Resilience, Skill Endowment and Diversity: Evidence from US Metropolitan Areas

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Abstract

By adopting the evolutionary approach to resilience, this paper discusses and empirically investigate the determinants of the ability of region to resist, absorb, and react to recessionary shocks. The recent 2008 Great Recession has extremely affected most of the advanced economies all over the World, leading scholars to study in details how different regions responded to the crisis. The aim of the paper is to contribute this literature analyzing the impact of technological, industrial and human capital composition on the short-term resilience. The empirical analysis is conducted on 295 U.S. Metropolitan Statistical Areas over the period 2008-2014. The main finding is that the most resilient regions are those characterized by a very diversified industrial structure. An excess of technological diversity, on the other hand, seems to thwart the ability to absorb external shocks. Lastly, our results suggest that the local occupational structure matters: a high endowment of high-level abstract skills has a positive correlation with regional resilience, though the moderating effect of technological diversity appears to be negative.

Keywords: regional resilience, human capital, technological diversity, industrial diversity

JEL classification codes: O18, O3, O51, R11

1 Introduction

The recent Great Recession of 2008 has renewed attention toward the analysis of the negative consequences of economic shocks. The crisis has severely impacted the majority of European countries as well as the US. The evolution of average per capita GDP in Metropolitan Areas (MSAs) of the United States (US) shows a period of fast and sustained output growth starting in 2001 until the beginning of the recession, marked by significant drops of GDP in 2008-2009 (Figure 1). The substantial losses in GDP and in employment affected countries and regions all over the word, albeit in an uneven fashion. This has alerted both researchers and policy makers towards the necessity to gain fine-grained understanding of the extent and the reasons behind differential ability to respond to recessionary shocks across regions, or regional resilience. Empirical work identifies various possible determinants of resilience, mainly region-specific characteristics such as the prevailing industrial mix or local innovative capacity. Less attention has been paid to the role of human capital and of the skill endowment of the local workforce.

The main premise of the present paper is that the interplay between skills endowment, technological structure and industrial structure, are key determinants of regional resilience and of the wide variety of outcomes. We contribute this debate by investigating the role of technological, industrial and human capital composition on the short-term resilience in 295 US Metropolitan Statistical Areas (MSAs) during the recent Great Recession. We measure the resilience of MSAs over the period 2008-2014 by quantifying, for each MSA, the difference between the presumed path which regional GDP would have followed in absence of shocks and its actual path (Capello and Lenzi 2016; Fratesi and Perucca 2018). The technological and industrial composition are captured by two novel indicators of diversity. Lastly, we rely on the task-based framework (D. H. Autor, Levy, et al. 2003) to construct measures of the occupational structure as a proxy for the skills endowment.

The present paper contributes the existing literature in several ways. First, we provide a new piece of empirical evidence on the determinants of resilience and the differences in regional response to the recent crisis by investigating simultaneously the role of industrial and technological structure. Further, our study on US Metropolitan Areas contributes a gap in the regional resilience literature that has largely focused on European countries and regions. Third, accounting for skill endowments by looking at the occupational structure, as opposed to reliance on traditional indicators based on the mean level of education, allows us to grasp important qualitative nuances of the dynamics of know-how and learning in local workforce. Moreover, our measure of short-term resilience, together with novel diversity and

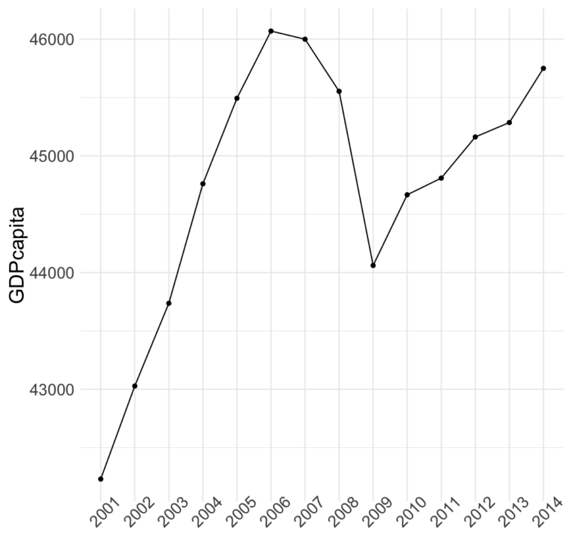


Figure 1: Average annual per capita GDP of US Metropolitan Areas over the period 2001-2014

skill endowment indicators, adds robustness to the empirical analysis allowing us to synthetically capture the different aspect of regional ability to resist, absorb and recover from recessionary shocks.

The main findings of the paper are three. First, regions with more a diversified industrial structure exhibited greater resilience in front of the 2008 crisis. Second, high technological diversity is found to thwart local resilience in the short-run. Third, a higher share of abstract-skilled workers is positively correlated with regional resilience. Interestingly, the interaction between local endowment of abstract skills and technological diversity is negative, signaling that in times of crisis abstract skills enable technological and economic development when the local knowledge base of regions is concentrated around cognitively proximate domains.

The rest of paper is organized as follows. Section 2 reviews the relevant literature on regional resilience and its determinants. The third section presents the data, the construction of the variables and empirical strategy. Results of the empirical analysis and a number of robustness tests are presented in Section 4. Section 5 sums up the main findings and concludes.

2 Theoretical background

2.1 Defining resilience

Although scholars widely contributed to add more clarity, the definition and meaning of the ability to comply with negative shocks, conceptualized with the notion of "regional resilience", has not yet received homogeneous consensus. The literature contemplates three definitions of resilience, each stemming from a different discipline. In engineering studies resilience is understood as capacity of a system, hit by a destabilizing shock, to return to its equilibrium path (Fingleton et al. 2012; Rose 2004). In a similar fashion, the ecological literature defines resilience in term of a system's ability to respond to disturbances by moving to a new steady-state equilibrium while maintaining its existing structure (Reggiani et al. 2002; Swanstrom 2008). The economic geography literature, instead, adopts an evolutionary approach to resilience and focuses on how systems (i.e. regions, countries) absorb and adapt to exogenous shocks in terms of both short-run response as well as long-term capacity to pursue new growth paths (Boschma 2015; Martin 2012; Martin and Sunley 2013). Martin (2012) further identifies four constitutive dimensions of resilience: resistance, recovery, re-orientation and renewal. *Resistance* relates specifically to the vulnerable of a regional economy in face of adverse shock. *Recovery*, instead, describes how fast a regional economy "bounces back" from the shock. Re-*orientation* and *Renewal* regard the extent to which the region changes and "renews" its economic structure after the shock.

2.2 The role of techno-industrial structure

The existing literature on regional resilience has largely explored the existence and the determinants of resilience in local economies, investigating the differences between and within regions and countries. Other than macroeconomic and international factors (Martin and Sunley 2013; Groot et al. 2011), these studies highlighted the importance of region-specific characteristics in shaping the ability of regions to absorb shocks (Martin, Sunley, et al. 2016). Among these sources, the industrial structure and the widely acknowledged trade-off between specialization and diversification has been particularly relevant in regional resilience studies. On one hand, a specialized region, being characterized by the prevalence of one or a few industries, is in principle less vulnerable to sector-specific disturbances. However, a specific sector being hit increases the likelihood of a collapse in the local economy. On the other hand, while diversified regions are more exposed to shocks, as their industrial structure covers a wide range of industries, it is less likely that a sector-specific shock may affect their economy as a whole (Essletzbichler 2007). According to the diversity argument, a diverse industrial structure should allow regional economies to spread the risk of adverse shocks in the short-run, since different industries may exhibit differential dependence on changes in demand, market and financial factors (Belke and Heine 2006; Davies and Tonts 2010). Scholars provided evidence that the shock-absorbing role of diversity may be more effective when the skill profile of local industries is related, and thus facilitates the mobility of workers within the region (Neffke and Henning 2013). Though, some degree of disconnection is desirable, as an excess of input-output and cognitive relationships may favor the transmission of the shock from the original sector trough others (Diodato and Weterings 2015). On these grounds, we put forth the hypothesis that US MSAs with a highly diversified industrial portfolio tend to be more resilient in socio-economic terms in the short-run.

A wide range of studies has extensively explored the role of innovation and technological structure as a determinant of regional growth and competitiveness (Quatraro 2010; Crescenzi and Rodríguez-Pose 2011). Focusing on the renewal and re-orientation dimension of resilience, technological innovation figured prominently in the literature among the fundamental regional-specific factors shaping the ability of regions to absorb shocks. This stream of literature builds on the Schumpeterian tenet that holds innovation as the key driver of long-term economic change by facilitating adaptation in the face of downturns in the business cycle (Schumpeter 1939; Schumpeter 1942). Prior studies have shown that technological innovation enables local economies to branch out of existing economic sectors (Boschma 2015; Kogler et al. 2017), by providing opportunities for new combinations that, generating new growth paths, may ensure regional renewal and reorientation (Boschma 2015). Existing literature suggests that the knowledge recombination in related technologies is crucial for the processes of long-term path creations (Frenken et al. 2007; Boschma, Minondo, et al. 2013). On the other hand, other studies provided evidence that a certain degree of unrelated variety is also critical for long-term adaptability, as it allows regions to access previously unexplored recombinations and generate technological breakthrough (Castaldi et al. 2015; Boschma 2015).

The resistance and recovery dimensions of resilience on the other hand have attracted less attention. Empirical assessments of the role and impact of innovative efforts on regional resilience in the short run are relatively scant (Bristow and Healy 2018). While it is widely acknowledged that regional inventiveness does play a key role among regional resistance factors, the rate and direction of this relationship in the short-run is still an open debate. In an analysis of 2008 pre-crisis structural conditions on EU regions, Crescenzi, Luca, et al. (2016) show that it is not technology-driven innovation per se that enables regional resistance, but rather "a generally innovation-prone environment". Bristow and Healy (2018), on the other hand, find that innovation leaders regions in Europe were more likely to resist the 2008 crisis, though their exploratory analysis shows that there are some notable exceptions to this. Focusing on the determinants of resilience in UK regions, Rocchetta and Mina (2019) found that technological coherence is an important driver of performances during economic crisis, as it can be easier for regions endowed with more coherent knowledge bases to exploit available technological competences and create new growth path.

Regions that diversify in related technology may take advantage of the complementarity of existing skills and know-how, recombining cognitively proximate sources of knowledge, which bear lower costs and uncertainty in innovative outcomes (Rocchetta and Mina 2019). It follows that, during recessions periods, an excess of cognitively distant technological capabilities in the knowledge base may undermine knowledge recombination processes, hampering the learning opportunities and the creation of new successful growth paths. On these grounds, our claim is that regions with highly technologically diversified knowledge bases may be more exposed to negative shocks in the short-run, and thus exhibit lower resilience.

2.3 The role of human capital

In modern economic growth theory, human capital has played a very central role. The knowledge embodied in human capital (particularly in high-skilled workers) represents a major source of a long run growth, made possible by increasing returns to scale (Lucas 1988; Romer 1990). The role of human capital has also been confirmed by the literature on regional growth. As human capital concentrates in regions and great cities, it attracts firms aiming at gaining competitive advantages and creates conditions for knowledge spillovers. In turn, the reduced cost of knowledge transfer allows to generate new knowledge, becoming an engine of local development (Barro 1991; Glaeser 2000).

Notwithstanding the increasing awareness of the importance of human capital in technological and economic development (Nelson and Phelps 1966; Vona and Consoli 2015), the role of skill endowment of the local workforce in relation to regional resilience remains still understudied. In a study on Britain Cities during the 2008 Recession, Lee (2014) founds that cities endowed with more high-skills experienced the smaller increases in unemployment. Similarly, Glaeser (2005) suggests that a strong base of skilled labor force has been crucial for Boston in surviving and reinventing itself after several crisis. In a similar vein, Crescenzi, Luca, et al. (2016) report a positive association between regional human capital and the economic performance of EU regions during the crisis. These contributions indicate that that high skilled workers can more easily switch from declining sector to stable ones as they can more quickly adapt their profiles to comply with new market and technological requirements. Therefore, given their higher adaptability, the prevalence of high skill labor may allow local economic system to adjust more promptly to the changes imposed by a shock. These arguments lead us to hypothesize that Metropolitan Areas endowed with higher shares of high skilled local workforce show stronger resilient capabilities.

3 Data, measures and empirical strategy

To investigate the determinants of regional resilience to the recent financial crash we collect data on patenting, industrial structure, employment and occupational task at the US Metropolitan Statistical Areas (MSA) level. According to the US Office of Management and Budget (OMB, 2010), MSAs are statistical areas "associated with at least one urbanized area that has a population of at least 50,000".[1] The OMB further specifies that MSAs comprises a central county (or counties) and adjacent counties with high degree of economic and social integration (measured through commuting flows). The OMB reviews the standard for delineating the areas every ten years, and constantly revises the delineations to reflect estimates of US Census Bureau population and commuting flows. This implies that the composition and the identification codes of MSA may vary over time. Moreover, some areas may disappear (due to population losses below the reference threshold), while some others may be newly identified. To ensure comparability and consistency of MSAs over time and across different data sources we follow the time-specific composition of each MSA and its relative identification code. To this end, we develop a detailed crosswalk allowing MSAs to be uniquely and coherently identified through their changing county composition. We exclude newly identified areas when their county composition is not clearly identifiable in prior years. Metropolitan Areas which were split into two or more areas by the OMB revisions were again aggregated into a unique MSA. Following this procedure, we identify a total of 295 coherent MSAs.

Information on per capita GDP for each MSA are extracted from the U.S. Bureau of Economic Analysis (BEA). Secondly, to construct our indicators of the occupational structure, we rely on the Occupational Employment Statistics (OES) program from the U.S. Bureau of Labor Statistics (BLS), which provides annual employment data by occupation profiles for MSAs. We make use of the Census Bureau County Business Pattern (CBP) data on U.S. establishments and employment by sector of activity (NAICS codes), and U.S. BEA Input-Output Accounts to measure the industrial diversity. Lastly, we exploit the information contained in the patent doc-

[1] The OMB 2010 report is available at `https://www.govinfo.gov/content/pkg/FR-2010-06-28/pdf/2010-15605.pdf`

ument filed at the USPTO to build our measure of technological diversity.[2]

3.1 Measuring Resilience

In empirical studies, the operationalization of resilience is still an open issue. In fact, the empirical construct has been measured in various ways and using different economic variables. To begin with, resilience can be captured by single and composite indexes (Sensier et al. 2016) or via time series parameters (Cellini and Torrisi 2014; Fingleton et al. 2012; Groot et al. 2011). Concerning the choice of the economic variable, a wide range of empirical studies measured resilience in term of fluctuation in the employment (or unemployment) levels (Fingleton et al. 2012; Martin 2012; Sedita et al. 2017). Others, instead, focused on more a more direct measure of output growth, i.e. real GDP and GDP growth (Cellini and Torrisi 2014). Though, in principle, all these routes are equally feasible, the choice of the "correct" economic variable responds to the specific research interest "and the different choices have pros and cons" (Cellini, Di Caro, et al. 2017; Di Caro 2015).

In this paper we use the annual real per capita GDP to build a novel indicator of resilience. We believe that the use of a direct output measure better suites our explanatory mechanisms of the short-term regional capacity to withstand recessionary shocks. Similar to Fratesi and Perucca (2018), our measure of resilience is based on the comparison between the presumed regional growth path in absence of crisis and the actual path. As a first step, using the data series from 2001 to 2007, we estimated the annual expected per capita GDP series for the period 2008-2014. The forecast is performed through the estimation of an ARIMA individually modeled for each MSA in order to take into account the spatial difference between the regions. In the forecast, we also include the average level of US per capita GDP to control for country specific patterns. Then, the indicator of resilience for each MSA is given by the annual difference between the actual (log) GDP level and the forecasted (log) GDP. A negative value of the index means that the region is experiencing a period of crisis as its actual output is well below the level which would have reached in the absence of a shock. On the contrary, when the difference between the actual and the forecasted value shrinks it may signal that, not only the region is strongly resistant to the crisis, but also that — if the index turns positive — it is absorbing and positively reacting to the shock, growing more than what would be expected. Figure 2 gives a visual illustration of the construction of our resilience measure. It shows the actual per capita GDP series from 2001 to 2014

[2] We are very grateful to Dieter Kogler and the UCD Spatial Dynamic Lab, Dublin for providing us the fully regionalized USPTO patent dataset

compared to its forecast over the period 2008-2014, in two MSAs. Figure 2a presents the case of Boston-Cambridge-Newton metropolitan area. Until the 2007, the area experienced a period of accelerated growth in terms of GDP, which is well captured by the estimated presumed path, that shows an almost constant increasing trend. However, the actual series highlights that the Boston area has been hit by the crisis between 2008 and 2009, then showing a modest growth until 2014 although it is well below the presumed path. On the contrary, the Pittsburgh metropolitan area (figure 2b) shows instead a sustained GDP growth after the 2009, reaching levels well above those presumed by the pre-crises trend. Therefore, according to our measure, areas like Pittsburgh have been highly resilient to the shock compared to others like Boston. Our claim is that measuring the resilience through the yearly difference by actual and presumed growth path has the advantage of incorporating different aspects of resilience, that could not be captured by other measures, still being synthetic and econometrically sound.

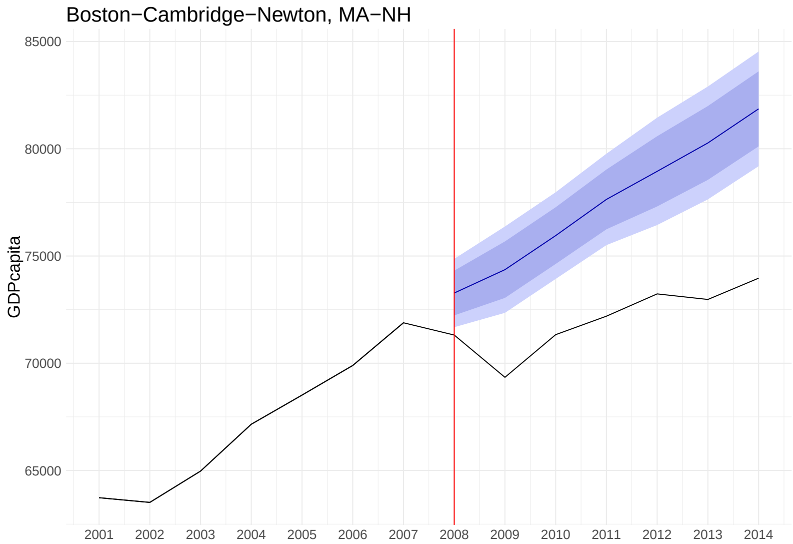
3.2 Technological and Industrial Diversity

The first two key explanatory variables aim at capturing the degree of diversity in the industrial composition and in the technological structure in US Metropolitan Areas. The concept of diversity has been operationalized in different way and by complementary measures. Other than the Simpson diversity,[3] a widely used index is the technological variety, related or unrelated. Computed by using the information entropy index (Shannon 1948), variety measures the extent of diversification in the knowledge base, within technological areas – Related Variety (RU) – and across all the technologies – Unrelated Variety (UV) (Frenken et al. 2007).[4]

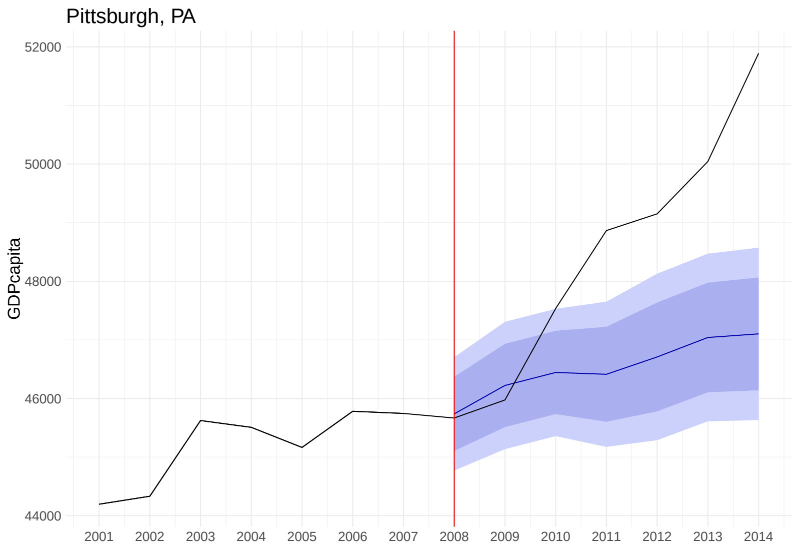
Recent advances in the field of Science and Interdisciplinarity, highlighted the importance of considering the intrinsic difference between knowledge components in constructing diversity indexes. According to the framework proposed by Rafols and Meyer (2010), diversity which "describes the difference in the bodies of knowledge that are integrated" (Rafols 2014), can be characterized by three distinct attributes: i) the number of distinct categories into which element can be classified, i.e. *variety*; ii) the evenness of the distribution of the elements across the categories, i.e. *balance*; iii) the degree of difference between the categories, i.e. *disparity.* Thus, an increase in diversity can be determined by an increase in each one of the above attributes. For

[3]The Simpson diversity is defined as the complement of the Herfindahl-Hirschman concentration index.

[4]The concept of variety, related and unrelated, has been mainly used to characterize sectoral or regional knowledge structure (Boschma, Minondo, et al. 2012; Content and Frenken 2016; Quatraro 2010)



(a) Boston-Cambridge-Newton, MA-NH



(b) Pittsburgh, PA

Figure 2: Actual (black line) and forecasted (blue line) annual per capita GDP series in two MSAs during the period 2001-2012. Shaded areas around the forecast represent the ARIMA estimation confidence intervals

example, the diversity in a patent increases with the number of distinct technological classes to which it is assigned to, with a more balanced distribution of the classes, but also with a higher difference (distance) between those technologies. Although the decomposition into related and unrelated allows the variety index to partly take into account disparity, by defining to sets with different disparity (Krafft et al. 2011), the entropy index better account for the number of distinct categories and the evenness of the distribution (Stirling 2007). To account for the disparity attribute, Stirling (2007) proposed an integrated measure of diversity which weights the distributions of the elements across categories by their cognitive distance. The Rao-Stirling index (or Integration Score) has been first proposed by Rao (1982) and it has been recently used in empirical studies on knowledge integration and interdisciplinarity (Rafols 2014).

In its simplest formulation, the index is given by:

$$\Delta_a = \sum_{i,j(i \neq j)} p_i p_j d_{ij} \tag{1}$$

where p_i and p_j are the proportion of element i and element j, respectively, and $d_i j$ is the cognitive distance between the two. Thus, it can be interpreted as the average cognitive distance between system's elements.

The variable capturing technological diversity is defined on the basis of the patenting activity that took place within the MSAs. The regionalized patents database is used in order to obtain a set of patents applications in each year for each MSA.[5] Then, we exploit the information contained in the patent document about the technological classification. Therein, each patent is associated with at least one (or usually more) technological class indicating the subject to which the invention relates. In this paper we choose to use the technological subclass of the Cooperative Patent Classification (CPC)[6] at the 4-digit level (CPC-4). Since in our case the unit of analysis is the regions (MSAs), the elements in the Stirling index are represented by technological classes to which a patent is assigned (co-classification). Thus, the technological diversity of the MSA a in a given year equals the relative proportion of 4-digit CPC classes within the patents developed in the MSA, weighted by their cognitive distance. As a measure of cognitive distance, we used the comple-

[5]Information on how patents have been assigned to the MSA and further details are presented in Boschma, Balland, et al. (2015)

[6]The CPC is a new patent classification system, jointly developed by the European Patent Office (EPO) and United States Patents and Trademark Office (USPTO). Based on the European classification system (ECLA), it is a more detailed version of the International Patent Classification (IPC).

ment of technological proximity computed by applying the cosine similarity to the symmetric co-occurrence matrix between CPC classes of all the patents applied to USPTO (from 1977).

The construction of the Rao-Stirling index for industrial diversity is based on the sectoral distribution of establishments. Using CBP data, we counted the yearly number of establishments in each industrial sector by MSA.[7] Thus, the industrial diversity is given by relative proportion of establishments among sectors, weighted by the cognitive distance between industries. Similar to the technological distance, we use the complement of industrial proximity as a proxy of cognitive distance between sectors. Following Los (2000) proximity is derived from the national Input-Output tables provided by US BEA. Industrial proximity between each pair of industries is given by the similarity of inputs purchased by two given industries from any other industry (cosine similarity).

The diversity index, by construction, ranges in the interval $[0, 1]$, with a value of 0 indicating a maximum concentration in the technological/industrial composition and a value of 1 when the region technological/industrial structure is perfectly diversified between technologies/sectors having the maximum cognitive distance.

3.3 Skill Endowment

To construct our proxy of the role of human capital and skill endowment in regional labor markets, we adopt the task-based framework proposed by D. H. Autor, Levy, et al. (2003) and its recent extension to the geographical level by D. H. Autor and Dorn (2013). The rationale behind the task-based framework s that occupations are vectors of tasks and of the matching know-how, or skills, that workers need to perform them (D. H. Autor, Levy, et al. 2003). By focusing on the connection between tasks and skills, rather than education-based proxies, this approach characterizes the configuration of occupations in terms of individual characteristics and allows capturing qualitative nuances in the local knowledge base (Consoli and Rentocchini 2015; Vona and Consoli 2015).

Following D. H. Autor, Levy, et al. (2003) work tasks are divided into three broad categories. First, we find tasks which require creativity, intuition, problem-solving and persuasion. Typical of professional, managerial, technical and creative occupations — such as law, medicine, science, engineering, marketing and design —, these so-called abstract tasks are performed by workers possessing high levels of education and analytical capabilities. On the other side of the occupational skill

[7] To be consistent with the industrial sectors identified in the Input-Output matrices we converted NAICS industrial codes to Input-Output sectors using tables provided by US BEA. A total 71 different industrial sectors have been identified.

spectrum are manual tasks, which require innate abilities like dexterity, sightedness, and language recognition and demand situational adaptability, visual and language recognition, and in-person interaction. The third broad task category consists of many middle-skilled cognitive and production activities, such as clerical work and repetitive production tasks. Routine tasks can be carried out by comparatively less-educated workers, requiring minimal worker discretion and the execution of precise codified instructions.

Constructing empirical measures of abstract, routine and manual task content by occupation-MSA entails a number of steps. First, indicators of task-intensity by occupation are created, merging job task requirements from the fourth edition of the US Department of Labor's Dictionary of Occupational Titles (DOT) (US Department of Labor 1977) to their corresponding Census occupation classification (D. H. Autor and Dorn 2013; D. H. Autor, Levy, et al. 2003; Dorn 2009). Then, task intensities are used to identify occupations as either abstract-, routine- or manual-intense. To perform this step we exploited the crosswalk provided by Acemoglu and D. Autor (2011), which directly map occupations from 2-digit SOC (Standard Occupational Classification) with the corresponding task intensity. Next, using the employment by occupation data from OES BLS, we calculate a task employment share for each MSA as follows:

$$ASH_{it} = \left(\sum_{j=1}^{J} L_{jit} 1\left[ATI_j\right]\right)\left(\sum_{j=1}^{J} L_{jit}\right)^{-1} \tag{2}$$

$$RSH_{it} = \left(\sum_{j=1}^{J} L_{jit} 1\left[RTI_j\right]\right)\left(\sum_{j=1}^{J} L_{jit}\right)^{-1} \tag{3}$$

$$MSH_{it} = \left(\sum_{j=1}^{J} L_{jit} 1\left[MTI_j\right]\right)\left(\sum_{j=1}^{J} L_{jit}\right)^{-1} \tag{4}$$

where ASH_{it}, RSH_{it} and MSH_{it} represent, respectively, the abstract, routine and manual employment share in MSA i at time t; L_{jit} is the employment in occupation j in MSA i at time t; 1 is an indicator function taking value 1 if the occupation is task intense (ATI_j for abstract intense occupation, RTI_j for routine and MTI_j for manual).

Table 1: Summary statistics of data

Statistic	N	Mean	St. Dev.	Min	Max
Resilience	2,065	−0.1010	0.1163	−0.6710	1.2171
Technological Diversity	2,065	0.6092	0.1514	0	1
Industrial Diversity	2,065	0.8948	0.0042	0.8776	0.9093
Share Abstract Skill	2,065	0.1940	0.0409	0.0830	0.3756
Share Routine Skill	2,065	0.3032	0.0351	0.1966	0.4493
Share of Manufacturing	2,065	0.0412	0.0159	0.0123	0.1640
Share of Finance	2,065	0.0403	0.0233	0.0000	0.3187
Patents Stock per capita	2,065	0.3410	0.4266	0.0000	4.7872

3.4 Descriptive Statistics

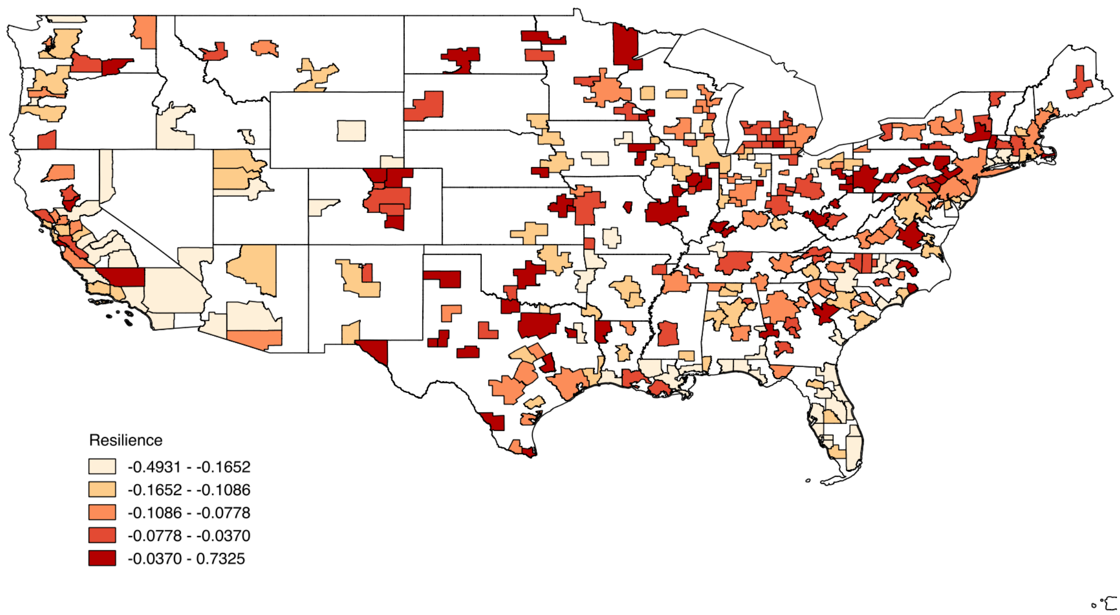
Descriptive statistics of the variables of interest are reported in Table 1. Figures 3,4 and 5 offer a graphical visualization of the geographical distribution over MSAs of our resilience measure and the three main explanatory variables: technological diversity, industrial diversity and local skill composition. Metropolitan Areas boundaries as well as State boundaries are outlined in black, while MSAs are colored according to the quintile rank of the distribution, where darker colors indicate higher quintiles. Figure 3 presents the geographical distribution of our dependent variable over the period 2008-2014. The figure confirms that the effect of the crisis on regional economies as well as their ability to react has been quite heterogeneous across MSAs. West coast and the North East seem to have had relatively better resilience performances, as the North Texas, Colorado and lakeside MSAs.

The distribution of pre-crisis technological diversity in Figure 4 panel 4a, shows that highly diversified inventive activities are more concentrated in coastal areas of North East, California and Florida. The geographic distribution of industrial diversity in Figure 4 panel 4b is more homogeneous and only slightly overlapping with the technological diversity. It shows high concentration in areas with high density and areas that heavily relies on industrial activities. This pattern resonates with the quintile geographic distribution of routine-intensive occupations in Figure 5b. Panel 5c refers, instead, to the distribution of manual-intensive occupations. Interestingly, there seems to be a substantial overlap between the geographic distribution of abstract employment share and of technological diversity.

3.5 Empirical Strategy

To investigate the effect of industrial and technological diversity on the regional ability to absorb the 2008 Great Recession, we estimate the following model for 295

Figure 3: Geographic distribution of average resilience across MSAs, 2008-2014 (quintiles)



U.S. Metropolitan Areas from 2008 to 2014:

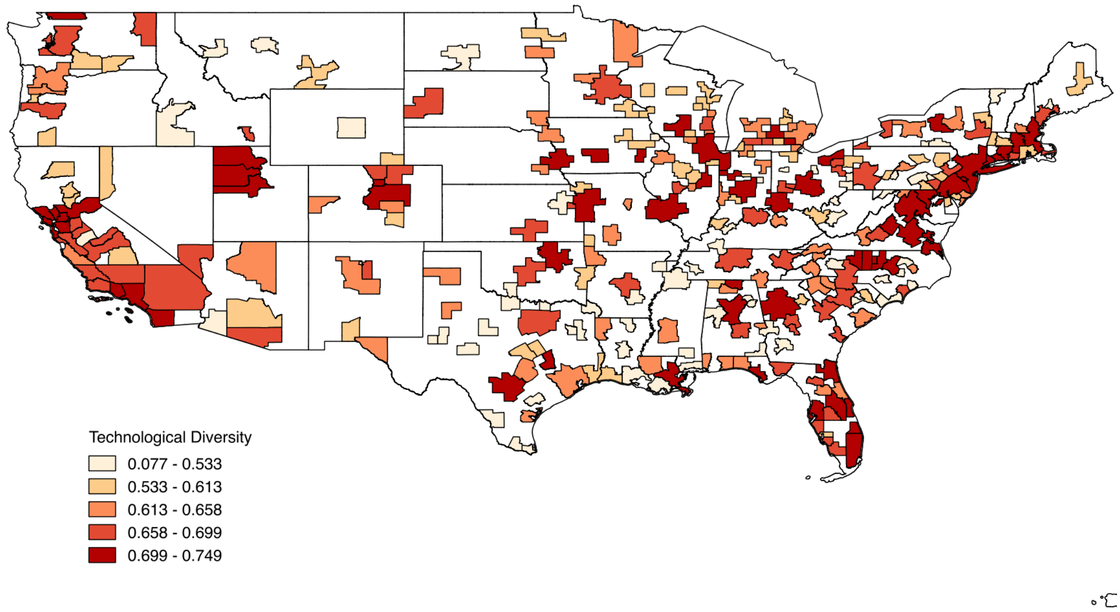
$$R_{it} = \alpha + \beta_1 I_{it-1} + \beta_2 T_{it-1} + \beta_3 HC_{it-1} + \beta_4 \Phi_{it-1} + \epsilon_{it} \tag{5}$$

where R_{it} is our GDP-based resilience indicator in MSA i at time t; I_{it-1} is the industrial diversity of MSA i at time $t-1$; T_{it-1} is the technological diversity of MSA i measured at time $t-1$; HC_{it-1} is a vector including our task employment shares: ASH_{it-1} and RSH_{it-1},representing respectively the abstract employment share and the routine employment share in MSA i at time $t-1$.[8] Φ_{it-1} comprises controls for local factors, measured at time $t-1$, that may affect the ability of an MSA to resist and react to the crisis, including the share of firms operating in the manufacturing sector, the share of employment in finance-related occupations and the stock of patents per capita and the MSA per capita GDP to control for Solow-style convergence ; ϵ_{it} is the error term.

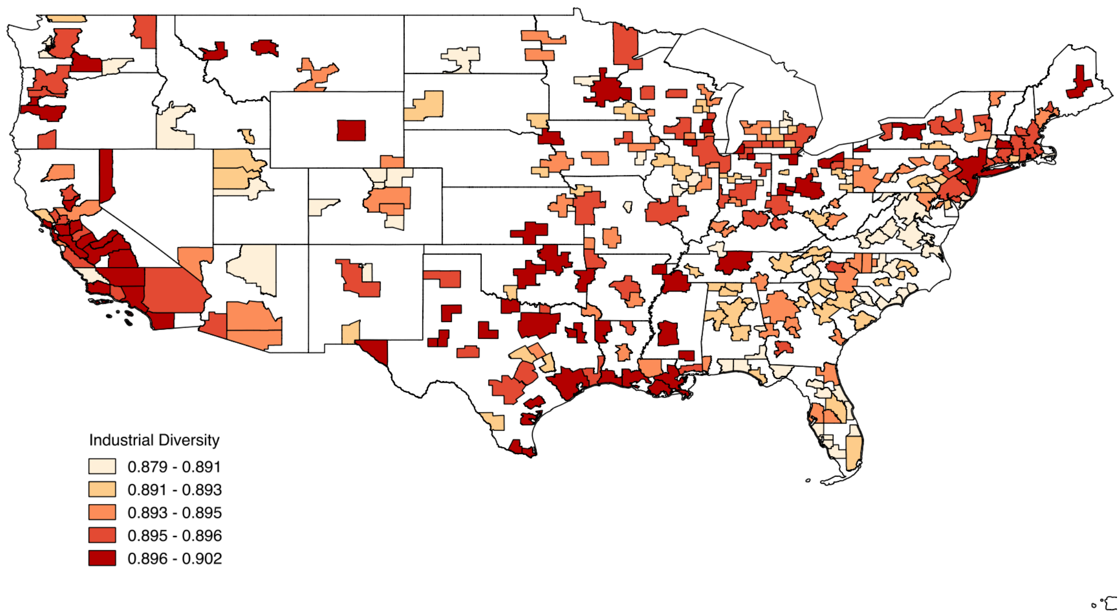
To test for the moderating effect of local skill endowment in MSAs on regional resilience we augment the previous model by estimating the following complete model:

[8] The share of employment in manual jobs (MSH_{it-1}) is used as reference category

Figure 4: Geographic distribution of average technological and industrial diversity across MSAs, 2001-2007 (quintiles

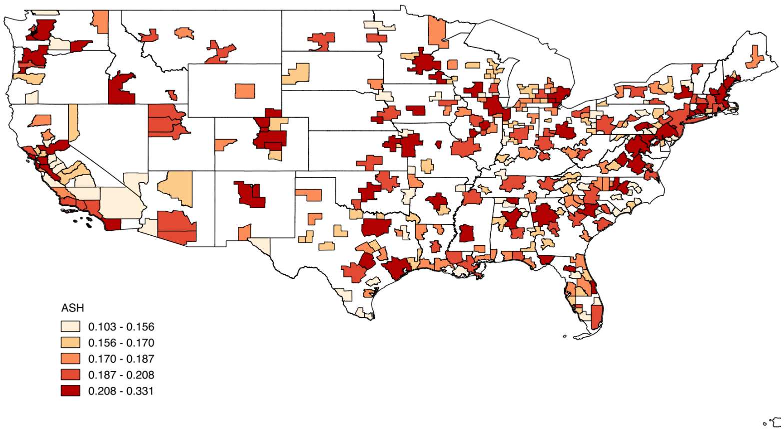


(a) Technological Diversity

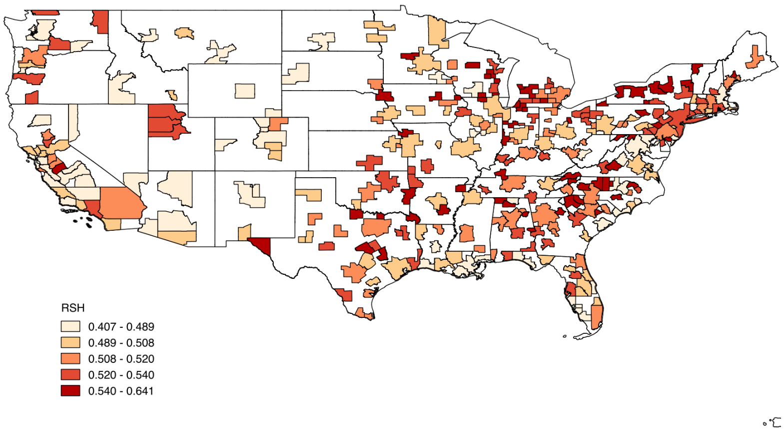


(b) Industrial Diversity

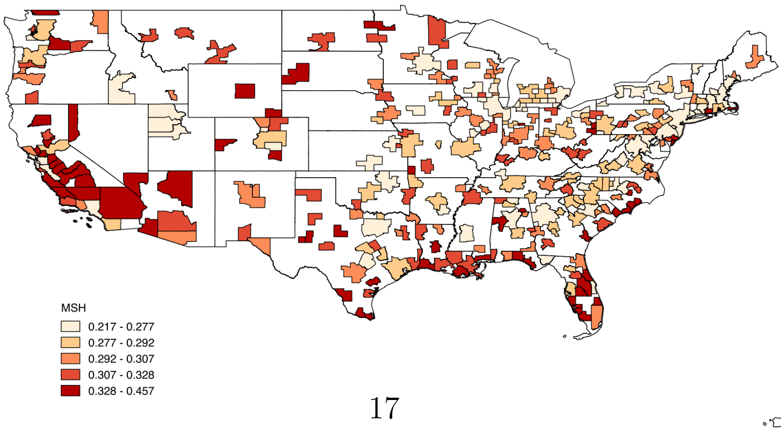
Figure 5: Geographic distribution of average abstract, routine and manual employment shares across MSAs, 2001-2007 (quintiles



(a) Abstract Employment Share



(b) Routine Employment Share



(c) Manual Employment Share

$$R_{it} = \alpha + \beta_1 I_{it-1} + \beta_2 T_{it-1} + \beta_3 HC_{it-1} + \beta_4 I_{it-1} * ASH_{it-1} + \Phi_{it-1} + \epsilon_{it} \qquad (6)$$

where $I_{it-1} * ASH_{it-1}$ represent the interaction term between the endowment of abstract skilled workers and the technological diversity. In all models we control for demographic heterogeneity by weighting each variable for the corresponding MSA population density, where independent variables are log transformed to ease the interpretation of results. Estimations are performed via year and State level fixed effect panel regressions with heteroskedastic-robust standard errors clustered at the MSA level to control for possible spatial correlation across MSAs.

4 Results

This section presents the result of the econometric analysis on the relationship between local structural characteristics – i.e. technological, industrial and occupational composition – and short-term resilience of US Metropolitan Areas. Table 2 reports estimates of equations 5 and 6. Column 1 shows the effect of our main explanatory variables controlling for the convergence term, while column 2 and 3 gradually include the vector of controls and the interaction term to test for moderating effect of the abstract employment share on technological diversity. All the models include year and state fixed effect.

We find a strong positive and significant association between industrial diversity and regional resilience during the 2008 crisis. On the contrary, the coefficient of technological diversity, while highly significant, is negative. Concerning the local skill composition, results show that the coefficient of abstract share (ASH) is positive and significant, signalling that a higher endowment of high-skilled workers is a positive predictor of regional resilience. Precisely, an increase of 1% in the share of abstract skilled workers is associated with about a 0.13% decrease in the difference between the presumed growth path and the actual one. Conversely, the association with routine skill is positive but statistically weaker (10% significance level).

These results hold when additional controls are included to the model (Column 2). As expected, regions with higher prevalence of manufacturing performed worse during the crisis. Further, the local innovative performances, as measured by the stock of total patents per capita, is highly positive and significant across all specifications. A 1% increase in the innovative performances is associated with an higher resilience of around 0.07%. Lastly, when controlling for share of employment in financial-related services, the coefficient of abstract employment share decreases in magnitude, though the prevalence of financial services does not have a significant effect.

The last column of Table 2 reports the results of the full model, estimating the moderating effect of local endowment of abstract-skilled workforce on the relation between technological diversity and resilience. The interaction term shows a negative and significant sign. All the other coefficients retain their significance and sign. To better disentangle the behavior of the interaction term, we report in Figure 6 a heat map of predicted values of our dependent variable for combinations of abstract employment share and technological diversity (left panel). The right panel, instead, shows the areas of significance for those predictions. As we can see, a prevalence of abstract skill is associated with increasing resilience (indicated by lighter colors). However, this positive effect strongly depends on the degree of technological diversification within the MSA. For example, high technological diversity is associated with higher resilience only for middle-low shares of abstract skill. These results highlight the crucial importance of human capital to short-term regional resilience. In line with recent research, while highly technologically diversified cities may suffer excessively the short-term adverse effect of a negative shock, abundance of high-skill workers, associated with a broadly innovation-prone environment, provides propitious premises for resilience (Crescenzi, Luca, et al. 2016).

4.1 Robustness

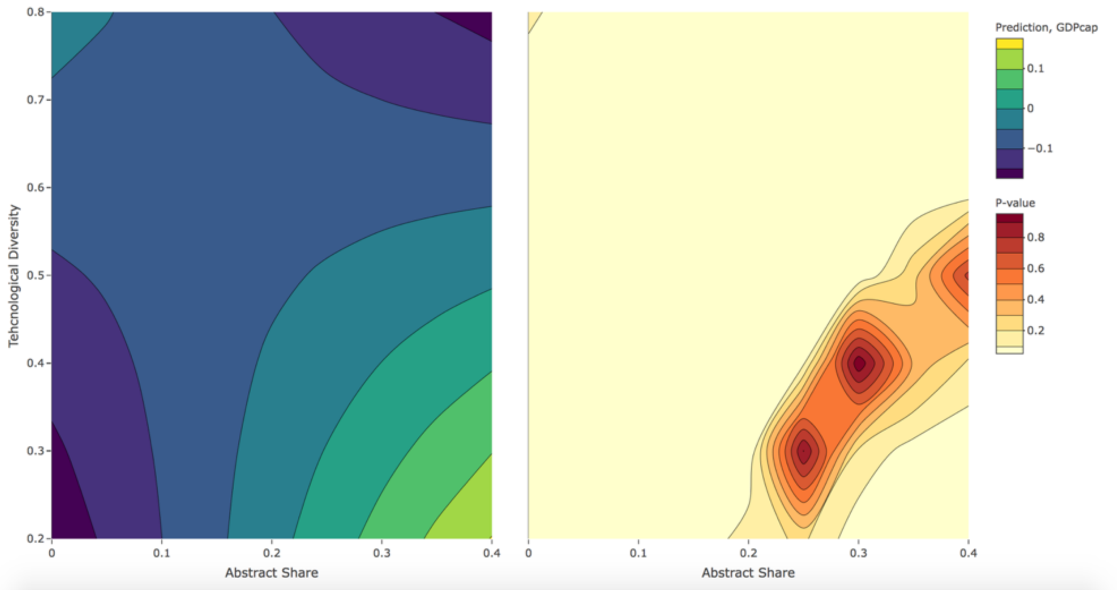
To test the robustness of the modelling strategy we perform the main estimations by using alternative measures of our main explanatory variables. Firstly, we include in the model specification a new measure of technological diversification. Column 1 and 2 of Table 3 presents the results of the estimation using the Shannon Entropy index, which validate our previous results. The Entropy index has negative and significant coefficient, while the industrial diversity and abstract employment share are still significant. When the interaction term is included (column 2), the moderating effect of abstract skills on (Entropy) technological diversity is negative and significant as in the previous estimations. Column 3 and 4 report the results of the same specifications including the ratio of Unrelated Variety over Related Variety. Both the coefficient of the ratio and the interaction term are positive and significant. The ratio is a measure of the relative importance of Unrelated variety with respect to Related variety. On the whole, these results suggest that diversification across

Table 2: Regression results of techno-industrial diversity and local skill composition on the resilience of US Metropolitan areas during the period 2008-2014

	Dependent variable:		
	Resilience		
	(1)	(2)	(3)
Tech Div	-0.0376^{***}	-0.0333^{***}	-0.2532^{***}
	(0.0100)	(0.0096)	(0.0671)
Ind Div	0.5114^{***}	0.6503^{***}	0.6582^{***}
	(0.1348)	(0.1406)	(0.1403)
ASH	0.1346^{***}	0.0719^{***}	0.2020^{***}
	(0.0251)	(0.0269)	(0.0458)
RSH	0.0874^{*}	0.0947^{*}	0.0704
	(0.0493)	(0.0554)	(0.0567)
GDPf	-0.0871^{***}	-0.0908^{***}	-0.0900^{***}
	(0.0113)	(0.0110)	(0.0109)
Tech Div*ASH			-0.1260^{***}
			(0.0386)
Share Manuf		-0.5107^{**}	-0.5945^{**}
		(0.2588)	(0.2593)
Share Finance		0.1564	0.1848
		(0.1194)	(0.1182)
Stock Patents pc		0.0676^{***}	0.0664^{***}
		(0.0142)	(0.0139)
Constant	0.1827	-0.1698	-0.0015
	(0.3304)	(0.3297)	(0.3377)
Year Effects	Yes	Yes	Yes
State Effects	Yes	Yes	Yes
Observations	2,065	2,065	2,065
R^2	0.4690	0.4768	0.4793
Adjusted R^2	0.4528	0.4600	0.4624
F Statistic	29.0025^{***}	28.4737^{***}	28.3094^{***}

Cluster-robust standard errors in parentheses
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Figure 6: Heat Map of Regression Predictions Left graph: predicted value of the dependent variable, lighter color indicates higher values. Right graph: significance level of predictions



technologically distant domains of know-how can be an important driver of short-term resilience. At the same time, to a certain extent specialized knowledge is required in order to allow regional economies to exploit recombination possibilities and develop creative solutions to react to the shock.

As a second robustness check we repeat the estimation using the complement of the Herfindahl-Hirschman concentration Index (Simpson diversity index) as a new measure of industrial diversity. The results are reported in Table 4 and fully confirm our previous findings.

Lastly, as a further robustness check we include an alternative measure of the local skill composition. We follow D. H. Autor, Levy, et al. (2003) and D. H. Autor and Dorn (2013) to match job task requirements to occupations. Next, occupations in the top employment-weighted third of task intensity are identified as either abstract-, routine- or manual intensive occupations. Then, task employment share for each MSA are calculated as in formula 2,3 and 4. Results, reported in Table 5 validate our approach and previous results.

5 Conclusion

This paper has analyzed the association between local economic structure and regional resilience. Relying on economic geography we investigate how the diversity in industrial composition and in technological structure correlate with differential

Table 3: Regression results of entropy based technological diversity on the resilience of US Metropolitan areas during the period 2008-2014

	Dependent variable:			
	Resilience			
	(1)	(2)	(3)	(4)
Entropy	-0.0064^{**}	-0.1247^{***}		
	(0.0028)	(0.0191)		
UV/RV			0.0015	0.0543^{***}
			(0.0011)	(0.0131)
Ind Div	0.6634^{***}	0.7347^{***}	0.6409^{***}	0.6668^{***}
	(0.1432)	(0.1447)	(0.1395)	(0.1409)
ASH	0.0715^{***}	0.3152^{***}	0.0589^{**}	0.0005
	(0.0272)	(0.0478)	(0.0258)	(0.0286)
RSH	0.1014^{*}	0.0793	0.0928^{*}	0.0871
	(0.0562)	(0.0551)	(0.0551)	(0.0544)
GDPf	-0.0911^{***}	-0.0902^{***}	-0.0934^{***}	-0.0918^{***}
	(0.0112)	(0.0109)	(0.0108)	(0.0108)
Entropy * ASH		-0.0688^{***}		
		(0.0110)		
UV/RV * ASH				0.0285^{***}
				(0.0069)
Share Manufacturing	-0.4093	-0.5409^{**}	-0.4896^{*}	-0.5363^{**}
	(0.2704)	(0.2646)	(0.2604)	(0.2588)
Share Finance	0.1431	0.2024^{*}	0.1207	0.1476
	(0.1194)	(0.1152)	(0.1223)	(0.1199)
Patents Stock pc	0.0710^{***}	0.0707^{***}	0.0720^{***}	0.0808^{***}
	(0.0142)	(0.0137)	(0.0144)	(0.0149)
Constant	-0.1984	0.0240	-0.1745	-0.3645
	(0.3345)	(0.3231)	(0.3310)	(0.3471)
Year Effects	Yes	Yes	Yes	Yes
State Effects	Yes	Yes	Yes	Yes
Observations	2,037	2,037	2,037	2,037
R^2	0.4754	0.4846	0.4742	0.4779
Adjusted R^2	0.4584	0.4676	0.4572	0.4607
F Statistic	27.9265^{***}	28.5110^{***}	27.7941^{***}	27.7548^{***}

Cluster-robust standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Table 4: Regression results of Simpson index of industrial diversity on the resilience of US Metropolitan areas during the period 2008-2014

	Dependent variable:	
	Resilience	
	(1)	(2)
Tech Div	-0.0523^{***}	0.0465
	(0.0094)	(0.0441)
Ind Div (Simpson index)	0.4014^{***}	0.3921^{***}
	(0.0481)	(0.0809)
ASH	0.2595^{*}	0.9339^{***}
	(0.1344)	(0.3012)
RSH	0.2208	0.1649
	(0.1402)	(0.2390)
GDPf	-0.1011^{***}	-0.1008^{***}
	(0.0077)	(0.0103)
Tech Div * ASH		-0.6052^{**}
		(0.2493)
Share Manufacturing	-0.5788^{***}	-0.5972^{**}
	(0.2023)	(0.2640)
Share Finance	0.0981	0.1242
	(0.1224)	(0.1206)
Patents Stock pc	0.0645^{***}	0.0618^{***}
	(0.0132)	(0.0145)
Constant	0.1034	0.0208
	(0.1827)	(0.2722)
Year Effects	Yes	Yes
State Effects	Yes	Yes
Observations	2,065	2,065
R^2	0.4772	0.4787
Adjusted R^2	0.4605	0.4617
F Statistic	28.5223^{***}	28.2376^{***}

Cluster-robust standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

Table 5: Regression results of D. H. Autor and Dorn (2013) based skill configuration on the resilience of US Metropolitan areas during the period 2008-2014

	Dependent variable:		
	Resilience		
	(1)	(2)	(3)
Tech Div	−0.0342***	−0.0295***	−0.3250***
	(0.0100)	(0.0098)	(0.1050)
Ind Div	0.5405***	0.6613***	0.6807***
	(0.1217)	(0.1312)	(0.1313)
ASH (Autor, D. et al. 2013)	0.5982***	0.4062**	1.3613***
	(0.1927)	(0.1992)	(0.3509)
RSH (Autor, D. et al. 2013)	−0.4770***	0.0500	0.1103
	(0.1647)	(0.1845)	(0.1844)
MSH (Autor, D. et al. 2013)	−0.1561	0.2161	0.1695
	(0.1481)	(0.1725)	(0.1721)
GDPf	−0.0769***	−0.0829***	−0.0818***
	(0.0102)	(0.0108)	(0.0108)
Tech Div*ASH			−0.9381***
			(0.2809)
Share Manuf		−0.7653***	−0.7922***
		(0.2827)	(0.2810)
Share Finance		0.0606	0.1001
		(0.1361)	(0.1338)
Patents Stock pc		0.0756***	0.0763***
		(0.0152)	(0.0150)
Constant	−0.3718	−0.7249**	−1.1489***
	(0.3375)	(0.3636)	(0.3957)
Year Effects	Yes	Yes	Yes
State Effects	Yes	Yes	Yes
Observations	2,065	2,065	2,065
R^2	0.4661	0.4753	0.4779
Adjusted R^2	0.4496	0.4583	0.4606
Residual Std. Error	0.8621	0.8553	0.8534
F Statistic	28.1941***	27.8602***	27.7046***

Cluster-robust standard errors in parentheses *p<0.1; **p<0.05; ***p<0.01

ability to absorb and recover from recessionary shocks across regions. The paper marks an important difference from existing literature by including in the analysis the role of human capital, and in particular the configuration of the skills in the local workforce. The analysis has been conducted at the territorial level of US Metropolitan Areas, thus enriching the literature on territorial heterogeneity in response to economic crisis, mainly circumscribed at the European level.

Our first result supports the diversification as a "shock absorber" argument. In fact, we found that industrial diversity exerts a positive impact on resilience. MSAs characterized by a diversified industrial structure, in which economic activities are widely distributed across industries, even those cognitively less related, show the better performances in terms of resilience. This means that the wide range of industries allowed the region to better absorb the shock by spreading the negative impact. However, our results suggest that the diversification argument does not hold when the technological configuration is accounted for. Our interpretation is that an excess of diversity in the regional technological base under adverse conditions may thwart the returns or recombination of cognitively distant pieces of knowledge. In other words, in the short-run it may be difficult for technologically diversified regions to develop new growth path to withstand the recessionary shock.

The configuration of local skills endowment plays also an important role. In particular, the endowment of high-level abstract skills is positively associated with regional resilience, meaning that these workers are more effective in adapting and relocating, and triggering new forms of localized demand to sustain the economy. Nevertheless, according to our results, the moderating effect of the latter on the technological diversity is negative. A possible interpretation is that abstract skills enable technological and economic development mostly in the short-run, when the knowledge base of regions is concentrated around cognitively proximate technologies.

References

Acemoglu, D. and D. Autor (2011). *Skills, tasks and technologies: Implications for employment and earnings.*

Autor, D. H. and D. Dorn (2013). "The growth of low-skill service jobs and the polarization of the US Labor Market". In: *American Economic Review* 103.5, pp. 1553–1597.

Autor, D. H., F. Levy, and R. J. Murnane (2003). "The skill content of recent technological change: An empirical exploration". In: *Quarterly Journal of Economics* 118.4, pp. 1279–1333.

Barro, R. J. (1991). “Economic Growth in a Cross-section of Nations”. In: *Quarterly Journal of Economics* 106, pp. 407–443.

Belke, A. and J. M. Heine (2006). “Specialisation patterns and the synchronicity of regional employment cycles in Europe”. In: *International Economics and Economic Policy* 3.2, pp. 91–104.

Boschma, R. (2015). “Towards an Evolutionary Perspective on Regional Resilience”. In: *Regional Studies* 49.5, pp. 733–751.

Boschma, R., P. A. Balland, and D. F. Kogler (2015). “Relatedness and technological change in cities: The rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010”. In: *Industrial and Corporate Change* 24.1, pp. 223–250.

Boschma, R., A. Minondo, and M. Navarro (2012). “Related variety and regional growth in Spain”. In: *Papers in Regional Science* 91.2, pp. 241–256.

— (2013). “The Emergence of New Industries at the Regional Level in Spain: A Proximity Approach Based on Product Relatedness”. In: *Economic Geography* 89.1, pp. 29–51.

Bristow, G. and A. Healy (2018). “Innovation and regional economic resilience: an exploratory analysis”. In: *Annals of Regional Science*. Vol. 60. 2, pp. 265–284.

Capello, R. and C. Lenzi (2016). “Relevance and utility of European Union research, technological development and innovation policies for a smart growth”. In: *Environment and Planning C: Government and Policy* 34.1, pp. 52–72.

Castaldi, C., K. Frenken, and B. Los (2015). “Related Variety, Unrelated Variety and Technological Breakthroughs: An analysis of US State-Level Patenting”. In: *Regional Studies* 49.5, pp. 767–781.

Cellini, R., P. Di Caro, and G. Torrisi (2017). “Regional resilience in Italy: do employment and income tell the same story”. In: *Handbook of Regions and Competitiveness: Contemporary Theories and Perspectives on Economic Development*, p. 308.

Cellini, R. and G. Torrisi (2014). “Regional Resilience in Italy: A Very Long-Run Analysis”. In: *Regional Studies* 48.11, pp. 1779–1796.

Consoli, D. and F. Rentocchini (2015). “A taxonomy of multi-industry labour force skills”. In: *Research Policy*. Vol. 44. 5, pp. 1116–1132.

Content, J. and K. Frenken (2016). “Related variety and economic development: a literature review”. In: *European Planning Studies* 24.12, pp. 2097–2112.

Crescenzi, R., D. Luca, and S. Milio (2016). “The geography of the economic crisis in Europe: National macroeconomic conditions, regional structural factors and short-term economic performance”. In: *Cambridge Journal of Regions, Economy and Society* 9.1, pp. 13–32.

Crescenzi, R. and A. Rodríguez-Pose (2011). "Theoretical framework: A spatial perspective on innovation and the genesis of regional growth". In: *Advances in Spatial Science*. Vol. 67, pp. 9–29.

Davies, A. and M. Tonts (2010). "Economic diversity and regional socioeconomic performance: An empirical analysis of the Western Australian grain belt". In: *Geographical Research* 48.3, pp. 223–234.

Di Caro, P. (2015). "Recessions, recoveries and regional resilience: Evidence on Italy". In: *Cambridge Journal of Regions, Economy and Society* 8.2, pp. 273–291.

Diodato, D. and A. B. Weterings (2015). "The resilience of regional labour markets to economic shocks: Exploring the role of interactions among firms and workers". In: *Journal of Economic Geography* 15.4, pp. 723–742.

Dorn, D. (2009). "Essays on Inequality, Spatial Interaction, and the Demand for Skills". In: *Dissertation no. 3613, University of St. Gallen* 3613, pp. 1–150.

Essletzbichler, J. (2007). "Diversity, Stability and Regional Growth in the United States, 1975–2002". In: *Applied Evolutionary Economics and Economic Geography*. Edward Elgar Publishing. Chap. 10, p. 203.

Fingleton, B., H. Garretsen, and R. Martin (2012). "Recessionary shocks and regional employment: Evidence on the resilience of u.k. regions". In: *Journal of Regional Science* 52.1, pp. 109–133.

Fratesi, U. and G. Perucca (2018). "Territorial capital and the resilience of European regions". In: *Annals of Regional Science*. Vol. 60. 2, pp. 241–264.

Frenken, K., F. Van Oort, and T. Verburg (2007). "Related variety, unrelated variety and regional economic growth". In: *Regional Studies* 41.5, pp. 685–697.

Glaeser, E. L. (2000). "The New Economics of Urban and Regional Growth". In: *The American Economic Review*.

— (2005). "Reinventing Boston: 1630-2003". In: *Journal of Economic Geography* 5.2, pp. 119–153.

Groot, S. P., J. L. Möhlmann, J. H. Garretsen, and H. L. De Groot (2011). "The crisis sensitivity of European countries and regions: Stylized facts and spatial heterogeneity". In: *Cambridge Journal of Regions, Economy and Society* 4.3, pp. 437–456.

Kogler, D. F., J. Essletzbichler, and D. L. Rigby (2017). "The evolution of specialization in the EU15 knowledge space". In: *Journal of Economic Geography* 17.2, pp. 345–373.

Krafft, J., F. Quatraro, and P. P. Saviotti (2011). "The knowledge-base evolution in biotechnology: A social network analysis". In: *Economics of Innovation and New Technology* 20.5, pp. 445–475.

Lee, N. (2014). “Grim down South? The Determinants of Unemployment Increases in British Cities in the 2008–2009 Recession”. In: *Regional Studies* 48.11, pp. 1761–1778.

Los, B. (2000). “The empirical performance of a new inter-industry technology spillover measure”. In: *Technology and Knowledge*.

Lucas, R. E. (1988). “On the mechanics of economic development”. In: *Journal of Monetary Economics* 22.1, pp. 3–42.

Martin, R. (2012). “Regional economic resilience, hysteresis and recessionary shocks”. In: *Journal of Economic Geography* 12.1, pp. 1–32.

Martin, R. and P. Sunley (2013). “On the notion of regional economic resilience: Conceptualization and explanation”. In: *Journal of Economic Geography* 15.1, pp. 1–42.

Martin, R., P. Sunley, B. Gardiner, and P. Tyler (2016). “How Regions React to Recessions: Resilience and the Role of Economic Structure”. In: *Regional Studies* 50.4, pp. 561–585.

Neffke, F. and M. Henning (2013). “Skill relatedness and firm diversification”. In: *Strategic Management Journal* 34.3, pp. 297–316.

Nelson, R. and E. Phelps (1966). “Investment in Humans, Technology Diffusion and Economic Growth”. In: *The American Economic Review* 56.3, pp. 69–75.

Quatraro, F. (2010). “Knowledge coherence, variety and economic growth: Manufacturing evidence from Italian regions”. In: *Research Policy* 39.10, pp. 1289–1302.

Rafols, I. (2014). “Knowledge integration and diffusion: Measures and mapping of diversity and coherence”. In: *Measuring scholarly impact*. Springer. Chap. 8, pp. 169–190.

Rafols, I. and M. Meyer (2010). “Diversity and network coherence as indicators of interdisciplinarity: Case studies in bionanoscience”. In: *Scientometrics* 82.2, pp. 263–287.

Rao, C. R. (1982). “Diversity and dissimilarity coefficients: A unified approach”. In: *Theoretical Population Biology* 21.1, pp. 24–43.

Reggiani, A., T. De, and P. Nijkamp (2002). “Resilience: An Evolutionary Approach to Spatial Economic Systems”. In: *Networks and Spatial Economics* 2, pp. 211–229.

Rocchetta, S. and A. Mina (2019). “Technological coherence and the adaptive resilience of regional economies”. In: *Regional Studies*, pp. 1–14.

Romer, P. M. (1990). “Endogenous Technlogical Change”. In: *The Journal of Political Economy* 98.5, S71–S102.

Rose, A. (2004). "Defining and measuring economic resilience to disasters". In: *Disaster Prevention and Management: An International Journal* 13.4, pp. 307–314.

Schumpeter, J. A. (1939). "Business Cycles: A Theoretical, Historical, and Statistical Analysis of the Capitalist Process". In: *Journal of Political Economy.*

Schumpeter, J. A. (1942). *Socialism, capitalism and democracy.* Harper and brothers.

Sedita, S. R., I. De Noni, and L. Pilotti (2017). "Out of the crisis: an empirical investigation of place-specific determinants of economic resilience". In: *European Planning Studies* 25.2, pp. 155–180.

Sensier, M., G. Bristow, and A. Healy (2016). "Measuring Regional Economic Resilience across Europe: Operationalizing a complex concept". In: *Spatial Economic Analysis* 11.2, pp. 128–151.

Shannon, C. E. (1948). "A mathematical theory of communication". In: *The Bell System Technical Journal.*

Stirling, A. (2007). "A general framework for analysing diversity in science, technology and society". In: *Journal of the Royal Society Interface* 4.15, pp. 707–719.

Swanstrom, T. (2008). "Regional resilience: A critical examination of the ecological framework".

Vona, F. and D. Consoli (2015). "Innovation and skill dynamics: A life-cycle approach". In: *Industrial and Corporate Change* 24.6, pp. 1393–1415.