The geography of production and sourcing in the weightless economy: Evidence from open-source software

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December 18, 2023

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This paper

Big Picture:

- How dispersed developers create great products.

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Focus of This Paper:

- How and where good Open Source Software (OSS) is produced.
- OSS no fixed costs, and no need for face-to-face interaction - pure online.
- Geography may not significantly impact OSS development.

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- Geography may not significantly impact OSS development.

Data:

- Writing code together – Collaboration (Github)
- Using other people's code – imported dependencies (Dependencies.io).

Open Source Software

Open Source Software (OSS) is everywhere

Open Source Software (OSS) has a vast landscape, `GitHub` hosts over 330 million repositories.

OSS plays an important roles in

- Websites (JavaScript)
- Operating systems (Linux, Android)
- Data (R Tidyverse, Python Pandas, Julia)
- Machine Learning and AI (PyTorch, LLaMA)

OSS mostly free, but present in fee-based platforms

- Overleaf

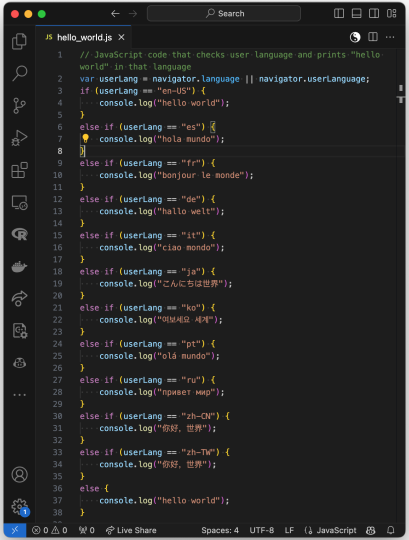
Focus on JavaScript

- JavaScript is one of the biggest programming languages

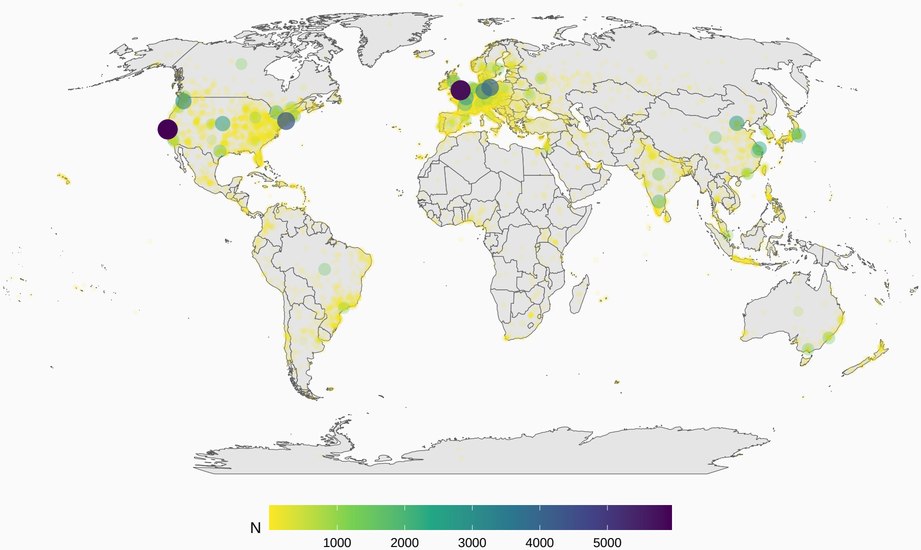
→ used in web development and app development

- NPM is a package manager

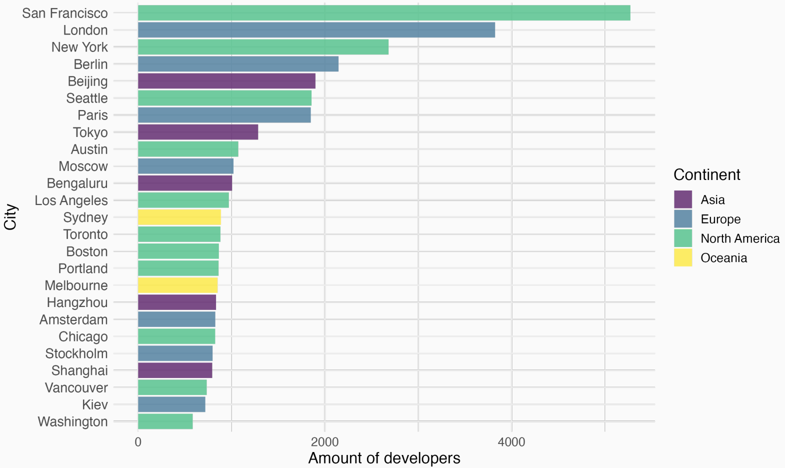
→ organizes packages and provides access



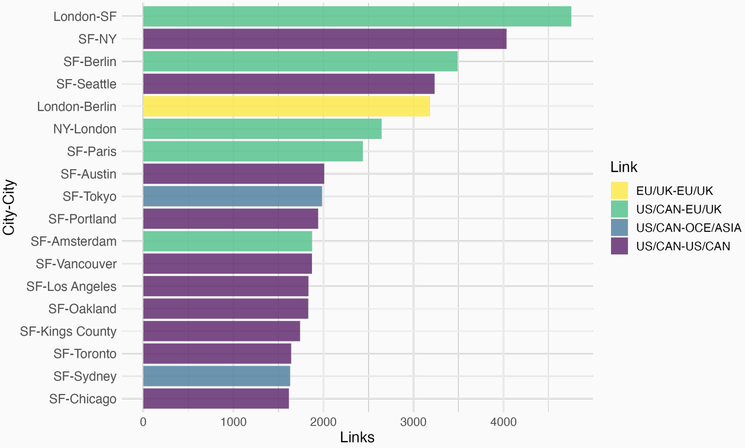
Global industry: Number of JavaScript developer per city



Top cities per number of developers



mmot popular city pairs: EU, US, EU-US



Most frequent city-pairs for repos developed from 2 cities

Search, Agglomeration and Selection

- Costs of setting up a partnership and maintaining it
- Search costs of inputs (code chunks)
  - Written together – finding a collaborator
  - Using already published code – finding a package
- Is successful code written within a city or over many locations?

- Agglomeration vs "selection to export"
  - Agglomeration – F2F meeting key, depends on "distance"
  - Selection – developers of best projects are able to cover this cost

Preview of Findings

- 1 Distance matters
  - 1a a lot for collaboration
  - 1b a little for dependencies
- 2 Code written in more cities more likely to be popular
- 3 Being in organization reduce spatial friction
  - 3a Collaboration and gravity
  - 3b Success and dispersion

** Possible Mechanism – in progress

- Mechanical. Same distribution of talent in cities. Best match may be elsewhere
- Costly search – self selection to export to collab with foreigners
- Comparative advantage: Certain types of code skills in SF vs others in Berlin
- Reverse causality – projects get popular more easily if done in many places.

** Possible Mechanism – in progress

- In progress – look at dynamics
- How joins what projects

Related literature

- **Geographical Distance / Network formation / Agglomeration**: Chaney (2014) Bernard et al. (2019) Davis and Dingel (2019) Bailey et al. (2021)
- **Gravity: Digital:** Blum and Goldfarb (2006) Anderson et al. (2018)
- **Frictions in services:** Stein and Daude (2007) Bahar (2020)
- **Patents and science**: Bircan et al. (2021), Head et al. (2019), Jaffe et al. (1993), Singh (2008)
- **OSS**: Lerner and Tirole (2002) , Laurentsyeva (2019) Wachs et al. (2022) Fackler et al. (2023)

Open source software vs patents and academia

- R&D and patenting
  - Need machines, secrecy, often top-down
  - Distance matters in collaboration
  - More cited patents – geographically focused authors
- Science (math, academic papers)
  - Similar, but often longer projects, not open, F2F important to think and discuss
  - Distance matters in collaboration
  - Major role of top Universities / Centers

Data, methods and results

Open Source vocabulary

- `Git`: Distributed version control system for software projects
- `GitHub`: A platform to collaboratively work on software projects
- `Dependency`: An imported package that provides a functionality
- `Package`: A unit of software, provision of a (bundle of) functionality
- `Repository`: A storage for a package (what we observe)
- `Commit`: The smallest unit of contribution

Data from GHTorrent and Libraries.io

Collaboration — Working on the same code with others

- `GHTorrent`: Tracks metadata on `GitHub` usage

→ Commits, locations and user organisations

- Row: One commit from a developer to a repository
- Focus on links: binary if a developer committed at all to a repository

Dependencies — Sourcing of intermediate inputs

- `Libraries.io`: Tracks data on single software repositories

→ dependency linkages

- Row: An imported dependency (package) to repo 1 from repo 2

→ Can be mapped to repositories on GitHub

Scope of data

- Data coverage: 2013 – 2019
- We know location as city for developers

- Contributions by 217K developers,
- 300K repos
- 17% of repos have multiple developers (ie have collaboration)

- 70K organizations, with 120K developers

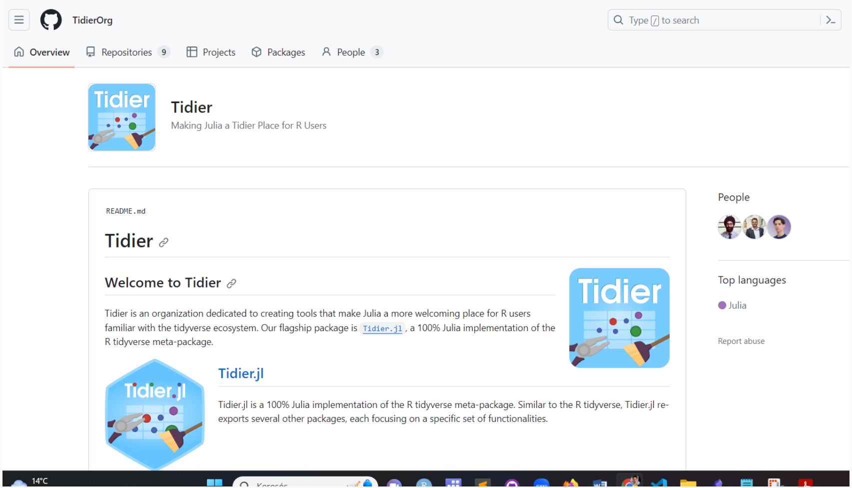
Organizations

- formally a (GitHub) permission system
- Collection of users
- Collection of projects

- We observe public memberships
  - Underestimate their presence.

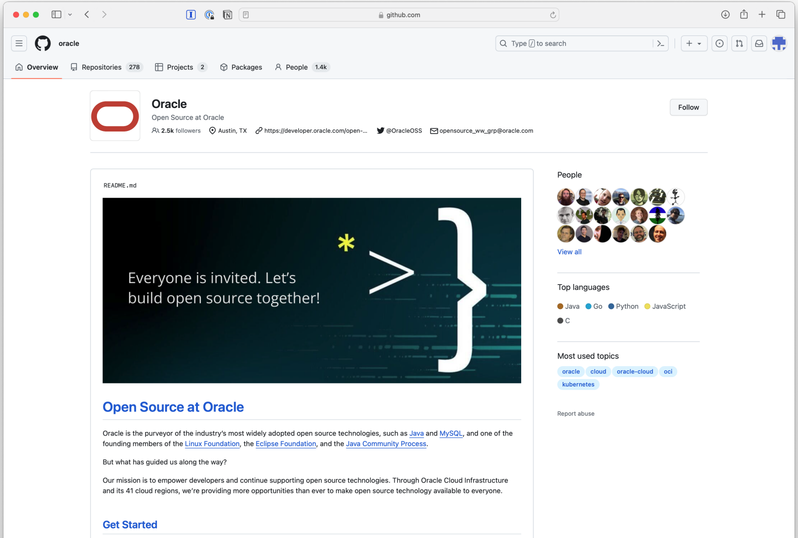
Organizations — Example 1: Tidier for Julia

- No formal org
- share info, practice
- 3 members



Organizations — Example 2: Oracle

- Company
- share info, practice, showcase
- 1.4k members



Raw data to regressions

- Collaboration – link developers who contribute to the same repo.
- Dependencies – link developers from one package using another

- One observation is one link
- Aggregated at city (city pair) level

MORE: Aggregation

** Search and maintenance costs

- Same model for collaboration and dependency import
- Link depends on search costs
  - Find a partner to collaborate on a project with
  - Find a dependency that can solve a particular problem
- Link depends on maintenance costs
  - Maintain a relationship of writing code
  - Maintain functionality with the imported dependency

** Search costs: where do people meet

- Personal meeting, esp. workplace (CEU, Oracle)
- Local community events, science parks (Xaccelerator)
- Regional events (R Ladies Auckland, VDSG Meetup, PyData Berlin)
- Conferences 1: dozens of events every month such CityJS Berlin, React Summit US,
- Conferences 2: developers directly such as Node-js fwdays23 in Kyiv, where new packages are presented.

- Learn about packages, devs: online forums, Stack Overflow, Twitter

Modelling search and maintenance

$$\Pr(Y_{od}|x_o, x_d, d_{od}) \approx \text{Poisson}[N_o \times N_d \times \exp(\beta_1 x_i + \beta_2 x_j + \beta_3 d_{ij})]$$

- Outcome: Number of links between cities o, d
- d_{ij} Distance measured as a set of indicators / log-linear
- Origin and destination city FE
- $N_o \times N_d$ -Exposure: Number of developers in city o x d

MORE: From logit to Poisson

Modelling search and maintenance costs

- Personal communication – distance in terms of travel
  - Same city – e.g. universities, office parks
  - Agglomeration (1-50km) – regional events
  - Regional (50-200km) – national conferences
  - Short trip (200-700km) – big conferences
  - Beyond 700km (*as base*) – global events
- Travel difficulty
  - Crossing borders
  - Visa requirement
  - Timezone difference
- Homophily/Communication costs — shared language

** What is an observation?

Two interpretations:

1. 10 billion potential developer pairs
2. 3.7 million city pairs

** Results 1: Distance key in contributions, marginally for dependencies

- Exclude links within organizations.
- Exclude small cities: 3.4m city pairs
- Origin city FE
- Dest. city FE.

Dependent Variables:	contr_value	dep_value	contr_value	dep_value
Model:	(1)	(2)	(3)	(4)
Variables				
dist_cat = Same city(0-1)	0.7440***	0.0556***		
	(0.0765)	(0.0106)		
dist_cat = Agglomeration (1-50)	0.5610***	0.0592***		
	(0.0793)	(0.0115)		
dist_cat = Region(50-200)	0.2400***	0.0270***		
	(0.0303)	(0.0094)		
dist_cat = Short trip(200-700)	0.0628***	0.0067**		
	(0.0107)	(0.0032)		
cities in same country	0.1635***	0.0145**		
	(0.0134)	(0.0071)		
common language	0.0815***	0.0244***		
	(0.0140)	(0.0060)		
visa free ravel	0.1348***	0.0325**		
	(0.0327)	(0.0148)		
tz_gap_nothigh	0.0319***	0.0102***		
	(0.0088)	(0.0033)		
ln(distance)			-0.0953***	-0.0109***
			(0.0075)	(0.0020)
Observations	3,790,927	3,202,079	3,791,039	3,202,175
Pseudo R^2	0.84942	0.98867	0.84883	0.98865

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

Results 1a: Distance important for collaboration

- Strong co-localisation effects for collaboration.
- Timezone, visa, language controls

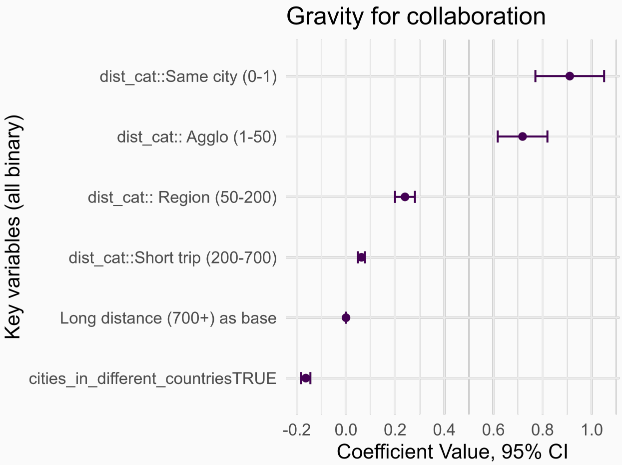


Figure 1: PPML estimates for Github collaborationn as measured in developer links.

Results 1b Distance matters for dependencies- a bit

- Only weak evidence of colocolisation of dependencies.
- Timezone, visa, language controls

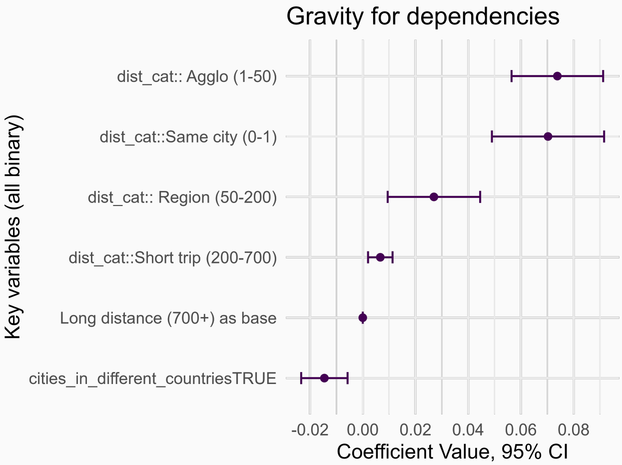


Figure 2: PPML estimates for project links as measured in dependency-developer links.

Results 1 Gravity for collaboration much greater than dependencies

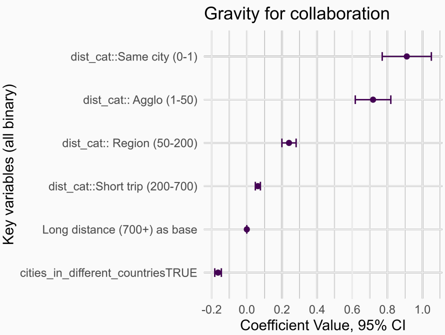


Figure 3: PPML estimates for Github collaborationn as measured in developer links.

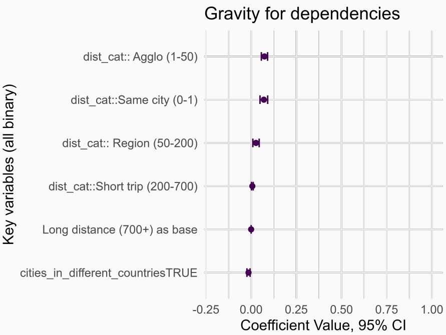


Figure 4: PPML estimates for project links as measured in dependency-developer links.

** Robustness to very popular dependencies

- Maybe a few very large repositories dominate and flatten the curve.
- Take out top 100 projects. Coefficients marginally higher (0.061 vs 0.055 for same city)

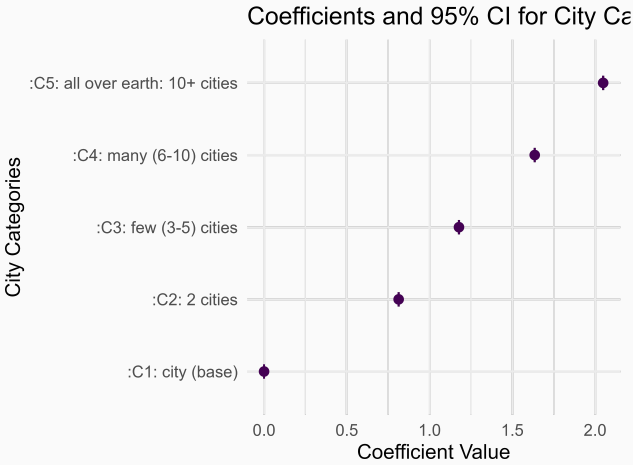
Success (popularity) and spatial dispersion

$$\Pr(Y_i|.) \approx \text{Poisson}[\exp(\beta_1 \mathit{ln\_devs}_i + \beta_2 \mathit{ln\_country/dev}_i + \beta_3 \mathit{ln\_city/country}_i)]$$

- Outcome: Number of repos importing this repo i

- $\mathit{ln\_devs}_i$ number of developers (log)
- $\mathit{ln\_country/dev}_i$ number of countries / developers (log)
- $\mathit{ln\_city/country}_i$ number of cities / countries (log)

Results 2: More popular dependency - higher spatial dispersion



- **Popularity**: how many times a repo was used as dependency for other repos
- **Spatial dispersion**: Number of cities (in categories) developers are located
- More widely adopted repos will be produced by developers located in more cities

Results 2: More popular dependency - higher spatial dispersion

- Only repos used as dependency at least once
- Exclude top few packages
- Robust to size (commits) and N of developers, N dependencies as confounders.
- Col3: only NPM

Dependent Variables:	quality2_count_dependents_all		quality1_count_dependents_npm
Model:	(1)	(2)	(3)
Variables			
Constant	8.499***	8.748***	3.176***
	(0.0002)	(0.0002)	(0.0017)
ln_count_cities	0.6906***		
	(0.0001)		
ln_count_developers		0.7332***	1.722***
		(0.0001)	(0.0011)
ln_cities_per_country		1.326***	1.790***
		(0.0004)	(0.0038)
ln_countries_per_developer		1.664***	2.526***
		(0.0003)	(0.0033)
Observations	15,812	15,812	15,812
Pseudo R^2	0.03537	0.05010	0.19981

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Results 3: Organizations reduce spatial frictions

- Confounder: Developers within organization collaborate and import dependencies *much much* more

- Heterogeneity: for collaboration it reduces distance elasticity by 1/3

- For repos in organization, dispersion across countries is 50% less relevant, cities 20% less relevant

MORE: Role of organizations

** Results 3: Organizations reduce spatial frictions

- Include organizations
  - Stacked data, in and out of orgs
- Exclude small cities: 3.4m city pairs
- Origin city FE
- Dest. city FE.

Dependent Variables:	contr_value	dep_value	contr_value	dep_value
Model:	(1)	(2)	(3)	(4)
dist_cat = Samecity(0-1)	0.5475***	0.0591***		
	(0.0530)	(0.0118)		
dist_cat = Agglo(1-50)	0.4096***	0.0120		
	(0.0680)	(0.0176)		
dist_cat = Region(50-200)	0.2311***	0.0180**		
	(0.0363)	(0.0091)		
dist_cat = Shorttrip(200-700)	0.0535***	0.0055*		
	(0.0117)	(0.0032)		
cities_in_same_country	0.1780***	0.0184**		
	(0.0157)	(0.0074)		
common_language	0.0970***	0.0310***		
	(0.0150)	(0.0074)		
visafree_travel	0.1717***	0.0449*		
	(0.0521)	(0.0246)		
tz_gap_nothigh	0.0286***	0.0099**		
	(0.0102)	(0.0039)		
ln_dist			**-0.0869*****	**-0.0114*****
			(0.0073)	(0.0028)
Within same organization	**5.663*****	**3.374*****	**5.680*****	**3.374*****
	(0.0886)	(0.1499)	(0.0888)	(0.1507)
Pseudo R^2	0.83384	0.98608	0.83312	0.98605

** Results 3: Organizations reduce spatial frictions

- Include organizations
  - Stacked data, in and out of orgs
- Exclude small cities: 3.4m city pairs
- Origin city FE
- Dest. city FE.
- *Language, TZ, visa not shown*

Dependent Variables:	contr_value	dep_value	contr_value	dep_value
Model:	(1)	(2)	(3)	(4)
dist_cat = Samecity(0-1)	0.6730***	0.0530***		
	(0.0820)	(0.0100)		
same_org × dist_cat = Samecity(0-1)	-0.4099***	0.0154		
	(0.1514)	(0.0678)		
	...	...		
cities_in_same_country	0.1761***	0.0160**		
	(0.0126)	(0.0066)		
same_org × cities_in_same_country	-0.0452	0.1467		
	(0.1176)	(0.1592)		
	...	...		
Within same organization	5.650***	3.282***	5.437***	3.425***
	(0.1125)	(0.1418)	(0.1545)	(0.3437)
ln_dist			-0.0937***	-0.0112***
			(0.0079)	(0.0021)
ln_dist × same org			**0.0338****	**-0.0075**
			(0.0133)	(0.0296)
Pseudo R^2	0.83402	0.98612	0.83318	0.98605

** Results 3b: Organizations reduce spatial frictions

- Only repos used as a dependency at least once
- Exclude top few packages

Dependent Variable:	quality2_count_dependents_all	
in_org	Not in irg	Within org
Model:	(1)	(2)
Variables		
Constant	8.819***	8.335***
	(0.0002)	(0.0004)
ln_count_developers	0.6391***	1.223***
	(0.0002)	(0.0004)
ln_countries_per_developer	1.702***	1.491***
	(0.0004)	(0.0007)
ln_cities_per_country	1.529***	0.5648***
	(0.0004)	(0.0008)
Observations	11,737	4,075
Pseudo R^2	0.05366	0.05326

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Discussion of results

Recap of results

- Strong localization of developers. Distance matters to find partners to develop with.
- Only limited role of geography for dependencies.
- Good code created in dispersed cities
- Within organisations distance matters less.

- Very much in progress.
  - Mechanism, role of selection
  - Dynamics
  - Other languages – other types of devs, distribution management

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Aggregation

Collaboration

- Start with the developer's link to a repository (via commits)
- Directed but (mostly fully) symmetric
- Transform it to developer to developer links
- Aggregate at city level

Links in the contribution network

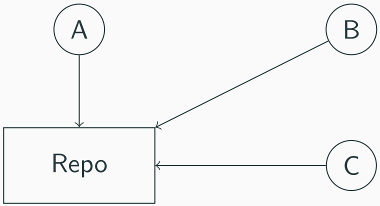

Figure 5: Developers commiting to a repository.

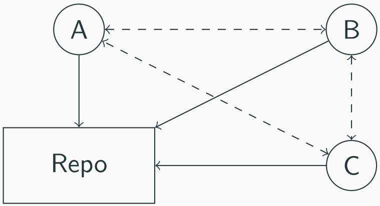

Figure 6: Developers commiting to a repository including implied contributor to contributor links.

Solid lines are what we **observe**. Dashed lines is what we **infer**.

Dependencies

- We observe a repository importing another one as dependency.
- Directed, not symmetric
- Transform it to developer to developer links
    - Use knowledge of producers of the dependency as well
- Aggregate at city level

Links in the dependency network

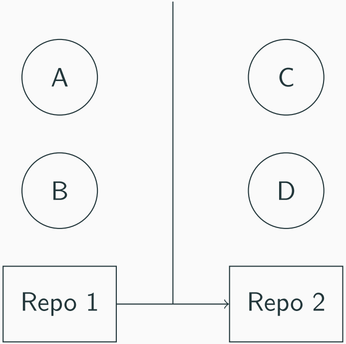

Figure 7: Dependency of repository 1 on repository 2 with the respective developers.

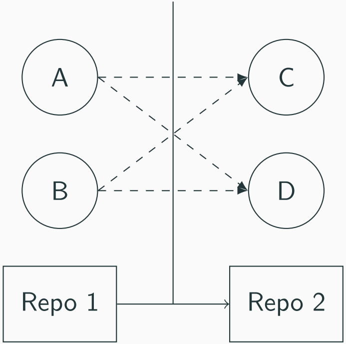

Figure 8: Dependency of repository 1 on repository 2 with the respective developers. Dashed lines indicate implied links between developers.

Again, solid lines are what we **observe**. Dashed lines is what we **infer**.

Aggregation – weights

- Two people with three repository will generate 3 links
- Unweighted by intensity in terms of commits

Aggregation - Variation at city level

- Key developer observable: city.
- We can aggregate up to city pairs.

- How many collaborations are there between London and San Francisco?
- How many dependencies made in London are imported by packages made in SF?

- Take into account that dependencies may be made in multiple cities. Single import – multiple cities get links

Example I: City-level aggregation of collaboration

Repository 1 developers: A in Vienna, B and C in Budapest.

- Vienna - Budapest: 1
- Budapest - Vienna: 2
- Budapest - Budapest: 1
- Vienna - Vienna: 0

Example II: City level aggregation of dependencies

Let repository 2 (D lives in Kiel) depend on repository 1 (A live in Vienna and B and C in Budapest.).

- Vienna - Budapest and Budapest - Vienna: 0
- Budapest - Kiel: 2
- Vienna - Kiel: 1

Note, that even though links are on level of repository, city links are based on the users.

Most packages are done in a few, few by many cities

- Most repositories are *located* in 1-3 cities.
- 1.6% done in dozen(s) of cities

Table 1: Cities per repository excluding single-developer repositories

Number of cities per repository	Share of Repositories
1	38.31%
2	38.20%
3 - 5	17.98%
6 - 10	3.89%
11-100	1.57%
100+	0.03%

Estimation metrics

Individual matching decision

Collaboration or dependency link between developer i and j,

$$\Pr(Y_{ij} = 1 | x_i, x_j, d_{ij}) = \Pi(\beta_1 x_i + \beta_2 x_j + \beta_3 d_{ij})$$

with

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

the logistic function

Assumption: Independence across links, add fixed effects

Aggregate to Poisson

In practice, distance only varies at the city level. Take origin city o and destination city d.

$$Y_{od} := \sum_{i \in o} \sum_{j \in d} Y_{ij}$$

$$\Pr(Y_{od} | x_o, x_d, d_{od}) = \text{Binomial}[N_o \times N_d, \Pi(\beta_1 x_i + \beta_2 x_j + \beta_3 d_{ij})]$$

Here $N_o \times N_d$ is the total number of *potential* links between cities o and d.

When Π is small,

$$\Pr(Y_{od} | x_o, x_d, d_{od}) \approx \text{Poisson}[N_o \times N_d \times \exp(\beta_1 x_i + \beta_2 x_j + \beta_3 d_{ij})]$$

Aggregate to Poisson (2)

We may also look at a subsample (like users not in the same GitHub organization)

$$Y_{od,\text{not org}} := \sum_{i \in o} \sum_{j \in d, j \notin \text{org}(i)} Y_{ij}$$

This changes the *exposure variable*,

$$\Pr(Y_{od,\text{not org}} | x_o, x_d, d_{od}) \approx \text{Poisson}[N_{od,\text{not org}} \times \exp(\beta_1 x_i + \beta_2 x_j + \beta_3 d_{ij})],$$

with $N_{od,\text{not org}}$ the number of user pairs in city o, d, *not sharing* an organization.

Important: $N_{od,\text{not org}}$ may be zero.

What is a Poisson regression?

First-order conditions for Maximum Likelihood:

$$\sum_o \sum_d x_i [Y_{od} - N_{od} \exp(\beta_1 x_i + \beta_2 x_j + \beta_3 d_{ij})] = 0$$
$$\sum_o \sum_d x_j [Y_{od} - N_{od} \exp(\beta_1 x_i + \beta_2 x_j + \beta_3 d_{ij})] = 0$$
$$\sum_o \sum_d d_{ij} [Y_{od} - N_{od} \exp(\beta_1 x_i + \beta_2 x_j + \beta_3 d_{ij})] = 0$$

- Level (not log) error terms are orthogonal to RHS variables.
- Exposure variable has fixed exponent of 1 ($\approx$ weighting).
- Standard errors computed from GMM, not ML. E.g., we allow for two-way city clustering.

Organizations and causality

Organizations and causality?

- Causal statement is: Organizations reduce spatial frictions (org $\rightarrow$ distance)
- Instead we see that link frequency within organizations tend to be less dependent on distance
- More dispersed developers create organization to co-ordinate (distance $\rightarrow$ org)
- Top developers gather in org and they don't care about distance confounding results. (topdev $\rightarrow$ org $+$ topdev $\rightarrow$ distance)

Organization and professionalism

- Another way to think about organizations is bringing some professionalism and "organization"
- Confirm when we look at top 10% of repos in terms of commits – distance friction also drops