

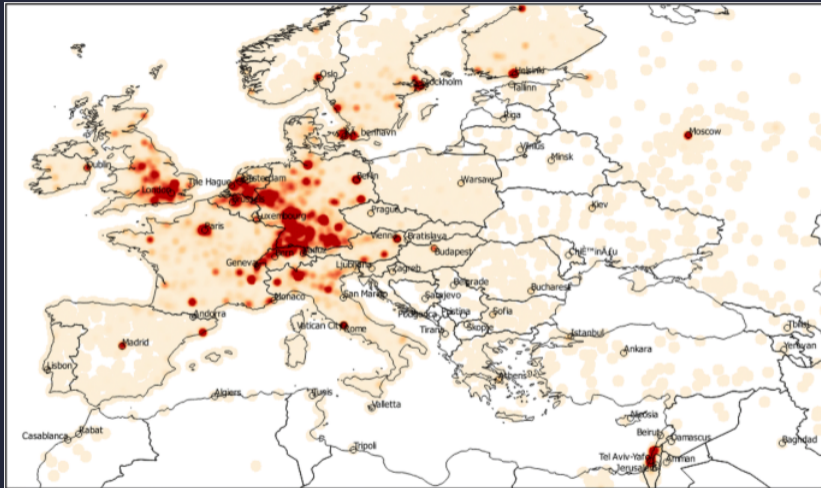
# Spatial data

DSIER [/di'zi:ɪər/] — Summer 2022

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# Patents' inventors location



Stek (2020)

# Patterns in Spatial data

## Why are inventors concentrated in certain locations?

### 1. common influences

- quality of education, infrastructures, etc.
- economic activity, jobs, etc.

### 2. spillover effects

- social interactions
- information sharing
- skill hubs

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- information sharing
- skill hubs

# Analysis of Spatial data

- Can you identify the two effects?
- Idea: Estimate the following model via OLS

$$y_{ig} = \gamma x_{ig} + \beta m_y(y_g) + \delta m_x(x_{ig}) + \epsilon_{ig} \quad (1)$$

- $y_{ig}$  is the number of patents of inventor  $i$  geolocalised in area  $g$
- $x_{ig}$  are individual characteristics (age)
- $m_y, m_x$  are aggregations of variables that are spatially connected with location  $g$   
→ e.g. avg. age and avg. number of patents in the same location

## Reflection Problem

The average outcome for the group is an aggregation of outcomes or behaviours over other group members, i.e. aggregation of individual characteristics over other group members

→ Multicollinearity

# Roadmap

1. Terminology and concepts
  - terminology with Spatial Data
  - simple indexes of spatial concentration
2. Non-randomness in spatial data
3. Spatial Models
4. Identification of Spatial Models
5. Application:
  - Dreher et al. 2019 on China Foreign Assistance

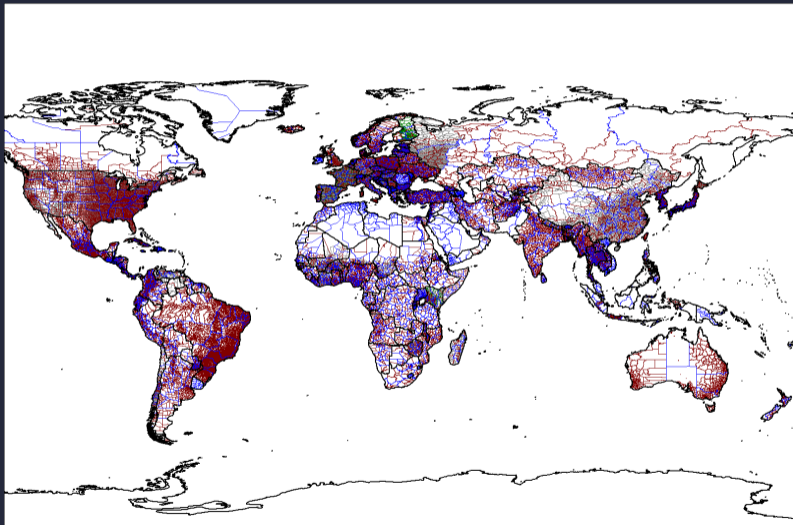


# TERMINOLOGY AND CONCEPTS

## Content of Spatial data

- position data in 2D (or 3D) (location of inventors)
  - sometimes entities: polygons
- attribute data (number of patents)
- metadata related to the position data (characteristics of location)

## Units of geographical space



## Simple indicators of concentration

How to measure concentration of patents across regions in a country?

- Krugman specialization/concentration index
- Spatial Gini Index

## Simple indicators of concentration

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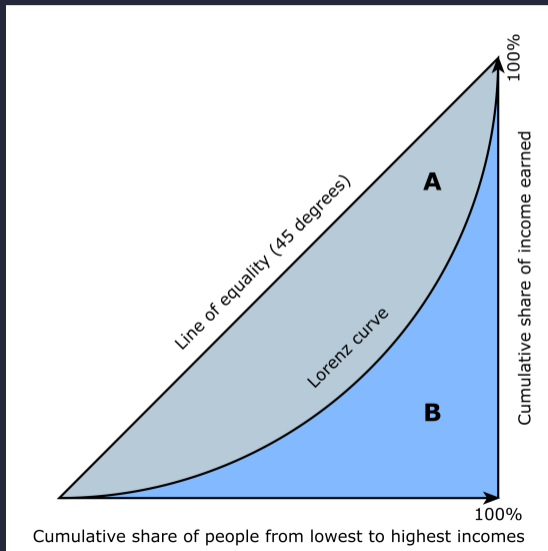
- Krugman specialization/concentration index

$$Conc = \sum_{g=1}^n |s_g - s| \quad (2)$$

where  $s_g$  is the number of patents per capita in region  $g$  with  $g=\{1, \dots, n\}$ , while  $s$  is the number per capita in the whole economy

# Gini Index

Rank people by income, instead of regions by number of patents



## Gini Index

It's equivalent to the **relative mean absolute difference**

$$G = \frac{\sum_{g=1}^n \sum_{j=1}^n |x_g - x_j|}{2 \sum_{g=1}^n \sum_{j=1}^n x_j} = \frac{\sum_{g=1}^n \sum_{j=1}^n |x_g - x_j|}{2n \sum_{j=1}^n x_j} = \frac{\sum_{g=1}^n \sum_{j=1}^n |x_g - x_j|}{2n^2 \bar{x}} \quad (3)$$

where  $x_g$  is the number of patents in region  $g$ . The Gini is the mean absolute difference of all pairs of regions of the country divided by the average,  $\bar{x}$ , to normalize for scale.

## Spatial decomposition of the Gini coefficient

Rey and Smith (2013) decompose the numerator as follows

$$\sum_{g=1}^n \sum_{j=1}^n |x_g - x_j| = \underbrace{\sum_{g=1}^n \sum_{j=1}^n w_{gj} |x_g - x_j|}_a + \underbrace{\sum_{g=1}^n \sum_{j=1}^n (1 - w_{gj}) |x_g - x_j|}_b \quad (4)$$

where  $w_{gj}$  is binary spatial weights expressing the neighbor relationship between locations  $g$  and  $j$ .

- $a < b$  positive spatial autocorrelation
- $a > b$  negative spatial autocorrelation



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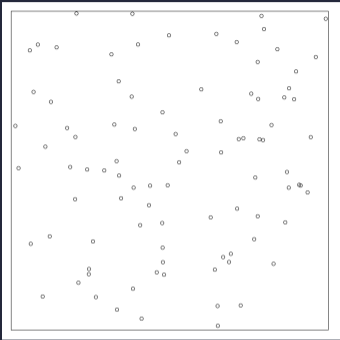
# Computing Spatial Autocorrelation

The X,Y coordinates refer to the geometric centroids of the 325 Municipalities in Greece (Programme Kallikratis) in 2011.

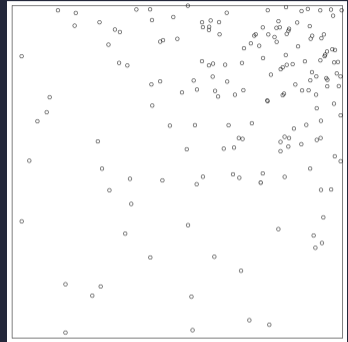
```
library(lctools)
data(GR.Municipalities)
names(GR.Municipalities@data)
 [1] "OBJECTID"   "X"          "Y"          "Name"       "CodeELSTAT" "PopM01"     "PopF01"     "PopTot01"   "UnemrM01"
[11] "UnemrT01"   "PrSect01"   "Foreig01"   "Income01"

myDF<-cbind(GR.Municipalities@data$Income01,GR.Municipalities@data$X, GR.Municipalities@data$Y)
myDF[!complete.cases(myDF),]
      [,1] [,2] [,3]
myDF.new<-na.omit(myDF)
bw<-12 # with 12 neighbours
wt<-'Binary' # each neighbour is weighted with the same weight
spGini(myDF.new[,2:3],bw,myDF.new[,1],wt)
      x
-----
Gini      0.14550
gwGini     0.00342 # this is a of the slide before (the inequality among nearest (geographically) neighbours)
nsGini     0.14208 # this is b (the inequality among furthest (geographically) neighbours)
gwGini.frac 0.02351
nsGini.frac 0.97649
```

# NON-RANDOMNESS IN SPATIAL DATA



Complete Random Allocation in 2D



Incomplete Random Allocation in 2D

# Point Process

Poisson process:

- $n$  points (denoted  $x_1, x_2, \dots, x_n$ )
- randomly spatially distributed in a region  $W$ 
  - each point  $x_i$  are selected from a random uniform distributed over  $W$
  - coordinates of each point location is independent
- $n$  is randomly generated from a Poisson distribution with intensity (EV)  $\lambda$

$$\Pr(X=k) = \frac{\lambda^k e^{-\lambda}}{k!} \quad (5)$$

The expected number of points to fall in a window with area  $|W|$  is  $\lambda|W|$

# Example of Point Processes

Generate a point pattern realization of the Poisson process

1. Homogenous (CRS): with  $\lambda=100$  points/unit area in a 2D window with domain  $x, y \in [0, 1]$

```
library(spatstat)
pois.pp <- rpoispp(lambda = 100, win = owin(c(0,1), c(0,1)))
plot(pois.pp)
```

2. Inhomogenous: with  $\lambda=f(x,y)$  points/unit area in a 2D window with domain  $x, y \in [0, 1]$

```
lambda.u <- function(x,y){1000 * x^2 * y^2 + 50}
pois.inh.pp <- rpoispp(lambda = lambda.u, win = owin(c(0,1), c(0,1)))
plot(pois.inh.pp)
```

## Relevance in Economics Literature

- Traditionally, indexes such as Gini, Krugman concentration are compared over time (e.g. Imbs and Wacziarg (2003))
- Detecting non-randomness is often non evident:
  - Ellison and Gleaser (1997): adjust index of spatial concentration for industrial concentration
  - See Combes and Overman (2004) for a discussion

# The economics of spatial Non-randomness

1. random allocation, characteristics of location varies
  - farmers randomly allocated, but their crops depends on soil etc. (Holmes and Lee, 2012)
2. non-random allocation, location characteristics no causal effect on outcomes
  - R&D in Silicon Valley (Ellison and Glaeser, 1997)
3. random allocation, interactions matters
  - college dormitory allocation and peer effect in the choice of majors (Sacerdote, 2001)
4. non-random allocation, interactions matters
  - childhood neighborhood (Gibbons, 2013)



# SPATIAL MODELS

## Linear Spatial Model

$$y_{ig} = \beta m_y(y_g) + \delta m_x(x_{ig}) + \theta m_z(z_{ig}) + \sigma m_v(v_{ig}) + \epsilon_{ig} \quad (6)$$

where

- $y_{ig}$  is the outcome of obs.  $i$  geolocalised in area  $g$
- $x_{ig}$  are individual characteristics
- $z_{ig}$  are characteristics of other entities or object other than  $i$
- $v_{ig}$  are unobservable characteristics
- $m(.)$  are aggregations of variables that are spatially connected with location  $g$ .
  - passive (externalities) vs deliberate (interactions)
  - pure technological externality or pecuniary externality

## Specifying the interconnections

Are typically LC of the observations in neighbouring locations with group weights

$$m_x(x, s_i) = \sum_{j=1}^M g_{ij}(s_i, s_j)x_j = G_{xi}x \quad (7)$$

where  $G_{xi}$  is a  $1 \times M$  row vector of the set of weights relating to location  $s_i$ , and  $x$  is an  $M \times 1$  column vector of  $x$  for locations  $s_1, s_2, \dots, s_M$ .

Matrix notation is more convenient for all observations  $i$ , where  $G$  is an  $N \times M$  matrix, so

$$m_x(x, s) = G_x x \quad (8)$$

and similarly for  $z$ ,  $y$ , and  $v$ .

## Specifying the interconnections

Which type of neighborhood is represented in the following interaction structure?

$$G = \begin{bmatrix} & 1 & 2 & 3 & 4 & 5 & 6 & 7 \\ 1 & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 & 0 & 0 & 0 \\ 2 & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 & 0 & 0 & 0 \\ 3 & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 & 0 & 0 & 0 \\ 4 & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ 5 & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ 6 & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ 7 & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \end{bmatrix}, \quad GG = \begin{bmatrix} & 1 & 2 & 3 & 4 & 5 & 6 & 7 \\ 1 & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 & 0 & 0 & 0 \\ 2 & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 & 0 & 0 & 0 \\ 3 & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 & 0 & 0 & 0 \\ 4 & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ 5 & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ 6 & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ 7 & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \end{bmatrix}. \quad (3.7)$$

## Type of spatial models

If  $N=M$  we can rewrite (5) using the interconnection matrix

$$y = X\gamma + G_y y\beta + G_x X\delta + G_z Z\theta + G_v V\sigma + \epsilon \quad (9)$$

Spatial Econometrics literature usually treat  $G_y = G_x = G_z$  (Spatial Lags)

Restrictions on this model

- Spatial Autoregressive model:  $\delta = \theta = \sigma = 0$
- Spatially Lagged model:  $\beta = \sigma = 0$
- Spatial Durbin Model:  $\sigma = 0$
- Spatial Error Model:  $\beta = \theta = 0$

## Identification in spatial models

- reflection problem
- correlated unobservables or common shocks
- sorting - presence of OVs correlated with location decision

## The reflection problem

Assume  $G = G_y = G_x = G_z$  and  $u = GV\sigma + \epsilon$  and rewrite (8)

$$y = X\gamma + Gy\beta + GX\delta + GZ\theta + u$$

$$Gy = GX \frac{(\gamma + \delta)}{(1 - \beta)} + GZ\theta + u$$

$$y = X\tilde{\gamma} + GX\tilde{\delta} + GZ\tilde{\theta} + \tilde{u}$$

with  $\tilde{\gamma} = \frac{\gamma}{(1-\beta)}$ ,  $\tilde{\delta} = \frac{\gamma\beta + \delta}{(1-\beta)}$  and  $\tilde{\theta} = \frac{\theta}{(1-\beta)}$ .

Manski (1993) "reflection problem":  $\beta$ ,  $\delta$  and  $\theta$  cannot be separately identified!

## Solutions to the reflection problem

- Use of non-linear functional forms
  - Brock and Durlauf 2001 use binary outcome and estimate the probability of smoking
- imposing exclusion restrictions
  - $\beta = 0$  no endogenous effects
  - assume away GX, no contextual effects (Gaviria and Raphael, 2001)
- use incomplete interactions s.t.  $GG \neq G$ 
  - non linearities in group membership: Calvo-Armengol et al. 2009, Liu and Lee 2010



## Spatially Correlated Shocks

Identification is a problem whenever  $u = G_v \sigma + \epsilon$  is correlated with  $x$  or  $z$

1. group membership is exogenous and correlation is due to OV
  - unobserved region characteristics that encourage inventors to patent (as human capital externalities in Moretti 2004)
2. group membership is endogenous and correlation is due to sorting
  - more innovative types move into areas with higher returns to innovation

## Solution to Spatially Correlated Shocks: Spatial Differencing

Consists in transforming variables by subtracting spatial means (Holmes, 1998)

In our setting it means knowing  $G_v$  and then multiply by a transformation matrix  $[I - G_v]$  to give:

$$y - G_v y = (X - G_v X)\gamma + (G_v - G_v G_x)X\delta + (G_z - G_v G_z)Z\theta + \zeta$$

If  $\text{plim}(G_v - G_v G_v)v = 0$  then OLS is consistent

When is it possible? When  $G_v G_v = G_v$ , block structure as before

APPLICATION



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Contents lists available at ScienceDirect

## Journal of Development Economics

journal homepage: [www.elsevier.com/locate/devec](http://www.elsevier.com/locate/devec)

## African leaders and the geography of China's foreign assistance

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## ARTICLE INFO

## JEL classifications:

D73

F35

P33

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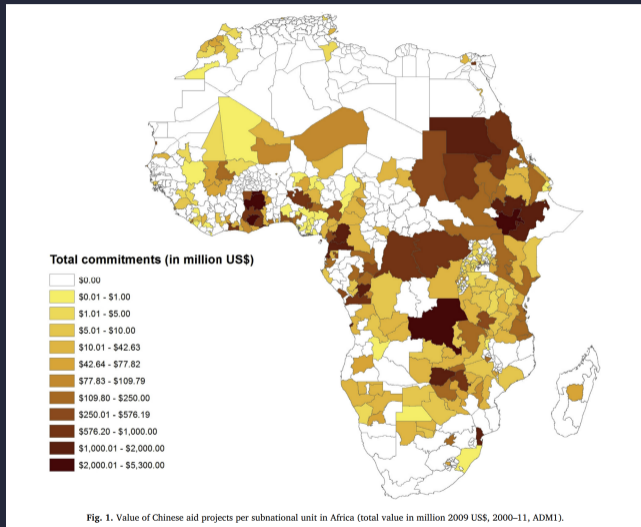
## Keywords:

foreign aid  
favoritism  
political capture

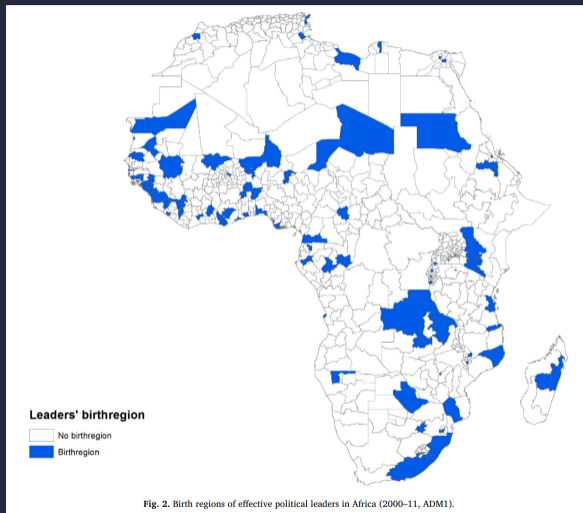
## ABSTRACT

We investigate whether foreign aid from China is prone to political capture in aid-receiving countries. Specifically, we examine whether more Chinese aid is allocated to the birth regions of political leaders, controlling for indicators of need and various fixed effects. We collect data on 117 African leaders' birthplaces and geocode 1650 Chinese development projects across 2969 physical locations in Africa from 2000 to 2012. Our econometric results show that political leaders' birth regions receive substantially larger financial flows from China in the years when they hold power compared to what the same region receives at other times. We find evidence that these biases are a consequence of electoral competition: Chinese aid disproportionately benefits politically privileged regions in country-years when incumbents face upcoming elections and when electoral competitiveness is high. We observe no such pattern of favoritism in the spatial distribution of World Bank development projects.

# Map of Chinese Aid Value



## Map of Leaders' birthplaces



## Empirical strategy

Do current political leaders' birthplaces matter for the allocation of Chinese aid?

$$Aid_{ict} = \alpha + \gamma Birthregion_{ict} + \epsilon_{ict}$$

where  $Birthregion_{ict}$  is equal to 1 if the political leader of country  $c$  in year  $t$  was born in administrative region  $i$ , and zero otherwise.

Problems?

They apply Spatial differencing:

$$Aid_{ict} = \alpha_{ct} + \delta_{ic} + \sum_j \beta_j X_{ic}^j + \gamma Birthregion_{ict} + \epsilon_{ict}$$

**Table 2**

Birth regions and China's aid I, ADM1, 2000–11.

|                          | (1)                 | (2)                 | (3)                 | (4)                 | (5)                | (6)               | (7)                | (8)                 |
|--------------------------|---------------------|---------------------|---------------------|---------------------|--------------------|-------------------|--------------------|---------------------|
|                          | Total OLS           | Total PPML          | ODA OLS             | ODA PPML            | Total OLS          | Total PPML        | ODA OLS            | ODA PPML            |
| Birthregion              | 0.688**<br>(0.324)  | 0.969***<br>(0.359) | 0.283<br>(0.209)    | 0.921<br>(0.564)    | 1.082**<br>(0.423) | 0.267*<br>(0.142) | 0.569**<br>(0.252) | 2.257***<br>(0.328) |
| Light2000 (in logs)      | 0.293**<br>(0.119)  | 0.218<br>(0.158)    | 0.242*<br>(0.125)   | -0.117<br>(0.444)   |                    |                   |                    |                     |
| Population2000 (in logs) | 0.087<br>(0.094)    | 0.389*<br>(0.227)   | 0.014<br>(0.089)    | 0.367*<br>(0.210)   |                    |                   |                    |                     |
| Capitalregion            | 4.164***<br>(0.544) | 1.558***<br>(0.431) | 2.837***<br>(0.459) | 2.988***<br>(1.023) |                    |                   |                    |                     |
| Mines (in logs)          | 0.117*<br>(0.067)   | 0.186*<br>(0.106)   | 0.003<br>(0.041)    | 0.224<br>(0.179)    |                    |                   |                    |                     |
| Oilgas                   | 0.070<br>(0.149)    | 0.326<br>(0.438)    | 0.077<br>(0.133)    | 0.036<br>(0.807)    |                    |                   |                    |                     |
| Area (in logs)           | 0.234**<br>(0.091)  | 0.367<br>(0.233)    | 0.183**<br>(0.080)  | -0.420<br>(0.497)   |                    |                   |                    |                     |
| Ports                    | -0.068<br>(0.193)   | -0.256<br>(0.684)   | -0.155<br>(0.150)   | -1.797*<br>(1.044)  |                    |                   |                    |                     |
| Roaddensity              | 1.145<br>(1.198)    | 1.406<br>(2.166)    | 1.181<br>(1.080)    | 4.137*<br>(2.360)   |                    |                   |                    |                     |
| Country-year FE          | Yes                 | Yes                 | Yes                 | Yes                 | Yes                | Yes               | Yes                | Yes                 |
| ADM1 FE                  | No                  | No                  | No                  | No                  | Yes                | Yes               | Yes                | Yes                 |
| R-squared                | 0.40                |                     | 0.35                |                     | 0.30               |                   | 0.28               |                     |
| Observations             | 8327                | 8327                | 8375                | 8375                | 8327               | 8327              | 8375               | 8375                |
| Regions                  | 709                 | 709                 | 709                 | 709                 | 709                | 709               | 709                | 709                 |

Notes: The dependent variable is Chinese total flows (in logs) in columns 1 and 5, Chinese total flows (in levels) in columns 2 and 6, Chinese ODA-like flows (in logs) in columns 3 and 7, and Chinese ODA-like flows (in levels) in columns 4 and 8. Standard errors (in parentheses) clustered at the country level. \*\*\* (\*\*, \*): significant at the 1% (5%, 10%) level.



# Spatial data

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