RESILIENCE IN ITALIAN LLMAS: THE ROLE OF SPECIALIZATION AND DIVERSIFICATION PATTERNS IN TWO RECENT CRISES

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Abstract. This paper investigates the resilience of local economic systems (LLMAs) in Italy over 2008 to 2022 distinguishing between two resistance periods (2008–13 and 2019–20) and two recoveries (2013–19 and 2020–22). The main focus is on the role of diversification patterns, to check whether –and to what extent- related/unrelated variety is important in determining local performance. We estimate a spatial model and include a number of control variables. Results show that relatedness is important both for resistance and for recovery; unrelated variety is less important. We also find significant spatial spillovers only for recovery, with ambiguous effects over time. Results confirm the country's general de-industrialization trend, coupled with growing importance for services, in particular for the less knowledge-intensive ones. While the South recovers better than the rest of the country, we tentatively explain this fact in terms of the role played by traditional services.

1. Introduction

When faced by the same exogenous shock, some regions react well and quickly; others lag behind. What lies behind this different behaviour? Which features are most important in determining local response? These questions have gained momentum in recent times, following the 2008 financial crisis, the subsequent sovereign debt crisis (2011-12) and the Covid-19 pandemic of 2020-21[1].

While the literature provides no universally accepted definition of resilience, a common approach follows an evolutionary perspective and focusses on an area's capability to restore, or improve, its pre-crisis performance, eventually adapting to new conditions (evolutionary, or adaptive, resilience)[2]. In this sense, it is possible to distinguish between an area's ability to: (i) withstand a shock in the short-run (resistance); (ii) restore previous paths and/or develop new ones in the longer term (recovery) (Martin, 2012; Martin and Sunley, 2015).

[1] The two shocks were quite different in nature. The 2008-13 Great Crisis, that evolved into the sovereign debt crisis, had both real and financial effects, causing the longest and deepest recession of peacetime. Its exogenous/endogenous character is still debated. The 2019-20 pandemic was short-lived and entirely exogenous. At least in part these differences may shape different local reactions.

[2] The other two definitions are engineering and ecological resilience. The first assumes that systems have an underlying long-run equilibrium path (à la Solow); it measures resilience in terms of the rapidity with which an economy restores it. The second one allows economies to evolve towards new paths (à la Schumpeter), depending on the magnitude of the shock. In this sense it is closer to the adaptive definition. See Martin and Sunley (2015).

Traditionally, the differences in regions' response to shocks are associated with the local production structure (the "industry mix"), often in connection with other features (Lagravinese, 2015). More recently, specialization and diversification have been enriched by the notion of "variety", with a focus on the combinability of existing knowledge and skills across local activities. This allows actors to deepen/ expand existing abilities, ultimately developing new trajectories. Put differently, innovation arises essentially as a combination of pre-existing local features; it proceeds incrementally branching from the sectors/technologies in which a territory has a competitive advantage. In this sense, innovative performance is largely related to the existing economic domain. The literature stipulates that diversified local economies with an adequate array of differentiated, but complementary, activities ("related variety") are apt to resist sector-specific shocks relatively well. They are able to reallocate labour and resources across sectors (industrial portfolio effect) and stand to benefit from consolidated ties, routines and procedures, which act as shock absorbers. By allowing the cross-fertilization across different but complementary activities, related variety may also promote recovery in the short run.

In other cases, innovation stems from a re-combination of technologies that mixes a firm's knowledge with that belonging to the context within which it operates. As firms draw from the externalities that are embedded locally, they generate truly innovative paths. Thus it is this type of diversified economic systems ("unrelated variety") that allows to develop new, high value-added activities that raise productivity, competitiveness and ultimately move the local economy towards new development paths. As diversification evolves towards more advanced activities and eventually moves from *niche* creation to adoption, the local system achieves recovery in the longer run[3,4].

With reference to Local Labor Market Areas (LLMAs)[5] in Italy, this paper explores the features that shape the local response to an exogenous shock; in particular, it aims at investigating the role of the local production structure, of variety and of diversification patterns in promoting resistance and/or recovery. It explicitly accounts for space by estimating a spatial model that measures spatial spillovers across units. Control variables are also introduced to check for other features that may affect resilience. The paper is organized as follows: par. 2 describes the data,

[3] Boschma, 2015. In some case it is suggested instead that, by relying strongly on market forces, unrelated diversification may offer less resistance. See Lazzaretti *et al*., 2022.

[4] The distinction between resistance and recovery, however, is not mechanical: in any moment the existing local features shape an area's future structural change possibilities, marking the interrelatedness between the two ideas. It follows that resilience is a process that has its roots in a region's production structure and in the complementarities that arise between it and the local knowledge bases. See Boschma, 2015

[5] LLMAs are self-contained units that are defined by commuting patterns; they are independent from administrative boundaries.

the model and the variables taken in consideration. Par. 3 provides a brief descriptive picture; par. 4 reports the results of the spatial regression analysis. Par.5 concludes.

2. Data, methodology and variables

The empirical study takes LLMAs as units of analysis and focuses on resilience and recovery in four key periods: two crises (2008–13 and 2019–20) and two recoveries (2013–19 and 2020–22). Data come from the ASIA Business Register of the Italian National Institute of Statistics (ISTAT) and cover active enterprises in industry, commerce, and services from 2007 to 2022. Firm-level data is aggregated by the 610 LLMAs identified by ISTAT in 2018.

As in much of the literature, we measure our dependent variable, resilience, with reference to employment[6]. Alternative measures consider value added (or GDP) (Armenise and Benassi, 2022) and/or productivity indicators (Boschma and Iammarino, 2009). However, Martin (2012) argues that employment is preferable when tracing local resilience. Di Caro (2015) adds that employment series in Italy are more articulated at a regional level; moreover, they avoid deflation.

As in Martini and Platania (2019), both resistance (y_{res}) and recovery (y_{rec}) indexes are modified to account for LLMAs.

$$y_{res} = \frac{(\Delta EMP_{llma}/EMP_{llma}) - (\Delta EMP_{nat}/EMP_{nat})}{|\Delta EMP_{nat}/EMP_{nat}|} \quad (1)$$

$$y_{rec} = \frac{(\Delta EMP_{llma}/EMP_{llma})}{(\Delta EMP_{nat}/EMP_{nat})} \quad (2)$$

where ($\Delta EMP_{llma}/EMP_{llma}$) and ($\Delta EMP_{nat}/EMP_{nat}$) are the percentage changes in employment respectively in the LLMA and in the country over a given period, measured as the difference between the first and last year of each period[7].

The main explanatory variables, related and unrelated variety, are measured through modified versions of Thiel's entropy index, calculated on employment at different levels of sectoral aggregation[8]. Related variety (*RV*) records diversification at the 5-digit Ateco level within 2-digit sectors. Unrelated variety (*UV*) registers variety between 2-digit Ateco sectors.

$$\boldsymbol{RV}_{llma} = \sum_{g=1}^{G} \frac{EMP_{g\ llma}}{EMP_{llma}} \sum_{s \in g} \left(\frac{EMP_{s\ llma}}{EMP_{llma}} \Big/ \frac{EMP_{g\ llma}}{EMP_{llma}} \right) log_2 \left(\frac{EMP_{s\ llma}}{EMP_{llma}} \Big/ \frac{EMP_{g\ llma}}{EMP_{llma}} \right)^{-1} \quad (3)$$

[6] See, among others, Di Caro (2015), Martin *et al.* (2016), Sedita *et al.* (2017), Cainelli *et al.* (2019)..
[7] That is, respectively, 2013 vs. 2008; 2019 vs. 2013; 2020 vs. 2019 and 2022 vs. 2020.
[8] Following Frenken *et al.* (2007) this measure is adopted, among others, by Boschma and Iammarino (2009), Sedita *et al.* (2017), Cainelli *et al.* (2019), Chen *et al.* (2024).

$$\boldsymbol{UV}_{llma} = \sum_{g=1}^{\boldsymbol{G}} \frac{EMP_{g\ llma}}{EMP_{llma}}\ log_2\ \left(\frac{EMP_{g\ llma}}{EMP_{llma}}\right)^{-1} \quad (4)$$

where $s = 1 \ldots n$ is the 5-digit sector belonging to 2-digit sector g, with $g = 1 \ldots G$.

Besides considering differentiation patterns, we control for a number of other variables. Thus, the population density (the average number of inhabitants above 15 years per square metres) reflects local demand for goods and services and local supply in the labour market. It also proxies the externalities that are linked to urbanization, as densely populated areas often house higher education institutions, big firms and organizations, which are likely to lead the local economy to react better to a crisis[9]. Along the same lines the density of firms (the number of firms over the population) may affect resilience by acting as a shock absorber[10]by offering relocation opportunities (industry portfolio effect).

With reference to the peculiar features of Italy's production system, we control also for the share of employment in small firms (below 2mn Euros turnover per year; median values reported by the ASIA Business Register, ISTAT). As pointed out by Frenken *et al.* (2007) this also provides information on the level of local competition. In the case of Italy, we expect that larger firms, being more dependent on external factors, are more exposed to crises, while smaller ones could be more sheltered. Other controls include the share of employment respectively in manufacturing firms, low technology ones (LOT) and in less knowledge-intensive services (LKIS). These variables are meant to capture the role of sectoral specialisation; we expect the manufacturing sector to be more hard hit by crises and services to react better[11]. Finally, we introduce a dummy to identify LLMAs located in the South or in the two main islands (the *Mezzogiorno*) to check for differences with respect to the more industrialised, market-oriented Centre-North. By the same token, Altitude (defined as the average elevation of firms' location in the LLMA) is used as a proxy that captures the degree of local isolation from external factors.

3. Descriptive statistics

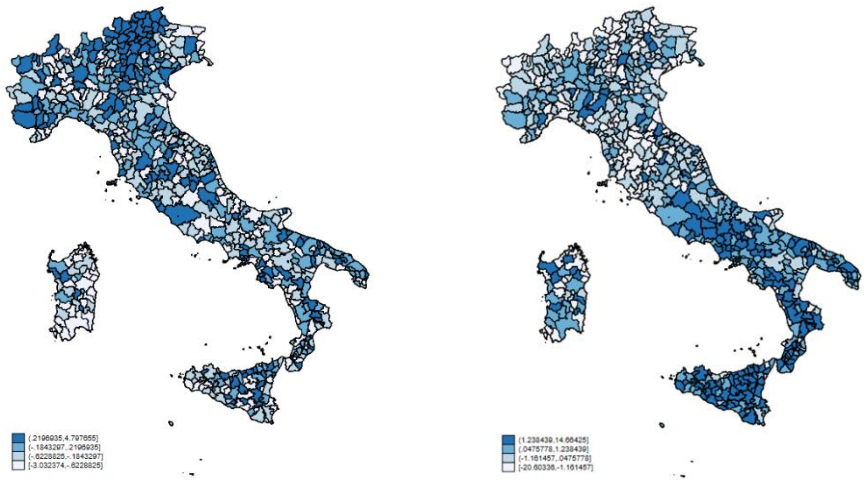
A preliminary view of the territorial pattern of resistance/recovery is shown in Figs. 1a and 1b; the distribution of relatedness/unrelatedness indexes in initial year 2008 is reported in Fig. 2. Fig.1a suggests a rather evident spatial pattern of resistance, especially in 2019-20. At least in part, this may reflect temporary restrictions on layoffs and job retention schemes. These policies, while implemented

[9] See Frenken *et al.* (2007), Faggian *et al*. (2018), Sedita *et al.* (2017), Cainelli *et al.* (2019) Chen *et al*. (2024).
[10] The opposite occurs in case of a sector-specific shock hitting less diversified LLMAs. In this case firm density acts as a shock diffuser (Boschma, 2015).
[11] Di Caro (2015).

nationwide, produced uneven effects across sectors, affecting employment dynamics differently[12]. However, the spatial pattern fades in recovery (Fig. 1b).

Fig.2 instead shows that relatedness/ unrelatedness distribute according to a rather clear-cut North-South divide, with *RV* being mostly higher in southern LLMAs and lower in central and northern ones. On the contrary, *UV* is low in the South and high in the Centre-North[13]. This uneven spatial distribution points to different diversification paths: while in the *Mezzogiorno* diversification occurs mainly within existing specialization patterns, in the Centre-North it is driven more by new paths. Figs. 1a and 1b also point to a connection between resistance and recovery, implying that the LLMAs that resist better are also those that recover faster. This appears evident especially in the two earlier periods[14].

Figure 1a – *Resistance patterns in Italian LLMAs (2008-13 and 2019-20).*



Source: our elaboration

Finally, the general picture outlined by Figs.1 and 2 seemingly runs counter the literature's indications in at least two respects. First, in 2008-13 it is the (more unrelated) Centre-North that resists better than the (more related) *Mezzogiorno*, somewhat disclaiming the suggestion that consolidated ties and routines, spillovers and the like act as shock absorbers[15]. Second, unrelatedness, which should encourage

[12] For instance, although national in scope, sector-specific policies in favour of construction or tourism could have created asymmetries against the more manufacturing-oriented Centre-North. An alternative view could focus on manufacturing alone, or consider a longer time span.

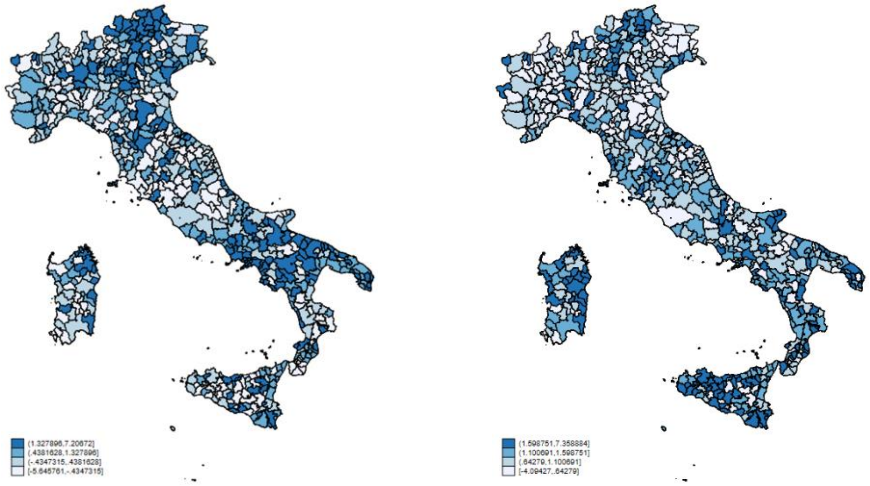
[13] Fig. 2 shows the distribution in 2008. Over time the divide, if any, strengthens.

[14] This finding is in line with that by Faggian *et al.* (2018) who describe a low resistance/low recovery pattern prevailing mostly in southern LLMAs over 2007-11. We find correlation coefficients around 0.6 throughout the whole period (falling marginally only during the Covid-19 crisis).

[15] The *Mezzogiorno* resists well in 2019-20, when it could be argued that exogenous factors were at play, due to the peculiar nature and territorial distribution of the Covid-19 pandemic in Italy.

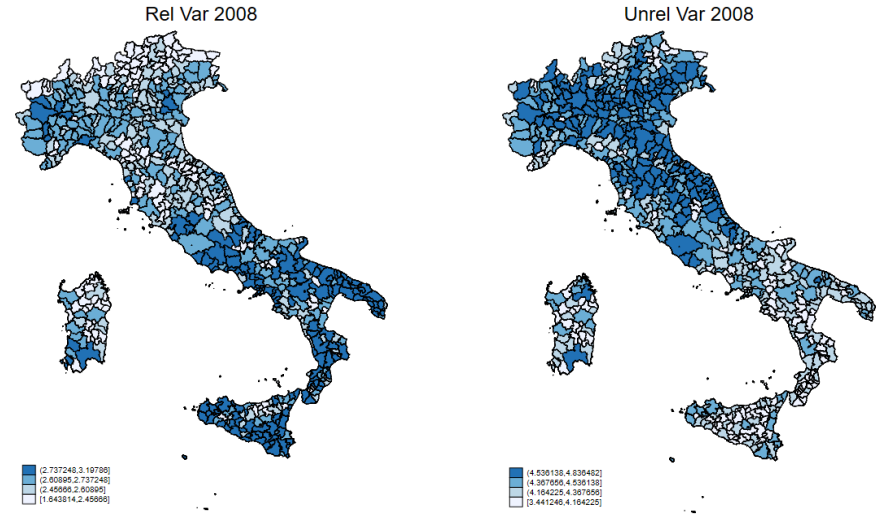
recovery inasmuch as it offers a wider portfolio of advanced, dynamic activities, associates rather weakly with it both in 2013-19, and (even less) in 2020-22.

Figure 1b – *Recovery patterns in Italian LLMAs (2013-19 and 2020-22).*



Source: our elaboration

Figure 2 – *Related and Unrelated Variety (2008).*



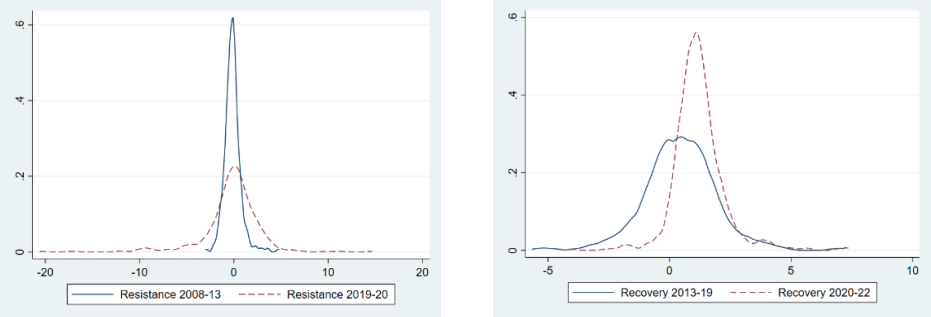
Source: our elaboration

Further detail is added by Fig. 3 that shows the kernel density of LLMAs' resistance/recovery indexes for the two crises under consideration[16]. While in 2008-

[16] The kernel density distribution estimates the probability density function of a continuous variable to represent its distribution. A tight, peaked kernel indicates a cluster around the mean. A flatter, wider,

13 LLMAs resist according to a homogeneous pattern (amounting to layoffs/freezing of new hiring), the pandemic produces strongly asymmetric effects, as some sectors (tourism, retail commerce) are hard hit and others (logistics, digital services) are boosted. In recovery this pattern is inverted: while in 2020-22 reactions are evidently clustered[17], it is interesting to note the dispersed response of 2013-19, when some LLMAs scale down employment and other raise it. This underlines the importance of other factors -the industry mix, firms' characteristics and strategies in driving recovery. These elements are the object of the following econometric analysis.

Figure. 3 – *Kernel density.*



4. Estimates and results

The presence of global spatial dependence in resilience patterns is tested through Moran's I statistic. For each time-period the index records high values that grow over time: these move from 0.29 (2008-13) to 0.45 (2013-19), to 0.61 (in the pandemic) and fall only slightly in 2020-22, reaching 0.58[18]. This means that LLMAs that resist/recover better (or badly) tend to cluster together.

The strong overall spatial correlation suggests that standard econometric models, which are based on the independence of each geographical unit, would yield biased results. Spatial models, that explicitly account for units located in space and allow for externalities and spillovers, should be considered instead[19].

The Spatial Durbin model (SDM) provides a flexible framework that encompasses most spatial models. It may be described as follows:

$$y = \beta_1 X + \beta_2 WX + \rho Wy + \varepsilon \quad (5)$$

one shows more heterogeneous values. Our estimations are based on the Epanechnikov kernel with bandwidth selected according to Silverman's rule.

[17] This could be linked to nation-wide extraordinary regulations (subsidies, transfers) addressing all firms and all sectors.

[18] All coefficients are highly significant.

[19] See, among others, Cainelli *et al.* (2019) and Chen *et al.* (2024).

where y is the resistance/recovery index for each LLMA; X is a NxK matrix of independent variables (N is the number of LLMAs; K that of independent variables); W is a NxN non negative (spectral normalized) spatial contiguity weights matrix (where element $w_{ij}=1$ if units i and j share a border; else $w_{ij}=0$); Wy is the spatial lag of y; WX is the spatial lag of X; ε is a $Nx1$ vector of errors with zero mean and σ^2 variance; β_1, β_2 and ρ are the response parameters to be estimated.

The SDM nests most spatial analysis models. Setting $\beta_2 = 0$ yields the spatial autoregressive model (SAR), which allows spatial dependence in the dependent variable of neighbouring units, but not in their covariates. Imposing the restriction that $\rho = 0$ leads to the spatially lagged X regression model (SLX), which assumes independence across the dependent variables but includes the characteristics of neighboring regions. When both parameters are set to zero, the model reduces to a standard non-spatial regression (OLS). Given the big cross-sectional dimension of the panel (610 units), statistical testing allows to select models in an easy and reliable way. We therefore choose to compare the SDM, the SAR and the SLX models through Likelihood Ratio (LR) tests[20] . Results suggest that the SAR specification is preferred for resistance periods while the SDM applies best to recovery.

Table 1 shows the estimated of model (5) for each period. Related variety shows a positive, significant impact on resistance, acting as a shock absorber both in 2008-13 and in 2019-20. It also acts as a recovery-promoter only in 2013-19 – not after the Covid-19 crisis . This confirms, and extends over time, previous results reached for Italy's LLMAs (Sedita et al., 2016, and Cainelli et al., 2019) and NUTS3 provinces (Boschma and Iammarino, 2009) . The interpretation of this result is straightforward: a more inter-related local economy offers a wider range of opportunities. It allows firms to reallocate skills and technologies, exchange knowledge and adjust to shocks.

Instead, unrelated diversification is mostly irrelevant for resilience. Variable *UV* shows a positive and significant coefficient only for resistance in pandemic-ridden 2019-20, when LLMAs offering a wide portfolio of activities benefit from shock absorbing effects. Again, this is generally confirmed by the literature[21].

[20] Results –available upon request- are not reported for the sake of brevity. Le Sage (2015) argues in favour of Bayesian techniques for model selection. This method has the advantage of integrating model uncertainity but requires prior assumptions that lie beyond the scope of the present study. We leave the issue for future research.

[21] However, exceptions do exist: Boschma and Iammarino (2009) find that unrelatedness leads to growth (and hence to resilience) in NUTS3 provinces only in terms of value added, and not for employment. For US units Chen et al. (2024) find that *UV* acts as shock absorbers, promoting resilience.

Table 1 – *Spatial Model Estimates: Resistance (2008-13; 2019-20) and Recovery (2013-19; 2020-22).*

	RES 2008-13	**REC 2013-19**	**RES 2019-20**	**REC 2020-22**
Rel_Var	**0.500*** **	**0.697*** **	**1.231*** **	0.226
	(0.143)	*(0.197)*	*(0.375)*	*(0.156)*
Unrel_Var	-0.0777	-0.0892	**0.639** **	-0.0787
	(0.121)	*(0.171)*	*(0.323)*	*(0.145)*
Population density	0.127	-0.268	0.00199	0.110
	(0.153)	*(0.313)*	*(0.441)*	*(0.205)*
Firm density	**-0.00456***	**0.00811** **	**-0.0197** **	**0.00625***
	(0.00255)	*(0.00393)*	*(0.00774)*	*(0.00327)*
% Small firms	**8.828** **	**25.79*** **	-1.595	-5.286
	(3.847)	*(6.004)*	*(9.921)*	*(4.660)*
% Manuf. firms	**-6.132*** **	**-7.930*** **	-2.451	1.247
	(1.857)	*(2.715)*	*(5.686)*	*(2.443)*
% LOT manuf.	**6.209*** **	**6.548** **	-1.650	-1.982
	(2.009)	*(3.009)*	*(6.610)*	*(2.901)*
% LKIS	**1.949***	**5.014*** **	**-23.12*** **	**7.167*** **
	(1.008)	*(1.448)*	*(2.597)*	*(1.045)*
Mezzogiorno	**-0.186***	**0.687*** **	0.126	**1.176*** **
	(0.105)	*(0.150)*	*(0.333)*	*(0.166)*
Altitude	**0.000730*** **	-8.14e-05	**0.00214*** **	2.60e-05
	(0.000152)	*(0.000190)*	*(0.000416)*	*(0.000193)*
W_y	0.275	**0.572*** **	-0.103	**-0.661*** **
	(0.199)	*(0.0957)*	*(0.131)*	*(0.146)*
e.y	-0.0736	-0.611***	0.309**	0.610***
	(0.239)	*(0.156)*	*(0.135)*	*(0.0986)*
W_x (pop. density)		**1.662*** **		0.105
		(0.536)		*(0.458)*
W_x (firm density)		-0.00399		**0.00656** **
		(0.00255)		*(0.00294)*
Constant	-0.919	**-2.987*** **	0.671	**-1.332***
	(0.648)	*(0.925)*	*(1.766)*	*(0.752)*
Observations	610	610	610	610
(Pseudo) R-squared	0.106	0.2479	0.460	0.276

*Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Analyzing the control variables shows that, contrary to previous findings, population density is not important[22], while firm density is. The latter shows a positive and significant coefficient in recovery (although values are low), and a negative one in resistance, when possibly many marginal firms exit the market.

[22] Boschma and Iammarino (2009) find the same result for NUTS3 provinces in 1995-2003.

A strong share of employment in small firms has a big and important effect on resilience in the first two periods, but is irrelevant in the following ones. The same occurs for the share of manufacturing, which shows a (big) negative effect in 2008-13 and until 2019; later it not significant. We interpret this as a reflection of the country's general de-industrialization process. Also the coefficients relative to LOT manufacturing firms – the traditional backbone of Italian industry – are positive and significant only in the first two periods. This contrasts previous results for which high shares of LOT manufacturing associate with low resilience (Compagnucci *et al.*, 2022). Coming to services, LKIS increasingly promote resilience (not in 2019-20), acting as shock absorbers and growth promoters. Again, this runs counter existing results, that find negative effects of LKIS for resilience.

As far as the North-South dimension is concerned, location in the *Mezzogiorno* rather unexpectedly associates positively and significantly with recovery; moreover, the coefficient grows over time. This is an interesting result; it confirms national statistics that record higher value added, employment and productivity growth in the region from the mid-'Nineties on[23]. Contrary to the literature's indications, we find that location in the sheltered, less diversified, *Mezzogiorno* has either a negative or an irrelevant impact on resistance. Finally, LLMAs located in high-altitude areas benefit from a modest, but significant, buffering effect in resistance. We explain this by assuming that these units probably identify more stable, self-contained systems with a strong public sector, leading to lower exposure to external shocks.

Coming to spatial effects, these matter only for recovery, but give ambiguous results. By activating positive spillovers on demand and on labour markets in neighbouring LLMAs, they promote recovery during 2013-19 but hamper it in 2020-22. In the latter case spatial effects seemingly amount to competition effects across LLMAs, leading to resource diversion, labour drain and firm relocation (see Chen *et al.*, 2024). We find that also population and firm density show positive and significant spatial effects in recovery: that of population counts most in 2013-19 and that of firms in 2000-20.

As a robustness check, we estimate model (5) using a second-level normalized contiguity weights matrix (with weight reflecting also the neighbours of each unit's neighbours As a robustness check, we estimate model (5) using a second-level normalized contiguity weights matrix (with weight reflecting also the neighbours of each unit's neighbours). The main results of our estimations remain unchanged.

[23] See Barca (2006), Boschma and Iammarino (2009) and Lazzaretti *et al*. (2022). Over 2007-22 the *Mezzogiorno* records higher growth of net firm creation in services than the North, (4.1% against 3.3%). Manufacturing firms instead fall less in the South (-11.5% with respect to -12.5%).

5. Conclusion

This paper analyses the resilience patterns of Italian LLMAs over two recent, wide-sweeping, shocks: the Great Recession and the COVID-19 pandemic. For both episodes, it distinguishes between resistance and recovery performance.

We estimate a model that allows for spatial dependence. Results highlight a number of points. First, we find that LLMAs' resilience changes over time: what appears important in the earlier periods often becomes less effective in later ones; also, not always resistance and recovery are affected by the same variables.

The main focus is on the impact of diversification patterns. In this domain we find that relatedness significantly promotes resilience, both in terms of resistance and of recovery; instead unrelated variety appears less important. We also find that the behaviour of neighbouring LLMAs has spatial effects mostly in recovery, producing negative spillovers in 2013-19 and positive ones in 2020-22.

Although the two crises are different in nature, the Great Recession deepening pre-existing local weaknesses while the 2019-20 pandemic possibly concealing them due to State intervention, we find a number of common results for the two episodes. First, the country's general de-industrialization trend is confirmed, coupled with the growing importance of services. We show that what matters for resilience is specialization in traditional, less knowledge-intensive sectors, such as food and beverages, accommodation, call centres and the like. We also show that firms in the *Mezzogiorno* recover better than those located elsewhere in the country. This represents a still largely unexplored phenomenon that, as such, claims further investigation. We tentatively link the good performance of southern LLMAs to the growing importance of traditional low-knowledge services.

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