It never rains but it pours:

Austerity and mortality rate in peripheral areas

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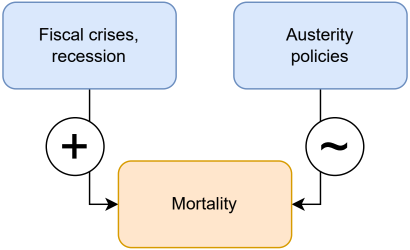
Rationale



Empirically, the studies on the effects of austerity policies on health, at least as represented by general measures like general mortality, are not conclusive. When austerity policies have been implemented in connection with fiscal crises due to recessions, most studies are unable to **disentangle** the effects of austerity from the one related to recessions, some of which can be positive

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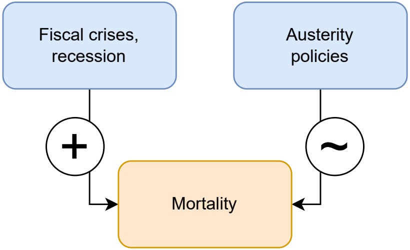

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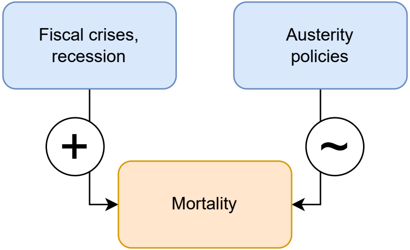

The challenge is due to the **overlapping effects** of recession (with mortality reduction effects) and austerity policies.

Rationale

Effects of austerity polices on:

- general mortality rate (Golinelli et al., 2017; Depalo, 2019; Arcà et al., 2020; Borra and Pons-Pons, 2020)
- mortality rates of specific population groups (Bordignon et al., 2020; Cirulli and Marini, 2023)
- avoidable mortality (*e.g.*, Arcà et al., 2020; Cirulli and Marini, 2023)
- mental health and consequences (De Vogli et al., 2013; Franklin et al., 2017)

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Aim of the paper

Assess if the austerity policies on health in Italy (Recovery Plans):

1. had an impact on the **health outcome** (i.e. mortality of the population) at **municipality level**
2. since annual mortality may mask seasonality phenomena, we use **monthly mortality** data as health outcomes at municipality level within the period from **1 January 2003 to 1 December 2018**
3. whether this impact has been different for different communities local (i.e. municipality), considering their **geographical distance** from hospitals (spatial heterogeneity)

Counterfactual approach

Comparing mortality changes at the municipal level in treated and untreated regions, before and after the implementation of RPs by geographical typology of municipality in terms of relative distance from hospitals.

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Empirical strategy

Two-way fixed effect specification

The standard DID setting is equivalent to a two-way fixed effects specification using time and unit as fixed effects; using a simple specification it can be defined as:

$$Y_{it} = \gamma_0 + \gamma_1 DID_{it} + \boldsymbol{\gamma_2 X_{it}} + \lambda_t + \lambda_i + \epsilon_{it} \quad (1)$$

where i is the i^{th} municipality, t represents the month of observation of the variable, within the period from 1 January 2003 to 1 December 2018, $\boldsymbol{X}$ is a matrix of control variables, λ_t and λ_i the fixed effects and, finally, the variable DID is an indicator variable equal to 1 if a municipality belongs to the Region under the RP during their RP period and 0 otherwise.

Two-way fixed effect specification

Estimating γ_1 require finding the value of $\hat{\gamma}_{1FE}$ that solves the following equation:

$$\hat{\gamma}_{1FE} = argmin \sum_{i=1}^{N} \sum_{t=1}^{T} \{(Y_{it} - \overline{Y}_i - \overline{Y}_t - \overline{Y}) - \hat{\gamma}_{1FE}(DID_{it} - \overline{DID}_i - \overline{DID}_t - \overline{DID})\}^2 \tag{2}$$

⇒ Is this specification correct for Italian setting?

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Italian recovery plans - a staggered setting

Overview of signature, entry and exit from RP by Region

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Abruzzo	6-Mar-2007	DGR n. 224 - March 13, 2007	-
Liguria	6-Mar-2007	DGR n. 243 - March 9, 2007	10-Apr-2010
Campania	13-Mar-2007	DGR n. 460 - March 20, 2007	-
Molise	27-Mar-2007	DGR n. 362 - March 30, 2007	-
Sicilia	31-Jul-2007	DGR n. 312 - August 1, 2007	-
Sardegna	31-Jul-2007	DGR n. 30/33 - August 2, 2007	31-Dic-2010
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Staggered DiD setting and bias sources

Potential bias sources for standard DiD approach:

1. Staggered entry into treatment by region
2. Staggered exit from the treatment by region
3. Endogeneity of the treatment
4. Spatially heterogeneous policy impact

Staggered DiD setting and bias sources

Potential bias sources:

1. Staggered entry into treatment by region

Recent literature emphasizes that two-way fixed effects models are typically biased when units are treated at different points in time = staggered DiD (Imai and Kim, 2019, Athey and Imbens, 2022, Goodman-Bacon, 2021, Callaway and Sant'Anna, 2021)

Imai et al. [2021] propose a **multiperiod DiD** methodology that addresses these issues to consistently estimate the ATT by matching on units with the same treatment history. This method connects two-way fixed effects models to matching methods, relaxing linearity assumptions.

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Staggered DiD setting and bias sources

Potential bias sources:

2. Staggered exit from the treatment by region

Imai et al. [2021] methodology (differently *e.g.* from Callaway and Sant'Anna, 2021 approach) also handles treatment exit at a generic time for each individual unit (even re-treatment).

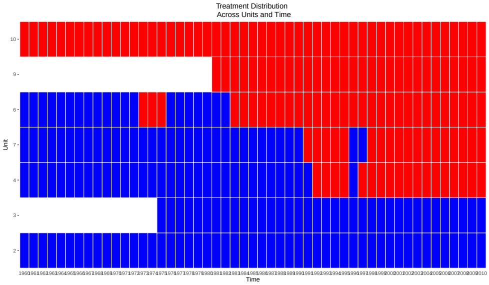


Figure 1: An example

Staggered DiD setting and bias sources

Potential bias sources:

3. Endogeneity of the treatment

Treatment is exogenous for the individual municipality:

- The municipality does not choose to join or not to join the RP, it is the Region that has to join at the request of the Ministry of Health
- Criteria for joining the RP are purely due to the Regional financial situation, not the quality of hospital care

Staggered DiD setting and bias sources

The approach proposed by Imai et al. [2021] can be illustrated in two main steps: in the first one, a subset of potential control observations using the treatment history at time t is extracted from the sample (we set 45 months as the pre-treatment lag), while in the second one, the initial control group is further refined in terms of outcome and a set of covariates, using the propensity score procedure. This approach provides more weight (W) to observations that have a similar set of comparisons in order to construct an ideal synthetic control, and less weight to those that are more different. Equation (2) can then be rewritten as:

$$\hat{\gamma}_{1FE} = argmin \sum_{i=1}^{N} \sum_{t=1}^{T} W_{it} \{ (Y_{it} - \overline{Y}_i^* - \overline{Y}_t^* - \overline{Y}^*) - \hat{\gamma}_{1FE} (DID_{it} - \overline{DID}_i^* - \overline{DID}_t^* - \overline{DID}^*) \}^2 \tag{3}$$

where W_{it} refers to weights and the asterisk indicates weighted averages using W_{it}.

Staggered DiD setting and bias sources

Potential bias sources:

4. Spatially heterogeneous policy impact

We expect the financial plan to have an impact on reduced healthcare provision with the closure of some hospitals and a decrease in beds, longer waiting lists, lower quality of treatment

But this impact occurs heterogeneously across the territory
$\Rightarrow$ **Our hypothesis to tested:** the further away the municipality is from supply location (hospital) the greater this impact will be

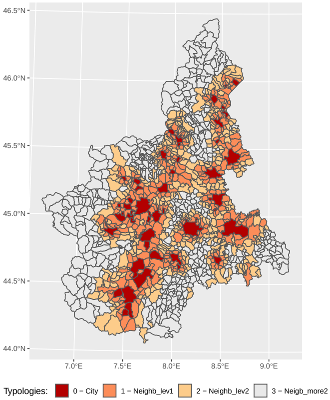
Geography - discrete spatial heterogeneity

Spatial characterisation of municipalities:

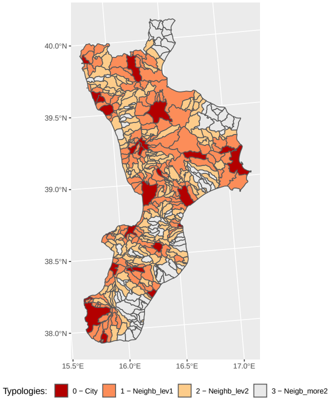
- "0 - Same city": the municipality hosts one or more hospitals;
- "1 - Neighb. level 1": the municipality does not host any hospital, but it is contiguous with a municipality that does;
- "2 - Neighb. level 2": the municipality does not host any hospital, but it is contiguous with a level 1 municipality neighbour;
- "3 - Neighb. more than level 2": the municipality does not host any hospital, but it is contiguous with a level 2 municipality neighbour.

$\Rightarrow$ The neighbourhood has to be defined

Geography - discrete spatial heterogeneity



(a) Region Piedmont



(b) Region Calabria

Figure 2: Municipalities by typology

▸ Spatial robustness

Final estimated model

Finally, since our specific research interest is to test the spatial stationarity of the γ_1 coefficients across the different municipalities, we will use a modified version of equation (3) to take account of our classification of municipalities above. Equation (3) thus becomes:

$$\hat{\gamma}_{1jFE} = argmin \sum_{i=1}^{N_j} \sum_{t=1}^{T_j} W_{ijt} \{ (Y_{ijt} - \overline{Y}^{*}_{ij} - \overline{Y}^{*}_{jt} - \overline{Y}^{*}_{j}) - \hat{\gamma}_{1jFE} (DID_{ijt} - \overline{DID}^{*}_{ij} - \overline{DID}^{*}_{jt} - \overline{DID}^{*}_{j}) \}^2 \tag{4}$$

where j (with j = 1,2,3,4) is the j^{th} typology of the i^{th} municipality in terms of distance from the nearest hospital.

After constructing the geographical and treatment variables, our matching rationale, from an empirical point of view, is to identify the closest untreated units, based on the propensity score, separately by neighbouring typology of municipalities.

DATA

Outcome variable: **Mortality rate** by gender and per month (2003 - 2018) at the municipality level (time series of 192 months $\times \sim$ 8,000 Municipalities $\Rightarrow \sim$ 1,500,000 rows)

Control variables: **Life expectancy at 65 years** and the **Age structure of the population** (65 years and over) collected by province and year;

Geographical classification: **Latitude and longitude** of the municipal centroid compared to the **location of the hospital**;

Treatment (DiD1): 1 = all the municipalities belonging to Regions under RP (first day of the following month) without exit; 0 otherwise.

DiD2 with exit.

Matching & pre-treatment tests

Treatment without exit

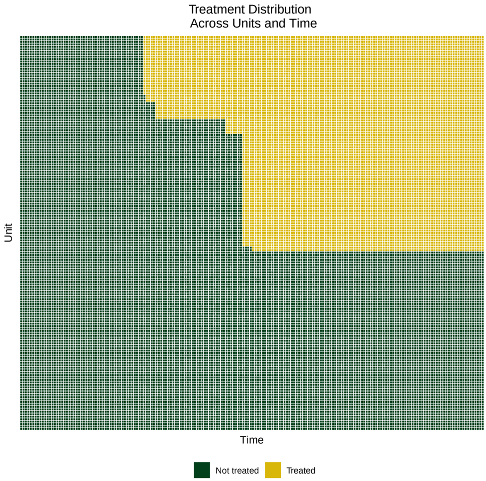


Figure 3: Without exit from treatment (DiD1), extract (10%) from group "3 - Neighb. more than level 2"

Treatment with exit

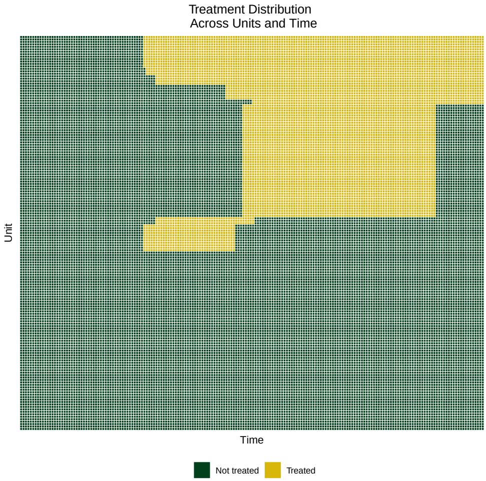


Figure 4: With exit from treatment (DiD2), extract (10%) from group "3 - Neighb. more than level 2"

Pre-treatment balance

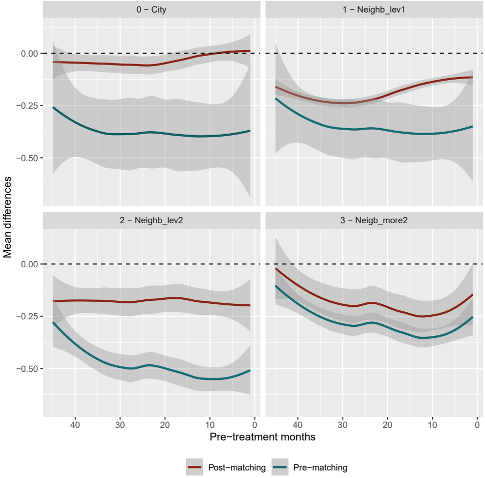


Figure 5: Balance (average difference of population) between pre and post matching by typology of municipality

Pre-treatment parallel trends

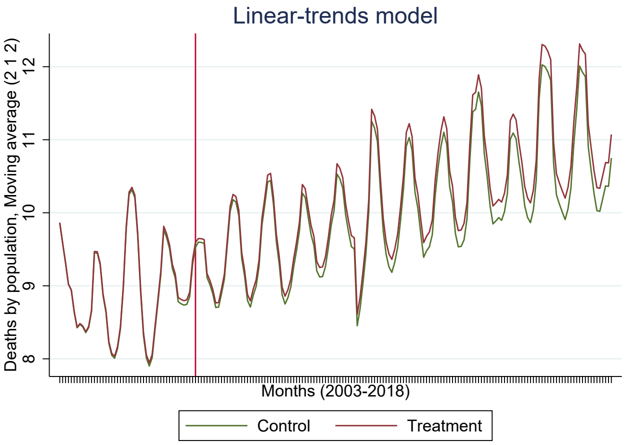


Figure 6: Graphical diagnostics for parallel trends

Main results

Estimated ATET

Estimated ATET by DiD

	Robust coeff.	Std. err.	t	P>t	[95% conf. interval]	
ATET (1 vs 0) DiD1	0.2653	0.0989	2.68	0.0090	0.0692	0.4614
ATET (1 vs 0) DiD2	0.1895	0.0759	2.50	0.0140	0.0386	0.3405

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Estimated ATET by reference group, estimation model, DiD and typology of municipality

Reference group	Estimation model	DiD	Typology of municipality	ATET	S.E.	t	p-value	[95% interval]	
Total	No Cov	DiD1	0	0.218	0.101	2.165	0.033	0.018	0.418
			1	0.337	0.104	3.237	0.002	0.130	0.543
			2	0.343	0.168	2.044	0.044	0.010	0.676
			3	0.717	0.277	2.593	0.012	0.165	1.269
		DiD2	0	0.262	0.094	2.791	0.006	0.075	0.448
			1	0.373	0.098	3.825	0.000	0.180	0.567
			2	0.476	0.158	3.010	0.003	0.162	0.789
			3	1.052	0.297	3.546	0.001	0.460	1.644
	Cov	DiD1	0	0.155	0.082	1.893	0.062	-0.008	0.318
			1	0.224	0.089	2.509	0.014	0.047	0.401
			2	0.173	0.153	1.131	0.261	-0.131	0.477
			3	0.622	0.284	2.190	0.032	0.055	1.189
		DiD2	0	0.193	0.076	2.526	0.013	0.041	0.345
			1	0.255	0.082	3.114	0.002	0.092	0.417
			2	0.291	0.146	1.993	0.049	0.001	0.580
			3	0.931	0.308	3.021	0.004	0.316	1.545

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Estimated ATET by typology of municipality

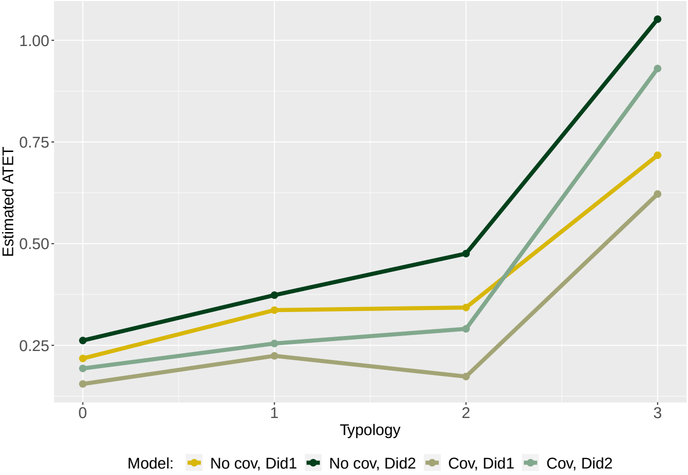

Figure 7: Estimated ATET by estimation model, DiD and typology of municipality, Reference group = Total

Estimated ATET by gender

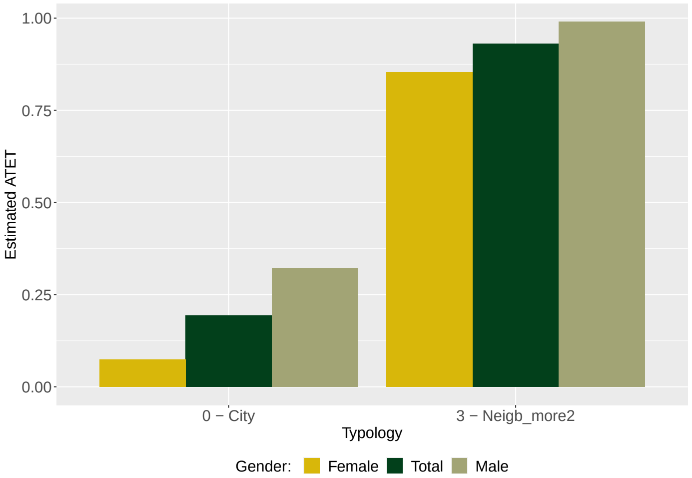

Figure 8: Estimated ATET by reference group and typology of municipality, estimation model = Cov, DiD = DiD2

Seasonality

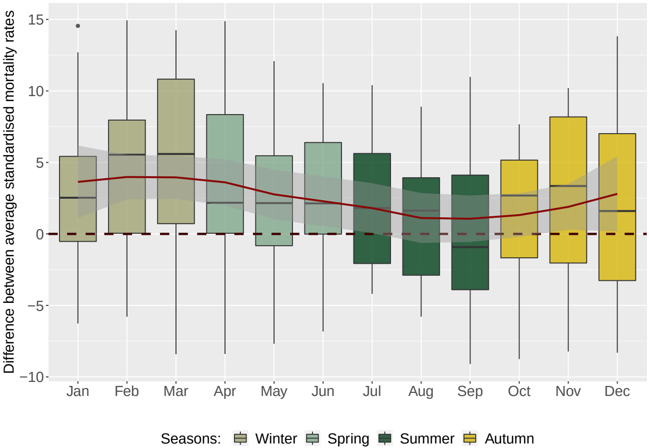

Figure 9: Seasonality of the differences between standardised average mortality rates (Treated - Untreated) by month, group "3 - Neighb. more than level", year 2007-2018

Final remarks

Main finding

By using **monthly** data on the dynamics of **municipal** mortality rates, we are able to gain two significant advantages:

1. the use of monthly data allows us both to detect whether the policy had an effect on seasonal mortality and to assess whether the policy had a greater impact on the population most vulnerable to seasonal diseases.
2. austerity policies involving cuts in healthcare services have a different impact at the local level, depending on the geographical distance from emergency services $\Rightarrow$ distance matters.

References I

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Robustness

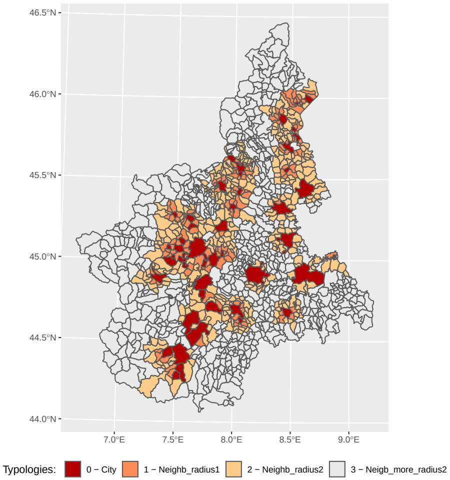

Figure 10: Municipalities by typology and radius, radius = 5 and 10 km, region Piedmont

Go back

Robustness

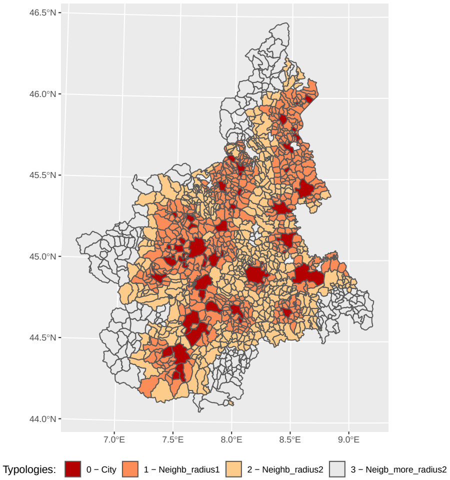

Figure 11: Municipalities by typology and radius, radius = 10 and 20 km, region Piedmont

Robustness

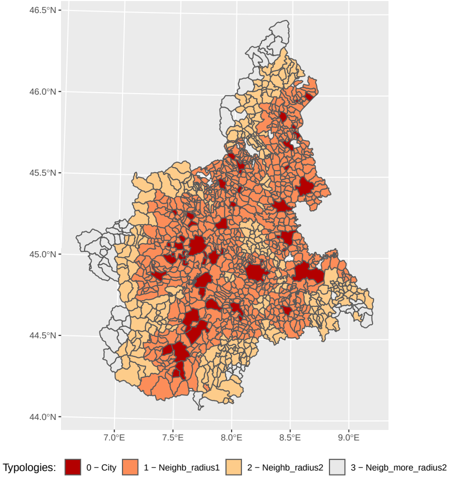

Figure 12: Municipalities by typology and radius, radius = 15 and 30 km, region Piedmont

ATET ROBUSTNESS

Table 1: Estimated ATET by typology of neighbourhoods between municipalities (contiguity and radius), DiD=DiD1, No control covariates

Typology	Neighbourhood criteria	ATET	S.E.	t	p-value	[95% interval]	
0 - City	Contiguity	0.218	0.101	2.165	0.033	0.018	0.418
	Radius 5-10 km	0.218	0.101	2.165	0.033	0.018	0.418
	Radius 10-20 km	0.218	0.101	2.165	0.033	0.018	0.418
	Radius 15-30 km	0.218	0.101	2.165	0.033	0.018	0.418
Level 1	Contiguity	0.337	0.104	3.237	0.002	0.130	0.543
	Radius 5-10 km	0.194	0.140	1.38	0.171	-0.085	0.474
	Radius 10-20 km	0.267	0.115	2.32	0.022	0.039	0.495
	Radius 15-30 km	0.359	0.114	3.14	0.002	0.133	0.587
Level 2	Contiguity	0.343	0.168	2.044	0.044	0.010	0.676
	Radius 5-10 km	0.299	0.143	2.09	0.040	0.015	0.586
	Radius 10-20 km	0.492	0.168	2.92	0.004	0.158	0.826
	Radius 15-30 km	0.355	0.261	1.36	0.178	-0.165	0.874
Level 3	Contiguity	0.717	0.277	2.593	0.012	0.165	1.269
	Radius 5-10	0.508	0.169	3.01	0.003	0.174	0.843
	Radius 10-20	0.575	0.415	1.39	0.171	-0.256	1.406
	Radius 15-30	2.910	0.914	3.18	0.005	0.998	4.823

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