When dispersed teams are more successful: Theory and evidence from software*

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Abstract

Who collaborates with whom when physical co-location is no longer a constraint? How does the geographic composition of teams influence project success? We develop a model of global team formation and collaboration in which individuals have heterogeneous and partially observable skills, collaboration incurs geographic frictions, and project success depends on the best idea developed in the team. The model yields five testable predictions: (I) collaboration is more likely among geographically proximate individuals; (II) only highly skilled individuals form long-distance collaborations due to selection effects; (III) geographically diverse teams produce higher-quality outcomes; (IV) the positive impact of diversity on success is stronger for more complex projects; and (V) there is a non-linear relationship between team size and project quality. We test these predictions using a highly granular dataset on open-source software development, where project success is measured through downstream usage. The open-source setting offers a unique empirical advantage: its transparency and absence of physical constraints allow us to isolate the role of team composition and collaboration frictions. Our findings confirm the model's predictions and suggest that the benefits of dispersed collaboration extend beyond software development to other knowledge-intensive activities.

Keywords: Open-source Software, collaboration, frictions, team formation, diversity
JEL Classification: F10, F14, L86, R12, O33

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1 Introduction

Modern communications technologies have revolutionized collaboration across space, and the production of services, like software development and other knowledge-intensive activities, should, in principle, be subject to only minor geographic constraints. Nevertheless, teams still tend to be closely co-located simply by virtue of belonging to the same firm. What happens if that boundary also falls?

In this paper, we study this question and investigate how the quality of projects interacts with the geographic composition of the teams that produce them. We do so by building a model of global team formation and test the model's predictions on a granular dataset of open source software developers from GitHub, the largest online collaboration tool for developing software.

Our findings have implications for sourcing decisions across the services sector and contemporary work arrangements in general, such as freelance engagements. One of our main findings is that geographically dispersed teams are typically associated with higher quality products. This effect, which we argue is driven mostly by selection, is more important than the traditionally discussed effects of agglomeration economics. We see this finding as another piece of evidence of the importance of the extensive margin, which is highlighted and emphasized by contributions in the international trade literature, such as Allen (2014), Chaney (2014), or more recently Eaton et al. (2022).

As such, our paper provides three contributions to the existing literature. First, we provide a model that features heterogeneous developers with partially observable skills, costly collaboration across locations, and a production function that depends on the best idea of team members. Project ideas have a general attractiveness that incentivize developers to contribute. Credit sharing between developers is, however, not equal, mirroring first author bias in academia. The model yields five testable implications: (I) collaboration is more likely among nearby persons; (II) there is selection as only highly skilled distant people form teams; (III) geographically diverse teams are more successful; (IV) for more complex projects the diversity-success elasticity is higher; and (V) there is a non-linear relationship between team size and project quality.

Our second contribution is providing novel descriptive evidence on open-source software (OSS) production using highly disaggregated data on the industry. Software in general, and OSS in particular, has become a fundamental part of modern life and the global economy. The "Open Source Monitor 2023"[1] found that more than three quarters of German firms use OSS, with over half actively contributing. Recently, Hoffmann et al. (2024) estimated the demand value of OSS at $\$8.8$ trillion globally. Beyond its economic importance, OSS

[1] See https://www.bitkom.org/sites/main/files/2023-11/Bitkom-Open-Source-Monitor-2023-EN.pdf.

by its very nature is characterized by its radical transparency: every step of the production process is openly documented, providing an exceptionally detailed and granular view of product development in practice.

The central part of the data comes from GitHub, the dominant platform for sharing and developing open source software.[2] As of 2024 there are more than 150 million registered users who work on roughly 500 million projects (Github, 2024). The platform builds on the versioning system `git`,[3] which manages and makes observable developer actions at the individual (commit) level and exhibits the location of developers. As an additional data source, we use `Libraries.io`,[4] which tracks linkages — so-called dependencies — between open source software projects. Downstream libraries will be our preferred measure of success along with Github's "Stars", a user appreciation marker.

Our third contribution is linking this data to our model and testing its empirical predictions. At the developer-location level, we find sizable distance elasticities. In our main analysis, we examine how project success varies with the geographic dispersion of team members and find that more dispersed teams tend to be more successful — an effect that is exacerbated by complexity of the project. We first analyze two-member teams and then generalize to multi-member ones.

The remainder of the paper is structured as follows. Section 2 reviews the related literature. Section 3 provides the empirical context and presents descriptive statistics on the data. In Section 4, we outline the model and derive empirical predictions, which we test and quantify in Sections 5 and 6. Finally, Section 7 concludes.

2 Related literature

Our study relates to three strands of the literature: team formation and production in teams, gravity frictions in international trade —more specifically its extensive margin — and generally to the literature on the economics of OSS.

First, this work relates to the broader trade literature, which makes the role of geographical distance specific in their models. Those models are typically models on network formation and accordingly, address the extensive margin of trade. The extensive margin of trade is interpreted as the outcome of a network formation model.

Chaney (2014) proposes a dynamic model to study the formation of a social network of importers and exporters. Firms may meet at random or through the already existing network. When using the existing already existing network, firms use their already

[2] See `https://www.github.com`.
[3] See `https://git-scm.com`.
[4] See `https://libraries.io`

established foreign contacts to meet close, that is, geographically close, firms. The model is estimated and supported by data using French exports in the years 1986 to 1992.

Another approach to network formation is proposed by Bernard et al. (2019). Using data for detailed Japanese Buyer-Supplier relationships, they argue that geographical distance plays an important role in shaping this network. To further validate their findings they use the opening of a passenger-only train line which allows for easier social network formation while leaving costs for shipment untouched. The results support the idea that search costs are significant for describing in this case a domestic trade network.

Again, using Japanese data Bernard et al. (2020) now explores the role of social networks for the formation of research teams that are working on patents. Using the building of bridges to lower costs of meeting and face-to-face contact. The findings suggest that people who were strongly affected by this infrastructure improvement had the biggest effects on the production of knowledge.

Our work is related to understanding the geography of services. Head et al. (2009) estimate gravity equations for services trade

Within services, The development of OSS is a knowledge-intensive task of typically highly skilled individuals. Thus, our work also relates to the work on geographical aspects of knowledge production as is common in the study of academic research teams or inventor groups working on patents. Lychagin et al. (2016) analyze US firm productivity spillovers and R&D activities, and find that the exact geographic location of a firm's researchers matters for knowledge spillovers. The aspect we focus on is the citations of research papers or patents.

Atkin et al. (2022) study the effect of face-to-face interactions on patent citations between firms in Silicon Valley. Their results show that these types of interactions are an important source of agglomeration gains as they lead to knowledge flows between establishments. These knowledge flows are measured by the observed patenting behavior of these firms.

Another related field is academia. Head et al. (2019) show that distance also matters here. However, they also find that ties that bind - past co-location, co-authorship, university links - strongly reduce the distance friction suggesting a big informational friction channel. The results are driven strongly by lower quality research papers, i.e. those for which it is harder to hear randomly about. Taste heterogeneity will also play a role in shaping geography and trade. Blum and Goldfarb (2006) studying the role of distance in website traffic argue that distance effects typically occur for taste-dependent goods.

One of the closest papers to ours in terms of the role of distance in collaboration is Catalini et al. (2020), who study co-authored chemistry research papers. They find that a drop in travel costs (entry of a low-cost airline) increased collaboration greatly. In their model and data, lower travel cost is beneficial mostly for researchers with relatively weaker local

peers and higher quality projects.

In terms of collaboration and diversity, a paper closely related to us AlShebli et al. (2018) who study the success of academic papers as a function of *ethnic* diversity of authors, and find a positive correlation. At the same time negative correlation between diversity and intensity of collaboration is found by Békés and Ottaviano (forthcoming) in a very different setting: professional soccer.

The role of face to face communication is studied in Battiston et al. (2021) who model communication as the tool to transmit information that helps peers (co-workers in a company) do their job better. In their model, workers trade the cost of communication to gains from it, and the benefit is more than proportional in nearby workers.

More recently, a surge of papers is using OSS data and content with related questions. For example Wachs et al. (2022) show that OSS contributors - even though most work can be conducted entirely remote - often cluster in locations like Berlin, New York, or Tokyo. The idea of clusters is also explored by Abou El-Komboz et al. (2022) who study the effect of cluster on single developers productivity. They propose to use the amount of commits of a developer as a measure of productivity and find positive effects for the effects of clusters on productivity.

The most closely related work to ours is understanding the role of distance in team formation. For instance, Laurentsyeva (2019) argues that distance in different non-parametric specifications negatively affects collaboration. Common language, on the other hand, is important for collaboration. Using also a gravity-type regression **?** uses a sample for developers living in the United States and shows that co-located developers work more intensely together. We start by confirming some results but using a different methodology better suited for our model we find some differences too.

Our work is also related to a new strand of literature that emphasizes the strong role of OSS in the economy. For example, Hoffmann et al. (2024) works to quantify the value of OSS. Chelkowski et al. (2021) talk about the role of large organizations after analyzing activity in 1300 projects for 21 years. They also argue for an important role in fostering collaboration. They argue that as projects mature, organizations as intermediaries are less needed.

3 Empirical context and data

3.1 Empirical context

Open Source Software (OSS) has emerged as a foundational element of the modern digital infrastructure, playing a crucial role in almost every aspect of technology today. From operating systems like Linux to programming languages like Python, OSS projects power a

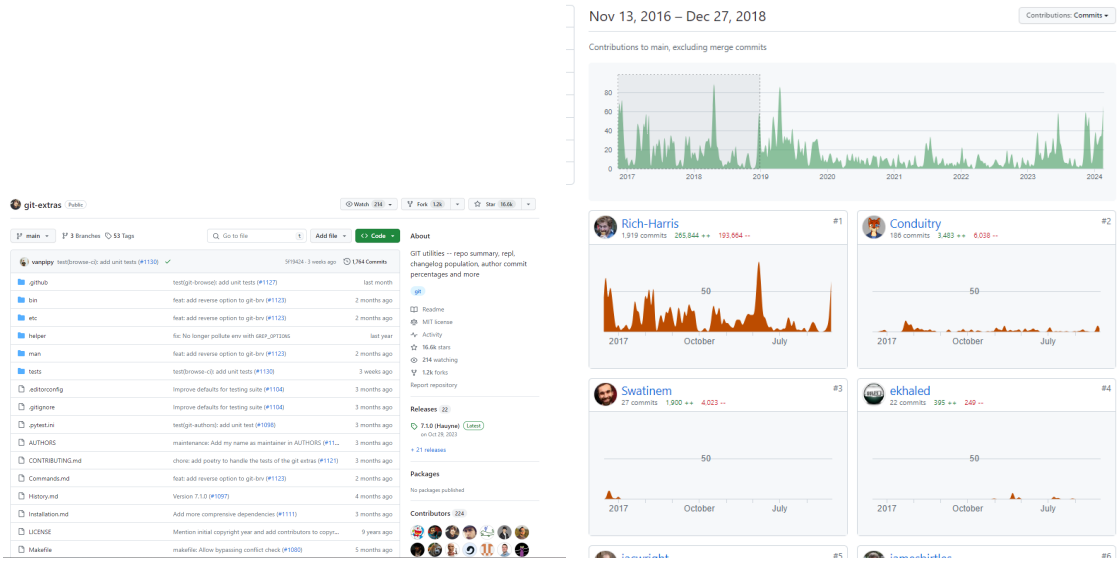
wide array of software systems and applications used worldwide. The collaborative and open nature of OSS enables developers from all over the world to contribute, innovate, and improve software continuously, breaking down traditional barriers associated with proprietary software development.

GitHub, the world's largest source-code management platform with about 80% of developers using it .[5] It is also the most widely used platform for open-source collaboration, serving as the central hub for OSS development. Founded in 2008, GitHub has grown exponentially to become the dominant platform for sharing and developing source code, with over 100 million registered users and more than 150 million repositories as of 2024. This platform provides a wide range of tools and services that facilitate collaboration, including version control, issue tracking, code review, and community engagement.

GitHub's impact extends beyond mere code hosting; it has also evolved into a social network where developers can share information about themselves, build professional profiles, and connect with peers globally. The platform's extensive community features, such as repositories, forks, pull requests, and "Stars" (similar to "likes" on social media), encourage collaboration and knowledge exchange on an unprecedented scale. GitHub's public repositories serve as a rich source of data for analyzing software development practices, team dynamics, and the impact of geographical dispersion on collaboration.

Given GitHub's prominence in the OSS ecosystem, it provides an ideal empirical context for studying dispersed team formation and collaboration. Unlike traditional software development environments, where teams are often co-located within the same organization, OSS projects GitHub can be developed by geographically dispersed teams. This makes it possible to explore how distance and diversity influence collaboration and project outcomes, providing insights that can be generalized to other knowledge-intensive activities.

[5]According to a 2020 survey, 82% of developers use Github as collaboration tool, with GitLab, another similar platform having 37% share, see `survey.stackoverflow.co/2020#technology-collaboration-tools-all-respondents`.



(a) GitHub Collaboration **(b)** Tracking of user activity (2017-2019)

Figure 1: Collaboration is done mostly online

Notes: Two screenshots of GitHub repositories. Panel (a) shows a repository with files, repository-level information, and a list of contributors. Panel (b) presents contributor-level activity graphs based on the number of commits per user in a given repository.

The screenshots in 1a highlight the detailed nature of the available data. Most importantly, it is possible to see which of the developers contributes in which intensity. This is something that remains in most cases impossible in other applications like patenting or academia.

3.2 Data overview

Our dataset comes largely from GHtorrent (see Gousios and Spinellis (2012)) and Libraries.io.[6]. GHtorrent provides detailed information on open-source software (OSS) projects hosted on GitHub, while Libraries.io maps software dependencies and input-output linkages among OSS projects. We integrate these input-output linkages from Libraries.io with the GHtorrent data to create our preferred measure of project success.

While there could selection in reporting location, we find that the country-level distributions derived from our user micro-data is very close to that from the GitHub Innovation Graph based on detailed location info. For details, see Section A.2.2 in the Appendix.

The dataset includes software projects developed on GitHub.com between 2012 and June 2019. Initially, it contains $73,228,443$ individual software projects. These projects range from simple scripts used for tasks like running linear regressions or building basic websites to advanced tools such as state-of-the-art machine learning applications. Across these projects, we observe $1,368,235,072$ commits, where a commit represents a code

[6] `Libraries.io`, last accessed on 07/07/2023

contribution—developers write and submit code to a repository, which we use as a measure of effort.

The dataset contains $18,763,332$ unique developer IDs associated with these commits. However, as is common in social network data, many projects are either not actively maintained or involve minimal contributions from developers. Our research focuses on smaller, potentially geographically dispersed teams that exhibit a certain level of activity. Therefore, we apply sample restrictions, retaining only projects with at least 4 development days and a minimum of 10 commits. This filtering reduces the sample to $10,173,295$ projects.

To address the issue of bot activity on GitHub, we manually identify and exclude common bot logins. Additionally, we conservatively exclude developers who are active in more than $1,500$ projects to mitigate potential biases from super high activity accounts. After these exclusions, the remaining projects are developed by $4,355,207$ developers. Of these, we are able to identify the locations of $1,362,106$ developers, assigning them to cities worldwide via an API.

Repositories and Developers Focusing specifically on projects with two developers, of which there are $1,732,734$ in our dataset, we can identify the location combination for both developers in $358,748$ projects, representing 20% of this subset. Developers may also belong to GitHub organizations, which can represent groups with similar interests or firms. In the subset of projects with two developers, only 7% of developers are in the same organization, and this percentage decreases to 4% in projects where we observe the locations of both developers.

For each project, we record the most commonly used programming language, measured by the amount of code (in bytes) contributed in that language. This results in a total of 356 different programming languages being represented in our dataset.

The main regressions we report will use different outcome measures to assess project success. One key measure is the number of "Stars" a project gained in the year following its initial publication. Stars on GitHub function similarly to "likes" on other social networks, indicating user appreciation of a project. An alternative measure of project quality relies on downstream dependencies. A dependency refers to the use of a project by another open-source project. Given its direct interpretation as usage, this is our preferred measure of project quality. However, it is only available for projects that are included in our second data source, Libraries.io, and where successful matching with GHtorrent data is possible.

With this description, we can dive into some more descriptive figures surrounding our data. To ensure consistence in our descriptive statistics and empirical analysis, we will only with the previously described data including its sample restrictions.

Starting with developers, we aggregated data at the repository (project level). As Table 1 suggests 72% of projects have only a single developer. After this the amount of developers is steeply declining.

Table 1: How many coders develop a package?

Developer Count	Frequency	Relative Frequency
1	7,363,371	0.72
2	1,732,734	0.17
3	630,856	0.06
4	304,326	0.03
5	142,008	0.01

Notes: Based on the full sample of repositories, the number of developers per repository which we identify in the GHtorrent data.

Next we look at how many developers contribute to multiple projects in our dataset. We find that roughly half of developers only have one single project that fulfills the sampling criteria.

Table 2: How many repos developers are involved in?

	Amount projects	Frequency	Relative Frequency
1	1	2131351	0.49
3	2-5	1627010	0.37
4	6-15	460154	0.11
2	15+	136671	0.03

Notes: Amount of projects each developer contributes to. Consider only projects with at least 4 development days and at least 10 commits.

Geography The geographical composition is then shown in 2. This map shows that the activity is concentrated in North America, Europe, India, China, Japan and to some extent Brazil.

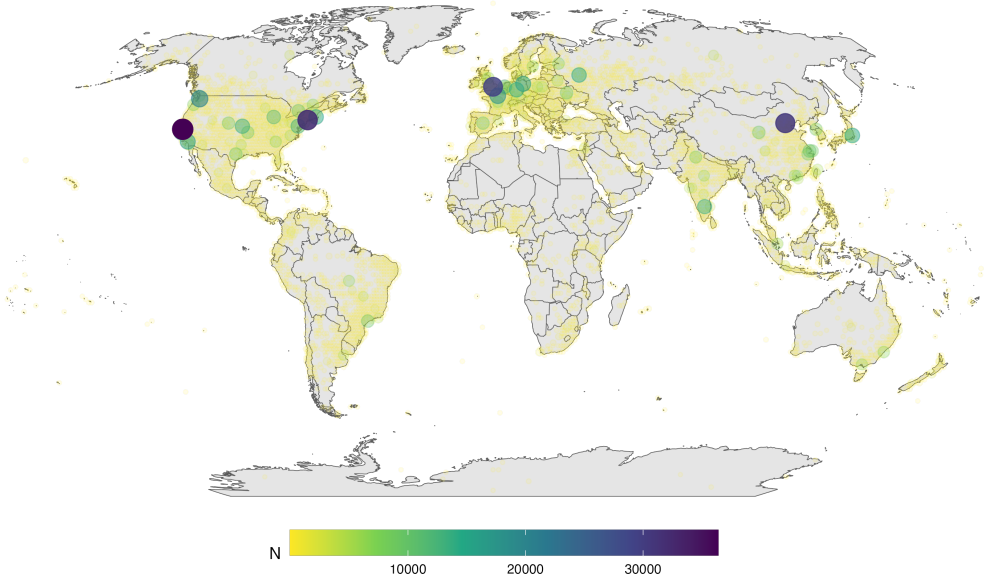


Figure 2: Developers per tenth of a square degree

Notes: World map depicting identified locations of open-source developers. Colour coding indicates clustering intensity with at most 5000 developers identified in San Francisco. Other technological hubs like New York, Beijing, London are clearly visible.

The chart in Figure 3 represents the locations of developers in the top 20 cities in our sample, the color coding represents different geographic regions. Cities in North America lead in terms of size and presence in top 20. They are followed by European centers like London and Berlin with Eastern European cities like Moscow and Kiyv also making it. Asian centers play a comparable role with Beijing and Tokyo coming on top.

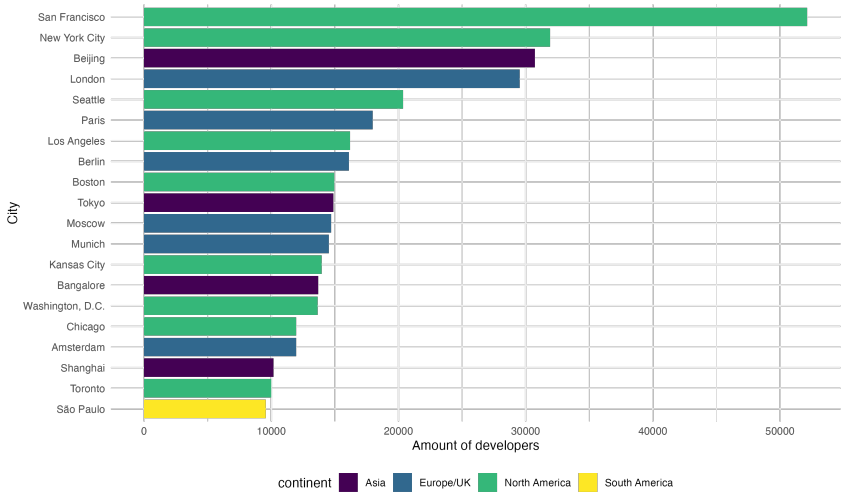


Figure 3: Contributors for Top 20 Cities

Notes: Barplot illustrating the amount of open-source developers in the top 20 cities with the most developers. Colour coding based on continents.

Figure 4 depicts a horizontal bar chart that illustrates the number of shared projects between developers residing in different city pairs in 2019. The chart nicely highlights that San Francisco is the central node in open-source collaboration. Generally, all pairs include North American cities again highlighting the outsized role of North America in the context of OSS.

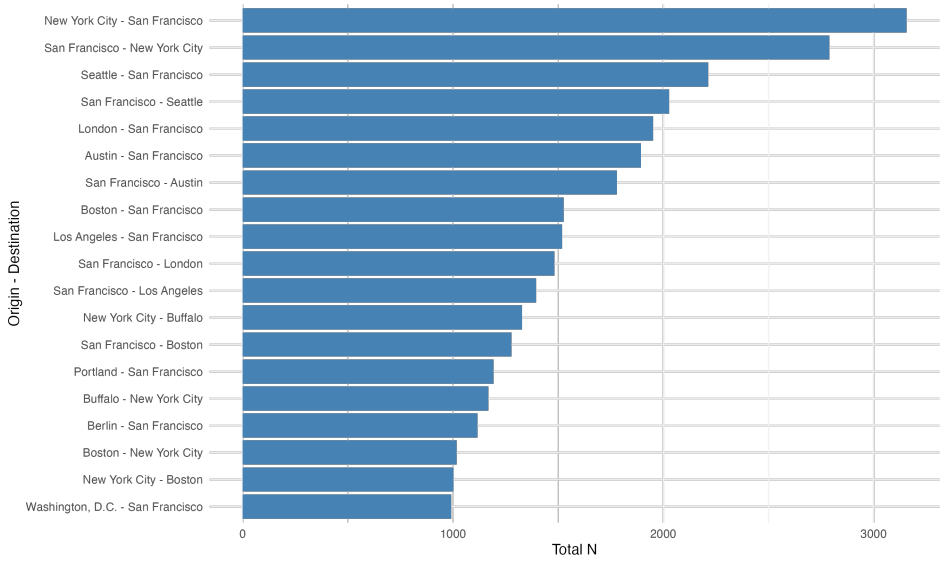


Figure 4: Links between city pairs

Notes: Barplot illustrating links between cities as measured by being active in the same repository. Same-city links are excluded from this figure. Color coding indicates world region pairs. Only one of the highest linked city pairs does not include the North American region.

The success of an open-source package is not trivial to measure. We propose two separate measures. One makes use of the social network structure of OSS development and relies on "Stars" which users can give to other projects. The other is downstream dependencies which can be through of direct usage of projects in other software projects. Similar to Input Output linkages. Distributions are depicted in 5.

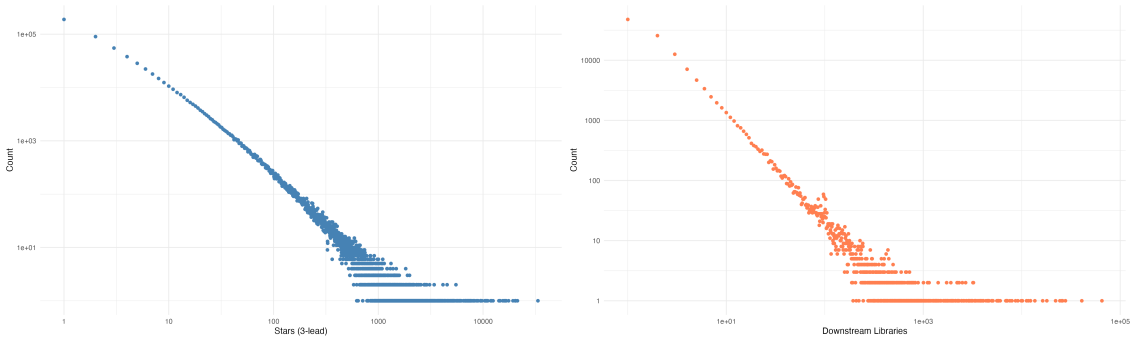


Figure 5: Distribution of quality measures.

Notes: Distribution of quality on a log scale. On the left panel the amount of stars a project received after three months. On the right panel the amount of downstream dependencies. Both exhibit a clear power law like curve. The amount of observations for the downstream libraries is sizeably lower because not all projects are hosted on package managers and can thus generate downstream linkages.

3.3 Work data

For all the empirical work, we restricted the dataset to study projects with up to 5 team members. Membership is defined as being an active developer: those committed in the quarter of starting the project and/or in the next one. The first committer is typically the one who hosts the project on their github page. The vast majority is single developer projects.

Table 3: Number of repositories by active team members

dev count	N_repos	share_repos	on_libraries_io	share_on_libraries_io
1	7,372,902	75.92%	269,218	3.65%
2	1,551,435	15.98%	50,526	3.26%
3	502,662	5.18%	12,915	2.57%
4	241,130	2.48%	4,019	1.67%
5	43,463	0.45%	437	1.01%

Notes: Active developers per repo, based on two quarters, up to 5 developers. Downstream dependency information come from libraries.io.

While as all repos may get stars, only a small fraction of repos are hosted on service like CRAN.

4 Model of global team formation and success

4.1 Model

We present a model of team formation and collaboration in open-source software development to guide our empirical analysis. The main idea is that team forms to jointly produce

a knowledge good of a certain quality. Quality depends on the composition of the team and on collaboration.

There are two frictions, one limiting collaboration, and one limiting team formation. Collaboration is limited by communication costs, such as language and cultural differences and time zone gaps. We will model this as an "iceberg" trade cost of ideas within the team. Team formation is further limited by incomplete sharing of credit between teammates. For example, if the main benefit of working on an open-source project is to improve job prospects in the U.S., then developers outside the U.S. will enjoy this benefit less.

Together with these frictions, the model aims to capture key features of the open-source industry:

1. Developers have heterogeneous skills that are only partially observable.
2. Collaboration across locations is costly.
3. Software quality depends on the best idea from the team.
4. There are convex returns to software quality in terms of adoption and recognition.

Figure 6 displays the outline of the model. Developer 1 and 2 are jointly considering to form a team and produce a piece of software together. The joint quality of the developers will determine the quality of the software. This, in turn, leads to “fame," or informal recognition by the community. How much this informal recognition matters to developers determines the payoffs. The two developers may care about kudos to different degrees. This closes the model as, in equilibrium, only developers who find it worthwhile to collaborate will form a team. Others will enjoy their outside option.

Setup Consider a set of developers $i = 1, \ldots, N$ located in different cities. Each developer i has a skill level Z_i, which is drawn from a Fréchet distribution:

$$\Pr(Z_i \leq x) = e^{-T_i x^{-\theta}}, \tag{1}$$

where $T_i > 0$ is an observable skill shifter and $\theta > 0$ is a shape parameter. A higher T_i indicates higher average skills, while θ governs the dispersion of skills. The Fréchet distribution is chosen for its tractability and its property of yielding closed-form expressions for maxima, which is crucial for our model of team production.

Team Formation Developers can choose to work on their own projects or join existing projects. When considering joining project p, developer i faces two key frictions:

1. A communication cost $\tau_{ip} \geq 1$ that reduces the effectiveness of conveying ideas.

2. A participation cost $d_{ip} \geq 1$ that captures the difficulty of joining and contributing to the project.

Both costs increase with geographic and cultural distance between the developer and the project team. We model these costs as:

$$\tau_{ip} = \text{distance}_{ip}^{\gamma_k} \tag{2}$$

$$d_{ip} = \text{distance}_{ip}^{\gamma_s} \tag{3}$$

where γ_k and γ_s are elasticities that may differ, capturing the idea that knowledge sharing and participation may have different sensitivity to distance.

Software Production If developer i joins project p, the quality of the resulting software depends on the best idea from the team:

$$X_p = \max_{j \in p} \{Z_j / \tau_{jp}\} \tag{4}$$

This captures the notion that in software development, a single brilliant idea or solution can drive the overall quality of the project. Given the properties of the Fréchet distribution, the quality of software X_p will also follow a Fréchet distribution with scale parameter:

$$\Phi_p = \sum_{j \in p} \tau_{jp}^{-\theta} T_{jp} \tag{5}$$

and shape parameter θ.

Payoffs The payoff from a project takes the form of recognition or "fame," which increases exponentially with software quality:

$$f(X_p) = e^{\alpha_p X_p}, \tag{6}$$

where α_p is a project-specific fame shifter. This fame shifter can also be interpreted as an idea quality draw that comes from some exogenous distribution. Crucially, this fame accrues only to the developer with the best idea on the team. The exponential form captures the idea that there are increasing returns to quality in terms of recognition and adoption in the open-source community. Better projects not only serve existing customers better but can also reach more customers.

Developer's Decision A developer i will join project p if the expected payoff exceeds their outside option of working alone. The probability that developer i's idea is the best in

the team, given their skill level Z_i, is:

$$\pi_{ip} = e^{-\Phi_{p\neg i}\tau_{ip}^{\theta} Z_i^{-\theta}} \tag{7}$$

where $\Phi_{p\neg i} = \sum_{j\in p, j\neq i} \tau_{jp}^{-\theta} T_{jp}$ captures the competitiveness of the existing team. The expected payoff from joining the project is then:

$$\mathcal{U}_{ip} = \pi_{ip} e^{\alpha_p Z_i} = e^{-\Phi_{p\neg i}\tau_{ip}^{\theta} Z_i^{-\theta} + \alpha_p Z_i} \tag{8}$$

The developer will join the project if:

$$\mathcal{U}_{ip}^{1/d_{ip}} > e^{\xi Z_i} \tag{9}$$

where ξ represents the quality of solo project ideas, and the left-hand side is adjusted by the participation cost d_{ip}.

Equilibrium In equilibrium, the distribution of skills for developers who join project p is Fréchet with scale parameter:

$$T_{ip} = T_i + \kappa \frac{\tau_{ip}}{d_{ip}} \sum_{j\in p, j\neq i} \tau_{jp}^{-\theta} T_{jp} \tag{10}$$

where κ is a constant related to the outside option. This equation captures how the selectivity of joining a project depends on both individual skills and team composition. The equilibrium is a fixed point of best responses to team composition: team members understand that others also have to agree to work on the project.

For a two-member team, this system of equations can be solved explicitly:

$$T_{1p} = T_1 + \lambda T_{2p}, \quad T_{2p} = T_2 + \lambda T_{1p} \tag{11}$$

where $\lambda = \kappa \tau^{1-\theta}/d$ captures the strength of complementarities in the team.

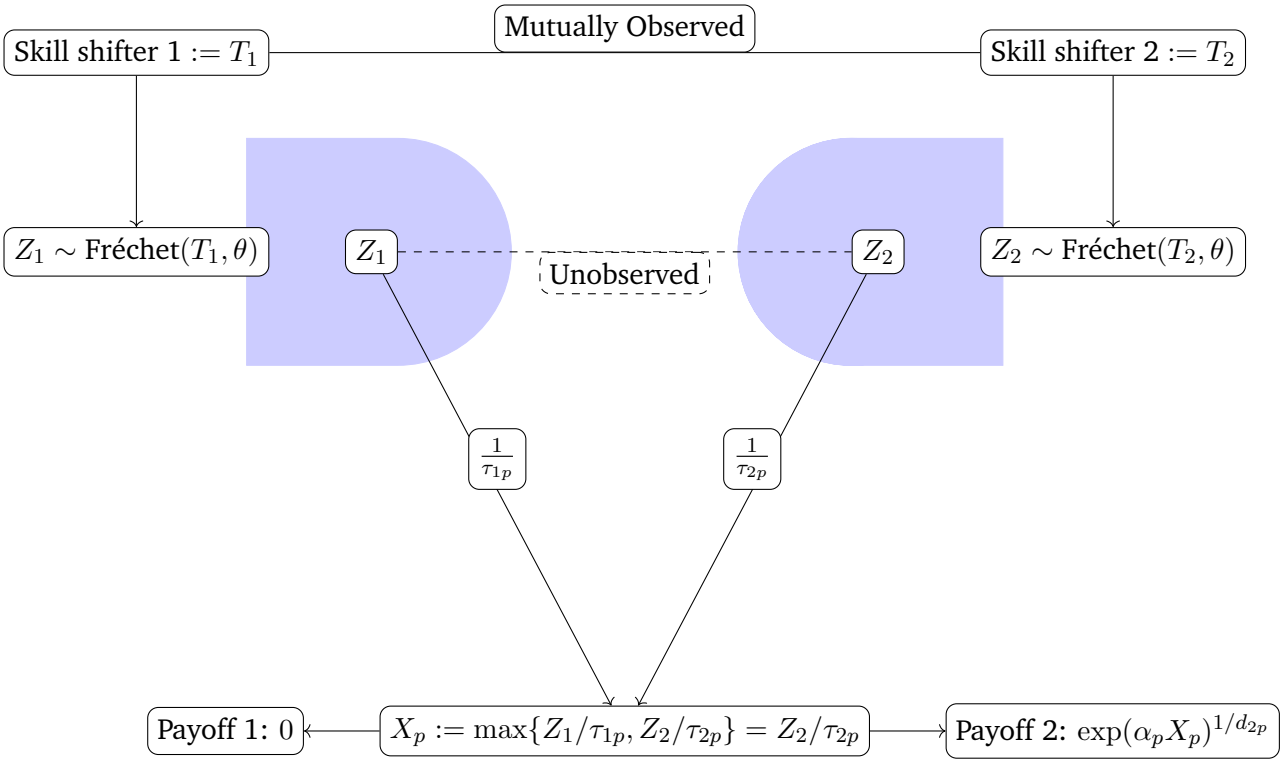


Figure 6: Visual representation of the model.

Notes: Visual representation of the model conditional on both developers have decided to collaborate. Developer 2 is assumed to have the higher draw from Fréchet distribution which leads to Developer 2 claiming the payoff for the project. Equilibrium conditions as are based on the mutually observable skills. The α_p acts as an attractor to projects.

Relaxing the payoff function To have a more general result, we can relax the strictness of the payoff function.

[TO BE ADDED]

4.2 Testable Implications

This model yields several testable implications.

1. Developers are less likely to collaborate across greater distances due to higher τ_{ip} and d_{ip}. This follows directly from equations (2) and (3).
2. Conditional on collaboration, more distant team members tend to have higher skills due to selection. This is a result of the equilibrium condition in equation (10), where higher τ_{ip} and d_{ip} require higher T_i for participation.
3. Projects with geographically diverse teams tend to produce higher quality software, as measured by adoption or recognition. This follows from equation (5), where a diverse team allows for drawing from a larger pool of potential best ideas.
4. The effect of geographic diversity on project quality is stronger for more complex

projects where communication and idea sharing are more important. This can be captured by allowing θ to vary with project complexity, with lower θ (higher dispersion) for more complex projects.

5. There is a non-linear relationship between team size and project quality. While larger teams increase Φ_p in equation (5), they also increase the selectivity of joining through equation (10).

In the following sections, we test these implications using data on open-source software development from GitHub and other sources. Our empirical strategy will involve estimating gravity-like equations for collaboration probabilities, as well as analyzing the relationship between team composition and project success.

5 Team formation

We build our dataset in a pseudodynamic version that contains three periods of time for each project. A before, current and after period. The before period is included to capture the prior experience of developers before starting the project. The current period is included to capture the amount of work effort exerted in the period of production, and finally, the after period captures success outcomes. Projects have static values such as the programming language and the quarter in which they were started. The location of developers will also be treated as a static variable, which does not change.

Our first relationship to show is that developers are less likely to collaborate across greater distances due to higher costs ((2) and (3).) To show this we start by aggregating data at city level to estimate a gravity model.

5.1 Setting up gravity

Given the large number of potential collaborators, the probability of relying on any single one of them is very small. Hence the number of links within any group of users will be well approximated by the Poisson distribution. In particular, we will take users in one city and users in another city, and form groups of such city-pairs. The number of links for a city pair is then approximately distributed Poisson, with a mean proportional to $n_{ij}\exp(-\beta'\mathbf{d}_{ij})$ and $n_{ij}\exp(-\gamma'\mathbf{d}_{ij})$ for dependencies., where n_{ij} is the number of user pairs in the city pair.

For example, if there are 5,000 developers in San Francisco, and 4,000 in Berlin, there are 20 million potential links, $n_{SF,Berlin} = 20,000,000$. By contrast, if Bielefeld has 200 developers, $n_{SF,Bielefeld} = 1,000,000$. The number of potential links serves as an *exposure* variable in the Poisson regression. City pairs with higher n are expected to have more links and also receive a larger weight in the regression. As a special case, if there are no

developers in a city, $n = 0$, that city does not contribute to the regression analysis.

We estimate city-pair gravity equations with links being established by collaboration. Take developer j with $j = 1, \ldots, J$ who are contributing to a software package i. We consider two developers j and k to be connected by collaboration if they contribute to at least one software package together. Formally, let $\mathbf{C}$ be a $J \times J$ matrix. The jkth element of this matrix is 1 if there is at least one software project on which developer j and k collaborate, and 0 otherwise. We set the diagonal $\mathbf{C}_{jj} = 0$ to rule out self-connections. Note that this matrix is symmetric.

If there are M cities, we can use an $M \times J$ city-aggregator matrix to add up all the links of users belonging to the same city. Denote this aggregator matrix by $\mathbf{M} = \mathbf{I}_M \otimes \mathbf{1}_{1 \times J}$.

Our outcome variables will be the $M \times M$ matrix

$$\mathbf{Y} = \mathbf{MCM}',$$

capturing the *number* of collaboration links between city pairs.

Take the element of this matrix corresponding to the origin city o and destination city d. By the Poisson approximation,

$$Y_{od} = \exp(\beta \tau_{od} + \nu_o + \nu_d) + \varepsilon_{od} \tag{12}$$

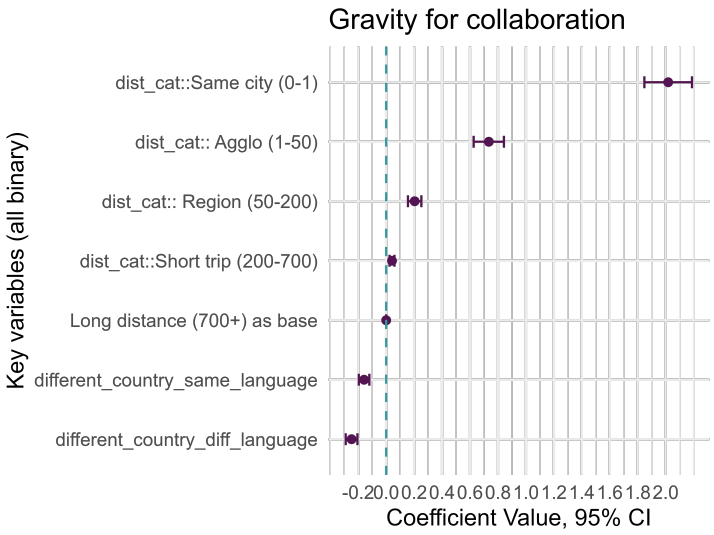
where Y_{od} are contribution links from city o to city d. Fixed effects are at the city level o and d and relevant distance metrics are captured in τ_{ij}. Finally, ε_{od} represents an orthogonal error term. The right hand side reflects a PPML estimator ((Santos Silva and Tenreyro, 2006)) in a standard gravity framework.

The variables of interest are given by the distance vector $\tau_{\mathbf{o}}\mathbf{d}\_do$ and its corresponding coefficients β. We consider standard frictions like geographic distance and common languages. To address potential non-linearities we report estimates for multiple functional forms. For more on the Poisson approximation, see Section A.1 in the Appendix.

5.2 P1: Nearby coders are more likely to form teams

We now estimate 12 model on the bilateral city level data. The gravity model results are shown in Table 4 while key coefficients are shown in Figure 7

Figure 7: Contribution and development links, core sample



Notes: Dependent variable is the count of links between cities. Sample: Exclude very small cities. Exclude within-organization links. PPML estimates for gravity equation

Table 4: Contribution and development links, core sample

Dependent Variable:	N of links between contributors		
Model:	(1)	(2)	(3)
Different city	-1.261***		
	(0.1055)		
ln distance | not same city	-0.0539***		
	(0.0060)		
dist_cat = Same city(0-1)		1.746***	2.018***
		(0.0772)	(0.0858)
dist_cat = Agglomeration(1-50)		0.6351***	0.7344***
		(0.0724)	(0.0873)
dist_cat = Region(50-200)		0.1905***	0.2039***
		(0.0319)	(0.0307)
dist_cat = Short-trip(200-700)		0.0245*	0.0416***
		(0.0127)	(0.0101)
different country, same language	-0.0792***	-0.1749***	-0.1581***
	(0.0229)	(0.0215)	(0.0184)
different country, diff language	-0.1910***	-0.2856***	-0.2476***
	(0.0369)	(0.0369)	(0.0322)
In same organization (0-1)	5.565***	5.556***	
	(0.0858)	(0.0855)	
Fixed-effects			
city_destination	Yes	Yes	Yes
city_origin	Yes	Yes	Yes
Pseudo R^2	0.84371	0.84385	0.86084
Observations	3,636,122	3,636,122	3,478,716

Notes: Dependent variable is count of links between cities. Sample: Exclude very small cities. Exclude within-organization links. PPML estimates for gravity equation. Standard errors, clustered at city_destination & city_origin level are in parentheses, ***: 0.01, **: 0.05, *: 0.1.

Core results (Column 3 of Table 4 and Figure 7) show strong localization and a steep decline by distance. Contributors who reside in the same city have 6.5 times (exp(2.018)-1) higher chance to work together than those who live in far away (700km +) segments of the same country. This suggests a massive co-location benefit. Agglomeration is also very high, suggesting a 2x higher chance. There is a sharp spatial decay and even 200km vs 700 gives only a 4% bump (and zero beyond). When physical trade cost is zero, and only face-to-face meeting costs count, the gravity model suggests massive co-location benefits, but no proximity gains beyond the commute distance. National borders also matter: Crossing a country is a 15% drop in probability, which rises to 25% if the countries don't share a language. Results are similar if we include pairs in organizations (column 2).

This confirms the role of distance. Not only is it true that more distant developers are less likely to collaborate but the point estimates are actually very large

6 Success and dispersion

We now bring our model predictions (2) to (5) to the data. The first prediction has been addressed in the first empirical exercise and has been motivated for the construction of the model in the first place.

6.1 P2 Distant team members have higher skill

The second prediction says that (conditional on collaboration), more distant team members tend to have higher skills due to selection.

Coder quality is not perfectly observed in our model. Neither it is on GitHub. On a given coder, people can look up many characteristics such as the number of repositories, past activity in terms of commits, number of stars, number of followers, personal information.[7]

The most relevant of these is past coding activity measured in commits. High activity is a sign of developer quality. Given the prominent display of activity on user profiles, we argue that this will capture the main mechanism discussed in the model.

We compute the average distance between the first developer and all the subsequent developers and run the following OLS regressions (6.1):

$$\bar{\text{Skill}}_{intl} = \beta_1 \text{AvgDistance}_i + \alpha_n + \lambda_t + \delta_l$$

where $\bar{\text{Skill}}_{intl}$ can either be the average amount of commits in the previous four quarters of developers in project i or the average amount of days active in the four previous quarters, β_1 is the parameter of interest and describes how average observed skill is related to the average distance in the project.

We first show results with two-member teams and then generalize to multiple-member teams.

Further, we include a set of fixed effects relating to the programming language, the time dimensions, the quarter, and the amount of developers in the project. Results for this regression are presented in 5.

[7] Have a look at `https://github.com/julianhinz/` to see what people looking for partners see.

Table 5: Dispersed teams have higher average skill

Dependent Variables:	Log(Average previous commits)	Log(Average previous days)
Model:	(1)	(2)
Variables		
Log(Avg Distance)	0.0366***	0.0229***
	(0.0034)	(0.0023)
Fixed-effects		
Language	Yes	Yes
Quarter	Yes	Yes
Developer Count	Yes	Yes
Fit statistics		
Observations	138,423	138,423
R^2	0.20480	0.16730
Within R^2	0.01421	0.01148

Clustered (Language) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The results align with the predictions of the model given the positive elasticities. A pair of coders in a repo with a 10% higher distance between them, have on average a 0.3% higher average previous commit count.

6.2 P3 Dispersed teams are more successful

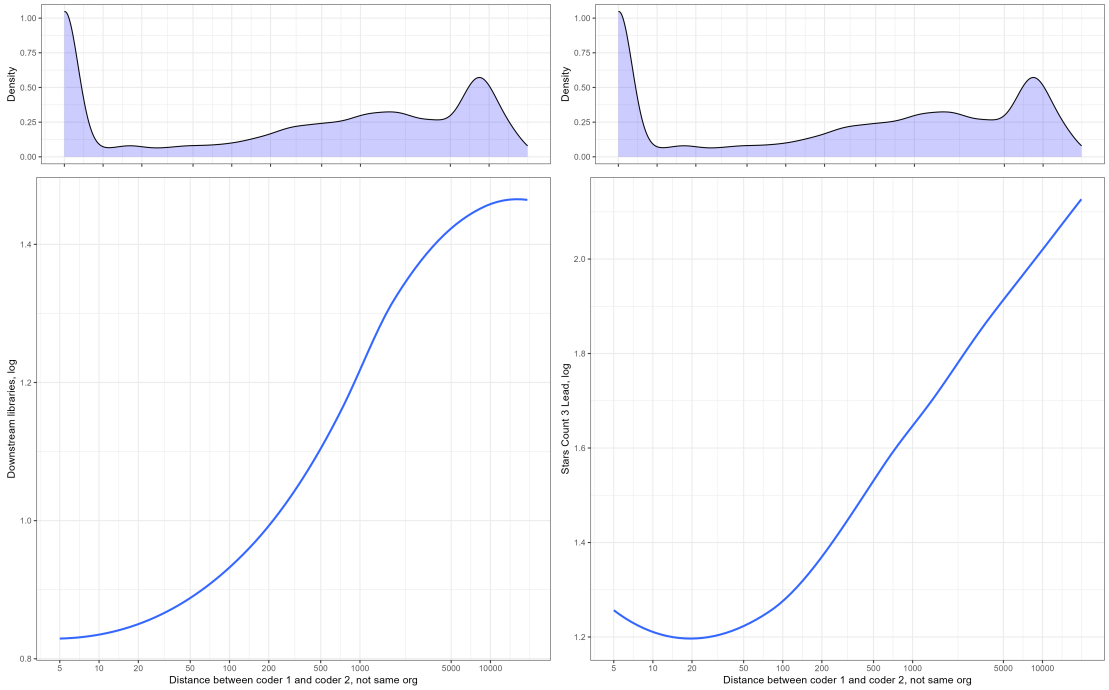
Measuring quality or success in OSS is not trivial. As outlined in the model, we think of success as the adoption of a project or visibility. Thus, to gauge the success of a project, we use stars and downstream dependencies. Downstream dependencies can be thought of as measuring technology adoption of a project. Naturally, a high amount of dependencies is a great approximation of success.

Stars, similar to likes on other platforms, can be given from users on GitHub to projects. This allows users to track the developments of the projects or simply give positive feedback. Stars will be considered with two-time horizons, once with a three-quarter lead and once with a 12-quarter lead. We aim to capture short-and long-term success of projects. We have more non-missing observations, but at the same time reverse causality is quite possible.

Before we start, please note that there is a great deal of missing location and distance information. As we saw earlier (Section 3.2), about 80% of location data is missing, so almost 90% of distance info is missing, too. The descriptive graph A1 however suggests that while we are working with a sample of developers, these can be regarded as representative.

Let us start by exploring two-member teams – repositories where during the *starting* quarter only two developers contributed. The graph below shows the clear log-log pattern for both downstream libraries and stars.

Figure 8: More dispersed teams are more successful



Notes: Repo level. Loess plot on success and distance between developer 1 and 2. Success is log number of downstream libraries (left panel) as well as log number of stars (right panel), distance is km between two developers, log scale. Kernel density by distance on upper graphs.

To get to the exact proposition, we estimate a Poisson model for the count of downstream library use S_{rt}, measured for project r at time (quarter) t, written in programming language l. The two coder qualities are denoted with η_o and η_d and measured as (ln) past number of commits:

$$S_{rt} = \exp(\beta_1 \eta_o + \beta_2 \eta_d + \beta_1 \tau_{od} + \nu_{tl}) + \varepsilon_{rt} \tag{13}$$

We control for language-time trends in popularity as it may confound the relationship.

The main results estimate regression 13 regarding propositions 3 are shown in Table 6. In column (1) we can see the coder quality, as measured with past experience, is positively correlated with success. This is true for both coders, but much more for the starting coder who can often also be thought of as the lead developer. The 0.37 log unit elasticity means that a starting coder with 10% more commits in the past 12 months, will typically start projects that can expect 4.4% more imports as a downstream repository. For the second coder it s 1.9%. Distance alone (column (2)) is positively correlated, with a point estimate of 0.147 coefficient. In column (3) we now partial out quality and see the point estimate drop to 0.104. The relationship remains once we add the complexity of the project.

Regarding Proposition (3) distance is positively correlated with success, and importantly,

when partialling out one measure of quality, the distance coefficient declines. These results confirm what we saw graphically earlier.

Table 6: Dispersed teams are more successful 1: downstream

Dependent Variable:	N downstream libraries			
Model:	(1)	(2)	(3)	(4)
Variables				
Coder 1 quality (ln past commits)	0.3684***		0.3461***	0.3459***
	(0.0736)		(0.0696)	(0.0705)
Coder 2 quality (ln past commits)	0.1784***		0.1604***	0.1603***
	(0.0370)		(0.0342)	(0.0343)
Distance (km, ln)		0.1475***	0.1037***	0.1033**
		(0.0431)	(0.0399)	(0.0401)
Repo complexity (sum commits, ln)				-0.0252
				(0.1598)
Fixed-effects				
quarter * language	Yes	Yes	Yes	Yes
Fit statistics				
Observations	9,803	9,803	9,803	9,803
Pseudo R^2	0.26539	0.21770	0.27416	0.27423

*Clustered (quarter-language) standard-errors in parentheses, ***: 0.01, **: 0.05, *: 0.1.*
Poisson model, downstream library count as dependent variable.
Repo complexity is top total commits over the first two quarters by developers.
Past commits refer to the 4 quarters before the start of this repo.

6.3 P3 Dispersion result confirmed in multi-member teams

We now repeat all previous exercises for teams with up to 5 members. Bilateral distance is replaced with average distance between the first developer and others. Coder quality is now measured with two variables, max and min quality – experience in terms of past commits.

Table 7: Multi-member teams

	Shared as Library		Downstream Libraries		Stars on GitHub	
	(1)	(2)	(3)	(4)	(5)	(6)
Distance Between Developers (ln)	0.0321***	0.0185***	0.2638***	0.2528***	0.1792***	0.1649***
	(0.0047)	(0.0045)	(0.0386)	(0.0415)	(0.0110)	(0.0110)
Max Coder quality (ln by Commits)		0.1326***		0.1833**		0.1494***
		(0.0104)		(0.0794)		(0.0113)
Min Coder quality (ln by Commits)		-0.0039		-0.0188		-0.0457***
		(0.0062)		(0.0299)		(0.0129)
Observations	513,197	489,211	45,045	44,030	603,918	576,324
Pseudo R^2	0.10285	0.10894	0.27119	0.27871	0.15470	0.16002
Quarter x Language fixed effects	✓	✓	✓	✓	✓	✓
Developer Count fixed effects	✓	✓	✓	✓	✓	✓

*Clustered (quarter-language) standard-errors in parentheses, ***: 0.01, **: 0.05, *: 0.1.*
Poisson model, shared library, downstream library count, and star count as dependent variable.
Developer distance is average distance to developer 1.

The results in Table 7 confirm that in this extended setting, teams with a greater average distance between members create repositories that will, on average, earn more stars and get more downloads. In terms of coder experience, the quality of the best coder matters. Repos with an experienced leader can expect to generate more downloads and stars.

6.4 P4 In complex projects, distance matters more

The fourth proposition is about the complexity of the project as a mediator. We measure complexity as the sum of commits by both developers in the first two-quarters of active development. Complex projects are those with at least 90 (top 10%) total commits.

Table 8: Dispersed teams are more successful 2: complexity

Dependent Variable:	N downstream libraries		
is complex repo:	Full sample	No	Yes
Model:	(1)	(2)	(3)
Variables			
Distance (km, ln)	0.1037***	0.0860**	0.2485***
	(0.0399)	(0.0394)	(0.0919)
Coder 1 quality (ln past commits)	0.3461***	0.3232***	0.0280
	(0.0696)	(0.0557)	(0.0979)
Coder 2 quality (ln past commits)	0.1604***	0.1561***	0.0943
	(0.0342)	(0.0253)	(0.0737)
Fixed-effects			
quarter * language	Yes	Yes	Yes
Fit statistics			
Observations	9,803	8,929	750
Pseudo R^2	0.27416	0.25175	0.69514

*Clustered (quarter-language) standard-errors in parentheses, ***: 0.01, **: 0.05, *: 0.1. Poisson model, downstream library count as dependent variable. Complex repo is top 10% in terms of total commits over the first two quarters by developers. Past commits refer to the 4 quarters before the start of this repo.*

Indeed, we find that more complex projects – where more efforts were invested in terms of commits – show a substantially stronger distance elasticity.

The effect of geographic diversity on project quality is stronger for more complex projects where communication and idea sharing are more important.

6.5 P5 Non-linearity in developer group size

The last proposition was about team size: suggesting a non-linear effect in team size growth. While the move from one to two developers is associated with big gains, adding even more developers beyond that is not as important. We estimate the following regression on our sample of projects:

$$Y_{itl} = \gamma \#Developers_i + \lambda_t + \delta_l$$

The marginal effects which refers to the differences between categories are displayed in 9.

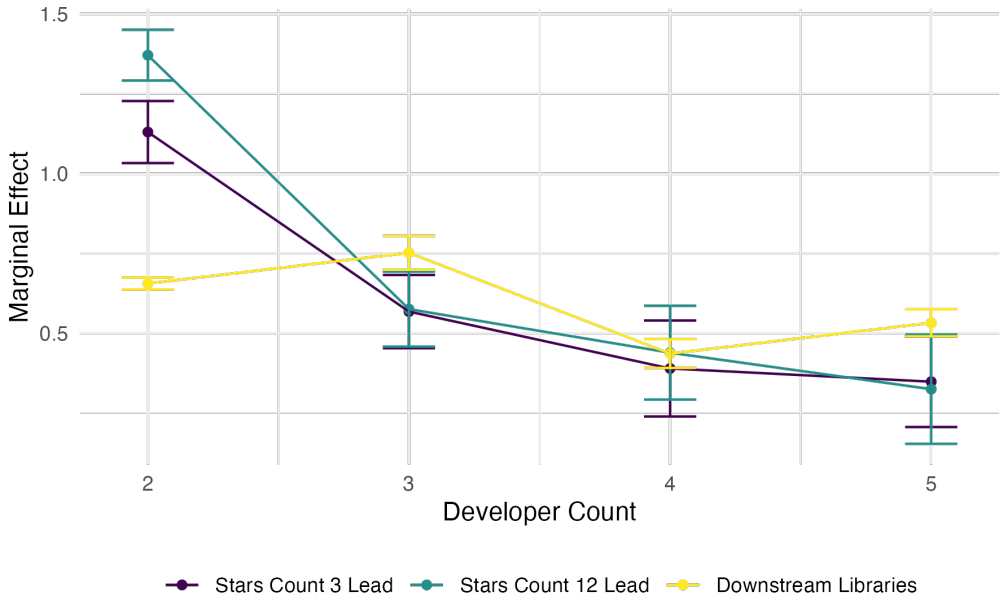


Figure 9: Non-linear effect of developer count increases on different software quality metrics.

For stars, the predictions of the model align with the data. While going from one developer to two is really beneficial, adding yet another developer only leads to limited gains. For downstream dependencies however, we can not confirm the non-linear nature of a team size effect as the estimate is relatively stable throughout.

7 Conclusion

Building on a model of team formation and success, along with granular data from open-source software, our analysis demonstrates that while geographically close developers are more likely to collaborate, teams composed of more distant partners tend to attract higher-skilled individuals, ultimately leading to superior project outcomes. This pattern is driven by selection effects, as only the most skilled individuals overcome the frictions of distance to form teams. Our model and empirical evidence further show that these benefits of geographic dispersion are especially pronounced in complex projects, where diverse expertise plays a critical role in success.

These findings extend traditional insights into agglomeration economies, showing that the advantages of physical co-location can, in some cases, be outweighed by the benefits of remote collaboration. By enabling access to a broader and more diverse talent pool, dispersed teams can unlock synergies that might remain untapped in more geographically concentrated settings. This has important implications for firms, policymakers, and the

broader knowledge economy: reducing barriers to remote collaboration — whether through improved digital infrastructure, better institutional support, or fostering online communities — can enhance productivity and innovation.

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A Appendix

A.1 Poisson approximation

We have a binary outcome $y_i \in \{0, 1\}$ for $i = 1, 2, ..., N$, with N very large. The probability of success is given by logit,

$$\Pr(y_i = 1|X_i) = \Pi(\beta X_i),$$

with $\Pi(z) = e^z/(1 + e^z)$.

The explanatory variable is vector valued and may take G distinct values with $G \ll N$. For example, it may be a same city dummy ($G = 2$) or the pairwise distance between K cities ($G = K^2 \ll N$).

The log likelihood contribution of observation i is

$$\ln \mathcal{L}_i = y_i \ln \Pi(\beta X_i) + (1 - y_i) \ln[1 - \Pi(\beta x_i)]$$

so that the total log likelihood in the sample is

$$\ln \mathcal{L} = \sum_{i=1}^{N} y_i \ln \Pi(\beta X_i) + (1 - y_i) \ln[1 - \Pi(\beta X_i)].$$

Consider a change of variables. The values in the sum will be repeated very frequently, because there are only G distinct values that X_i can take. Let Z_g denote the gth possible value of X_i. For example, for a same-city dummy, $Z_1 = 0$ and $Z_2 = 1$.

Let $n_g := \|i : X_i = Z_g\|$ denote the number of observations for whom X_i takes its gth possible value. We will also call this group g.

Within this group, some observations have $y_i = 1$. Their count will be $n_{g1} := \|i : X_i = Z_g, y_i = 1\|$. Similarly, we denote $n_{g0} := \|i : X_i = Z_g, y_i = 0\|$. Trivially, we have $n_g = n_{g0} + n_{g1}$.

For example, suppose X_i is a same-city dummy. Then $G = 2$, with $g = 1$ denoting not in the same city. $g = 2$ being the same city. Then n_{11} denotes the number of user pairs that are *not in the same city* and *have a link*.

Given this change of variables, we can rewrite the sum of log likelihood as

$$\ln \mathcal{L} = \sum_{g=1}^{G} n_{g1} \ln \Pi(\beta Z_g) + n_{g0} \ln[1 - \Pi(\beta Z_g)].$$

Maximizing with respect to β yields

$$0 = \sum_{g=1}^{G} n_{g1} \frac{\Pi'(\beta Z_g)}{\Pi(\beta Z_g)} Z_g - n_{g0} \frac{\Pi'(\beta Z_g)}{1-\Pi(\beta Z_g)} Z_g = \sum_{g=1}^{G} \frac{\Pi'(\beta Z_g)}{\Pi(\beta Z_g)[1-\Pi(\beta Z_g)]} Z_g [n_{1g} - \Pi(\beta Z_g) n_g].$$

The term in brackets is the error term in a regression trying to predict the number of links on group g. That error term is orthogonal to Z_g. The fraction at the beginning provide some weighting across groups,

$$\frac{\Pi'}{\Pi(1-\Pi)} = 1 - \Pi(\beta Z_g).$$

When predicting links in a sparse graph, the probability of $y_i = 1$ will be very small, so that $\Pi \approx 0$ and the weight is ≈ 1.

Then the first-order condition for ML can then be approximated by

$$0 = \sum_{g=1}^{G} Z_g [n_{1g} - e^{\beta Z_g} n_g].$$

This is *exactly* the FOC for a Poisson ML, with n_g as an exposure variable.

A.2 Data Appendix

These subsections carefully outline all steps performed in assembling the data.

A.2.1 GitHub Torrent

We use the latest regular data dump of 2019 June and download the corresponding MySQL dump. We start our analysis from the raw data collecting all commits. In total these are $1,368,235,072$ time stamped commits. We exclude from this all commits that come from users who are labeled as *fake* in the GHtorrent data and keep only commits where the *authorid* correspond to the *committerid*.[8]. In total this leaves us with $1,173,770,331$ commits.

The entire dataset contains information for $125,542,578$ projects, after our exclusions, we loose projects without any commits and those only done by *fake* users. We reduce sizably to only $68,516,806$ projects.

For our main analysis, we only care about projects with some threshold amount of activity. Thus, we define a very low threshold of a project to end up in our main sample of having at least 3 commits and at least 2 active days. This further reduces our sample to a total of $29,673,852$ which make up $1,068,882,586$ which is 91% of commits of non-fake users.

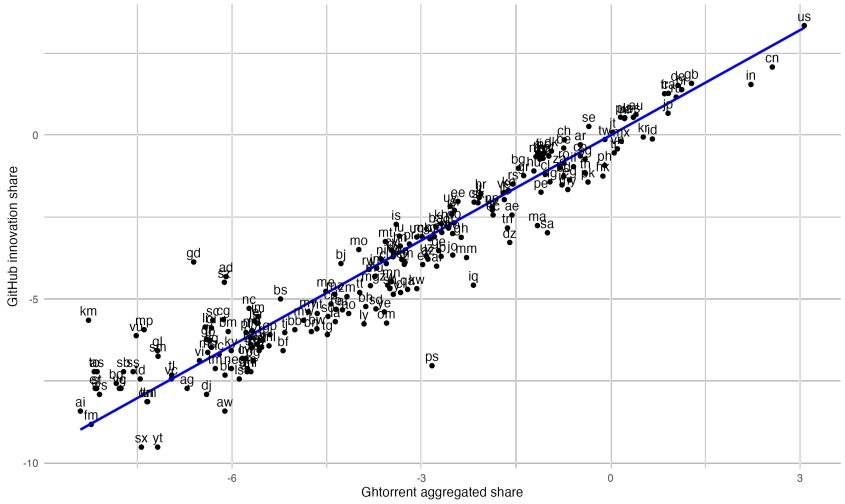
[8]One commit can have different instances of authors and committers. We want to have the original creator of the code – thus we take the authors.

Experience measures will also be build on these commits as we believe that it is a verified assumption that commits with some slight activity are the better signal and therefore it is worthwhile leaving out 9% of commits.

These projects which surpass this threshold are developed by a total of $8,630,439$ developers. Of these projects $6,618,947$ are developed by teams with more than developer.

A.2.2 Data quality

The location data that we exploit in this project relies on self-reported user data. Naturally, this raises the question of representatives of the data. To test this, we aggregate our data to the country level such that we have the amount of developer per country. From this, we compute the country-level shares. This we compare with the data provided from the GitHub innovation Graph[9] which does not rely on self-reproted data but can use IP-addresses. Simply regressing these shares on each other gives us a reassuring slope of 1 with and R^2 of about 0.9. The figure is presented in A1.



Appendix Figure A1: Comparison shares in GHtorrent and GitHub Innovation

Notes: Comparison of aggregegated country shares from our micro-developer level dataset and aggregated shares provided by GitHub innovation graph. Our data relies on user-self reported data wheras GitHub innovation graph uses IP addresses. The slope of log-log regressions or simple OLS on shares is at 1 suggesting our data is indeed representative.

[9](https://innovationgraph.github.com)