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# SPATIAL DYNAMICS OF COMMUNITY DISASTER RESILIENCE IN RURAL AREAS. EVIDENCES FROM CENTRAL ITALY AFTER THE 1997 EARTHQUAKE

**Abstract.** Socio-natural disasters are a global issue but, being the intersecting result of an uncontrollable nature and a complex society, they cannot have a unique global solution. Similar hazards could indeed result in different (or none at all) disasters depending on the affected territorial and social context.

Italy presents itself as an interesting and peculiar context and case study. Due to its particular geographical characteristics, three out of four major seismic event of the last decades, affected the country rural areas, in particular around the Central Apennines.

Rural communities, inhabiting this area, are burdened by decades-old processes of ageing and depopulation but, by controlling and taking care of the territory, they are important strategic resources for all Italian society. After the last major socio-natural disaster a question has arisen: are rural communities of Central Italy sentenced to be completely abandoned?

Through the framework of Community Resilience, the study envisions a time-sensitive quantitative analysis functional to observe resilience's dynamics over different degrees of rurality in Central Italy. We adopted a quasi-experimental strategy, making use of the communities' internal population variation as a proxy for community resilience, and a suitable control group to isolate – and individuate – the effect of the Community Resilience triggered by the disaster.

Our results highlight a stabilising effect, where the affected communities depopulate with slower rates in comparison with the control group. Moreover, we observed that different degrees of rurality in the affected area are not directly correlated with better or worse performance in population variation.

**Keywords:** Rural community resilience, natural disaster, quasi-experimental methods, disaster resilience

## I. Introduction

Nowadays an increasing number of people around the world have been affected by disasters triggered by natural hazards (Guha-Sapir *et. al.* 2016). Natural phenomenon like tsunami, earthquakes, landslides, floods, volcanic eruptions, hurricanes or droughts occurs almost daily in different parts of the globe, but the occurrence of such events alone does not make a disaster. Natural events become disasters when they hit anthropised territories, affecting the communities living there; that is when a destructive force (nature) meets the built environment and its social and economic structure (society). Therefore, a more proper way to indicate such events would be 'socio-natural disasters' (Mela *et al.* 2017), rather than the more commonly used expression 'natural disasters'.
In the last two decades, especially since the publication of the Hyogo Framework for Action, the public attention on this topic has risen and much has already been done to reduce damage and improve the effectiveness of the recovery process caused by natural hazards with the complicity of society. Such actions and studies, intersecting – in a way – nature and society, falls under the wide umbrella of the concept of disaster resilience.
Socio-natural disasters are a global issue but, being the intersecting result of an uncontrollable nature and a complex society, they cannot have a unique global solution. Similar hazards could indeed result in different (or none at all) disasters depending on the affected territorial and social context. Studies on disaster resilience, as well as the policies to both prevent and recover from them, are then bound to the context of application.
Italy is a very interesting context and case study. The entire peninsula sits on the meeting point between the Eurasian Plate and the Adriatic Plate. As a result, the Apennine Mountains – crossing the country from North to South – contain many seismic faults, causing Italy to have an incredibly high amount of tectonic activity and seismic hazardous events (Valensise *et al.* 2017).
The '2016 Central Italy Earthquake' is the last large disastrous event occurred in Italy as the result of a specific natural event (a seismic swarm started in late summer 2016) intercepting a specific social context (rural communities of Central Italy). Despite the impact of this socio-natural disaster being still incalculable, it has at least raised the public level of attention on the topic of rural communities living in earthquake-prone areas, bringing out an important question: how can we avoid that these mostly rural

inhabited areas – already prone to depopulation and economic lagging – will be completely abandoned after the last disastrous event?
Since 2012, the Italian government has faced the general issue of depopulation of rural communities with the institution of the SNAI (National Strategy for Inner Areas) initiative enacted by the Italian Agency for Economic Development and Cohesion. According to the strategy, rural communities should find their own developing strategy (place-based policies) and the National Administration should guide them by providing know-how, organisation and the resources needed (Barca *et al.* 2012; Lucatelli 2014). All this because rural communities are incredibly important for a country like Italy, where more than 40% of its territory is mountainous. Rural communities, dispersed in the mountainous inner areas, are indeed strategic resources for all Italian society for instance by controlling and taking care of the territory.
A major disastrous event, like the 2016 Central Italy Earthquake, could be a point of no return for such communities in the depopulation process. In order to better understand the role played by such events on the depopulation process, this paper focuses on rural communities of Central Italy affected by earthquakes, exploring the relationship between different characteristics and degree of rurality, and the community ability to perform positively (to be resilient) after a disastrous event.
We aim at understanding if a socio-natural disaster can be an opportunity for the affected communities, by triggering the community ability for resilience and putting in motion changes affecting also the depopulation process. Focusing our study on different degrees of rurality, we want to observe the dynamics of population variation of rural communities affected by a socio-natural disaster to test if there is a causal relation or a threshold between rurality and positive trends and performances after the event.

The study envisions a longitudinal time-sensitive analysis – considering a period both before and after the earthquake – to observe the resilience dynamics in the specific context of Central Italy rural communities, making use of the communities' internal population variation as a proxy of resilience (Chamlee-Wright and Storr 2010; Aldrich 2013). The use of population variation as a proxy for resilience is not common, despite not being new, but it allows us to study the effects and dynamics of resilience accordingly with a context suffering from prolonged processes of depopulation. It will enable us to understand what happens when socio-natural disasters hit an area characterised by such cumulative processes.

The nuance of the study is given by both the quasi-experimental technique we employ and our context-bound framework. Indeed, we are thus able to indirectly isolate the effect of community resilience[1] using a control group and highlight what – in the conclusions – we call a double effect of space. First, we show how the earthquake resulted in a stabilising effect on population variation, where being a more or less rural community linearly correlate. However, such correlation does not persist when trying to explain better or worse performances in the years after the earthquake.

The paper is organised in four sections. Section one (*Introduction*) will introduce the research and present the theoretical framework while discussing the relevant literature. Section two (*Data and Methods*) presents the data utilised for the research and the methods and techniques used to analyse them. In the third section (*Presentation and discussion of results*) we present and discuss the main results making use of both maps and regression tables. Section four (*Conclusions*) presents our interpretation of such results for the Italian context and provides insights on possible policy implications and connected future researches.

## 2. THEORETICAL FRAMEWORK

Over the last two decades the concept of resilience, especially in the context of disaster studies, quickly became one of the main focus of academic studies and public policies to improve the response of society to adverse events. Interesting enough, the word 'resilience' is not a specific term of any field in social sciences. It was imported from physics during the 1970s where it describes the ability of a material to bend and then bounce back to its original equilibrium, rather than breaking after the stress is applied (Bodin and Wiman 2004; Zolli and Healy 2012; Wilson 2014; Martin e Sulley 2006). Over time, and across different fields, the concept of resilience has been framed – and defined – in many ways, according to the different subjects of study. The most prolific of these frames is probably the one of *regional resilience*, receiving most of its contributes from the fields of economic geography (Martin 2012; Carpenter 2015; Christopherson *et al.* 2010; Simmie and Martin 2010; Modica and Reggiani 2015) and disaster studies (Mayunga 2007; Cutter *et al.* 2008; Carpenter 2015). As argued in Faggian, Gemmiti, Jacquet and Santini (2018) most of these contributions focus on traditional economic indicators and fail in representing the

[1] We employ population variation as proxy for the effect of community resilience. Thanks to our experimental design we are able to isolate such effect from the general trend of population variation in Italy.

complexity of the social world. A very similar – and still very prolific – framework, proposed from sociological contributions, is the one of *community resilience*; this approach, largely used not only in sociological studies but also in studies on natural disasters (Gaillard 2007), focuses on capturing resilience along a series of sub-dimensions of the social structure (Faggian, Gemmiti, Jacquet and Santini 2018), highlighting the complexity of society and making it a key strength of the approach. Positioning ourselves inside the framework of community resilience, we adopt the definition given by Norris *et. al.* (2008) which has the advantage to be quite open and concise while highlighting, at the same time, all the important characteristics of the ability to be resilient.

Norris defines community resilience as a "Dynamic process composed by many adaptive capacities to response and change after adverse events" (Norris *et al.* 2008).

This definition has indeed many advantages. Other than being light, communicative and very adaptable to different fields, it has two important advantages from our perspective.

First, it defines resilience as a dynamic process – rather than an ability –, highlighting how it is not fixed in time but is sensible to the temporal dimension. Moreover, Norris' definition also has the benefit of stressing that community resilience is composed of many adaptive capacities, framing resilience as a complex concept without enclosing it into this or that field or dimension. Whit this definition Norris frames resilience as made of many adaptive capacities, all concurring to the same dynamic process. Expanding from the definition, we could say that the composition of resilience (the ability for resilience) is a complex concept but the resulting dynamic process (the effect of resilience) is not complex and can be singularly individuated.

Most sociological studies focus their attention on how this ability for resilience is composed (Gaillard 2007; Cutter *et. al.* 2008; Fisher and McKee 2017). This study does not involve directly the ability for resilience itself (how community resilience is composed), rather it focuses on studying and explaining the causal relationship between the effect of community resilience and the geographical and spatial distribution of rural communities. Indeed, while the composition of communities' resilience ability is complex, we are able – performing an ex-post longitudinal study – to indirectly isolate the effect of community resilience.

In particular, we will focus our attention on Italian rural communities, not by looking at the dichotomous differences between urban and rural communities, but instead by exploring the differences between different characteristics and degree of rurality.[2] Where the use of the dichotomy urban-rural highlights the common factors and dynamics of being either rural or urban, our framework focuses on the internal differences of rural areas as not being homogeneous defined (Cloke 1977).
Building on previous studies on community disaster resilience, it seems clear that the ability is composed differently for community living in rural areas compared to the ones living in urban environments (Cutter *et al.* 2016), producing different effects and performances between urban and rural communities. Despite the presence of a large number of works, a big problem – from our point of view – is that most major studies on disaster resilience are developed for urban contexts (Peacock *et al.* 1997; Vale and Campanella 2005; Chamlee-Wright and Storr 2009; Haas *et al.* 1977; McCreight 2010) and studies developed on and for rural communities represent only a residual category (Gaillard 2007; Solnit 2009; Wilson 2014; Sanders *et al.* 2015; Cutter *et al.* 2016).
The point here is that rural communities are very different from urban communities, under many levels. Either if you look at the social or economic structure of such communities, or at how relationships and social bonds are shaped, at their infrastructure or institution (Barca *et al.* 2012; Roberts *et al.* 2017; Faggian, Modica and Urso 2018); rural communities are inherently different. It is important then, even for policy implications, to study rural communities with a specific approach. An approach which holds as bedrock their specific characteristics and dynamics.

While exploring the relationship between different characteristics of rurality and the effect of community disaster resilience, our goal is to answer a question about *if* being more or less rural can have an impact on the community ability to perform positively (to be resilient) after a disastrous event. We focus our study on the communities affected by the 1997 Umbria and Marche earthquake, which allows us to perform an ex-post longitudinal study, considering a period of time both before and after the earthquake. This empirical strategy will allow us to focus on the effect of community resilience, triggered by the disastrous event and channeled over the reconstruction period.

2 We use the term 'degree of rurality' to frame our approach in opposition to the largely used dichotomy 'Urban vs Rural'. Indeed, rather than comparing urban and rural contexts, we focuse only on rural contexts and compare them among each other on different characteristics of rurality.

## 3. Data and methods

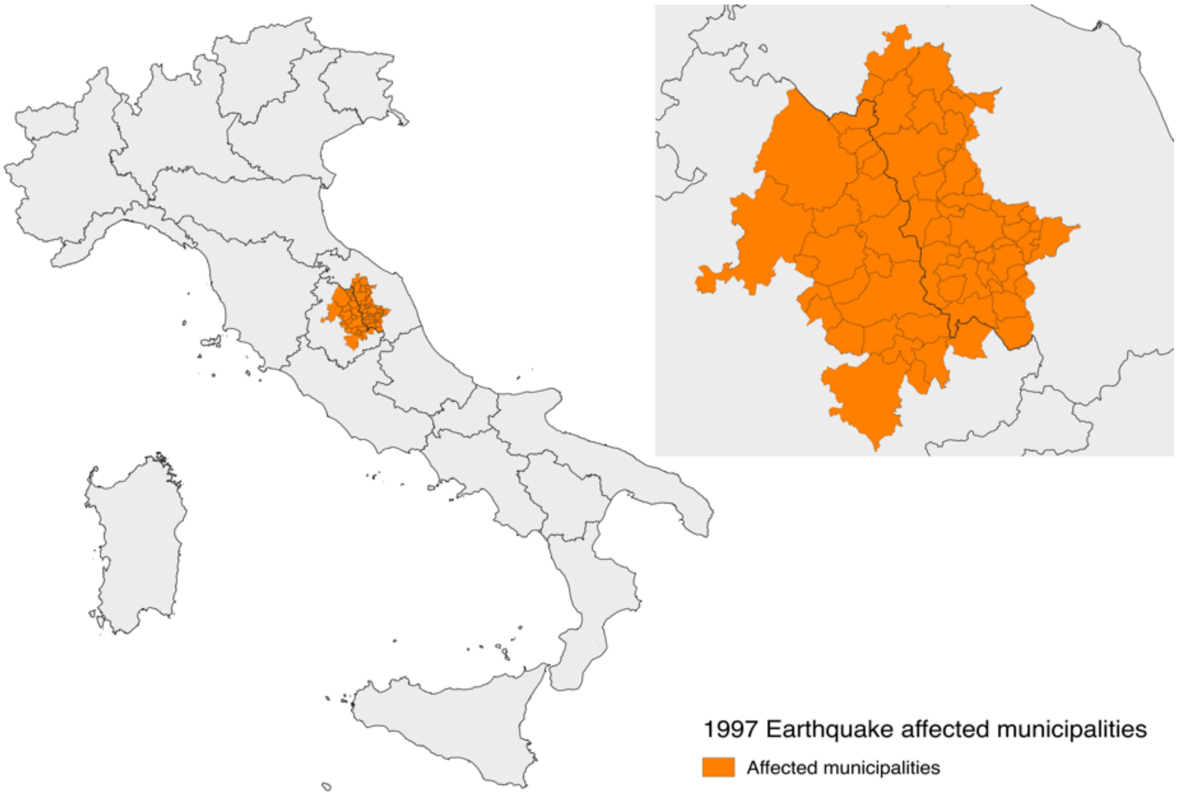
Our empirical strategy starts from the context of our interest, namely the resilience ability of rural communities living in Central Italy in response to a socio-natural disaster. Central Italy is not an administrative boundary *per se*. It rather indicates the rural and mostly mountainous area at the interception of the four regions of Marche, Lazio, Abruzzo and Umbria without any major city. This area holds all the peculiar traits of rural communities and it is located right over an active tectonic fault, where seismic events are quite common and sometimes extremely devastating (Valensise *et al.* 2017).

In the cluster of disaster resilience studies, such as in the near cluster of economic resilience, the holders of this ability are mostly identified as an aggregate entity varying on a scale going from the neighbourhood level, to the city, regional or even national level (e.g. Tatsuki and Hayashi 2000; Aldrich 2013; Kusumastuti *et. al.* 2014; Carnelli and Frigerio 2017; Wilson *et al.* 2018). Ideally, the concept of resilience – community resilience in our framework – could be applied at different levels of aggregation, depending on the subject of interest. Generally, such studies have the tendency to make use of the most disaggregate unit available, but this does not represent a rule as it should be the balancing result between the subject of interest, availability of data and unit of analysis, and aim of the research. This is why, an example among others, in theirs contribute on regional economic resilience Faggian, Gemmiti, Jacquet and Santini (2018) decided to employ the local labour system (LLS) level of analysis rather than the municipality one, despite the less disaggregated level of the LLS and the fact that data for this level of analysis are more time consuming and difficult to find.

Following this same logic, for our contribution in the study of community disaster resilience in the rural context of Central Italy, we decided to employ, as aggregate level of analysis, the administrative boundaries of municipalities. Indeed, administrative boundaries are particularly relevant in our context due to the fact that local administrations are quite involved in the reconstruction process after a socio-natural disaster. This is especially true in a context – like the Italian one – where the public sector is not only involved but leads and directs these processes. Moreover, this enable us to contextualise our study in the scientific and public discussion on depopulating rural communities, where – for both historical and administrative reasons – municipal boundaries are commonly used as unit of analysis (Lucatelli 2014).

The study is focused on rural communities of central Italy affected by the seismic events started in September-October 1997 and ended in March 1998. The affected area is administratively divided under the two Italian regions (NUTS 2) of Umbria and Marche and four provinces (NUTS 3), namely Ancona, Macerata, Perugia and Pesaro-Urbino. The area is here identified following the law[3] establishing it for a total of sixty-one municipalities. It is important to note that our final affected area will indeed be smaller, fifty-five municipalities. We excluded six municipalities from our analysis which, despite being listed inside the affected area, were only marginally affected by the earthquake and/or were big centres, over 25k inhabitants, with a radically different socio-economic structure that could have altered our results.

MAP 1 • 1997 EARTHQUAKE AFFECTED MUNICIPALITIES




3 Ord. 13.10.1997, n. 2694, G.U. n. 241, 15.10.1997. And Ord. 28.11.1997, n. 2719, G.U. n. 282, 03.12.1997.

As previously stated, this work represents an explorative study on the effects of disaster resilience ability for rural communities in Central Italy, by looking at population variation of the area before and after the earthquake of 1997. For this study, we are particularly interested at looking on the role of spatial and geographical characteristics of municipalities; particularly at looking if they have relevant effects on this ability and if these characteristics are able to identify successful paths in the short/medium-run recovery after an earthquake.
In order to carry on this analysis, we rely on a popular time-sensitive quasi-experimental technique known as 'Difference in Difference' (Bertrand *et al.* 2004; Lechner 2011). Indeed, this technique enables us – via the comparison of our affected municipalities with a control group over a period of time before and after the earthquake – to isolate the effect of a treatment. The treatment, in the context of this study, is the occurrence of an earthquake. Moreover, we are also interested in observing possible differences inside the treatment group, especially between the better and worse performing groups by repeating the analysis only for the one and the other and looking for patterns.

We are required to meet all the canonic assumption of an OLS model and to structure our database in panel form. In addition, DiD requires also a parallel trend assumption (Abadie 2005) between the treatment group and the control group for the period of time before the treatment. Considering our goals and the selected technique – alongside all the assumptions we need to meet – our empirical strategy could be represented in five steps:

1. Selection and construction of the variables.
2. Selection of a suitable control group.
3. Modelling the Difference in Difference analysis.
4. Identify better and worse performing groups of municipalities inside the treatment group.
5. Perform a comparative analysis on these groups.

The following paragraphs will account for steps 1, 2 and 4 in details. Steps 3 and 5 will be further described while discussing the results.

*3.1 Selection and construction of the variables*

For this study, we relied on freely available quantitative data provided by the Italian National Institute for Statistics, ISTAT. Our aggregate units of analysis are, indeed, the municipalities as the smallest administrative boundary identified in the 2001 Italian Census. Municipal borders are here used to identify communities. Indeed, the risk of not identifying entirely a community – or, on the other hand, collapsing more communities into one unit – is well counterbalanced by the fact that municipalities are important administrative units.

At municipal level we made use of many explanatory variables (*b* to *f*) to study the yearly variation of population (*a*):

a. *Population Variation*, calculated yearly. This is our dependent variable, used here as a proxy for the effect of resilience. We calculated the yearly share of variation, for a time period going from 1991 to 2011. Considering that the shock occurred between 1997 and 1998, we defined the years 1991-1996 as the before treatment period and 1999-2011 as the after-treatment ones. Yearly population variation is calculated as the percentage difference in population between one year and the following, using the reconstructed resident population for inter-census years (ISTAT).

b. *Population size*. We divided municipalities into 7 categories based on total residents. The intervals are intentionally disproportionate towards the low population levels since this is our focus. The seven categories are: municipalities under 500 inhabitants, between 501 and 1000, between 1001 and 2500, between 2501 and 5000, between 5001 and 10000, between 10001 and 25000, and municipalities with 25001 or more inhabitants. Municipalities are subdivided into these categories using data on resident population for the year 1996, hence in the before treatment period (data: ISTAT, reconstructed resident population for inter-census years).

c. *Mountainous degree*. Our indicator is based on a more precise distribution of municipalities for altitude zones. Again, the intervals were designed to better depict the specificities of our study area, hence median altitude on the sea level (data from ISTAT) was used to assign the municipalities. The categories are: 0-299 m a.s.l.; 300-599 m a.s.l.; 600-899 m a.s.l.; 900-1199 m a.s.l., 1200-1499 m a.s.l., 1500-1999 m a.s.l., 2000-2499 m a.s.l. and above 2500 m a.s.l. . We care to note that no municipality in our affected area falls in the last three categories.

d. Concentration of population. In order to account for the spatial distribution of population inside municipal territory, we designed this variable accounting for the share of population living in cities, villages and hamlets. The variable is constructed using census data, from the 1991 Italian census, and considers four categories: 'Non concentrated'; 'Concentrated single center' if more than 70% of the population lives in a single center; 'Concentrated two/three centres' if more than 70% of the population lives in two or three centres.
e. *Distance from the nearest pole*. The last spatial characteristic that we were able to consider, is the distance from the nearest pole. The attraction factor of poles as centres for services and labour market plays a central role as a pulling factor for migrations (Mabogunje 1970; Clark 1992). The distance here is calculated for every municipality as the linear distance from its centroid to the ones of the nearest pole. Poles, here, are identified as municipalities with more than 25,000 inhabitants (our elaboration on ISTAT data).
f. *Provincial fixed effects*. In order to control for other provincial specific factors, especially due to possible provincial policy or administrative decision, we included a dummy at NUTS3 level for which province they belong to.

It is important to note that municipalities administrative boundaries are identified as for the 2001 census, hence all administrative variation occurred before and after (specifically in the period of time 1991-2001 and 2001-2011) are traced back to the units identified for the 2001 census. All data have been then corrected – when needed – accordingly.

### *3.2 Selection of a suitable control group*

The second step in our empirical strategy is to develop a suitable control group for our analysis. This is a core step for our research since the control group should give us the baseline on which calculate the treatment effect on affected municipalities. The adequate selection of control group is fundamental. Indeed, selecting a viable control group will enable us to indirectly isolate the effect of community resilience triggered by the earthquake.

We had two precise needs guiding the construction of the control group: being similar and comparable to our treatment group especially from a spatial and geographical point of view, and meeting the parallel trend assumption required by the model. In order to perform all of this, we employed a common matching technique (Rosenbaum and Rubin 1985), making use of a popular matching algorithm via Stata known as psmatch2 (Leuven and Sianesi 2003 - Stata module).

Matching algorithms are incredibly useful, by easily doing for us a lot of the computational work required to match our case study over a population of more than eight thousand units.

The parallel trend between treatment and control group on population variation before the 1997 earthquake was here the main concern. We needed to match our treatment group with a control having the same population variation trend, as well as similar spatial and geographical characteristics. Since the algorithm does not allow for panel data we resolved by using the mean population variation for the years 1991-1996 as the output variable – namely the main matching variable. Considering that the mean variation is a relative value, we also restricted the matching only to municipalities under 25k inhabitants and we considered the absolute population at our first observation in time, 1991, as one of the covariants in the matching process.

Also, in order for our control group to best reflect the geographical and spatial characteristics of our treatment group, we considered two other characteristics. First, we restricted the matching again to exclude every coastal municipality and municipalities over 2000 m a.s.l. Second, we employed both categorical and continuous variables again as covariants to reflect the characteristics of our treatment group.

We employed a matching factor of 1 to 10, meaning that for every unit in the treatment group we located the 10 most suitable ones for the control group. Table 1 shows the fairly similar distribution between treatment and control group over the main geographical and spatial characteristics.

TABLE 1 • DESCRIPTIVE SPATIAL AND GEOGRAPHICAL STATISTICS FOR TREATMENT AND CONTROL GROUP

| | Mountain degree | | | | | |
|---|---|---|---|---|---|---|
| | <=299 | 300-599 | 600-899 | 900-1199 | 1200-1499 | |
| Treatment | 5 | 27 | 13 | 7 | 3 | |
| Control Group | 62 | 150 | 143 | 69 | 29 | |
| | **Population size** | | | | | |
| | < 500 | 501-1000 | 1001-2500 | 2501-5000 | 5001-10000 | >100001 |
| Treatment | 9 | 9 | 18 | 8 | 8 | 3 |
| Control Group | 58 | 74 | 153 | 102 | 40 | 26 |
| | **Concentration of population** | | | | | |
| | Not concentrated | Concentrated single center | Concentrated two or three centres | Concentrated multiple centres | | |
| Treatment | 35 | 4 | 7 | 9 | | |
| Control Group | 239 | 76 | 52 | 86 | | |

Considering the Italian context of rural communities, we also checked socio-economic indicators and the geographical distribution of the control group on the Italian territory to avoid eventual bias due to omitting important variables (Wooldridge 2013).

Table 2, shows means and standard deviations for common socio-economic indicators in our treatment and control group. Data are provided by Istat, for the 2001 census. No indicators suggest relevant socio-economic differences between the two groups.

As final step to validate our control group, we checked its geographical distribution on the Italian territory. Problems could generate over an excessive geographical clusterisation of the control in the Northern or Southern part of Italy since they have a fairly different history and cultural development. Map 2 shows the distribution over the national territory. Our control group well represents the diversity of Italian rural areas, both in the North and South part of the peninsula. The map shows only a light clusterisation of the control over the Apennine ridge between Toscana, Emilia-Romagna and Liguria, which is ideal since the area is quite similar (both from a spatial, geographical and socio-economic perspective) to our treatment group.

TABLE 2 • DESCRIPTIVE SOCIO-ECONOMIC STATISTICS FOR TREATMENT AND CONTROL GROUP

| | Treatment | Control Group |
|---|---|---|
| Dependency Index | 0.66 | 0.63 |
| | (0.13) | (0.15) |
| Education Inequality* | 1.34 | 1.31 |
| | (0.07) | (0.08) |
| Pct Foreigners | 0.03 | 0.02 |
| | (0.02) | (0.02) |
| Employment | 0.95 | 0.92 |
| | (0.02) | (0.07) |
| Female Employment | 0.38 | 0.37 |
| | (0.04) | (0.04) |
| Pendolarism | 0.43 | 0.41 |
| | (0.06) | (0.08) |
| Employed in Agricolture only | 0.06 | 0.07 |
| | (0.04) | (0.06) |
| Electoral Participation, 1999 European elections | 0.82 | 0.76 |
| | (0.1) | (0.06) |
| Pct religious Marriages | 0.72 | 0.75 |
| | (0.25) | (0.24) |

* Ratio between Pct of people with no high school diploma and people with a university degree. Source: Istat, Census 2001.

*3.3 Modelling the difference in difference analysis*

In order to have a measure of the impact of the earthquake on population variation over depopulating Italian rural communities, we made use of a popular technique

known as difference in difference analysis (Lechner 2011). Our universe is composed by two groups of municipalities, a treatment group (municipalities affected by the earthquake) and control group (municipalities not affected by the earthquake), the latter is developed via matching techniques. Yearly population variation is observed for both groups in the period before and after the treatment, their comparison is thus used to estimate the effect of the treatment (DD effect).
The starting point is our dependent variable, population variation, which is modelled by the following equation

$$Y_i = \alpha + \beta T_i + \gamma t_i + \delta(T_i * t_i) + \varepsilon_i \qquad \text{(dependent variable)}$$

The coefficient $\alpha, \beta, \gamma, \delta$ are unknown parameters, while $\varepsilon_1$ is the random unobserved error containing the determinants omitted by the model. Coefficients are interpreted as follows:

$Y_i$ = Dependant variable (Yearly variation in population)
$\alpha$ = Constant
$\beta$ = Treatment group specific effect
$\gamma$ = Common (between treatment and control) time trend
$\delta$ = True effect of the treatment

In order to measure the impact of the earthquake we estimated the differences in average population variation for the treatment group (T) before and after the treatment subtracting the same difference for the control group (C). The treatment period is indicated by 1 (after treatment) and 0 (before treatment). The resulting estimator is called, "difference in difference" estimator (DD)

$$\delta_{DD} = \overline{Y}_1^T - \overline{Y}_0^T - \left(\overline{Y}_1^C - \overline{Y}_0^C\right) \qquad \text{(DD estimator)}$$

This estimator, known also as "double difference" estimator, takes the difference between the pre-post comparison of the treatment group and subtracts the difference from the same comparison in the control group (which serves as baseline capturing the time trend). The resulting $\delta_{DD}$, or simply "DD" is hence able to capture the variation generated by the treatment.

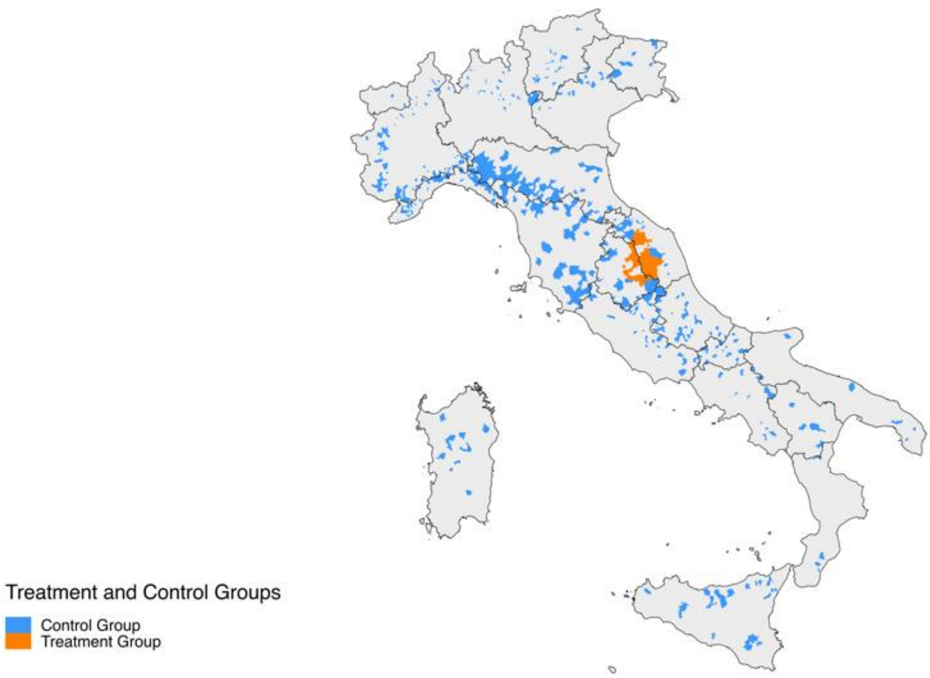
*3.4 Identify better and worse performing groups of municipalities inside the treatment group*

Finally, in order to highlight differences inside the treatment group and detect – if any – driving geographical and spatial effects, we first have to define better and worse performing groups of municipalities.

We followed the same logic than before by looking at performances in population variation, also considering that a general trend of depopulation is consolidated for mountainous and rural communities across all Italy. We defined as 'good performing municipalities' all the affected municipalities that in the 5 years period after the earthquake had a better population variation ratio than in the 5 years before.

In the same way, we defined as 'better performing municipalities' all the affected municipalities in the fourth quartile of the after-before population variation ratio. And, on the other hand, we identified a group called 'bad performing municipalities', when population variation in the after-period is worse than before, and the 'worse performing municipalities' group identifying the first quartile of the ratio.

MAP 2 • TREATMENT GROUP AND CONTROL GROUP



## 4. PRESENTATION AND DISCUSSION OF RESULTS

### *4.1 Effect of the earthquake on population variation*

In the discussion of our empirical strategy, we have shown how we decided to operationalise the concept of community resilience. The operationalisation of a concept is, indeed, a heuristic process meant to translate it into indicators and measurable variables. Where most of the concepts are easily operationalised, the early stage of development of the concept of resilience in social sciences makes the process more complex. We shaped our empirical strategy to deal with this problem by going from a single theoretic definition of community resilience (as a "Dynamic process composed by many adaptive capacities to response and change after adverse events") to splitting the concept into two for its operationalisation: the ability for resilience and the effect of resilience.

Operatively the ability for resilience of communities is a complex adaptive ability composed by a set of capacities, where instead the effect of resilience is the combined effect that such ability has over time in response to a disturbance of the system. This paper focuses solely on the effect of resilience in dealing with a socio-natural disaster and – like for the selection of our unit of analysis – some key factor guided our operationalisation strategy. These key factors can be represented in a simple question: resilience to what?

Indeed, the effects of resilience (and consequently how to measure them) change drastically by changing what we are interested in. More economically grounded studies on community resilience may be interested in economic performances, and then employing economic indicators such as GDP, employment, indicators for innovation and so on (Hassink 2009; Christopherson *et. al.* 2010; Faggian, Modica and Urso 2018). Likewise, studies on recovery from socio-natural disasters may want to focus on physical or institutional infrastructures (Haas *et al.* 1977; Carpenther 2015; Carnelli and Frigerio 2017).

Our specific interest in community disaster resilience of Central Italy rural communities drove us to select population variation as a proxy for the effect of resilience. This is not completely new. Indeed, the variation of population over time – declined in various forms, from population growth to the rate at which different areas repopulate after a disaster – has been already used in literature on disaster resilience in many different contexts indicated as an observable effect of resilience of the community (Chamlee-Wright and Storr 2009; Aldrich 2013).

Our first step was to perform a difference in difference analysis between our affected municipalities and our control group to isolate the earthquake effect on population variation. To do so, we run a regression on panel data for our 55 municipalities composing the treatment group and for 453 municipalities selected as control group over a 20 years time span between 1991 and 2011. The earthquake's effect ("DD Effect" coefficient) is given by the interaction between the time trend and the treatment group.
Results are reported in table 3.
The first column of the table shows some interesting results. First, there is a significant ($t = 2.44$) positive effect on population variation after the earthquake. This does not mean that after the earthquake the affected municipalities started repopulating. Rather, it means that – after the earthquake – the affected municipalities performed better (in terms of population variation) than the control group, which is what was expected to happen without the earthquake itself. The simplest way of saying it is that the affected municipalities performed better than expected after the treatment.

Inside our framework, this represents the consequences of the ability for community resilience in the recovery period triggered by the earthquake of 1997. Effect which is, here, isolated from spatial and geographical characteristics thanks to our controls.
Indeed, from a spatial and geographical point of view, common and well-supported trends can be easily identified by looking at the coefficients. These suggested trends show a well-known, but not so endearing, situation for Italian rural communities. All the coefficients are highly significant ($p<0.001$) and indicate that smaller communities perform worse than bigger ones. Especially in the case of municipalities under 500 inhabitants, here our baseline category. The concentration of inhabitants in cities, villages and hamlets also plays an important role in population variation. Interesting enough not only where more than 70% of population is concentrated in those centres these perform better, but is also the case that we have generally better performances when inhabitants are concentrated over two or three poles rather than a single one.
Physical geography also plays a substantial role here, where communities situated in mountainous areas, especially over 900 m a.s.l., perform worse than the ones sitting on hill ground. Finally, the distance from the nearest pole[4] – expressed here in meters

[4] In the framework of our study poles are identified as cities over 25,000 inhabitants, since they generally are the places around which services and job market gravitate.

– identifies a strong correlation where the farther a community sits from a pole the worst it performs.

The second set of results comes from the comparison between the first column and column two to four, where we report the results of the same regression on different subsets of the treatment group. Namely, these subsets are: "Good Performing municipalities" (2), "Better Performing municipalities" (3), and "Worse Performing municipalities" (4).

There are two things we believe to be important to notice. First, by looking at the coefficients for the DD effect – column (2) and column (3), in this case, since column (4) is not significant – it is confirmed that we identified the subgroups effectively. In column (4) the DD effect coefficient for the "Worse performing municipalities" is not significative (t = –1.56). This suggests that even in the bottom one of our performance subsets the treatment still had a stabilising effect turning the expected negative coefficient into a not significative one.

Indeed, the other coefficients behave as expected by growing - almost doubling - between columns one and two, and then growing again in column three. On the other hand, however, all the coefficients for the controls change only marginally. This lack of substantial change between the controls' coefficients of column one and columns two to four is incredibly relevant. It highlights that there is no clear clusterisation of good or worse performing municipalities over one or another variables, therefore suggesting no discernible relations between better or worse performing municipalities and the spatial and geographical characteristics. This internal dimension to the affected area will be more extensively elaborated in the next paragraph.

Our results support the idea of a common trend where rural communities - i.e. smaller communities, living in mountainous areas further from poles of services - have more difficulties dealing with variation of population. On the other hand, they also indicate that the earthquake had on this area somewhat of a stabilising effect, resulting in the affected municipalities behaving better than the one in the control group.

Also, the comparison of coefficients for the same variable - exemption made for the mountains degree, where the ordinality is clear - does not suggest the existence of ordinalities of sort. In other words, rural communities do suffer more from depopulation, but our results suggest that the relationship with spatial and geographical characteristics is not purely linear.

TABLE 3 • DIFFERENCE IN DIFFERENCE COMPARISON TABLE

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Affected Area | Good Performing | Best Performing | Worse Performing |
| Time Trend | -0.00227*** | -0.00227*** | -0.00227*** | -0.00227*** |
| | (0.000415) | (0.000415) | (0.000415) | (0.000415) |
| Treatment Group | -0.00523*** | -0.00763*** | -0.00824*** | 0.0155 |
| | (0.00120) | (0.00113) | (0.00216) | (0.00799) |
| DD Effect | 0.00318* | 0.00627*** | 0.00888*** | -0.0144 |
| | (0.00130) | (0.00119) | (0.00235) | (0.00924) |
| < 500 | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) |
| 501 – 1000 | 0.00414*** | 0.00427*** | 0.00420*** | 0.00422** |
| | (0.00116) | (0.00123) | (0.00124) | (0.00128) |
| 1001 – 2500 | 0.00382*** | 0.00420*** | 0.00448*** | 0.00511*** |
| | (0.00110) | (0.00116) | (0.00117) | (0.00121) |
| 2501 – 5000 | 0.00529*** | 0.00555*** | 0.00601*** | 0.00639*** |
| | (0.00115) | (0.00121) | (0.00124) | (0.00127) |
| 5001 – 10000 | 0.00586*** | 0.00659*** | 0.00711*** | 0.00789*** |
| | (0.00118) | (0.00124) | (0.00126) | (0.00131) |
| 10001 – 25000 | 0.00470*** | 0.00488*** | 0.00574*** | 0.00680*** |
| | (0.00125) | (0.00131) | (0.00134) | (0.00138) |
| Not Mountainous/ Hills | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) |
| 600 – 899 | -0.00377*** | -0.00367*** | -0.00377*** | -0.00375*** |
| | (0.000519) | (0.000531) | (0.000549) | (0.000565) |
| 900 -1199 | -0.00621*** | -0.00586*** | -0.00599*** | -0.00595*** |
| | (0.000859) | (0.000906) | (0.000932) | (0.000940) |
| 1200 – 1499 | -0.00602*** | -0.00626*** | -0.00631*** | -0.00680*** |
| | (0.00145) | (0.00147) | (0.00148) | (0.00153) |
| Sprawled | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) |
| Monocentric | 0.00159*** | 0.00129** | 0.000866 | 0.000627 |
| | (0.000460) | (0.000467) | (0.000499) | (0.000511) |
| Bi/Tri-centric | 0.00392*** | 0.00376*** | 0.00322*** | 0.00340*** |
| | (0.000584) | (0.000598) | (0.000648) | (0.000667) |
| Distance from nearest Pole | -0.000000338*** | -0.000000343*** | -0.000000338*** | -0.000000339*** |
| | (3.19e-08) | (3.21e-08) | (3.27e-08) | (3.31e-08) |
| _cons | 0.0115*** | 0.0114*** | 0.0113*** | 0.0111*** |
| | (0.00176) | (0.00179) | (0.00180) | (0.00182) |
| N | 10040 | 9600 | 9200 | 9020 |
| adj. R-sq | 0,124 | 0,131 | 0,13 | 0,131 |
| | | | Standard errors in parentheses | * p<0.05, ** p<0.01, *** p<0.001 |

*4.2 Internal spatial and geographical differences*

In the second step of our analysis, we used logistic regressions to study the relationship between the performance of municipalities and spatial and geographical characteristics for the affected area. Indeed, the first step of our analysis suggests that, despite a common trend of rural communities being more afflicted from depopulation in Italy, there is no consistent relation inside our affected group of municipalities between these characteristics and their performance. Map 3 shows the spatial distribution of affected municipalities by different performance groups and, in black provincial boundaries. It is noticeable that worse performing municipalities are somewhat concentrated in the southern area of Macerata's province. But, exception made for this, no other pattern is immediately manifest.

In order to examine this relation more in-depth, we focused our analysis on good and best-performing groups of municipalities to highlight eventual clusters over different categories. Logistics regression were run first over every Italian municipality under 25,000 inhabitants (for baseline), and then solely on the affected area. The dichotomous dependent variables used were the ones representing 'Good' and 'Best' Performing municipalities. Such groups of municipalities were selected ex-post via the difference in the after-before population variation ratio. Good and best performing municipalities both perform better in the after-period, the group of best performing holds the most positive ratios.

Table 4 summarises our results.

Column one (1) shows the results for all Italian municipalities under 25,000 inhabitants. They mostly confirm the pattern which sees smaller municipalities and more mountainous ones, situated farther from service poles, being less represented in the success group. The logistic regression was run on a wide set of municipalities (7425 Obs.). All variables are significative, at least at $p < 0.05$, exception made for the categorical variable representing the concentration of population in one or few centres (against more sprawled municipalities) which is not significant. This suggests that this kind of spatial distribution differences might be more relevant for our rural communities but it fades when using a wider dataset.

In other words, such rural – smaller municipalities and more mountainous ones, situated farther from service poles – communities had more problems and, generally, a worse yearly mean population variation over time. These facts, per se, do not uncover anything new, indeed this first column is our baseline to interpret the next two columns.

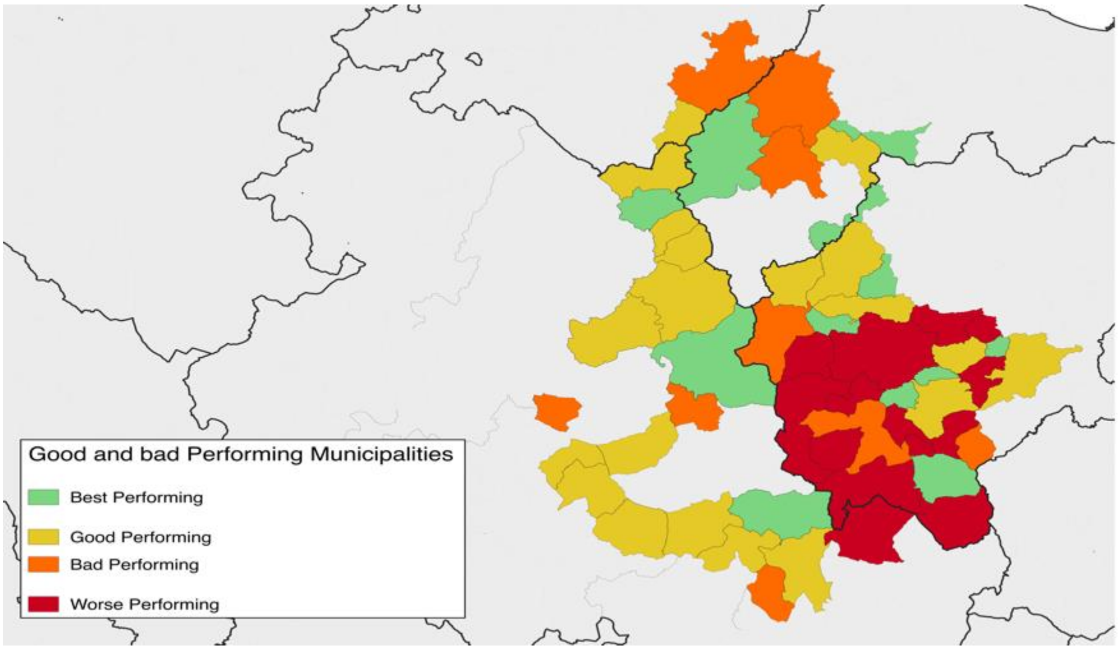
TABLE 4 • LOGIT COMPARISON

| | Italy | Affected municipalities | |
|---|---|---|---|
| | success_general | success | super_success |
| Distance from nearest Pole | -0,00000906** | -0,000125 | -0,000277* |
| | (0,00000290) | (0,0000956) | (0,000139) |
| Mountain Degree | | | |
| Not Mountainous/ Hills | 0 | 0 | 0 |
| | (.) | (.) | (.) |
| 600-899 | -0,209* | 0,659 | 1,091 |
| | (0,0858) | (1,031) | (1,173) |
| 900-1199 | -0,374** | -3,475 | 0 |
| | (0,114) | (1,950) | (.) |
| 1200-1499 | -0,386* | 3,431 | 5,043 |
| | -0,151 | (2,709) | (3,341) |
| 1500-1999 | -0,0572 | . | . |
| | (0,164) | . | . |
| 2000-2499 | -0,0770 | . | . |
| | (0,246) | . | . |
| >2500 | -0,574 | . | . |
| | (0,726) | . | . |
| Population Concentration | | | |
| Sprawled | 0 | 0 | 0 |
| | (.) | (.) | (.) |
| Monocentric | -0,0774 | 2,106 | -0,812 |
| | (0,0789) | (1,961) | (2,150) |
| Bi/Tri-centric | -0,0355 | 3,366 | 2,226 |
| | (0,0749) | (1,908) | (1,531) |
| Population size | | | |
| <500 | 0 | 0 | 0 |
| | (.) | (.) | (.) |
| 501-1000 | 0,244* | 3,391 | 3,381 |
| | (0,101) | (2,061) | (2,364) |
| 1001-2500 | 0,252* | 0,641 | -1,058 |
| | (0,104) | (1,835) | (1,797) |
| 2501-5000 | 0,249* | 0 | -1,129 |
| | (0,112) | (.) | (2,314) |
| 5001-10000 | 0,490*** | 1,557 | 0,0845 |
| | (0,122) | (2,081) | (1,985) |
| 10001-25000 | 0,388** | 0,316 | 0 |
| | | (2,316) | (.) |
| _cons | -0,133 | 1,921 | 2,250 |
| | (0,150) | (3,018) | (2,228) |
| Obs | 7425 | 47 | 43 |
| adj. R-sq | 0,074 | 0,28 | 0,254 |
| | | Standard errors in parentheses | * p<0.05, ** p<0.01, *** p<0.001 |

Column two (2) and three (3) report the results for the logistic regressions on the possibility to be part of 'Good performing' (2) and 'Better performing' (3) groups, only for the municipalities affected by the 1997 earthquake in our case study. The results are pretty clear to report. All the selected predictors here lose any explanatory power they had in the baseline regression. Indeed, when fitting the model over our specific case study, it does appear that such geographical and spatial characteristics are not able to explain the distribution of municipalities over 'Good' and 'Better' performing groups.

Interpreted inside our theoretical framework, these results suggest that even though our predictors are able to partially explain the differences in the general trend of population variation over time, the same predictors fail at the job when dealing with only our earthquake affected municipalities, losing any explanatory power. Different characteristics and degrees of rurality do not create significant differences over the effect of community resilience triggered by the disastrous event.

MAP 3 • SPATIAL DISTRIBUTION FOR PERFORMANCE GROUPS




These results, coupled with the ones from the difference in difference, are the main findings of this study. They support the hypothesis that spatial and geographical characteristics, despite having a clear and well established general effect on population variation, do not have the similar penalising role on community resilience after an earthquake. These finding suggest that, the effect of community resilience for an all-rural earthquake affect area is fairly consistent over different degrees of rurality.

## 5. Conclusions

### *5.1 The double effect of space*

We started this study with a question about the role of spatial and geographical characteristics for the community disaster resilience of Italian rural communities. Although we analyse only one case study, the 1997 earthquake's affected area, we believe our quasi-experimental design for this paper is able to provide interesting insights on this causal relation, which can be generalised at least for the Italian context of rural community.

The first result that our study highlights is that the 1997 earthquake had a general stabilising effect on population variation in the affected area. Indeed, the DD effect in Table 3 indicates that such communities generally performed better than they had before. We called it a stabilising effect because the ratio of population variation in the after-period does not become positive, but instead it simply turns to be less negative compared to what it should have been without the earthquake. We believe this to be an interesting first result calling for a more in-depth analysis of the phenomenon via comparative studies.

Our intuition to explain it is that such effect is related to the completely public founded nature of the reconstruction process and policies. Public reconstruction was able to drive and support the resilience capacity embedded in the communities (Imperiale and Vanclay 2016), generating a stabilising effect on population variation for all the affected area.

The main focus of this study is space, for which we have isolated the effect of community resilience over different spatial characteristics and degrees of rurality. What emerges from the interpretation of our results is the presence of a 'double effect' of space.

On the one side, we are able to identify a well established spatial and geographical effect which shows that rural communities are less able to contrast a negative population variation trend over time. Inside our framework, we used population variation over time as a proxy for the effect of community resilience, hence our contribution here supports the idea that rural communities are penalised in this regard

from their geographical and spatial characteristics. Moreover, we were able to show the existence of a direct ordinality in those characteristics. By comparing rural communities among each other, rather than rural against urban communities, we were able to explore the characteristics of rurality on different levels. Our results indicate the presence of a correlation between municipalities ratio of population variation over time and them being situated in a more mountainous and high above sea level area far from big cities of centres of labour and services agglomeration. In the same way, also the internal spatial distribution of population - as well as the size of communities - shows a similar ordinality where smaller and more sprawled communities perform worse in the same regard.
The contribution of our study to the literature on resilience of rural communities comes from comparing, on the same characteristics, good and bad performing communities after a disaster. Indeed, our initial expectation when designing the research was to find a similar ordinal pattern showing a clusterisation of better performances in less rural areas, or at least indications of such correlation between rural characteristics and performance in population variation after the earthquake. Interesting enough our results show no detectable spatial and geographical patterns that enable us to identify better and worse performing municipalities when dealing with the aftermath of a socio-natural disaster. Indeed, all the coefficients and the relative standard deviations for our difference and difference, not only maintain the same ordinality but they also remain very constant across every regression. Considering that the effect of the earthquake varies accordingly to the different iterations - it almost doubles between the baseline and the regression for the "Good Performing" (2) - and also the considerable lack of explanatory power of the mentioned characteristics in identifying good and bad performing municipalities, our results suggest that spatial and geographical characteristics might only play a minor (minor than expected at least) role than expected.

Building on these first contributions, there are a series of research directions open for the future. Italy is not only largely composed of rural communities, but many of them are also disaster prone areas. The study of the relationship between such communities and their disaster resilience ability is then largely relevant both from an academic point of view and from a policy one.

Indeed, our contribution suggests that when dealing with a socio-natural disaster these communities are not less, neither more, resilient than urban ones; they are differently resilient.

Our study deals only with geographical and spatial characteristics of rural municipalities while isolating the effect of community resilience via our quasi-experimental empirical strategy.

In the end, what this study points out is that community disaster resilience works differently for these rural communities and that a combination of social, economic or institutional characteristics might play a more decisive role in community disaster resilience for rural communities. We were able to determine ex-post 'Good' and 'Bad' performing municipalities, showing that the spatial characteristics we considered were not able to explain their differences. More research is needed to understand which social, economic and institutional characteristics drive different performances. Nonetheless, our study is a starting point in this direction by identifying 'good' and 'bad' performing municipalities in relation to different spatial and geographical characteristics.

Rural communities are an important asset for Italian administrations and are often subjects of study and implementation of policies. Arguably, no other Italian territory is today more in need of public support and tailored policies than Central Italy. In this regard, our study and the future research that it will open up, can provide a useful framework and baseline to design effective policies tailored to the context which - following our results - could be successfully applied to different degrees of rurality.

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