is not statistically significant, making this result only suggestive. However, if taken seriously, this estimate suggests that it is not simply Google Maps' entry that matters, but also the extent to which the competitor is used in a given country.

Overall, these results are striking because they offer the first quantitative evidence that contributors to open source communities are significantly affected by the competitive environment. In particular, it seems like competition from Google Maps has a negative effect on total contributions to OpenStreetMap.

[Insert Table 2 Here]

Examining Pre-Trends

In order to explore the dynamics of our baseline result and provide a stronger test for the validity of our quasi-experimental design, we examine the difference in trends between treated and yet-to-be-treated countries before Google Maps' entry using our baseline regression framework. If Google Maps enters where OpenStreetMap contributions are already decreasing, we would see a negative pre-trend before the quarter of entry. If the negative trend starts after the entry event, we can be relatively confident that it is the competitive entry that causes a reduction in contributions and not the other way around. Further, by estimating how and when contributions start decreasing we can understand the dynamics of the overall negative effect of competition on contributions. Accordingly, we estimate difference-in-difference regressions (similar to the baseline analysis), except we estimate the effect of competition separately for every quarter before and after Google Maps' entry. separately, rather than simply one average estimate for the *Post Google Entry* variable. Specifically, we estimate regressions of the form:

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

where *f* represents the Poisson or log-OLS functional form and 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 -1 a quarter before Google Maps enters a country and is equal to +1 the quarter after Google Maps has entered. If the parallel trends assumption is justified, we should find estimates of β_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. As the chart makes clear, the pre-trends assumption seems to hold: it does not appear that contributions are changing before OpenStreetMap faces commercial competition. This finding significantly helps to increase confidence in the research design. Further, these results show that the negative effect of competition kicks in immediately after Google Maps' entry and its magnitude keeps growing over time. Note that for all these graphical results, we employ the log-OLS functional form and we present estimates from this specification in tabular form.

[Insert Figure 3 Here]

Robustness Checks

Alternate Specifications: In addition to our main regressions, the entry model and the graphical analysis, we also evaluate the robustness of our specification to alternate modeling assumptions in Table 5 (Cols 1-3). In the first model, 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. As the estimates on Post Google Entry in Columns 1 and 2 indicate, the impact of competition on overall contributions remains negative and significant in both models.

Next, 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. In the spirit of Bertrand et al. (2004), we randomly assign each country to one of the five quarters in which Google Maps entered and use this entry time to estimate a new *Post Google Entry*$_{it}$ variable that we employ in the regression testing the baseline specification.[12] 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. As shown in Column 3, the estimates from this regression are no significantly different than zero, suggesting that our results are not driven by mechanical artifacts of our setup or variable definitions, but are indeed driven by the specific timing of Google Maps' entry.

Coarsened-Exact-Matching (CEM) Sample: Finally, note that our specifications so far have looked at the variation in Google Maps' entry within the set of 87 countries in our sample. In this research design, the counterfactual for communities that face competition in a given year t_1 are communities that will face competition in a future year t_2 where $t_2 > t_1$. Note however, that our baseline sample does not include any countries that never face competition as the counterfactual group. It has been shown that such a design with no "never treated" units is valid in the event study context as long as the pattern of effects is the same for all "treatment cohorts" (Abraham and Son 2020, Goodman-Bacon 2019). Another benefit of such an approach is that it limits the analysis to a homogenous set of countries that differ only in their timing of competition. However, as a further robustness check, we estimate our main specifications on a parallel sample of 160 countries (79 who ever experience entry in our data and 81 control). These countries are chosen using a coarsened-exact-matching (CEM) procedure based on a coarsened matching of countries' GDP, population, income category, region and internet and mobile phone penetration (Iacus et. al 2012). The one important caveat with this sample, is that we do not know for sure whether and when Google Maps' entered the control counties. Since Google Maps is available globally as of 2019, it is quite likely that OpenStreetMap in these countries do experience competition, but we do not possess the exact date on which such competition might have begun. Our estimates here are therefore likely to be conservative if some of the countries in the control sample also face competition. Acknowledging this

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

caveat, we present results from this alternate sample in Table A3. The first column uses the baseline specification with a fixed effect for every matched country pair and a quarter fixed effect. The next column is similar except it includes an income X quarter fixed effect instead of the quarter fixed effect. As is clear from these results, the negative effect of Google Maps' competition on total OpenStreetMap contributions remains in this broader sample as well, although these are relatively imprecisely estimated.

Taken together, our robustness checks and the CEM sample help to establish the validity of our baseline finding that competition has a significant and negative effect on total contribution within OpenStreetMap.

Mechanisms Driving Changes in Contributions

Our finding that commercial competition has an important effect on contributions to OpenStreetMap. This result provides the first empirical response to calls in past research to study the potentially important role of commercial competition in shaping contributions to open source. More generally, our results encourage future research looking to adopt an ecological approach to unpack the drivers of contributions to open source platforms.

We find in our context that the entry of Google Maps has a *negative* effect on driving contributions to OpenStreetMap. From a phenomenological perspective this finding has important implications for both researchers and managers looking to understand the impact of commercial competition on an open source competitor. For example, our research helps to explain the variance in people’s tendency to contribute to different open source platforms and the circumstances in which open source platforms are likely to thrive, prevail, or fail.

However, the implications for a more general theory of competition in open source platforms are less clear. The negative effect we find could mean that theoretical mechanisms predicting a positive effect are invalid. However, it is also plausible that, in this case, the mechanisms predicting a negative effect outweigh the mechanisms predicting a positive effect and that both types of mechanisms have some validity under different conditions. To build a more generalizable theory, it is important to explore the moderators of the effect of competition in order to understand the conditions in which the negative effect we find gets stronger or weaker. In addition to establishing the potentially important role of competition, our setup therefore offers the opportunity to explore whether the effect of competition is homogeneous or heterogeneous across different subgroups of contributors and set the stage for future theoretical work in this area.

The Heterogeneous Effect of Competition: New vs. pre-existing contributors

In order to unpack the negative effect on contributions that we find, we follow the approach of prior studies that examine how an effect varies across subgroups (e.g., Zavyalova et al. 2016). Doing so may allow us uncover heterogeneous treatment effects and to partially isolate the mechanisms at play. Specifically, we examine two groups of contributors. The first group of *pre-existing contributors* are those who joined OpenStreetMap before 2009, when Google Maps began expanding in the 87 markets we look at. These contributors therefore were motivated to contribute to OpenStreetMap when it was the only online navigation tool available.[13] The second group we look at, *new contributors*, are individuals who are making a contribution for the first time in a specific quarter starting in 2009q1. The group of new contributors therefore changes each quarter. This differentiation is interesting because new and pre-existing contributors are likely to differ along various dimensions, most notably their awareness of and their attachment to OpenStreetMap. They may thus differ in the degree to which the mechanisms we speculated about affect them. We thus use this differentiation to learn about the different mechanisms via which commercial competition affects contributions to open source.

We speculated that commercial competition could result in a decrease of contribution because it constitutes a substitute and may thus reduce consumption of the open source platform. Such a

[13] Note that we use contributors who were active before 2009, i.e. before Google Maps starts expanding in *any* country to be our sample of pre-existing contributors. Our results are not sensitive to this choice and go through if this sample was constructed based on contributors who were active before the specific data in which Google Maps enters their country.

competition-induced reduction of consumption can be expected to affect particularly contributions from new contributors because consumption often precedes contributions. So, if competition reduces consumption, less people start to contribute (i.e., less contributors). The commercial competition has the effect that consumption decreases and so potential new contributors may simply never become aware of the open source platform and the opportunity to contribute to it. We also speculated that commercial competition could result in an increase of contributions because of the interaction between contributors' attachment to the open source platform and commercial competition. Such an effect would only affect pre-existing contributors because to become attached to the open source platform implies to form a cognitive and emotional connection to the platform (Ashforth and Mael, 1989). Only pre-existing contributors can have formed such a connection prior to Google's entry. The suggested mechanism underlying an increase of contributions in response to competition is thus more likely to affect pre-existing contributors.

In order to examine whether pre-existing contributors respond differently to competition than potential new contributors, we split the sample into contributions from pre-existing contributors and new contributors. For the first analysis, we identify the population of 2,127 pre-existing community members who were active in our set of 87 countries before Google Maps started expanding (i.e., before 2009) and we record observations at the member-quarter level between 2006 and 2015. In other words, our main dependent variable, $\text{Contributions}_{ijt}$, captures the number of contributions made by contributor *i* in time *t* in country *j* where contributor *i* must have made a contribution before 2009. In the second analysis, the main dependent variable is $\text{Contributions}_{jt}$, which is the number of contributions in country *j* in quarter *t* made by new contributors, i.e., those contributors whose contributions in all time periods before *t* equals zero. The key question is whether these two groups respond any differently to competition.

The results from these analyses are presented in Table 3 (pre-existing contributors) and Table 4 (new contributors). In both tables, Column 1 presents estimates without a term for Google Maps' Entry and the following columns add in the key independent variable and controls. All models include country and time fixed effects. Interestingly, the coefficients on all four models in Table 3 (Columns 2–5) are positive and statistically significant. The main coefficients remain significant even when the specifications include over 2000 fixed effects (one for each pre-existing contributor), which tends to increase the size of the standard errors and so decreases significance.[14] Overall, the estimates indicate about a 1.8-2% *increase* in contributions per quarter from pre-existing contributors after the entry of Google Maps. Collectively, across all pre-existing contributors, this translates into a sizable increase in the total number of contributions.

Table 4 presents the results from our analysis of new contributors. This estimation uses the same sample and research design as the baseline regression, but now we estimate the impact of Google Maps on new member contributions instead of total contributions. We find that it is the new contributors who have a negative response in the face of commercial competition and are driving the overall effect. Column 4, which provides estimates with all controls, suggests that commercial competition reduces contributions from new contributors by about 55% per quarter. Put another way, if new contributors made 100 contributors in the last quarter of 2008, in the first quarter of 2009 they made only 45 contributions.

[INSERT TABLE 3 & TABLE 4 HERE]

Figure 4 presents a striking comparison of these results. In this figure, we provide a similar analysis to the "pre-trends" analysis in Figure 3. However, we run this analysis separately for new contributors (Panel A) and pre-existing contributors (Panel B). As Panel A makes clear, contributions from new contributors decline each quarter after Google Maps enters, but not before. Panel B, meanwhile, shows a rather different pattern. There, change in contributions from pre-existing contributors hovers around 0 until Google Maps enters, and then contributions increase each quarter. Quantitative estimates can be found in Table 6 (Columns 3–6).

[14] Note that since we include fixed effects for each pre-existing contributor, we are also controlling for any country-level differences between countries.

[INSERT FIGURE 4 HERE]

Finally, in line with the robustness checks we conducted for the baseline analysis, we present robustness to these findings as well in Table 5 (Columns 4–9) and Table A3 (Columns 4–6). These results seem to hold for Poisson specifications, differential time trends, and a CEM matched sample, and they are robust to the placebo exercise we conducted before. Further, our results for new member contributions is based on the number of contributors who are making their first contribution in a given quarter. This definition of new user is admittedly arbitrary and so in Table A2 we examine alternate definitions of new users (those who have been active in the previous 2 quarters or the previous 6 quarters), and we find that the negative effect on contributions remains robust. In other words, it does not matter if we measure new contributors are those making their first contribution in a given quarter, or those who are "relatively new" (having contributed in the last few quarters for the first time). The effect of competition on contributions for this group is still negative.

Our findings reveal that Google Maps negatively affects OpenStreetMap's ability to attract contributions from potential new contributors but positively affects its ability to attract contributions from pre-existing contributors. This is a significant finding because it suggests that theoretical mechanisms that predict a positive response to competition and those that predict a negative response both have merit. A general theory of the role of competition should therefore help us understand the conditions under which one response is more likely than the other. With a view to informing such a theory, we delve deeper into the mechanisms underlying the response of new and pre-existing contributors in response to competition. We first evaluate the question of why new contributors might reduce contributions and then turn to the reasons shaping pre-existing contributors' positive response to competition. Our goal is not to provide a complete theory of the role of competition, but to arbitrate potential channels that might be important building blocks of such a theory.

Mechanisms Driving the Reduction in Contributions from New Contributors

We start by exploring what drives the decrease in contributions from new contributors. We speculated earlier that a decrease in contributions could result if fewer people use the open source platform after the entry of a competitor. This could negatively affect contributions (1) by reducing the pool of potential new contributors because consuming often precedes contributing, or (2) by reducing the motivation of new contributors and thus the average number of contributions per new contributor because they perceive the impact of their contributions isn't that meaningful in the presence of a commercial competitor.[15]

To gain more insight, we decompose the negative effect of competition on new member contributions along these two margins. We employ the baseline specification but now the main dependent variable is either the total number of unique new contributors in a given quarter or the average number of contributions made in that quarter by a new contributor (contributions by new contributors/new contributors). Columns 1 and 2 in Table 7 presents estimates from this analysis. These results show that competition reduces both the flow of new users and the average number of contributions per new user. However, in percent terms, the effect on the number of new contributors is much larger: following competitive entry, the number of new contributors decreases by about 30% while the number of contributions per new user decreases by about 16%. Thus, we have suggestive evidence that both mechanisms could be at work: the pool of potential new contributors decreases and the motivation of new contributors declines. In the context of Google Maps, it appears that the decrease in the pool of potential new contributors is the more important mechanism.

[INSERT TABLE 7 HERE]

[15] Another possibility is that a user might register to contribute but never make a single contribution in the face of competition. However, we are not able to quantify the risk set of registered users who do not contribute since we cannot match a user to a country without data on the location of their contribution.

Another test for the role of the reduced pool for potential new contributors in explaining the negative effect would exploit the High Competition variable we discussed before. Since greater traffic to Google Maps will reduce the flow of consumers, and thus potential new contributors to OpenStreetMap, we should expect that the negative effect of competition should be larger in regions experiencing a higher degree of competition. Col (5) of Table 4 presents these estimates suggesting that the effect is more negative in regions experiencing a higher degree of competition (although the interaction is not significant). Overall, the results therefore suggest that reducing the pool of potential new contributors is a relatively important channel through which competition affects contributions to open source platforms.

Mechanisms Driving the Increase in Contributions from Pre-Existing Contributions

Next, we investigate potential mechanisms driving the increase in contributions from pre-existing contributors. Interestingly, this positive response does not change much even when competition from Google Maps is particularly intense. In fact, as shown in Table 3, Column 5, the coefficient on the High Competition variable is quite small and close to zero. This result suggests the level of competition from a commercial alternative is not a factor in the mechanism leading existing contributors to increase their contributions.

Prior work on open source platforms identifies *attachment* as an important source of motivation for contributors (e.g., Shah 2006; Ren et al. 2012). Because of this attachment, pre-existing contributors may be concerned about the demise of the platform in the face of competition (Zavyalova et al. 2016) and so may increase their contributions in order to keep the platform alive and vibrant. As Gaudeul (2007, 250) describes in her examination of LaTeX, “Dynamism was highest when LaTeX was under the highest threat of losing market share to its alternatives.” Our finding that pre-existing contributors increase contributions is consistent with the argument that attached contributors are likely to increase contributions in the face of competition.

To further investigate this mechanism we turn to past work that has investigated the sources of contributor attachment in open source platforms (Ren et al. 2012). We focus on two factors that prior work has found to be critical in explaining contributor attachment: *ideology* and *social interaction*. By ideology, we refer to a strong belief in the core tenets of open source, that everyone has the opportunity to contribute knowledge to the platform and that the resulting knowledge is made freely available (Lakhani and Wolf 2005; Shah 2006; Stewart and Gosain 2006; Koh, Kim, Butler, and Bock 2007; Belenzon and Schankerman 2015). Ideology may be particularly salient when the open source platform faces a commercial competitor, which reflects a very different value system. The entrance of a commercial competitor renders the ideological difference more salient. Contributors may be concerned that the commercial competition leads to the demise of the open source platform, and the dominance of a commercial ideology. The stronger the ideological motivation of contributors, the stronger their attachment, and the stronger we therefore expect their response to be in the face of commercial competition. This mechanism appeared to operate when the commercial company DuPont entered the field of gene-sequencing, which made the "open" ideology more salient to members of the open source gene-sequencing community. This community then increased their efforts aimed at defending the scientific logic (Murray, 2010).

Another basis of attachment is the social interactions that contributors engage in with their fellow contributors either electronically or face-to-face. Research shows that contributors often form strong bonds with other contributors and that these bonds positively affect their motivation to contribute (Zhang and Zhu 2010; Ren et al. 2012). While the social interaction with fellow peers generally motivates people to contribute, it may be particularly important when the open source platform faces competition. Contributors may be concerned that the competition might lead to the demise of the platform, and that as a result they will lose their valued relationships to their fellow contributors. In the absence of social interaction, competition may render the already challenging task of building the open source platform seem insurmountable and leave contributors directionless. Thus, an attachment to the open source platform that is anchored in social interaction may make people increase their contributions when the platform faces competition.

It is also possible that some pre-existing contributors are affected more than others through channels other than attachment. In particular, research suggests that contributors are motivated by their standing and derive benefits from having a high standing in the community (Johnson 2002; Chen et al. 2010). For example, contributors of high standing may enjoy high status in the community so that other members may defer to them and they may leverage their standing in an open source community into career opportunities. Given that having a high standing on a platform that is in demise is likely to count for little, contributors with high standing may increase their contributions to preserve the platform more than other contributors.

We now turn to quantitatively examining the relative importance of attachment (through ideology and social interaction) and standing in shaping the response of pre-existing contributors to commercial competition. Because our analysis is based on indirectly measured variables, our tests here should be considered preliminary and unlike our analysis so far do not have a causal interpretation. Our hope is that these results inspire more empirically robust analyses of the mechanisms through which competition affects contribution activity.

With that caveat, we first test the role of ideology-based attachment. We do not possess any direct or individual level measures of the extent to which contributors might be attached to the open source community due to its ideology. Instead, we develop two proxies at the country level that measure the extent to which individuals contribute and consume open source. To measure contributions, first, we count the average number of Github contributions (or "pushes") per capita in each country. This measure provides an indication of ideological motivations since it counts the number of times an average individual contributes to an open source software development platform. Second, to measure open source consumption, we measure the market share of the open source browser Mozilla Firefox in each country relative to its commercial competitors, which may express the population's ideological commitment to open source software even when strong, commercial alternatives are available. While our measure of Github contributions comes from 2018, we are able to measure the relative share of Firefox in 2009, just before Google Maps started its global expansion, providing a more contemporaneous measure of ideological motivations.

Table 8, Columns 1 and 2 report the results from the regression analysis that incorporates these measures. We create a binary variable "High-Ideology" that we code as 1 if a contributor lives in a country with above-median Github contributions or above-median Firefox share. As the results show, while the coefficient on the main effect is not significant (though still positive), contributors living in countries with a strong open source ideology have a greater positive (statistically significant) response to competition than contributors in countries with a weaker open source ideology. Contributions increase by 2.3% when ideology is measured by Github and 1.5% when measured by the share of Firefox in the local market. These results provide preliminary empirical evidence that ideology-based attachment may be one important reason why pre-existing contributors increase their contributions in response to commercial competition.

Next, we turn to evaluating the role of attachment drive by social interaction. We collect data on the extent of social interaction in country-based OpenStreetMap communities by manually collecting information on the presence of mailing lists, a type of online interaction, and social events, an offline interaction, as of 2014. The existence of country-specific mailing lists is not automatic—a community member needs to request that a new list be created—suggesting that members desire greater community interaction. In addition to mailing lists, 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!"[16] A significant portion of these events are documented in a global database that we use to code whether a country has ever hosted community events.[17] Note that we do not have accurate data on the timing of *when* mailing lists were created or when the first mapping party was held. Instead, 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 contributors.

Table 8, Columns 3 and 4 report the results from the regression incorporating our measures of social interaction. As with the results on ideology, the coefficient on the main effect is not statistically significant (though still positive). However, contributors living in countries with a mailing list or local events have a greater positive and significant response to competition as compared to contributors who do not. In countries with a mailing list, contributions from pre-existing contributors increase by 2.0% while contributions increase by 1.6% in countries with local social events.

Finally, we test the impact of a pre-existing contributor's standing, shown in Columns 5 and 6 of Table 8. We code pre-existing contributors as having high standing if they ranked in the top five contributors, or have made 10 or more independent contributions in a given country when Google Maps enters. We find little support for the proposition that pre-existing contributors with a high standing in the community respond by increasing their contributions more than other pre-existing contributors. In fact, if anything, there is some evidence of reversion to the mean since the coefficient on this term is negative. Further, the presence of a mailing list or an event could be seen as validating the standing of a community member. In other words, the reason that measures of social interaction predict a positive response, is not because of the social benefits per se, but because they reinforce the standing of key contributors. Our results using the direct measures of standing rule out such a story. More generally, since we do not find any variation in the response depending on the number of contributions made by pre-existing members we

[16] http://wiki.openstreetmap.org/wiki/Mapping_parties
[17] http://wiki.openstreetmap.org/wiki/Current_events

can also rule out the story that personal value from OpenStreetMap is driving the reaction of pre-existing contributors since those who make the most modifications are the ones who have personalized OpenStreetMap the most to their personal benefit.

Finally, in Table 8 column 7 we combine all three measures we have developed to evaluate which one most strongly predicts the positive response to competition by pre-existing contributors. We measure social interaction using the presence of a mailing list and ideology using Github contributions for this analysis (but the results are not sensitive to the particular combination of measures that we choose). Overall, it seems that the ideological variables have the strongest and most robust effect on the positive response of pre-existing contributors. The coefficient on the social interaction variable is still positive but loses significance and reduces in size to about 0.7%. As before, the coefficient on the standing variable is still negative and not significant. Therefore, of the two drivers of attachment, it seems that ideology might matter more in shaping pre-existing contributor's response to competition.

Given that the analysis so far should be seen as associative rather than causal, as an additional test of our results we do one more robustness analysis using a matched sample analysis. Specifically, we matched 512 contributors in countries that rank above-the-median in terms of ideology (as measured by Github contributions) with 512 contributors in countries that rank below-the-median on a variety of dimensions including: the total number of annual contributions in 2006, 2007 and 2008; the quarter when they were exposed to Google Maps entry; the income category of the country, and the region of the world where the country is located. Results from the matched analysis are presented in Table A4. As before, we find that users who are in above-median countries in terms of ideology-based attachment (measured using Github contributions in Column 1 and Firefox share in Column 2) are the ones who respond positively to Google Maps competition. As before, this result holds even when we include variables for contributor standing and opportunities for social interaction. This additional analysis thus provides some further empirical evidence that ideology may be the dominant mechanism causing pre-existing contributors to increase contributions, although this claim should be examined further in subsequent research.

[INSERT TABLE 8 HERE]

Overall, our empirical analysis provides preliminary insight into which mechanisms explain the increase in contributions among contributors who are already attached to the community. Our analysis suggests that an ideological attachment to open source seems to matter most while attachment for the social interaction within communities are also important. Notably, standing in the community does not seem to be associated with the positive response. Our finding is consistent with prior research on competition and ideology. The detailed account by Murray (2010) shows how it may require the entrance of a competitor who operates according to an alternative logic, to render people aware of the ideological difference. This finding is also consistent with public statements by members of the open source community. In an article published in the Guardian with the title "Why the world needs OpenStreetMap", the author Serge Wroclawski (2014), a contributor to OpenStreetMap, points out:

> *"Every time I tell someone about OpenStreetMap, they inevitably ask "Why not use Google Maps?" From a practical standpoint, it's a reasonable question, but ultimately this is not just a matter of practicality, but of what kind of society we want to live in. [...] no one company should have a monopoly on place".*

Discussion

In this paper we analyze the effect of commercial competition on contributions to open source platforms by studying the effect of the competitive entry of Google Maps on contributions to OpenStreetMap. We find competition to have a meaningful effect on contributions. In particular, the overall effect on contributions is negative. When we analyze contributions from potential new and pre-existing contributors separately, we find that the former decrease while the latter increase. We then explore possible mechanisms that cause these heterogeneous effects. Our evidence suggests that contributions from new contributors go down because competition causes consumption of OpenStreetMap to go down, and contributors are usually consumers first. When exploring what causes the increase in contributions by pre-existing members, our evidence suggests that open source ideology and social interactions stemming from the platform play important roles.

Tendency to Contribute to Open Source

Our primary contribution is to look beyond the intra-community determinants of contributions to open source by examining the role of commercial competition. We answer the call for research to go beyond examining the micro-factors that underlie people's tendency to contribute to open source, and to investigate the role of macro-factors in an open source platform's environment (Von Krogh et al. 2012; Hill and Shaw 2019). We show how the macro-environment of an open source platform, specifically the competition it faces, affects its contributors' tendency to contribute. The interaction of competition (macro) with the mechanisms driving contributors' attachment, specifically ideological inclination (micro) and social interaction (micro), illustrates that macro-factors affect the tendency to contribute via micro-factors. Our finding that competition can have a negative or a positive effect points to the intricate relationship between the macro-environment and people's motivation to contribute to open source. Our results thus underscore the need and promise of taking an ecological perspective.

Beyond illustrating the importance of macro-factors such as competition, these findings also inform our understanding of micro-factors. Prior research has pointed to the important role of ideology and social interaction (e.g., Shah, 2006, Kraut et al. 2012, Ren et al. 2012) our study suggests that they are particularly relevant in the presence of competition. These findings also have methodological implications for future research on micro-factors: our findings suggest that research on micro-factors should account for macro-factors so as to avoid biased estimates. For example, if research on ideology focused exclusively on open source platforms that face competition, it may result in biased estimates of the effect of ideology.

Another contribution is highlighting the importance of awareness and consumption of the open source platform in fostering contributions. While prior work has often pointed out that the number of consumers is an important motivator because contributors care about the impact their contributions have (e.g., Jeppesen and Frederiksen 2006; Boudreau and Jeppesen 2014), we illustrate that the more important mechanism could be a reduction in the consumption of the platform in the face of competition. The overall negative effect of commercial competition on contributions to open source platforms is mostly due to the competition-induced reduction of awareness and consumption. Prior literature on the tendency to contribute may have underrepresented this effect because researchers often study the motivation of people who have *already* contributed, not of *potential* new contributors. Our research illustrates the need to focus more on potential new contributors.

Competition between Open Source and Commercial

We contribute by making a foray into our understanding of the competition between open source and commercial platforms. We answer the call for more research on competition between these two paradigms (Lerner and Tirole 2002, 2005). Prior work on the effect of commercial competition on open source provided rich accounts through qualitative accounts (Gaudeul 2007) or by developing formal models (Baake and Wichman 2003; Casadesus-Masanell and Ghemawat 2006; Athey and Ellison 2014), but fell short of providing systematic evidence on the effect of commercial competition on contributions to open source. The evidence we provide shows that competition does have an effect on contributions.

The finding that competition does have an effect is important as it implies that it is not enough to compare and contrast open source and commercial, but that one must examine the effect they have on one another. This insight informs a long-lasting debate among researchers and practitioners asking whether open source or commercial is superior (e.g., Giles 2005). The finding that the two affect one another cautions against oversimplified answers to that question. Even if commercial platforms are found to be superior, that superiority may in part result from how they affect open source platforms. In other words, in the presence of commercial competition, open source may just not be able to reach its full potential.

Our study also helps to explain the contradictory assumptions about the effect of competition in prior work. Casadesus-Masanell and Ghemawat (2006) as well as Athey and Ellison (2014) assume competition has a negative effect, whereas Lerner and Tirole (2002, 2005) as well as Gaudeul (2007) propose it has a positive effect. Our findings support both viewpoints. While we found in our setting competition has a negative effect in the aggregate, our analysis across different types of contributors showed that contributions from potential new contributors decreased while contributions from pre-existing contributors increased. Our research explores some of the mechanisms that explain why competition may be associated with a decrease or an increase of contributions.

Our research also illustrates how the *external* force of competition can change the *internal* composition of a platform. Commercial competition affects *from whom* the open source platform receives contributions. In our setting competition led to fewer contributions from new contributors but more contributions from pre-existing contributors. This differential, and in our case even divergent, effect reveals that the effect of commercial competition is contingent on the state of the open source platform. If the open source platform already has a substantial number of pre-existing contributors, competition may have a positive effect in aggregate.

Policy and Managerial Implications

Our study is highly relevant for actors who are dependent on or are considering building an open source platform. It directs them to take into account factors such as the share of pre-existing contributors, the social fabric among them, and the general ideological inclination to more accurately predict how an open source platform may evolve in terms of future contributions. It also suggests that open source managers may help render their platform robust against competition by fostering consumption of their platform and sponsoring social interactions via events and mailings. Our study is also relevant for managers of commercial platforms who must decide which markets to enter and when. Commercial platforms could exploit our finding that open source platforms are particularly vulnerable if they still depend on recruiting new contributors, if there is little interaction among contributors, or if the population is not inclined towards open source. Finally, our research is also informative for managers of commercial firms that consider leveraging open source to act upon their value chain. For example, Gambardella and von Hippel (2019; also see Baake and Wichman 2003) develop a formal model of downstream firms co-developing an open source platform for upstream inputs that would foster upstream competition and lower their dependence on the proprietary upstream supplier they currently rely on. Our study illustrates that downstream firms are likely to struggle to recruit new voluntary contributors given the commercial competition the open source platform would face. Downstream firms would need to undertake the development themselves. Taken together, our study informs managers operating in ecosystems that are or could be shaped by open source platforms.

Boundary Conditions, Limitations, and Future Research

Our work is also subject to boundary conditions. We study the competition between open source platforms and commercial alternatives using the case of OpenStreetMap versus Google Maps. We want to be careful in generalizing from this case as there is an enormous variety among open source platforms and commercial alternatives, thus competition may play out differently for other open source platforms. One particularity is that Google Maps constituted a formidable competitor. At the time of the launch, Google enjoyed a high amount of trust, which may have made people more comfortable with the commercial alternative than they would have been had another tech giant provided it (Microsoft, for instance, enjoyed much less trust at the time). Also, Google Maps was freely available. If Google had instead charged for Google Maps, people may have been more eager to consume and contribute to OpenStreetMap in order to ensure there was a free alternative. While these characteristics may bound our finding regarding the negative effect of competition on contributions, they also make this a conservative setting in which to examine whether competition can, under certain circumstances, have a positive effect. Further to some extent, "competition" might mean different things in our context including sowing confusion about which platform will reign, a loss of hope in the existing project along with the more traditional explanation of altering outside options. In fact, competition might mean an ideological threat to pre-existing users, while to new users it might simply be a functional substitute. We are unable to tease apart these fine grained distinctions. Our findings on the theoretical mechanisms that cause competition to have a positive effect are thus likely to hold broadly. Another particularity is that map-related information is of crucial importance with widespread implications (Nagaraj 2018, Nagaraj and Stern 2020). The ideological motivation to contribute in order to make sure that map-related information continues to be open source even if there is a functional substitute available may be stronger than in other settings.

Our research is subject to limitations. Most notably, while our research design provides us with an instrument to estimate the effect of competition on contributions, we lack instruments for the mechanisms we study. For example, we do not have a quasi-random assignment of ideological inclination towards open source. Also, our measures are only proxies (e.g., usage of open source browsers as an operationalization of ideological inclination towards open source). Given these limitations our empirical findings may serve as the basis of propositions that can be empirically tested by future work. For example, we propose based on our findings that ideological inclination towards open source fosters a stronger response to commercial competition. Future work could find a way to overcome the outlined limitations. An ideal test would randomize ideological inclination and commercial competition. Ideological inclination could vary among contributors due to varying exposure in ideological information (e.g., email newsletter, participation in seminars) or may vary for historical reasons (cp. Giorcelli and Moser, 2019). Combining such a design with a quasi-random variation in competition would allow the outlined proposition to be tested.

Future research may also advance our understanding of competition between commercial and open source more broadly. One promising avenue is to explore alternative dimensions and different stakeholders. For example, future research may explore how stakeholders' perception of open source and commercial alternatives varies in terms of accountability and reliability. Specifically, researchers could examine when actors choose open source or commercial platforms. There is rich anecdotal evidence—for example, the decision by the city of Munich to adopt Linux instead of Microsoft—but to the best of our knowledge no systematic evidence on how stakeholders perceive these alternatives and how it shapes their choice. Future research may also explore empirically the strategies that open source and commercial platforms deploy to compete with one another (see Sen 2007 and Sacks 2015 for formal theory). While our study illustrates that this competition constitutes a crucial challenge for open source platforms, commercial platform developers are also highly concerned about the competition. For example, former Microsoft CEO Steve Ballmer states, "Non-commercial software products in general and Linux in particular present a competitive challenge for us and our entire industry and they require our concentrated focus and attention" (quoted in Darrow 2003). Ideally, researchers find a setting where platforms are exposed to comparable competitive challenges but pursue divergent strategies to allow for the examination of the antecedents and consequences of these strategies.

Overall, our paper illustrates the potentially large and hereto understudied effect that commercial competition has on open source platforms. It is not enough to compare and contrast the performance of these two paradigms, but rather we must understand how they are likely to affect one another. Such an understanding is likely to help us better appreciate the dynamics of open source communities and competitive strategy in markets with open source products. Our paper provides one small step in this direction.

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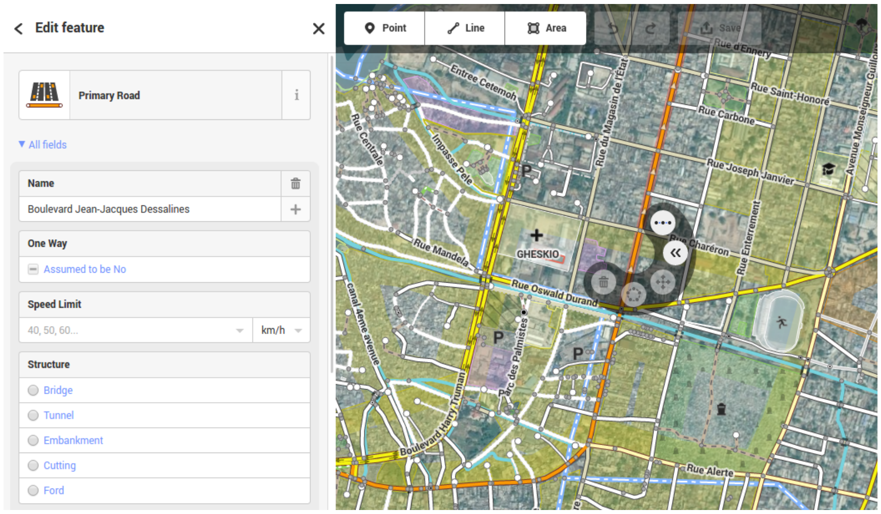
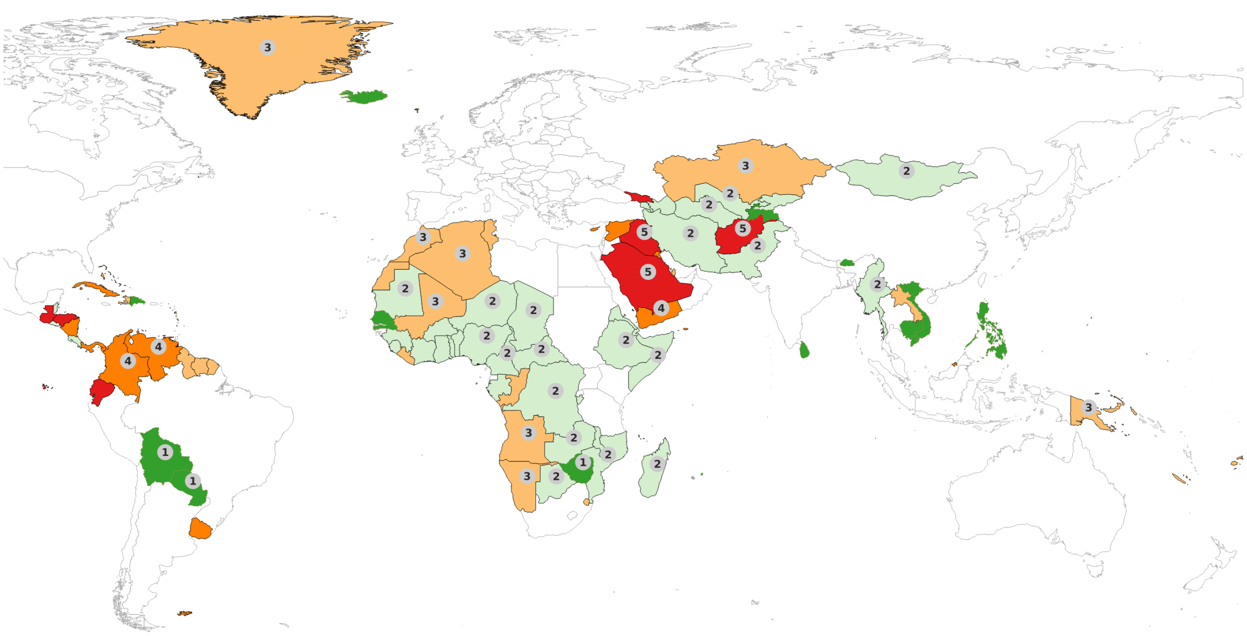
Tables and Figures

FIGURE 1. Overview of OpenStreetMap: Making a Contribution



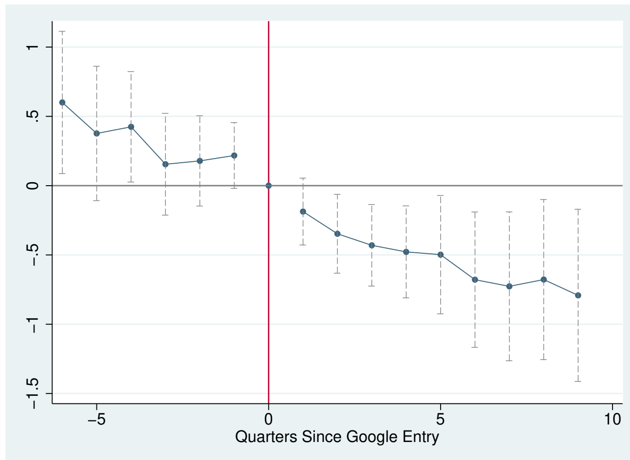
Note: Screenshot of a member making a contribution (adding a street) on OpenStreetMap in Port-au-Prince, Haiti.

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.

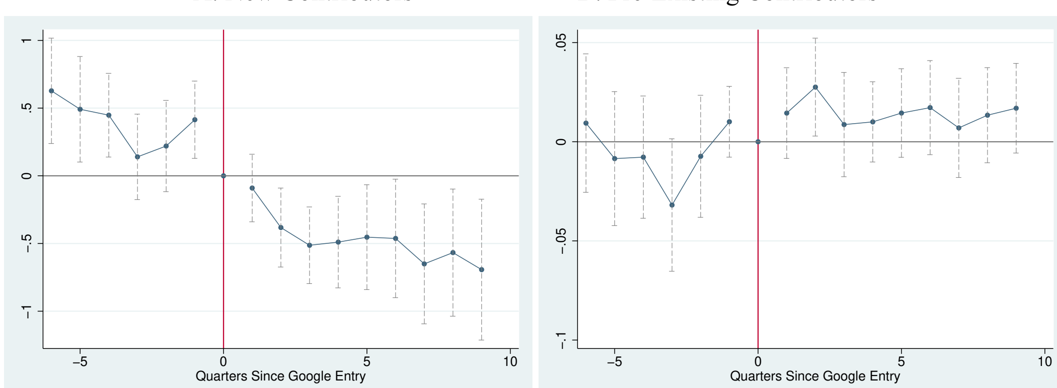
FIGURE 3. The Effect of Competition on Contributions



Note: This figure plots estimates (and confidence intervals) of β_t from the event study specification. Quarters are represented on the x axis and the outcome variable on the y-axis is $Contributions$. Coefficients (and 90 pct confidence intervals) from Log-OLS models are presented.

FIGURE 4. Comparing the Effect of Competition between Pre-Existing and New Contributors

A. New Contributors B. Pre-Existing Contributors



Note: This figure plots estimates (and confidence intervals) of β_t from the event study specification described in the paper. On the x axis is quarter. Panel A is based on 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 log-ols models.

Table 1. Summary Statistics (Country-Quarter Level)

	Mean	SD	Median	Min	Max
Outcomes					
New Member Contribs	297.9	1224.3	33.0	0	27034
Overall Contributions	692.3	2098.2	79.0	0	44774
New Members	26.2	58.8	10.0	0	1373
Total Members	39.1	77.3	15.0	0	1557
Timing Variables					
Post	0.6	0.5	1.0	0	1
Year	2010.5	2.9	2010.5	2006	2015
Controls					
Population (millions)	0.2	0.3	0.1	0	2
GDP per capita (in 100s USD)	0.1	0.2	0.1	0	1
Mobile Penetration (per 100)	71.7	42.8	70.4	0	232
Internet Penetration (per 100)	20.0	21.1	11.6	0	98

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

Table 2. The Impact of Competition on Total Contributions

	(1) Contribs	(2) Contribs	(3) Contribs	(4) Contribs	(5) Contribs
Post Google Entry		-0.58^{***}	-0.58^{***}	-0.51^{***}	-0.39^{**}
		(0.17)	(0.17)	(0.18)	(0.19)
Post Google X High-Competition					-0.25
					(0.17)
Population (millions)	2.92^{*}		2.61	2.86^{*}	2.55
	(1.59)		(1.65)	(1.59)	(1.56)
GDP per capita	2.70		2.56	2.85	3.15
	(2.41)		(1.73)	(2.37)	(2.49)
Mobile Penetration	0.0086^{***}			0.0081^{***}	0.0078^{**}
	(0.0031)			(0.0031)	(0.0031)
Internet Penetration	-0.0030			-0.0030	-0.0011
	(0.0085)			(0.0085)	(0.0083)
Country FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
N	3192	3480	3224	3192	3192
Adj. R2	0.84	0.84	0.84	0.84	0.84

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 $Ln(Contributions_{it}+1) = \alpha + \beta \times Post\ Google\ Entry_{it} + X_{it} + \gamma_i + \delta_t + \varepsilon_{it}$. This specification is estimated using logged OLS models. The outcome variable is logged $Contributions_{it}$ (inflated by one) and is measured as the total number of edits in a given country 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. γ_i and δ_t indicate fixed effects for country and quarter respectively. The control variables X_{it} include population, GDP, internet penetration, and mobile penetration, and they vary at the country-year level. Clustered standard errors at the country level are reported.

Table 3. The Impact of Competition on Contributions from Pre-Existing Contributors

	(1) Contribs	(2) Contribs	(3) Contribs	(4) Contribs	(5) Contribs
Post Google Entry		0.018^{*}	0.018^{*}	0.020^{**}	0.021^{**}
		(0.0094)	(0.0097)	(0.0099)	(0.0096)
Post Google X High-Competition					-0.0020
					(0.0096)
Population (millions)	0.079		0.072	0.082	0.081
	(0.075)		(0.078)	(0.076)	(0.076)
GDP per capita	-0.12		-0.087	-0.12	-0.13
	(0.090)		(0.065)	(0.092)	(0.089)
Mobile Penetration	0.00020			0.00023	0.00022
	(0.00015)			(0.00015)	(0.00016)
Internet Penetration	-0.000045			-0.000053	-0.000035
	(0.00031)			(0.00032)	(0.00030)
Community Member FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
N	80524	85080	80800	80524	80524
Adj. R2	0.057	0.056	0.057	0.057	0.057

Standard errors in parentheses

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

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

Table 4. Impact of Competition of Contributions from New Contributors

	(1) Contribs	(2) Contribs	(3) Contribs	(4) Contribs	(5) Contribs
Post Google Entry		-0.62***	-0.60***	-0.55***	-0.48***
		(0.14)	(0.15)	(0.15)	(0.17)
Post Google X High-Competition					-0.13
					(0.14)
Population (millions)	4.23**		3.99**	4.16**	4.00**
	(1.80)		(1.85)	(1.79)	(1.77)
GDP per capita	0.12		-0.18	0.29	0.44
	(2.57)		(2.09)	(2.55)	(2.61)
Mobile Penetration	0.0070**			0.0065**	0.0063**
	(0.0028)			(0.0028)	(0.0028)
Internet Penetration	-0.0047			-0.0048	-0.0037
	(0.0082)			(0.0081)	(0.0081)
Country FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
N	3192	3480	3224	3192	3192
Adj. R2	0.78	0.78	0.78	0.79	0.79

Standard errors in parentheses

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

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

Table 5. Evaluating Robustness to Alternate Specifications

	Total Contrib			New			Pre-Existing		
	(1) Poisson	(2) Diff. Trends	(3) Placebo	(4) Poisson	(5) Diff. Trends	(6) Placebo	(7) Poisson	(8) Diff. Trends	(9) Placebo
main									
Post Google Entry	-0.19***	-0.53***	-0.026	-0.27***	-0.54***	-0.091	0.78***	0.021*	0.00053
	(0.0052)	(0.18)	(0.14)	(0.0084)	(0.16)	(0.11)	(0.037)	(0.012)	(0.0090)
Population (millions)	2.91***	1.79	2.93*	3.66***	3.16*	4.24**	4.23***	0.069	0.079
	(0.049)	(1.52)	(1.60)	(0.076)	(1.73)	(1.79)	(0.22)	(0.073)	(0.075)
GDP per capita	-8.87***	3.23*	2.71	-6.94***	0.88	0.14	-2.43***	-0.11	-0.12
	(0.091)	(1.77)	(2.43)	(0.16)	(1.17)	(2.61)	(0.70)	(0.083)	(0.090)
Mobile Penetration	0.0098***	0.0064**	0.0086***	0.0074***	0.0051**	0.0070**	0.0067***	0.00019	0.00020
	(0.000082)	(0.0025)	(0.0031)	(0.00012)	(0.0021)	(0.0028)	(0.00055)	(0.00016)	(0.00015)
Internet Penetration	0.0014***	0.0073	-0.0030	-0.017***	0.0040	-0.0048	0.044***	-0.000013	-0.000045
	(0.00020)	(0.0064)	(0.0086)	(0.00031)	(0.0060)	(0.0082)	(0.0011)	(0.00032)	(0.00031)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Quarter	Inc. X Quarter	Quarter	Quarter	Inc. X Quarter	Quarter	Quarter	Inc. X Quarter	Quarter
Age FE	No	No	No	No	No	No	No	No	No
N	3192	3192	3192	3192	3192	3192	80524	80524	80524
Adj. R2		0.85	0.84		0.79	0.78		0.057	0.057

Standard errors in parentheses
$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

Table 6. Robustness Check: Comparing Pre-trends between Treatment and Control Communities in Log-Linear Models

	Total Contributions		New		Pre-Existing	
	(1)	(2)	(3)	(4)	(5)	(6)
Google-Entry(-6)	0.71	0.60	0.72	0.63	0.012	0.0094
	(0.31)**	(0.31)*	(0.23)***	(0.23)***	(0.021)	(0.021)
Google-Entry(-5)	0.44	0.38	0.54	0.49	-0.0072	-0.0085
	(0.29)$^{+}$	(0.29)	(0.23)**	(0.23)**	(0.020)	(0.020)
Google-Entry(-4)	0.48	0.42	0.49	0.45	-0.0067	-0.0078
	(0.24)*	(0.24)*	(0.19)**	(0.19)**	(0.018)	(0.019)
Google-Entry(-3)	0.19	0.15	0.17	0.14	-0.031	-0.032
	(0.22)	(0.22)	(0.19)	(0.19)	(0.020)$^{+}$	(0.020)$^{+}$
Google-Entry(-2)	0.21	0.18	0.24	0.22	-0.0067	-0.0073
	(0.20)	(0.20)	(0.20)	(0.20)	(0.018)	(0.018)
Google-Entry(-1)	0.23	0.22	0.42	0.41	0.010	0.010
	(0.14)$^{+}$	(0.14)$^{+}$	(0.17)**	(0.17)**	(0.011)	(0.011)
Google-Entry(1)	-0.20	-0.19	-0.10	-0.090	0.014	0.014
	(0.14)	(0.15)	(0.15)	(0.15)	(0.014)	(0.014)
Google-Entry(2)	-0.38	-0.35	-0.41	-0.38	0.027	0.028
	(0.17)**	(0.17)**	(0.17)**	(0.18)**	(0.015)*	(0.015)*
Google-Entry(3)	-0.47	-0.43	-0.54	-0.51	0.0078	0.0087
	(0.17)***	(0.18)**	(0.17)***	(0.17)***	(0.016)	(0.016)
Google-Entry(4)	-0.53	-0.48	-0.52	-0.49	0.0089	0.010
	(0.20)***	(0.20)**	(0.20)***	(0.20)**	(0.012)	(0.012)
Google-Entry(5)	-0.56	-0.50	-0.50	-0.45	0.013	0.014
	(0.25)**	(0.26)*	(0.22)**	(0.23)*	(0.013)	(0.013)
Google-Entry(6)	-0.75	-0.68	-0.52	-0.46	0.016	0.017
	(0.29)**	(0.29)**	(0.26)**	(0.26)*	(0.014)	(0.014)
Google-Entry(7)	-0.80	-0.73	-0.70	-0.65	0.0057	0.0070
	(0.32)**	(0.32)**	(0.26)***	(0.27)**	(0.015)	(0.015)
Google-Entry(8)	-0.75	-0.68	-0.62	-0.57	0.012	0.013
	(0.34)**	(0.35)*	(0.28)**	(0.28)**	(0.014)	(0.014)
Google-Entry(9)	-0.88	-0.79	-0.76	-0.69	0.015	0.017
	(0.36)**	(0.37)**	(0.30)**	(0.31)**	(0.014)	(0.014)
Google-Entry(10)	-1.04	-0.96	-0.83	-0.77	0.012	0.013
	(0.43)**	(0.44)**	(0.35)**	(0.35)**	(0.013)	(0.013)
Population (millions)	2.52	2.76	3.90	4.07	0.068	0.078
	(1.62)$^{+}$	(1.57)*	(1.84)**	(1.78)**	(0.076)	(0.074)
GDP per capita	2.43	2.72	-0.24	0.21	-0.080	-0.11
	(1.64)$^{+}$	(2.28)	(2.02)	(2.46)	(0.064)	(0.091)
Mobile Penetration		0.0077		0.0061		0.00021
		(0.0031)**		(0.0029)**		(0.00015)
Internet Penetration		-0.0031		-0.0047		-0.000041
		(0.0085)		(0.0081)		(0.00031)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3224	3192	3224	3192	80800	80524
Log-likelihood	-4486.8	-4422.7	-4535.8	-4482.8	-18773.1	-18825.5

Standard errors in parentheses
$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table provides estimates from Figure 3 (cols 1 and 2) and Figure 4 (cols 3-6), using the time-varying, log-linear specification $Ln(Y_{it}+1) = \alpha + \Sigma_z \beta_t \times 1(z) + \gamma_i + \delta_c t + \varepsilon_{ict}$ where γ_i and δ_t represent country and region fixed effects respectively for country or contributor i and quarter t. z represents the "lag", or the quarters relative to a "zero quarter", which marks the quarter when a country first faced competition from Google Maps except for $z > 10$ and $z < -6$ where z equals 10 and -6 respectively.

Table 7. Evaluating the Effect of Competition on Number of Contributors (Extensive Margin) vs. Contributions per Contributor (Intensive Margin)

	New		Pre-Existing		Total Contributions	
	(1)	(2)	(3)	(4)	(5)	(6)
	Contributors	Avg. Contribs	Active(0/1)	Contribs	Contributors	Avg. Contribs
Post Goog. Entry	-0.32***	-0.16**	0.0024	0.020**	-0.31***	-0.15
	(0.089)	(0.076)	(0.0042)	(0.0099)	(0.090)	(0.094)
Population	2.57*	0.47	0.010	0.082	2.20*	-0.025
	(1.30)	(0.48)	(0.020)	(0.076)	(1.26)	(0.58)
GDP/cap.	0.32	-0.33	-0.032	-0.12	0.79	1.50*
	(1.78)	(0.62)	(0.034)	(0.092)	(1.85)	(0.83)
Mobile Users	0.0041**	0.0019*	0.000051	0.00023	0.0045**	0.0034**
	(0.0020)	(0.0011)	(0.000049)	(0.00015)	(0.0021)	(0.0014)
Internet Users	-0.0013	-0.0028	-0.000069	-0.000053	-0.0017	-0.00062
	(0.0056)	(0.0029)	(0.00011)	(0.00032)	(0.0060)	(0.0035)
FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3192	3192	80524	80524	3192	3192
Adj. R2	0.84	0.54	0.13	0.057	0.88	0.63

Standard errors in parentheses

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

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

Table 8. Evaluating the Heterogenous Effect of Competition on Pre-Existing Contributors

	Ideology		Social		Standing		All
	(1) Github	(2) Firefox Share	(3) Maillist	(4) Events	(5) Rank	(6) Contribs	(7) —
Post Google Entry	0.014	0.011	0.019*	0.014	0.047***	0.029***	0.039**
	(0.011)	(0.012)	(0.010)	(0.0095)	(0.015)	(0.0098)	(0.016)
Post X High-Ideology	0.024**	0.016*					0.023**
	(0.011)	(0.0081)					(0.010)
Post X High-Social			0.017	0.017*			0.011
			(0.011)	(0.0097)			(0.0096)
Post X High-Standing					-0.048*	-0.079**	-0.050*
					(0.026)	(0.033)	(0.027)
Post X Mid-Size	0.00014	-0.0031	-0.0065	0.0018	-0.021*	-0.0017	-0.021*
	(0.0096)	(0.0098)	(0.0097)	(0.0088)	(0.012)	(0.010)	(0.012)
Post X Large	-0.0058	-0.0049	-0.0070	-0.00077	-0.024	0.00082	-0.032*
	(0.011)	(0.012)	(0.012)	(0.012)	(0.019)	(0.012)	(0.017)
N	80524	80524	80524	80524	80524	80524	80524
adj. R^2	0.056	0.056	0.056	0.056	0.057	0.057	0.057

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

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

Appendix

Table A.1. Entry Model

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

Standard errors in parentheses

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

Note: This table provides estimates of a model predicting the timing of Google Maps entry based on country and openstreet-map characteristics. The key dependent variable is the quarter in which Google Maps enters.

Table A.2. Alternate Definitions of New Member Contributions

Panel A: 2 Quarters

	(1)	(2)	(3)	(4)	(5)
	Contribs	Contribs	Contribs	Contribs	Contribs
Post Google Entry		-0.56^{***}	-0.54^{***}	-0.50^{***}	-0.34^{**}
		(0.14)	(0.15)	(0.15)	(0.16)
Post Google X High-Competition					-0.33^{**}
					(0.14)
Population (millions)	2.55		2.29	2.48	2.07
	(1.65)		(1.75)	(1.66)	(1.48)
GDP per capita	-1.30		-2.37	-1.04	-0.84
	(2.64)		(2.23)	(2.56)	(2.59)
Mobile Penetration	0.0068^{**}			0.0062^{*}	0.0057^{*}
	(0.0031)			(0.0031)	(0.0030)
Internet Penetration	-0.012			-0.012	-0.0098
	(0.0094)			(0.0093)	(0.0092)
Country FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
N	2692	2922	2700	2692	2692
Adj. R2	0.66	0.66	0.66	0.67	0.67

Standard errors in parentheses

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

Panel B: 6 Quarters

	(1)	(2)	(3)	(4)	(5)
	Contribs	Contribs	Contribs	Contribs	Contribs
Post Google Entry		-0.56^{***}	-0.54^{***}	-0.50^{***}	-0.34^{**}
		(0.14)	(0.15)	(0.15)	(0.16)
Post Google X High-Competition					-0.33^{**}
					(0.14)
Population (millions)	2.55		2.29	2.48	2.07
	(1.65)		(1.75)	(1.66)	(1.48)
GDP per capita	-1.30		-2.37	-1.04	-0.84
	(2.64)		(2.23)	(2.56)	(2.59)
Mobile Penetration	0.0068^{**}			0.0062^{*}	0.0057^{*}
	(0.0031)			(0.0031)	(0.0030)
Internet Penetration	-0.012			-0.012	-0.0098
	(0.0094)			(0.0093)	(0.0092)
Country FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
N	2692	2922	2700	2692	2692
Adj. R2	0.66	0.66	0.66	0.67	0.67

Standard errors in parentheses

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

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

Table A.3. CEM and Time-Varying Trends

	Total Contrib.		New User Contrib.	
	(1)	(2)	(3)	(4)
Post Google Entry	-0.44	-0.44	-0.42*	-0.42*
	(0.27)	(0.27)	(0.23)	(0.23)
Cntry-Pair FE	Yes	Yes	Yes	Yes
Time FE	Quarter	Income X Q	Quarter	Income X Q
Sample	CEM	CEM	CEM	CEM
N	6400	6380	6400	6380
Adj. R2	0.79	0.80	0.75	0.76

Standard errors in parentheses

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

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

Table A.4. Testing Ideology Using 512 Matched Users

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

Standard errors in parentheses

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

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