Inequality and resilience:
An analysis of Spanish municipalities during the Great Recession

Fabian Geelhoedt
Universitat de Barcelona fabian.geelhoedt@gmail.com

Vicente Royuela (Corresponding author)
AQR-IREA Resarch Group, Universitat de Barcelona. 08034, Barcelona, Spain.
vroyuela@ub.edu

David Castells-Quintana
Department of Applied Economics. Univ Autonoma de Barcelona. 08193 Bellaterra, Barcelona, Spain.
AQR-IREA Resarch Group, Universitat de Barcelona. 08034, Barcelona, Spain.
David.Castells.Quintana@uab.cat

Abstract:

In this paper we study an association almost neglected in the literature, that between income inequality and economic resilience. In particular, we explore the response of employment rates in the face of the crisis of 2008 and how income inequality levels may have affected this response. To do so, we construct two measures of resilience—resistance and recoverability—using data on total employment and self-employment for 995 Spanish municipalities during the Great Recession. Our results provide evidence of the threats that high levels of inequality pose for economic resilience, showing that average income is the most important mediating factor of this association.

Key words:

Resilience, Income inequality, Great Recession, Spain, Municipalities

1. Introduction

Income inequality and economic resilience have separately gained momentum in the academic literature and political debate since the Great Recession. The recession represented a major global economic downturn, with deep socio-economic consequences felt almost everywhere. But the Great Recession also provided a unique "natural" experiment to study the heterogeneous response of different locations to economic shocks. While recovery has been under way for many years, there have been important heterogeneities in the way different locations, both across countries and within them, have responded to the crisis. Understanding these heterogeneities is of great value, as it can guide sound policy design to better resist future shocks and to recover from them.

One key factor that deserves special attention is inequality. The Great Recession was associated with a worsening in the distribution of income in most countries and regions worldwide (Milanovic, 2019). But income inequality has been signaled not only as a consequence, but also as a key trigger of instability (see for instance Lewin et al., 2018), and therefore as an important root cause of the recent global crisis (see for instance Rajan 2010, Brescia 2010, Martins 2010, Peet 2011, and Tridico 2012). Consequently, inequality may help us explain heterogeneous policy responses across different locations.

In this paper, we study the association between income inequality and economic resilience. In particular, we study how inequality can play a role in the resistance and recoverability of economic areas to economic shocks. We analyze the evolution of total employment and self-employment during and after the shock experienced during the Great Recession. We look at Spain as one of the countries where the impact of the crisis was the hardest. For Spain, the Great Recession was the deepest and longest depression since the civil war in the 1930s: 3.5 million jobs were lost, unemployment rates rose to

25%, and there were significant declines in wages, housing prices, and even population (Royuela et al. 2016). Similarly, poverty risk rates increased (from 23% to 29%), and in most regions of the country inequality rose (Castells-Quintana et al. 2019a). Using detailed data at the municipal level, we construct resilience indices for 995 Spanish municipalities between 2003 and 2018. This allows us to study differential responses across Spain in the face of the crisis of 2008 and the role of the within-municipality distribution of income.

In relation to the literature, our paper mainly connects to two strands. On one hand, our paper connects to studies on economic resilience. The literature on resilience has drastically grown since the Great Recession (Ubago Martínez et al., 2017) and has made efforts to clarify the concept of resilience (e.g., Martin & Sunley, 2015); constructed ways to measure resilience, mainly through output data and employment data (e.g., Ringwood, Watson & Lewin, 2019); and gauged the determinants of resilience (e.g., Di Caro & Fratesi, 2018). On the other hand, our paper connects to the literature on the causes and consequences of income inequality. This strand in the literature has taken a reinforced appraisal in the last few years, especially in relation to economic functioning, since income inequality has been put forward as a central player in the materialization of the Great Recession (Rajan, 2010), leading to a growing body of literature on the role of income inequality in engendering financial crises (e.g., Van Treeck, 2014; Bordo & Meissner, 2012). Conversely, some interest has been generated around the effects of the Great Recession on income inequality (e.g., Stockhammer, 2015; Agnello & Sousa, 2012). Despite the growing study of resilience and the new impetus in understanding the consequences of inequality, the literature has so far directed little attention to income inequality as a potential determinant of economic resilience. To the best of our knowledge, only Lewin et al., (2018) and Rahe et al. (2019) study the association between income inequality and resilience looking at U.S. counties.

Our paper contributes to the literature in different ways. First, by analyzing the role of income inequality on economic resilience in Spain, we are the first to look at the inequality-resilience relationship in a context different than the US. Second, we provide a valuable addition by extending the analysis of economic resilience to the study of self-employment, as self-employment has been identified as a mechanism to escape unemployment and as a gateway to entrepreneurial activity. Third, looking at more desegregated data—municipalities and monthly data vs. yearly data, which most other studies use—allows us to better and more precisely track the regional response to economic shocks. Finally, by considering a longer time frame (2003-2018), we are able to study not only resistance, as seen in previous papers, but also recoverability.

The rest of this paper is organized as follows: section 2 set our theoretical framework giving an overview of the related literature; section 3 presents our data, describing our measures of resilience and income inequality; in section 4 we perform econometric analysis and present our main results; and section 5 presents a discussion and our conclusions.

2. Resilience, its determinants, and the role of inequality: Theoretical framework and literature review

Resilience

Although not wholly new to economics, resilience has recently become a popular topic of investigation in the field (Ubago Martínez et al., 2017). Resilience entered economic discourse only after being first studied in contexts of engineering, ecology, and psychology[1] (Martin & Sunley, 2015), resulting in its three leading interpretations: engineering resilience, which is the ability of a region to bounce back from a shock; ecological resilience, which considers a change in growth patterns of regions after a shock (Martin, 2012); and adaptive resilience (Martin & Sunley, 2015). This exercise follows a description of adaptive resilience as put forth in Martin & Sunley (2015). In their interpretation of resilience, economies are considered as systems. First, economic systems run some antecedent risk of, or are otherwise vulnerable to, shocks to their industries, firms, workers, and institutions; second, they resist the shock to those agencies to some extent; third, they are able to administer the required changes to the routines of their agencies to maintain the core function of the system; and fourth, they recover from the shock to different degrees and in different ways.

Measuring resilience

One of the issues in measuring resilience is the lack of a standard set of quantitative indicators (Ubago Martínez et al., 2019). Some authors use employment outcomes to measure resilience (e.g., Fingleton et al., 2012; Martin, 2012; Kitsos and Bishop, 2018; Rahe et al., 2019), because employment outcomes take longer to recover than output (Martin, 2012). In addition, using employment outcomes allows for consideration of labor market conditions and their impact on regional economies (Eriksson & Hane-Weijman, 2017) and the social costs of job loss (ESPON, 2014). Employment outcomes are also independent of deflation (Di Caro, 2014) and are statistically stable (Sensier, Bristow, & Healy, 2016). Others argue that output measures are better suited for measuring resilience

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[1] Although some authors have been wary of potential repercussions to its intellectual clout if incautiously expanded to different scientific fields (Martin, 2015), others maintain that the concept of resilience is essentially the same in each field (Bhamra, Dani, & Burnard, 2011); some even argue that understanding resilience in various contexts is conducive to a complete understanding of the concept.

due to their closer link to the determinants of resilience (Fratesi & Perucca, 2018), while Lewin et al. (2018) use personal income data. Ubago Martínez et al. (2019) find a middle ground by creating a composite resilience index using employment and output data.

Other authors use composite measures that include various regional characteristics besides employment or output to capture the uniqueness and complexity of different regions, although variable selection and weighting schemes are somewhat idiosyncratic (Ringwood et al., 2019). For instance, Briguglio et al. (2019) base their resilience index on macroeconomic stability, microeconomic market efficiency, proper governance, and social development characteristics; Kahsai et al. (2015) use industrial diversity, entrepreneurial activity and business dynamics, human and social capital, scale and proximity, and physical capital; and Lu & Dudensing (2015) use industrial sector sales changes.

Determinants of resilience

As a relatively novel strand in the literature, the study of the determinants of resilience remains limited and inconclusive. However, several determinants of resilience have been put forward, including the level of economic development, sectoral specialization, human capital, innovation, institutions, and levels of urbanization. In general, more developed economies are expected to be more resilient (Deller & Watson 2016; Giannakis & Bruggeman 2017). However, some authors have found a negative relationship between levels of development and resilience (Crescenzi et al. 2016; Annoni, et al. 2019), and argue that this may be due to regional convergence: as lagging regions catch up, their associated lower levels of development should be linked to higher growth. It is also unclear whether more economic specialization is most conducive to economic resilience. Specialized economies provide regions with a competitive edge (Annoni, et al. 2019) by their association with greater productivity growth (Van Oort et al. 2015). For Spain, Cuadrado-Roura & Maroto (2016) find evidence that Spanish regions that specialized in dynamic industries and sectors were better able to exploit higher productivity growth. However, industrial specialization may increase the vulnerability of a region to economic downturns (Brown & Greenbaum, 2017; Crescenzi et al., 2016; Deller & Watson, 2016). Moreover, sectoral linkages facilitate the diffusion of economic shocks and thereby obstruct resilience, especially within localized industrial supply chains (Giannakis & Bruggeman, 2015; Martin, 2012). Although sectoral structure is important, Martin et al. (2016) stress that it is especially regional competitiveness that explains heterogeneity in resilience. Recently, Kitsos et al., (2019) have also considered industrial embeddedness as a resilience factor, which results in an inverted U-shaped relationship.

Human capital is another potential determinant of resilience, being pivotal to regional capacities for adaptation and recovery after economic shocks (Crescenzi et al. 2016; Clark & Bailey 2018; Nyström 2018). Regions that host a more educated workforce will benefit from greater knowledge creation and absorptive capacity, making them better fit to adapt to sudden economic shocks or medium-term economic changes. Workers with higher levels of education are more able to move into the more dynamic parts of an economy, easing the recovery process (Martin & Gardiner, 2019). An especially important mechanism through which knowledge creation bolsters economic performance is its capacity to generate innovation. Indeed, innovation is a key factor in enhancing regional competitiveness and shaping regional labor market resilience (Chapple & Lester 2010; Martin 2019; Zhiwei et al. 2019; Annoni et al. 2019), as high innovation rates facilitate the adaptive capacity of firms. Moreover, innovative regions attract more high-skilled workers, allowing, for instance, the attraction of knowledge-intensive functions in multinational firms that are less likely to be badly impacted by an economic shock (Crescenzi et al. 2019).

Proper regional institutions also improve the economic resilience of a region. Strong institutions harness enterprises against the potential risks faced in times of economic downturn and design policies aimed at supporting businesses and jobs, helping the region to be more adaptive after a shock (Annoni et al. 2019). Ezcurra & Rios (2019) provide evidence that higher quality local governments positively affect resilience.

Agglomeration can also be a force for resilience. Large cities are likely to attract high-skilled workers and enjoy more diverse economic activities with more productive and innovative firms (Martin 2019). They have been shown to enhance the resilience of their host regions (Capello et al. 2015). However, Dijkstra et al. (2015) provide evidence that EU metropolitan regions were more vulnerable to the 2008 economic crisis than rural regions, although this may have been due to the collapse of the real estate-related economic activities that were prevalent in cities—an idiosyncrasy of this particular crisis. Regardless, large cities are generally highly connected to international markets and may be more susceptible to being affected by economic crises that originate elsewhere in the economic network compared to rural regions (Donald et al. 2014; Dijkstra et al. 2015).

Income inequality and resilience

Income inequality has long been studied as a potential determinant of economic growth. Most earlier studies tended to focus on inequality and growth at the country level. Some of these studies identified positive effects of inequality on growth in the short-run (e.g., Forbes 2000; Rodríguez-Pose & Tselios 2010); in high-income countries (Barro 2000); and in countries with low initial inequality levels (Chen 2003). Other studies found that the relationship turns negative in the long-run (e.g., Bertola 1993); in low-income countries (Barro 2000); and in countries with high initial inequality levels (Chen 2003, Castells-Quintana et al., 2018). Finally, looking at the impact of the Great Recession, Royuela et al. (2019) provide evidence of a general negative short-run association between inequality and growth in OECD countries.

High levels of inequality were also found to have been a structural cause of the Great Recession (Rajan 2010; Brescia 2010; Martins 2010; Peet 2011; Tridico 2012). In addition, high levels of inequality are also expected to reduce the economy's ability to resist economic downturns. Many reasons explain this. In highly unequal societies, many individuals tend to be highly indebted (van Treeck and Sturn 2012), which reduces their capacity to react to negative income shocks. Higher income households have a lower propensity to consume and have better opportunities to escape from taxes, which lowers public revenue capacity thereby limiting the ability of governments to provide public goods and safety nets (Van Treek, 2012). High inequality levels are associated with the concentration of political power, which reduces needed policy responses (Kumhof and Ranciere 2010) and demotivates workers to be connected to the labour market (Hopkins and Kornienko, 2006). Finally, inequality represents a transmission channel from economic shocks to systemic crisis in a self-reinforcing process (Cairo-i-Cespedes and Castells-Quintana 2016).

The empirical connection between inequality and resilience has been almost unexplored to date. To the best of our knowledge, only Lewin et al. (2018) and Rahe et al. (2019) analyze the inequality-resilience relationship, looking at the impact of the Great Recession in U.S. counties. Lewin et al. (2018) show that more unequal U.S. counties were more prone to enter into recession after the economic shock. The study relied on data for 639 urban regions. Rahe et al. (2019) extend this analysis to all U.S. counties and consider the degree of job loss rather than the likelihood of entering recession. They found that higher levels of income inequality increased job loss in populous counties and decreased job loss in the smallest counties.

3. Data and stylized facts

In 2011, Spain had 8,116 municipalities, with 1,308 having over 5,000 inhabitants. Our empirical analysis relies on data for 995 Spanish municipalities for which we have data on income inequality (Hortas and Onrubia, 2014).[2] We consider Social Security registered jobs at the municipal level as employment outcomes. We use monthly data from January 2003 to December 2018 and consider total registered employment and self-employment (autónomos). These variables are defined in terms of registered jobs and not in terms of registered workers. Consequently, our analysis is focused on the local conditions to create jobs opportunities rather than the influence on the activation of local labor market forces. Next we describe our interest variables: the indices of resilience and inequality.

Resilience indices

Our dependent variable is a measure of resilience. Following our theoretical framework, we focus on two dimensions of resilience: resistance, Res^m and recoverability, Rec^m, and we focus on total employment and self-employment.[3]

To construct measures for resilience, we follow Martin (2019) and compare the change in a variable at the municipal level with the change at the national level.[4] We also allow

[2] This dataset considers all municipalities of the Common Fiscal System in Spain, excluding the Basque Country and Navarra.
[3] The current exercise only partially captures resilience and leaves analyses of vulnerability and adaptability to inquiry for further research.
[4] In the Online Supplementary Material we display a complete overview of the derivation of the indices and an interpretation of their values.

variable contraction and expansion periods for each municipality m and for the entire country $\mathcal{N}$.[5] The indices for municipality m in relation to country $\mathcal{N}$ for contraction period $[\tau-\kappa, \tau]$ and expansion period $[\upsilon-\lambda, \upsilon]$ are therefore defined as:

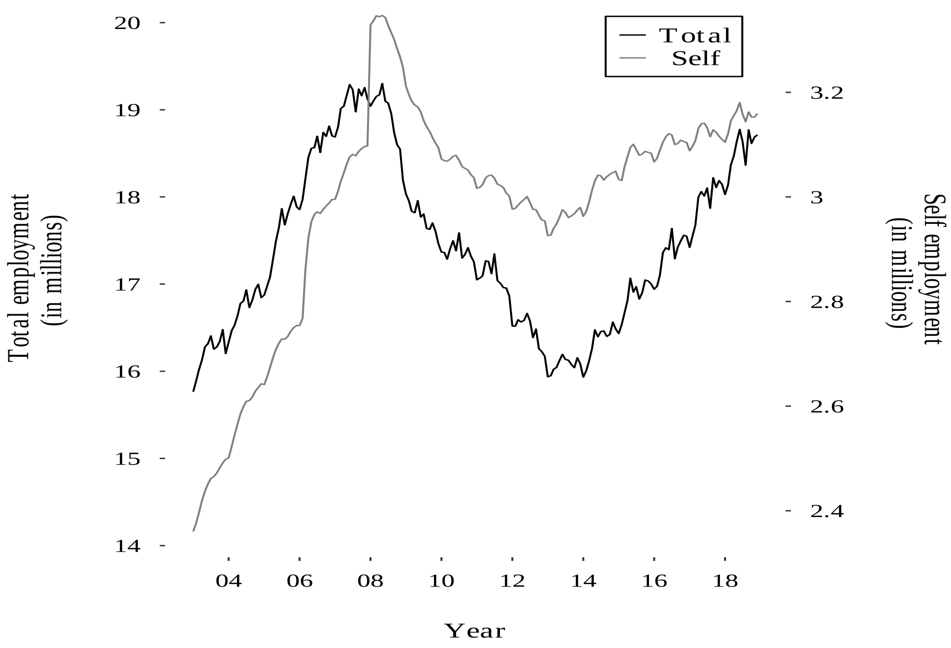
$$Res^m \triangleq \frac{\Delta_{(\tau-\kappa)^m}^{\tau^m} Y^m}{\left|\Delta_{(\tau-\kappa)^{\mathcal{N}}}^{\tau^{\mathcal{N}}} Y^{\mathcal{N}}\right|} + 1 \qquad\qquad Rec^m \triangleq \frac{\Delta_{(\upsilon-\lambda)^m}^{\upsilon^m} Y^m}{\left|\Delta_{(\upsilon-\lambda)^{\mathcal{N}}}^{\upsilon^{\mathcal{N}}} Y^{\mathcal{N}}\right|} - 1.$$

Both indices, Res^m and Rec^m, center around 0 with positive values for Res^m (Rec^m) indicating a smaller decline (greater increase) in variable Y^m relative to the change in variable $Y^{\mathcal{N}}$. In line with Rahe et al. (2019), we use employment data to construct the indices. We use data from the Spanish social security register on monthly employment from 2003 to 2018 for all Spanish municipalities and let national employment equal the sum of employment for all municipalities in the sample. Figure 1 shows the evolution of total employment and self-employment in Spain during our period of study. As Figure 1 shows, from 2003 to 2008 the Spanish economy saw a large increase in both total employment and self-employment. With the crisis of 2008, employment outcomes decreased steadily until 2013, when recovery seems to have started. However, when comparing self-employment with total employment, some significant differences arise in terms of the response to the crisis: at the end of the contraction, while total employment contracted to only 1.1% above its initial value at the start of 2003, self-employment contracted to 23.9% above its initial value.

[5] Although it is possible to fix the contraction and expansion period for all municipalities as the national periods, this ignores the fact that some municipalities start to contract and/or expand earlier or later than the country at aggregate. Indeed, the correlation between indices constructed with variable and fixed periods are not perfect, although high: 0.670 for total employment resistance; 0.779 for total employment recoverability; 0.939 for self-employment resistance; and 0.882 for self-employment recoverability.

Following Han & Goetz (2015), we identify the national peak ($(\tau - \kappa)^{\mathcal{N}}$) as the month with the maximum level of national employment and the national trough ($\tau^{\mathcal{N}}$) as the earliest month with the minimum level of national employment. We subsequently identify municipal peaks ($(\tau - \kappa)^{m}$) as the latest month with the maximum level of municipal employment within 2 years before and 2 years after the national peak. The municipal troughs (τ^{m}) are taken as the earliest month with the minimum level of municipal employment after the municipal peak. We let the start of the national and municipal expansion ($(\upsilon - \lambda)^{\mathcal{N}}$ and $(\upsilon - \lambda)^{m}$) equal the trough and take the end of the national and municipal expansion ($\upsilon^{\mathcal{N}}$ and υ^{m}) as the last period for which there is available data, namely December 2018. The peak dates for national total and self-employment coincide in May 2008. The trough date for national self-employment predates that of national total employment by one year, namely January 2013 as opposed to January 2014. For total employment in municipalities, the most common peak date is July 2007 and the most common trough date is August 2013. The minimum peak date is June 2006 and the maximum peak date is April 2004. The minimum trough date is August 2007 and the maximum trough date is December 2018. For self-employment in municipalities, the most common peak date is April 2008 and the most common trough date is January 2013. The minimum peak date is June 2006 and the maximum peak date is April 2010. The minimum trough date is May 2007 and the maximum trough date is December 2018.

Figure 1: Evolution of employment, Spain 2003-2018



As may be seen from the minimum and maximum values of the peak and trough dates, in some municipalities employment contraction and expansion periods were not so clearly defined. As in Rahe et al. (2019), we finally excluded them from our main analysis.[6] Table A1 in the appendix displays the descriptive statistics for all municipalities. Due to the use of a sample of Spanish municipalities, the mean of the indices is not 0, as the indices are scaled according to the sum of all municipalities. The indices of resistance are negative, indicating that the average municipality in the sample is *less* resistant than Spain as a whole. The opposite happens for the indices of recoverability, which are positive on average.[7]

[6] We performed several robustness checks including the excluded municipalities. We did not see major changes.

[7] The density plots of the four indices and the inequality measures are reported in the Online Supplementary Material.

Inequality indices

To measure inequality, the current work employs the Gini coefficient and the $\text{Atkinson}_{0.5}$ index obtained from Hortas and Onrubia (2014). The dataset includes indices for up to 1,178 Spanish municipalities with more than 5,000 inhabitants from 2004 to 2007.[8] The mean value of the sample is 0.449, and values for different municipalities range between 0.263 and 0.659. The majority of municipalities fall below the mean value. The $\text{Atkinson}_{0.5}$ values, taking an intermediate aversion to inequality, shows that on average 18.9% of total income must be foregone to obtain a satisfying level of inequality for the municipalities in the sample, ranging from 8.8% to 40.7%. For the main results, we consider the Gini coefficient and use the $\text{Atkinson}_{0.5}$ measure for robustness checks.

Other variables

In our analysis, and following our theoretical framework, we also consider other variables potentially relevant to resilience and that may play a role in the inequality-resilience relationship. First, we consider the initial level of development of the municipality. For less developed regions, it is possible that income inequality has a positive effect on employment resistance, as when per capita income levels are sufficiently low and the concentration of low-income earners is high, it may be easier to curb lay-offs. However, as per capita income rises this positive effect may become less pronounced, or even reverse. To measure the initial level of development, we use data on the mean income per inhabitant in 2006.

Second, we consider the economic specialization of the municipality. Income inequality in highly specialized economies might have a negative effect due to the relatively low

[8] The number of observations depends on the year: 1,135 observations are available for 2004, 1,152 for 2005, 1,172 for 2006, and 1,178 for 2007.

spread of employment across sectors. As an economic shock hits a highly unequal and highly specialized region, this might require businesses to lay-off more employees as decreases in demand will be more concentrated. In more diverse regions, this effect may become less pronounced, as employment spreads across sectors and higher levels of income inequality may safeguard the relative cost-efficiency that comes with a larger base of low-income earners and the need to lay-off workers may not be as pronounced. We measure sectoral diversity using employment data across different sectors and constructing a Herfindahl index: $Herfindahl_m = \sum_{i=1}^{n} \left(\frac{E_{m,i}}{E_m}\right)^2$, where $E_{m,i}$ is employment in sector i municipality m. We consider up to 17 different sectors.[9] Note that in $Herfindahl_m \in (0,1]$, 1 indicates that employment is concentrated in one sector and values close to 0 indicate that employment is dispersed over many sectors.

Third, we consider human capital. In regions with low levels of human capital it is possible that income inequality allows for a lower decrease in employment. Low-human capital regions have fewer high-skilled workers and more low-income workers, so firms may be more averse to lay-offs. In contrast, if a larger portion of the population is high-skilled it might become more attractive to lay-off workers in regions with higher levels of income inequality due to the relatively smaller contribution to firm productivity of the large portion of low-income earners. We measure human capital through the share of population holding a university degree and the share of population in various age cohorts from 25 to 49 (as in Giannakis and Bruggeman 2017). Population cohorts are included to account for age effects related to human capital, although it might also be considered a

[9] The considered sectors are: i) agriculture, livestock, hunting and forestry; ii) fishery; iii) manufacturing industries; iv) extraction industries; v) production and distribution of water, gas, and energy; vi) construction; vii) commercial activities; viii) hotel industry; ix) transport, storage, and communications; x) financial intermediation; xi) real estate; xii) public administration; xiii) education; xiv) health; xv) personal services; xvi) home activities; and xvii) extraterritorial organs.

measure of demographic structure. The share of population holding a university degree is directly available in the census, while we calculate the share of age cohorts as a percentage of total population.

Fourth, we consider innovation. The exploitation of innovations might require absorptive capacities that are mainly available to highly skilled workers, which in turn is associated with inequality. To measure innovation, it would be ideal to have data on R&D expenditures. However, such data are not readily available at the municipal level, so we proxy innovation by taking the share of employment in high- and medium-tech sectors as detailed by the OECD.[10]

Fifth, we take into account institutions. In places with better institutions it is possible that income inequality has a positive effect on employment retention. These regions may have practices in place that engender a reluctance to lay-off employees if a larger proportion are low-income earners, while in regions with worse institutions it might be easier for employers to lay off larger shares of low-income workers to cut costs. We proxy institutions by using two proxies. We use data from the 2001 Spanish census to generate two indices that are obtained from a Principal Component Analysis (PCA). For the first index (Local Environment), we follow the European Quality of Government Index philosophy and consider several indicators on the provision of public services, control of criminality, and law enforcement. We complement this with an index proxying family structure (Family) as in Castells-Quintana et al. (2015).[11]

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[10] These sectors include (i) manufacture of pharmaceutical products; (ii) aeronautic, spatial and machinery construction; (iii) chemical industry; (iv) manufacture of electrical materials and equipment; (v) manufacture of motor vehicles and trailers; and (vi) manufacture of other transport materials.

[11] In particular, for service provision we use data on the share of households complaining about: (i) contamination; (ii) little cleaning in the area; (iii) few green areas in the area; and (iv) crime and vandalism. For family structure, we use data on: (i) the share of divorced and separated couples; (ii) the average number of children per nuclear family; (iii) the share of non-marital cohabitation; and

Sixth, we consider urbanization. It is possible that income inequality allows for greater resistance to employment loss in highly urbanized regions; urban regions are better connected to job markets with larger firms that are able to keep a larger portion of low-income earners employed. However, in more densely populated areas the effect of income inequality may become less favorable, as more low-income earners will have to compete to maintain their job. To measure urbanization, we consider the log population in 2001 and a dummy variable indicating whether the municipality belongs to a Functional Urban Area (FUA) or not, which also proxies market access.[12]

We obtain data for our measures of population, sectoral diversity, human capital, institutions, and innovation from the 2001 census in Spain. Using data from 2001 also has the advantage of reducing reverse causality from our resilience outcomes measured for the 2008 crisis. Data for mean income comes from Hortas and Onrubia (2014). Data on FUAs is obtained from the OECD.

Figure 2: Correlation matrix, heat map

(iv) an emancipation indicator for individuals between 30 and 34 years old. The results of the PCA analysis are reported in the Online Supplementary Material.

[12] According to the OECD (2012): "a FUA consists of a densely-inhabited city and a surrounding area (commuting zone) whose labour market is highly integrated with the city."

Figure 2 shows a heat map of the correlation matrix between the main variables of interest and the controls. Income inequality measures are weakly correlated with the resilience indices, being positive for total employment resistance and self-employment recoverability and very close to zero for total employment recoverability and self-employment resistance. It is possible that other factors moderate the relationship between the two variables. Three of the main moderators of the association are the initial level of inequality, the level of prior development, and population, as identified in the literature on income inequality and economic growth. Mean income is positively associated with inequality and with the resilience measures, being stronger the association with the indices of resistance.

4. Empirical analysis

To formally test the associations between our resilience indices and inequality measures, the following models are estimated:

$$Res_e^m = \alpha + \gamma ineq_m + \langle \beta, X \rangle + \epsilon_m \tag{1}$$

$$Res_e^m = \theta + \delta ineq_m + \langle \phi, X \rangle + \epsilon_m \tag{2}$$

where Res^m and Rec^m correspond to resistance and recoverability measures in municipality m and for employment measure e, $ineq_m$ is the inequality measure, X are our set of controls, and ϵ_m is the idiosyncratic error term.

Considering that the inequality-resilience association may be moderated by other regional characteristics, x, we also consider more flexible specifications with interaction terms:

$$Res_e^m = \alpha + \gamma_1 ineq_m + \gamma_2 Gini_m \times x + \langle \beta, X \rangle + \epsilon_m \tag{3}$$

$$Res_e^m = \theta + \delta_1 ineq_m + \delta_2 Gini_m \times x + \langle \phi, X \rangle + \epsilon_m \tag{4}$$

We estimate equations (1) to (4) on our sample of Spanish municipalities. We estimate by OLS and clustering errors at the provincial level to account for locally correlated errors.

Table 1 shows our main results from estimations of equations (1) and (2). As the results show, there is a negative association between initial levels of income inequality and both resistance and recoverability in both employment outcomes. The association is significant for resistance and recoverability in self-employment and for recoverability in total employment. The coefficient suggest that a 1% higher Gini coefficient translates into 1% less resistance in self-employment and 2% less recoverability in both total and self-employment.

Regarding other potential determinants of resilience, our results show that municipalities with a higher mean income tend to have greater resistance and recoverability. Similarly, municipalities with a higher share of university degree holders, larger population size, and that belong to a FUA appear to have greater resistance. However, larger population size appears to be negatively associated with lower recoverability. The results of the proxies of human capital and innovation are not robust for all specifications: higher shares of education are associated with greater resistance in total employment and are insignificant everywhere else, while higher shares of employment in high tech sectors are negative and only marginally significant for recoverability of self-employment.

Having higher shares of population between 30 and 34 years of age are positively associated with recoverability in both types of employment. Finally, it is interesting that our control for institutions using a family structure composite index (positively associated with non-traditional family structures) is significant in all regressions, with a negative parameter for total employment and a positive parameter for self-employment. Table A2 in the Appendix provides the robustness check to our main results using the Atkinson_{05} index. Most results hold, and now we also find a significantly negative parameter of inequality in the resistance measure for total employment.

When sequentially introducing all covariates, we find average income to have a major effect on the sign and significance of inequality.[13] These results call us to consider potential nonlinearities in the inequality-resilience relationship by introducing the Gini coefficient interacted with other variables. The results are reported in Table 2. We start considering the Gini index in linear and quadratic terms. Our results yield a positive coefficient for the linear term and a negative coefficient for the quadratic term. Figure 3 plots the marginal effects, suggesting a severe penalty for those municipalities with higher levels of inequality, particularly in terms of resistance (with results for recoverability not being precisely estimated).

Table 1. Main results, linear specification

VARIABLES	(1) Resistance Total Employment	(2) Recoverability Total Employment	(3) Resistance Self Employment	(4) Recoverability Self Employment

[13] The Online Supplementary Material displays tables with the sequential introduction of all covariates to show the effect on the interest variables.

Gini	-0.00265	-0.0218***	-0.0103***	-0.0218*
	(0.00408)	(0.00577)	(0.00356)	(0.0117)
Av Income	0.00820	0.0532**	0.0669**	0.0880**
	(0.0129)	(0.0214)	(0.0261)	(0.0400)
log Population	0.0708***	-0.115*	0.00709	-0.202***
	(0.0212)	(0.0580)	(0.0228)	(0.0703)
Herfindahl index	0.00897*	0.00777	-0.00117	0.0154
	(0.00507)	(0.0107)	(0.00786)	(0.0148)
High Tech	0.989	-0.850	0.0582	-2.367*
	(0.732)	(0.859)	(0.606)	(1.192)
% University degree	0.0376***	-0.0120	0.0122	-0.00916
	(0.00569)	(0.00907)	(0.00839)	(0.0119)
% Age 25-29	-0.0938**	0.0746	-0.0538	-0.133*
	(0.0351)	(0.0619)	(0.0369)	(0.0762)
% Age 30-34	0.00819	0.0589	0.0732***	0.220**
	(0.0272)	(0.0778)	(0.0253)	(0.0894)
% Age 35-39	0.0490	0.0539	0.0814*	0.0152
	(0.0317)	(0.0763)	(0.0411)	(0.0836)
% Age 40-44	-0.0844*	0.0646	0.00657	0.0255
	(0.0457)	(0.0706)	(0.0459)	(0.101)
% Age 45-49	0.0401	-0.0398	0.0493	0.0913
	(0.0522)	(0.0489)	(0.0453)	(0.0855)
% Age 50-54	-0.0807	0.0215	-0.00596	-0.0740
	(0.0635)	(0.0744)	(0.0549)	(0.109)
%Age 55-59	0.0216	0.0676	-0.0185	0.280***
	(0.0270)	(0.0652)	(0.0437)	(0.0942)
Family	-0.125***	0.178**	-0.138***	0.640***
	(0.0449)	(0.0739)	(0.0389)	(0.108)
Local	0.0174	-0.00505	-0.0103	-0.00735
	(0.0191)	(0.0200)	(0.0155)	(0.0394)
inFUA	0.109*	0.0459	0.157***	0.0909
	(0.0640)	(0.0951)	(0.0524)	(0.116)
Observations	985	985	955	955
R-squared	0.417	0.316	0.468	0.555

Robust standard errors in parentheses, clustered by province. *** p<0.01, ** p<0.05, * p<0.1. All estimates include a dummy for every province.

Table 2. Main results, quadratic effects, and interactions

	(1)	(2)	(3)	(4)
	Resistance Total Employment	Recoverability Total Employment	Resistance Self Employment	Recoverability Self Employment
Gini	0.0508**	0.0115	0.0901***	0.0871
	(0.0209)	(0.0364)	(0.0224)	(0.0594)
$Gini^2$	-0.000644**	-0.000400	-0.00121***	-0.00131*
	(0.000249)	(0.000440)	(0.000272)	(0.000749)
Av Income	0.0358*	0.0704**	0.119***	0.144**
	(0.0179)	(0.0338)	(0.0162)	(0.0570)
log Population	0.0669***	-0.117*	-0.000260	-0.210***
	(0.0224)	(0.0593)	(0.0216)	(0.0737)
Observations	985	985	955	955

R-squared	0.423	0.317	0.491	0.560
Gini	0.00326	-0.00947	0.0116**	0.00240
	(0.00504)	(0.00971)	(0.00513)	(0.0126)
Gini x Av Income	-0.000656	-0.00137	-0.00242***	-0.00267*
	(0.000440)	(0.000871)	(0.000447)	(0.00147)
Av Income	0.0525	0.146**	0.231***	0.268**
	(0.0374)	(0.0723)	(0.0358)	(0.125)
log Population	0.0690***	-0.118*	0.000519	-0.209***
	(0.0215)	(0.0593)	(0.0214)	(0.0728)
Observations	985	985	955	955
R-squared	0.419	0.319	0.493	0.560
Gini	0.0176	-0.0675**	0.00378	-0.0712*
	(0.0202)	(0.0316)	(0.0222)	(0.0383)
Gini x log Pop	-0.00216	0.00486	-0.00150	0.00525
	(0.00214)	(0.00323)	(0.00218)	(0.00399)
Av Income	0.00920	0.0510**	0.0676**	0.0856**
	(0.0134)	(0.0204)	(0.0264)	(0.0387)
log Population	0.159	-0.314**	0.0685	-0.417**
	(0.0978)	(0.141)	(0.0990)	(0.188)
Observations	985	985	955	955
R-squared	0.418	0.316	0.468	0.555

Note: Robust standard errors in parentheses, clustered by province. *** p<0.01, ** p<0.05, * p<0.1. All regressions include province dummies and the same controls as those in Table 1.

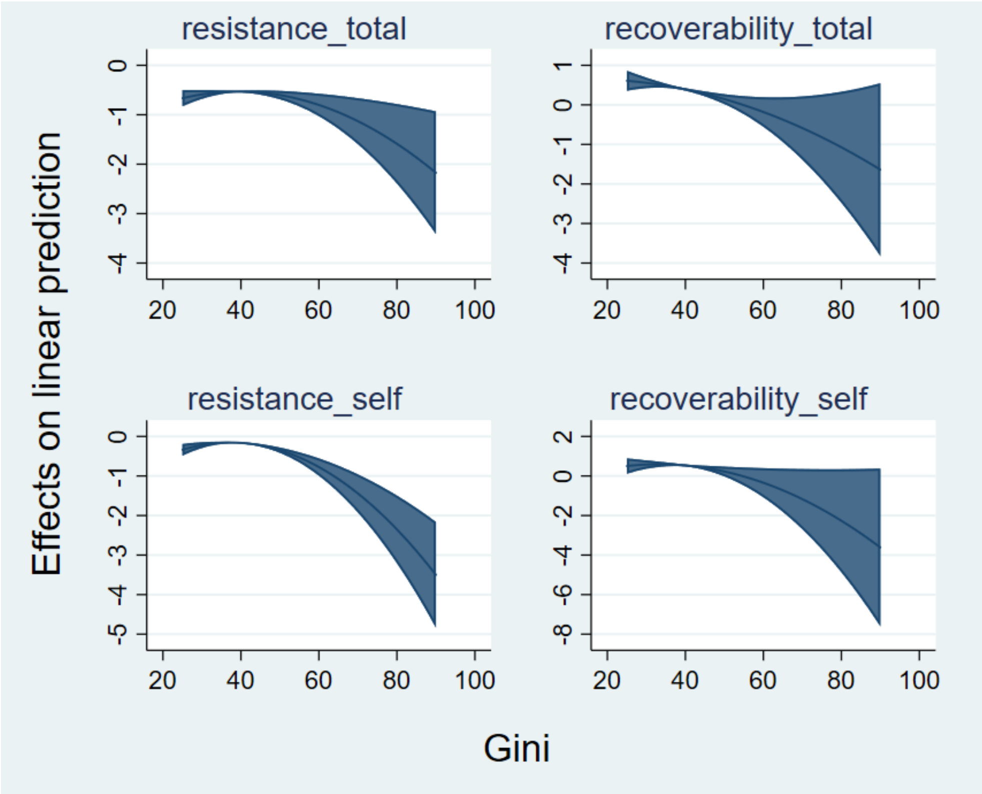
As for the interaction between inequality and average income, we find negative coefficients that are significant for the recoverability measures.[14] This suggests that even in municipalities with high average incomes, which are associated with greater resilience, inequality reduces resistance and, particularly, recoverability. Finally, we find no significant parameters in results for the interaction with population. Still, the marginal effects are indeed significant and negative for smaller municipalities (see panel c of

[14] The robustness checks for the Atkinson$_{05}$ index are reported in the the Online Supplementary Material.

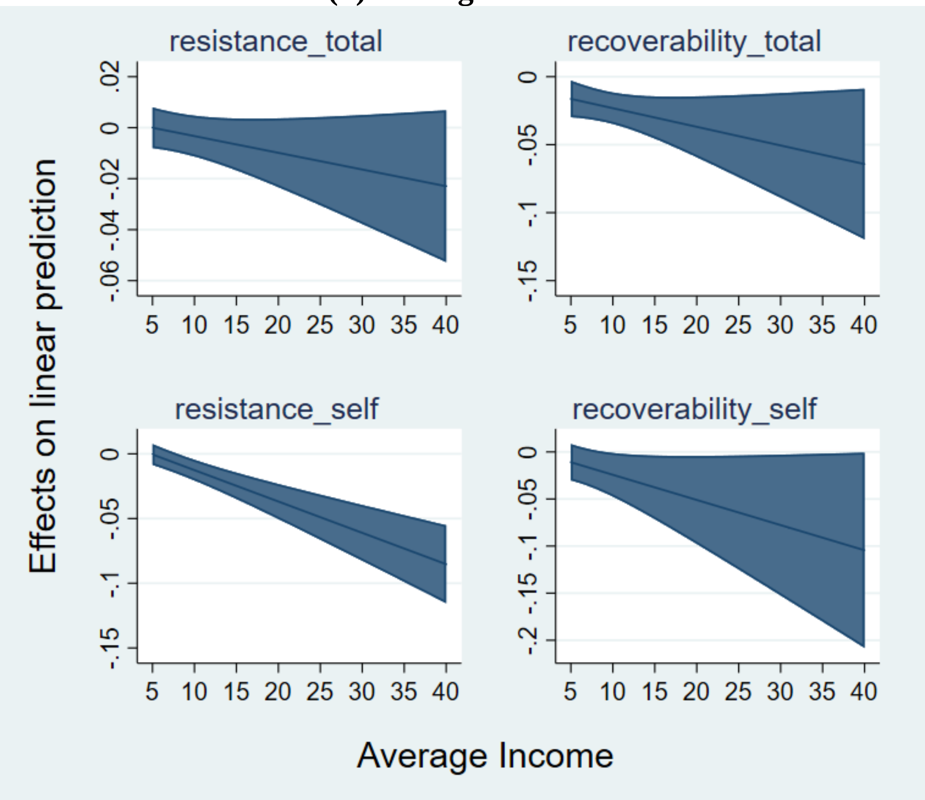
Figure 3): in smaller places, inequality reduces recoverability, but this penalty is lower for larger places.

Figure 3. Marginal effects of the linear prediction

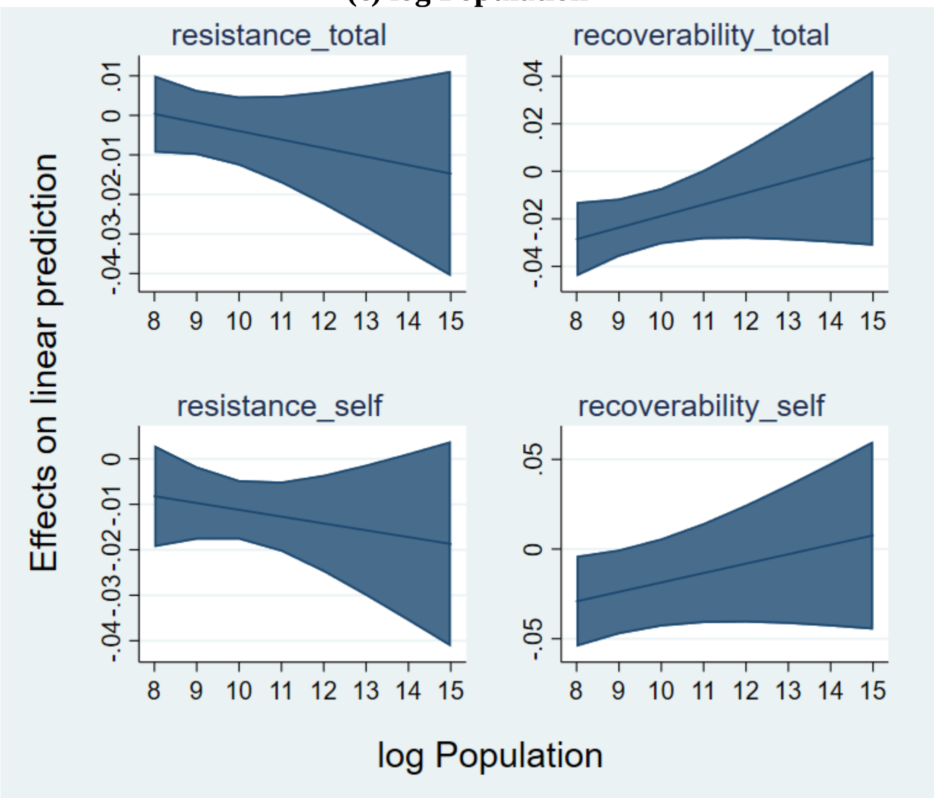
(a) Gini Index



(b) Average Income



(c) log Population



5. Discussion and Conclusion

This paper studies the association between inequality and resilience—a relationship almost totally neglected in the literature to date. This is also the first paper to present evidence of the role of income inequality in economic resistance and recoverability for regions not in the U.S. We focus on employment and self-employment, relying on detailed data for 995 Spanish municipalities during the Great Recession. By means of municipality-specific timings, we estimate the effect of inequality, using both Gini coefficients and Atkinson indices, in both resistance and recoverability, controlling for a wide list of potential determinants of resilience.

Our results suggest that income inequality is associated with lower economic resilience. In particular, we find that municipalities with more unequal distribution of income have lower levels of resistance to economic shocks (i.e., the 2008 economic crisis) and lower levels of recoverability. These negative outcomes are more robust for measures based on self-employment than for those based on total employment.

By means of interactions with mediating factors, we also investigate the way inequality is playing such a negative role. We find that more unequal municipalities are also those with higher average income. While average income plays a positive role in resilience, particularly for self-employment and recoverability, the interaction with inequality is negative for recoverability. In other words, when wealth is equally distributed it seems to have a stronger role in helping territories escape from the crisis. Finally, we have not found a significant mediating factor of city size, although the marginal effects for smaller municipalities display a significant and negative effect for recoverability measures. This result is the opposite to the results of Rahe et al. (2019), although their findings are for resistance, for which we find no significant mediator effect of population.

Our results provide some valuable insights to policy makers. Policies aimed at reducing income inequality seem to have the additional advantage of increasing the resistance of regions to economic shocks as well as easing their recovery after these shocks. In particular, as we have shown, a better distribution of income can improve the resilience of regions in terms of employment and self-employment. Better employment outcomes can lead to better economic performance and can lessen social disparities, and this in turns can lead to greater resilience to future shocks. In any case, homogeneity in inequality reduction policies may not be desirable, as policies might differ according to employment type and interventions may be more dire in places where income inequality is more injurious to employment resilience.

Our results also call for further research. Evidence form other economic shocks and across different geographies is required to draw more general conclusions. Also, further research could test our results using different measures of resilience and alternative estimation and identification strategies. Finally, a deeper understanding of the dynamics behind the association between income inequality and resilience is needed, as is special attention to the role that specific policies may play in this regard.

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Appendix

Table A1. Descriptive Statistics

	N	Mean	St Dev	Min	Max
Resistance Total Employment	1037	-0.5525	0.5972	-3.0309	1.0567
Recoverability Total Employment	1037	0.3946	0.9237	-0.9711	8.5969
Resistance Self Employment	1007	-0.1989	0.5735	-2.3136	1.2237
Recoverability Self Employment	1007	0.5422	1.4372	-1	9.7551
Gini	1023	39.6145	5.9009	25.6670	91.4399
Atkinson 05	1023	15.0145	5.4140	6.5310	83.6977
averageIncome	1023	8.8184	3.5576	2.8656	40.4124
Herfindahl Index	1038	14.5782	5.0413	9.0376	44.4519
%University degree	1038	10.2180	5.7251	2.1400	45.8400
High Tech	1038	1.7276	1.3955	-1.6082	7.6371
Age2529	1038	8.4483	1.1591	4.7002	13.6598
Age3034	1038	8.4757	1.2737	5.5601	15.9832
Age3539	1038	8.3133	1.0410	5.3989	13.0389
Age4044	1038	7.5431	0.8369	4.9270	12.6770
Age4549	1038	6.2692	0.8373	4.3083	10.6751
Age5054	1038	5.6360	0.8180	3.5331	8.9836
Age5559	1038	5.0379	0.8001	2.3897	9.3415
Family index	1034	0.0297	0.0372	0	0.2851
Local Environment	1038	1.1613	1.1033	-0.7245	6.5252
log Pop	1028	9.6166	0.9711	8.5174	14.9561
FUA dummy	1038	0.4769	0.4997	0	1

Table A2. Robustness check. Atkinson$_{05}$ Index

VARIABLES	(1) Resistance Total Employment	(2) Recoverability Total Employment	(3) Resistance Self Employment	(4) Recoverability Self Employment
Atkinson05	-0.00843*	-0.0205***	-0.0184***	-0.0281**
	(0.00460)	(0.00713)	(0.00368)	(0.0135)
Av Income	0.0205	0.0551**	0.0856***	0.105**
	(0.0145)	(0.0230)	(0.0240)	(0.0441)
log Population	0.0735***	-0.116**	0.0106	-0.200***
	(0.0215)	(0.0576)	(0.0230)	(0.0694)
Herfindahl index	0.00882*	0.00854	-0.00118	0.0158
	(0.00502)	(0.0106)	(0.00775)	(0.0146)
High Tech	0.947	-0.806	0.00685	-2.387**
	(0.741)	(0.845)	(0.604)	(1.184)
% University degree	0.0341***	-0.0158*	0.00584	-0.0169
	(0.00605)	(0.00907)	(0.00794)	(0.0116)
% Age 25-29	-0.0968***	0.0780	-0.0572	-0.133*
	(0.0350)	(0.0610)	(0.0373)	(0.0758)
% Age 30-34	0.00200	0.0583	0.0640***	0.212**
	(0.0273)	(0.0775)	(0.0238)	(0.0897)
% Age 35-39	0.0503	0.0521	0.0829*	0.0156
	(0.0320)	(0.0763)	(0.0418)	(0.0845)
% Age 40-44	-0.0896*	0.0620	-0.00146	0.0171
	(0.0463)	(0.0697)	(0.0460)	(0.0988)
% Age 45-49	0.0352	-0.0400	0.0421	0.0849
	(0.0513)	(0.0485)	(0.0439)	(0.0833)
% Age 50-54	-0.0851	0.0214	-0.0128	-0.0804
	(0.0635)	(0.0738)	(0.0538)	(0.111)
%Age 55-59	0.0232	0.0625	-0.0172	0.279***
	(0.0269)	(0.0646)	(0.0443)	(0.0931)
Family	-0.114**	0.175**	-0.121***	0.653***
	(0.0429)	(0.0756)	(0.0406)	(0.107)
Local Environment	0.0157	-0.00422	-0.0126	-0.00895
	(0.0192)	(0.0204)	(0.0155)	(0.0391)
inFUA	0.103	0.0505	0.150***	0.0875
	(0.0627)	(0.0953)	(0.0506)	(0.114)
Observations	985	985	955	955
R-squared	0.419	0.313	0.476	0.556

Robust standard errors in parentheses, clustered by province. *** p<0.01, ** p<0.05, * p<0.1. All estimates include a dummy for every province.

Online Supplementary Material for the paper "Inequality and resilience: an analysis of Spanish municipalities during the Great Recession"

Resilience indices

Following Martin (2019):

$$I^{t,t-k}(Y) \triangleq \frac{\Delta_{t-k}^{t}Y - \mathbb{E}[\Delta_{t-k}^{t}Y]}{|\mathbb{E}[\Delta_{t-k}^{t}Y]|}.$$

Here, $I^{t,t-k}$ is an index of the variable Y in the time interval $[t-k,t]$, where $\Delta_{t-k}^{t}Y$ is the growth rate of Y in $[t-k,t]$ given by $(Y^{t}-Y^{t-k})/Y^{t-k}$, and $\mathbb{E}[\cdot]$ is the expected value. For the current exercise, it is useful to compute the index for a set of economic systems. Let each atomic economic system be denoted by $m \in \mathcal{M}$, where $\mathcal{M} \subset \mathcal{N}$ is a subset of a higher-order economic system $\mathcal{N}$. For instance, a province m is a member of a set of provinces $\mathcal{M}$, which in turn constitutes a country in a free-trade zone $\mathcal{N}$. It is now possible to define the above index for an economic system $m \in \mathcal{M}$ as:

$$I_{m}^{t,t-k}(Y^{m}) \triangleq \frac{\Delta_{t-k}^{t}Y^{m} - \mathbb{E}[\Delta_{t-k}^{t}Y^{m}]}{|\mathbb{E}[\Delta_{t-k}^{t}Y^{m}]|},$$

where the expected value $\mathbb{E}[\Delta_{t-k}^{t}Y^{m}]$ is taken to be $\Delta_{t-k}^{t}Y^{\mathcal{N}}$. This equation can then be rewritten as:

$$I_{m}^{t,t-k}(Y^{m};Y^{\mathcal{N}}) = \frac{\Delta_{t-k}^{t}Y^{m}}{|\Delta_{t-k}^{t}Y^{\mathcal{N}}|} - sgn(\Delta_{t-k}^{t}Y^{\mathcal{N}}).$$

where for non-zero real values of x[15]

$$sgn(x) = \frac{x}{|x|} = \begin{cases} -1 & \Leftrightarrow \quad x < 0 \\ 1 & \Leftrightarrow \quad x > 0 \end{cases}$$

returns the sign of x.

Define a time interval $[t-k,t]$ to be a contraction period *iff* $sgn(\Delta_{t-k}^{t}Y^{\mathcal{N}}) = -1$, and an expansion period *iff* $sgn(\Delta_{t-k}^{t}Y^{\mathcal{N}}) = 1$. Letting $[\tau-\kappa,\tau]$ be a contraction period and letting $[\upsilon-\lambda,\upsilon]$ be an expansion period, define the resistance index $Res^{m}(\cdot) \triangleq I_{m}^{\tau,\tau-\kappa}(\cdot)$ and the recoverability index $Rec^{m}(\cdot) \triangleq I_{m}^{\upsilon,\upsilon-\lambda}(\cdot)$ to obtain the indices. The value of these indices can be interpreted as:

$$\begin{cases} Rec^{m}, Res^{m} \in (-\infty, 0) & \Leftrightarrow \quad m \text{ is less resistant or recoverable than } \mathcal{N} \\ Rec^{m}, Res^{m} = 0 & \Leftrightarrow \quad m \text{ is equally resistant or recoverable as } \mathcal{N} \\ Rec^{m}, Res^{m} \in (0, \infty) & \Leftrightarrow \quad m \text{ is more resistant or recoverable than } \mathcal{N} \end{cases}$$

[15] If $x = 0$ it is possible to define $sgn(x) = 0$. As becomes apparent in the following paragraphs, this case never holds in the current exercise.

Inequality measures

The main independent variable of interest is income inequality. Inequality can be measured in various ways, and relevant measures may depend on the research question at hand. To ensure that measures of inequality "behave well", it is possible to specify the following 5 axioms for an inequality measure $E(\cdot)$ on a vector $\mathbf{y}$: $(y_1, y_2, \ldots, y_i, \ldots, y_n)$ of n units of income y_i (Litchfield, 1999):

- *The Pigou-Dalton Transfer Principle (PDT)* (Dalton, 1920, Pigou, 1912). Let $\mathbf{y}'$ be a vector obtained by a transfer δ from $y_j \in \mathbf{y}$ to $y_i \in \mathbf{y}$, where $y_i > y_j$, and $y_i + \delta > y_j - \delta$, then PDT is satisfied *iff* $E(\mathbf{y}') \geq E(\mathbf{y})$.
- *Income Scale Independence (ISI)*. For any scalar $\rho > 0$, ISI is satisfied *if* $E(\mathbf{y}) = E(\rho\mathbf{y})$.
- *Principle of Population (PP)* (Dalton, 1920). For any scalar $\rho > 0$, PP is satisfied *if* $E(\mathbf{y}) = E(\mathbf{y}[\rho])$, where $\mathbf{y}[\rho]$ is a concatenation of the vector $\mathbf{y}$, ρ times.
- *Anonymity*. For any permutation $\mathbf{y}'$ of $\mathbf{y}$, anonymity is satisfied *if* $E(\mathbf{y}) = E(\mathbf{y}')$.
- *Decomposability*. Decomposability is satisfied *if* $E(\cdot)$ is related consistently to any constituent part of the income distribution.

These axioms, especially the first 4, are intuitively desirable for a measure of income inequality to have, and a measure that satisfies all of them is hence preferred. It can be shown that any measure $I(\cdot)$ that satisfies all axioms belongs to the Generalized Enthropy (GE) class (Litchfield, 1999). Another popular measure, namely the Atkinson class, is ordinally equivalent to the GE class, while another popular measure, the Gini coefficient, in general only satisfies the first 4 axioms. Moreover, while the Gini coefficient satisfies PDT, it responds differently to transfers in opposite tails of the distribution than to transfers in the middle of the distribution (United Nations, 2015). The Gini coefficient satisfies decomposability only if partitions of $\mathbf{y}$ are non-overlapping: in other words, the sub-groups of the population do not overlap in $\mathbf{y}$.

The GE class can take on values in $(0, \infty)$, where a value of 0 indicates perfect equality. Particular GE measures depend on a parameter α, which gives weights to the distance between incomes. For lower values of α, changes in the lower tail of the distribution have a greater impact on the measure value; for higher values of α, changes in the higher tail of the distribution have a greater impact on the measure value. Setting α equal to $0/1/2$ recovers the Theil's L/Theil's T/coefficient of variation. Let $\overline{y} = (1/n)\sum y_i$ be the arithmetic mean income, let w_i be the weight given to observation i, let $\overline{w} = \sum w_i$, then the GE class is given by:

$$GE_\alpha = \frac{1}{\alpha(\alpha-1)}\left[\left(\sum_{i=1}^{n} \frac{w_i}{\overline{w}} \left(\frac{y_i}{\overline{y}}\right)^{\alpha}\right) - 1\right].$$

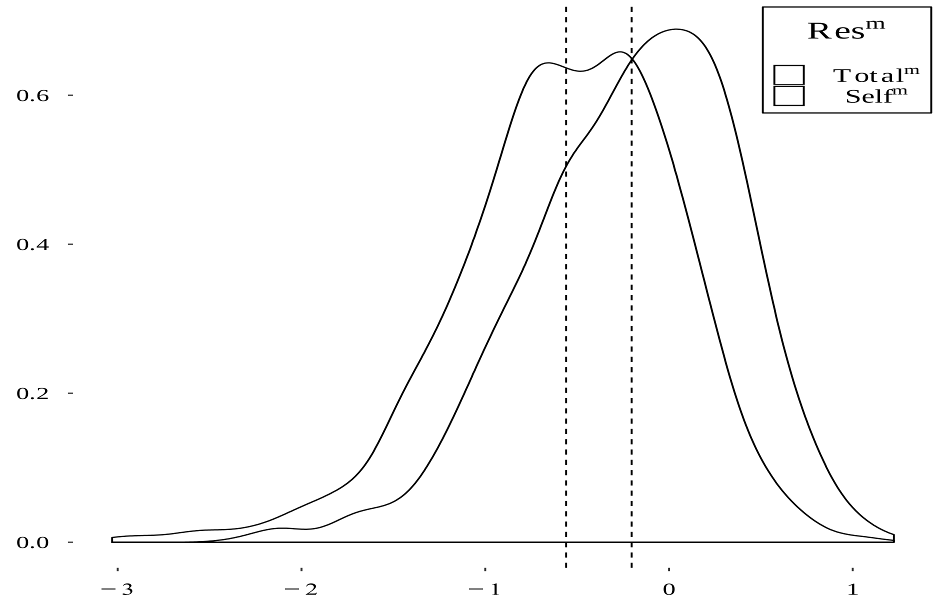
The Gini coefficient is given by:

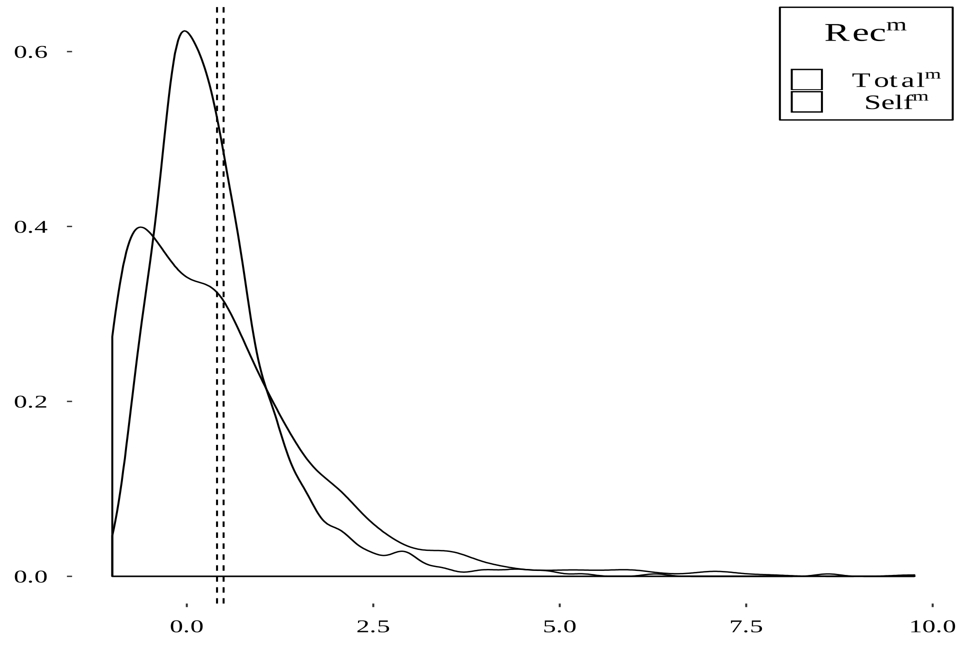
$$Gini = \frac{\overline{w}+1}{\overline{w}} - \sum_{i=1}^{n} \left(\frac{2(\overline{w}-i+1)}{\overline{y}\overline{w}}\right) y_i$$

Let ϵ be the aversion parameter, and then the expression for the Atkinson class is given by:

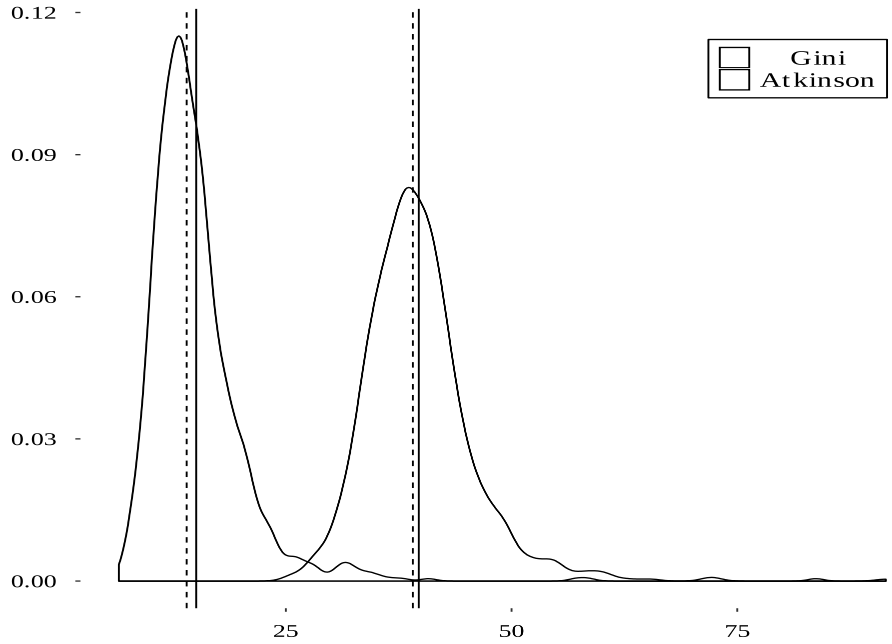
$$Atkinson_\epsilon = 1 - \left[\frac{1}{n}\sum_{i=1}^{n} \left(\frac{w_i}{\overline{w}}\right)\left(\frac{y_i}{\overline{y}}\right)^{1-\epsilon}\right]^{\frac{1}{(1-\epsilon)}}, \quad \begin{matrix} \epsilon > 0 \\ \epsilon \neq 1 \end{matrix}.$$

Density distribution of Resistance and recovery at the municipality level





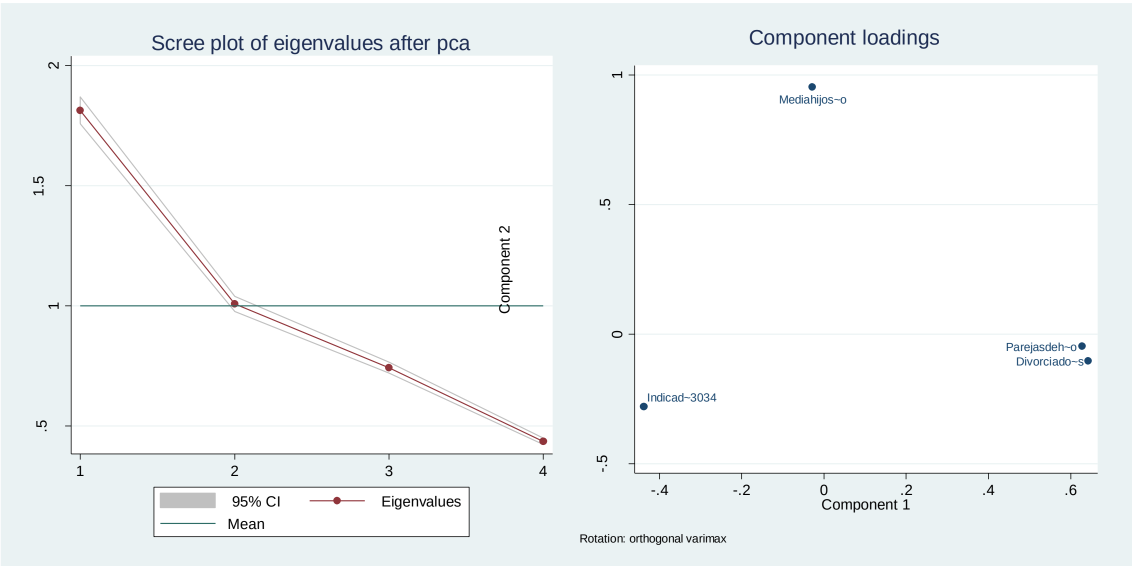
Inequality at the municipality level, density distribution



Principal components results – Family structure

	Comp1	Comp2	Comp3	Comp4
% divorced and separated couples	0,643	-0,104	0,247	0,718
Average number of children per nuclear family	-0,028	0,953	0,294	0,062
% non-marital cohabitation	0,628	-0,046	0,355	-0,691
Emancipation indicator for individuals 30-34	-0,438	-0,280	0,852	0,059
Variance	1,786	1,035	0,743	0,436
Cumulative share	0,447	0,705	0,891	1

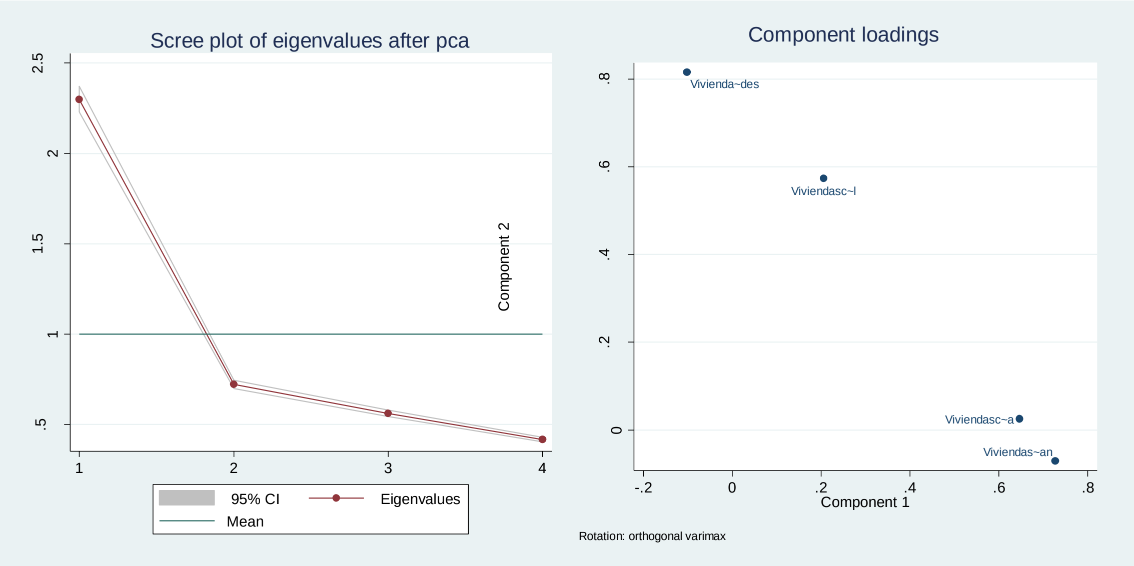
Note: Rotated loadings. Orthogonal Varimax



Principal components results – Public Environment

	Comp1	Comp2	Comp3	Comp4
Contamination	0,647	0,025	0,757	0,092
Little cleaning	0,206	0,574	-0,099	-0,787
Few green areas	-0,102	0,816	-0,010	0,570
Crime and vandalism	0,727	-0,071	-0,646	0,220
Variance	1,549	1,472	0,562	0,417
Cumulative share	0,387	0,755	0,896	1

Note: Rotated loadings. Orthogonal Varimax



Sensitivity analysis of the step-by-step introduction of covariates. Gini index regressions.

Resistance Total Employment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gini	0.00331	0.0106***	-0.00693	-0.00732	-0.00361	-0.00738	-0.00328	-0.00266	-0.00370	-0.00265
	(0.00619)	(0.00368)	(0.00470)	(0.00491)	(0.00462)	(0.00513)	(0.00410)	(0.00407)	(0.00410)	(0.00408)
averageIncome			0.0618***	0.0602***	0.00739	0.0223	0.0102	0.00835	0.0116	0.00820
			(0.0152)	(0.0145)	(0.0135)	(0.0169)	(0.0123)	(0.0123)	(0.0130)	(0.0129)
Herf				-0.00524	0.00550	0.00714	0.00652	0.00606	0.00733	0.00897*
				(0.00438)	(0.00477)	(0.00487)	(0.00532)	(0.00544)	(0.00528)	(0.00507)
University					0.0373***	0.0376***	0.0422***	0.0431***	0.0374***	0.0376***
					(0.00589)	(0.00725)	(0.00623)	(0.00640)	(0.00566)	(0.00569)
Age Cohorts						YES	YES	YES	YES	YES
Family							-0.121***	-0.116**	-0.126***	-0.125***
							(0.0449)	(0.0441)	(0.0435)	(0.0449)
Environment							0.0444***	0.0425**	0.0207	0.0174
							(0.0164)	(0.0165)	(0.0195)	(0.0191)
hightech								1.089	1.129	0.989
								(0.719)	(0.715)	(0.732)
logPopulation									0.0762***	0.0708***
									(0.0206)	(0.0212)
inFUA										0.109*
										(0.0640)
Province Dummies	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	989	989	989	989	989	989	989	985	985	985
R-squared	0.001	0.286	0.333	0.335	0.372	0.388	0.403	0.405	0.413	0.417

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

Resistance Self-Employment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gini	0.00417	0.0135***	-0.0178***	-0.0182***	-0.0171***	-0.0161***	-0.0117***	-0.0117***	-0.0119***	-0.0103***
	(0.00651)	(0.00464)	(0.00392)	(0.00390)	(0.00366)	(0.00412)	(0.00385)	(0.00375)	(0.00364)	(0.00356)
averageIncome			0.111***	0.109***	0.0933***	0.0856***	0.0713***	0.0712***	0.0719***	0.0669**
			(0.0140)	(0.0133)	(0.0272)	(0.0309)	(0.0264)	(0.0264)	(0.0262)	(0.0261)
Herf				-0.00497	-0.00169	-0.00135	-0.00376	-0.00383	-0.00356	-0.00117
				(0.00570)	(0.00687)	(0.00693)	(0.00733)	(0.00737)	(0.00752)	(0.00786)
University					0.0112	0.00801	0.0125	0.0130	0.0118	0.0122
					(0.0123)	(0.0106)	(0.00915)	(0.00924)	(0.00853)	(0.00839)
Age Cohorts						YES	YES	YES	YES	YES
Family							-0.140***	-0.137***	-0.139***	-0.138***
							(0.0411)	(0.0413)	(0.0419)	(0.0389)
Environment							-0.000913	-0.000867	-0.00529	-0.0103
							(0.0146)	(0.0147)	(0.0152)	(0.0155)
hightech								0.250	0.256	0.0582
								(0.657)	(0.654)	(0.606)
logPopulation									0.0153	0.00709
									(0.0241)	(0.0228)
inFUA										0.157***
										(0.0524)
Province Dummies	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	959	959	959	959	959	959	959	955	955	955
R-squared	0.002	0.244	0.410	0.412	0.415	0.442	0.457	0.458	0.459	0.468

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

Recoverability Total Employment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gini	0.00261	-0.00959**	-0.0241***	-0.0234***	-0.0243***	-0.0178***	-0.0232***	-0.0238***	-0.0223***	-0.0218***
	(0.00551)	(0.00437)	(0.00627)	(0.00657)	(0.00683)	(0.00624)	(0.00576)	(0.00567)	(0.00537)	(0.00577)
averageIncome			0.0512**	0.0541**	0.0674**	0.0415*	0.0583**	0.0595**	0.0547**	0.0532**
			(0.0199)	(0.0215)	(0.0311)	(0.0213)	(0.0218)	(0.0222)	(0.0219)	(0.0214)
Herf				0.00949	0.00678	0.00700	0.00860	0.00895	0.00708	0.00777
				(0.0121)	(0.0124)	(0.0100)	(0.0104)	(0.0105)	(0.0106)	(0.0107)
University					-0.00939	-0.0140*	-0.0199**	-0.0205**	-0.0121	-0.0120
					(0.00888)	(0.00818)	(0.00858)	(0.00890)	(0.00912)	(0.00907)
Age Cohorts						YES	YES	YES	YES	YES
Family							0.166**	0.163**	0.178**	0.178**
							(0.0700)	(0.0690)	(0.0722)	(0.0739)
Environment							-0.0372	-0.0357	-0.00364	-0.00505
							(0.0238)	(0.0237)	(0.0202)	(0.0200)
hightech								-0.732	-0.791	-0.850
								(0.824)	(0.805)	(0.859)
logPopulation									-0.112*	-0.115*
									(0.0570)	(0.0580)
inFUA										0.0459
										(0.0951)
Province Dummies	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	989	989	989	989	989	989	989	985	985	985
R-squared	0.000	0.245	0.258	0.260	0.261	0.299	0.307	0.309	0.316	0.316

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

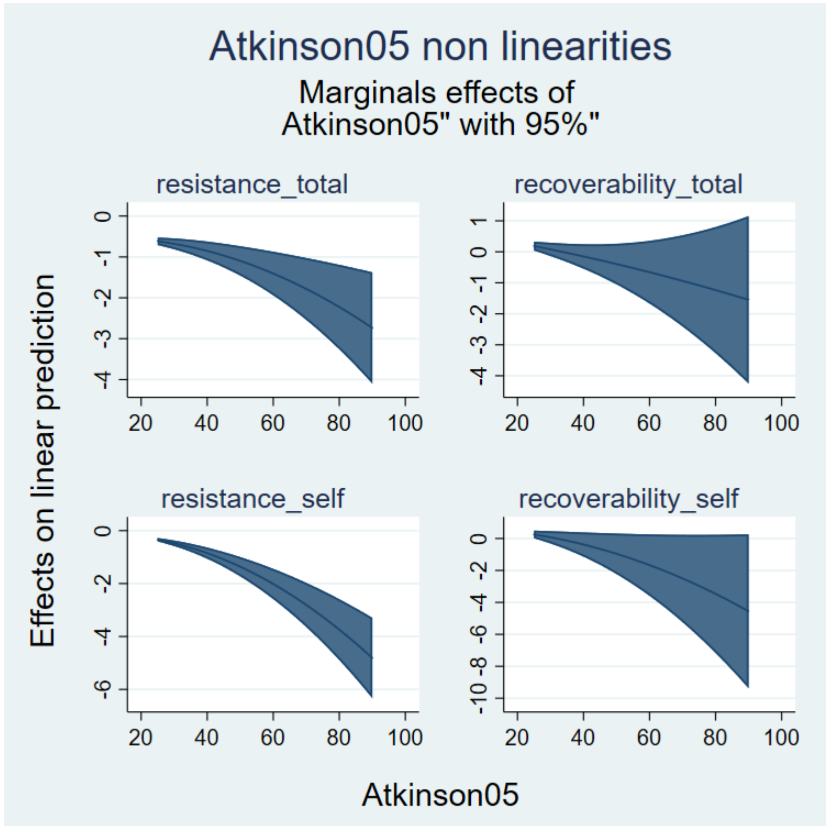
Recoverability Self-Employment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gini	0.0136	0.0143**	-0.0139	-0.0143	-0.0127	-0.00486	-0.0251**	-0.0254**	-0.0227**	-0.0218*
	(0.00882)	(0.00703)	(0.0124)	(0.0123)	(0.0125)	(0.0124)	(0.0112)	(0.0111)	(0.0111)	(0.0117)
averageIncome			0.0998**	0.0982**	0.0756	0.0365	0.100**	0.0990**	0.0908**	0.0880**
			(0.0389)	(0.0417)	(0.0556)	(0.0394)	(0.0406)	(0.0407)	(0.0398)	(0.0400)
Herf				-0.00544	-0.000801	0.00763	0.0163	0.0175	0.0140	0.0154
				(0.0212)	(0.0183)	(0.0160)	(0.0148)	(0.0152)	(0.0145)	(0.0148)
University					0.0159	-0.00224	-0.0237*	-0.0237*	-0.00937	-0.00916
					(0.0157)	(0.0125)	(0.0132)	(0.0129)	(0.0121)	(0.0119)
Age Cohorts						YES	YES	YES	YES	YES
Family							0.631***	0.614***	0.640***	0.640***
							(0.102)	(0.101)	(0.105)	(0.108)
Environment							-0.0677*	-0.0614*	-0.00447	-0.00735
							(0.0372)	(0.0366)	(0.0396)	(0.0394)
hightech								-2.179*	-2.253*	-2.367*
								(1.171)	(1.184)	(1.192)
logPopulation									-0.197***	-0.202***
									(0.0701)	(0.0703)
inFUA										0.0909
										(0.116)
Province Dummies	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	959	959	959	959	959	959	959	955	955	955
R-squared	0.003	0.395	0.418	0.418	0.419	0.483	0.535	0.545	0.554	0.555

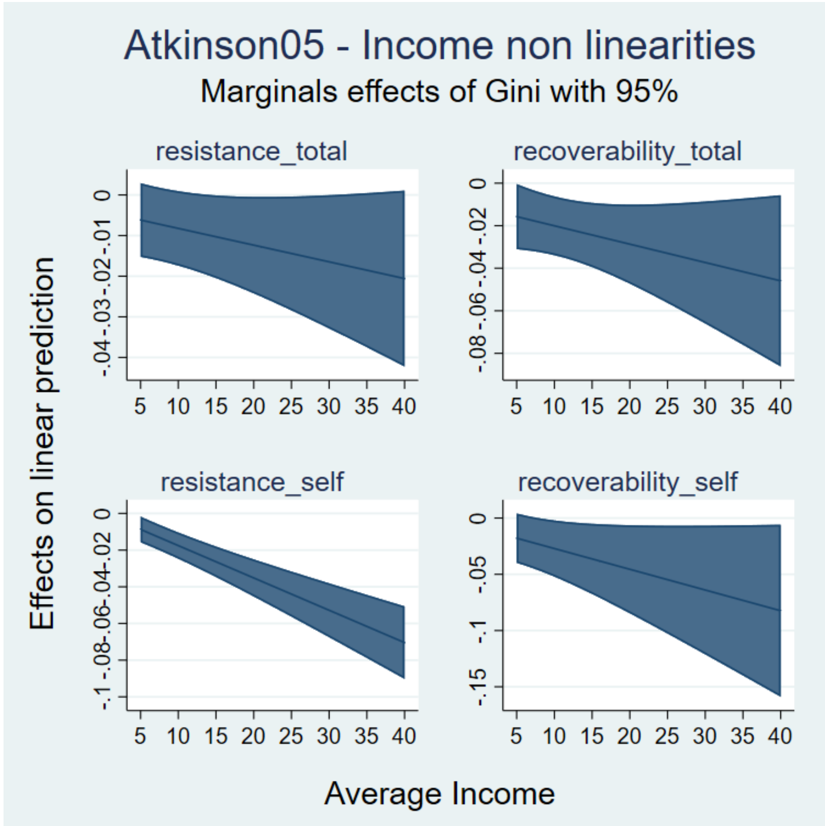
Robust standard errors in parentheses, clustered by province. *** p<0.01, ** p<0.05, * p<0.1

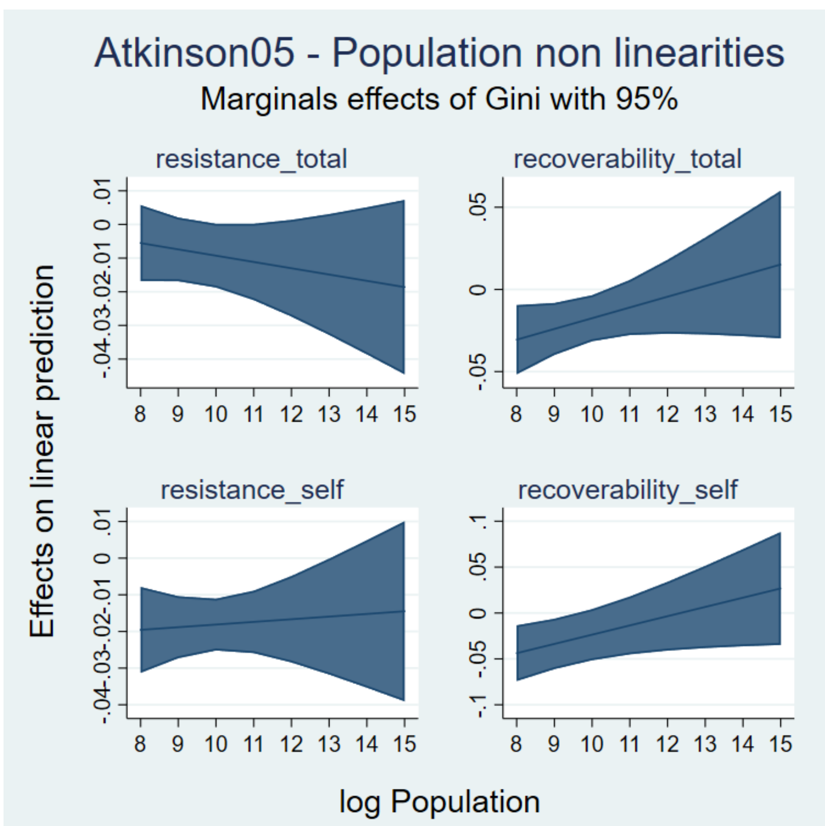
Models with interactions. Marginal effects of the linear prediction. Atkinson$_{05}$ Index

	(1)	(2)	(3)	(4)
	Resistance Total Employment	Recoverability Total Employment	Resistance Self Employment	Recoverability Self Employment
Atkinson$_{05}$	0.00602	-0.0167	0.0118*	-0.000481
	(0.00738)	(0.0128)	(0.00587)	(0.0163)
Atkinson$_{05}$ ^{2}	-0.000336**	-8.68e-05	-0.000700***	-0.000639
	(0.000132)	(0.000258)	(0.000137)	(0.000395)
Av Income	0.0388**	0.0598*	0.124***	0.140**
	(0.0162)	(0.0311)	(0.0146)	(0.0533)
log Population	0.0737***	-0.116**	0.0112	-0.199***
	(0.0222)	(0.0577)	(0.0221)	(0.0708)
Observations	985	985	955	955
R-squared	0.423	0.313	0.493	0.559
Atkinson05	-0.00412	-0.0114	0.000107	-0.00868
	(0.00493)	(0.00941)	(0.00393)	(0.0117)
Atkinson05 x Av Income	-0.000411	-0.000863	-0.00176***	-0.00184*
	(0.000297)	(0.000631)	(0.000277)	(0.00101)
Av Income	0.0397	0.0953**	0.168***	0.192**
	(0.0240)	(0.0447)	(0.0209)	(0.0791)
log Population	0.0730***	-0.117*	0.00886	-0.202***
	(0.0218)	(0.0583)	(0.0220)	(0.0711)
Observations	985	985	955	955
R-squared	0.420	0.315	0.497	0.560
Atkinson05	0.00941	-0.0828*	-0.0254	-0.124**
	(0.0212)	(0.0416)	(0.0236)	(0.0477)
Atkinson05 x log Pop	-0.00187	0.00653	0.000724	0.0101**
	(0.00218)	(0.00415)	(0.00233)	(0.00488)
Av Income	0.0210	0.0536**	0.0855***	0.103**
	(0.0148)	(0.0218)	(0.0239)	(0.0412)
log Population	0.103**	-0.220**	-0.000997	-0.361***
	(0.0461)	(0.0848)	(0.0469)	(0.118)
Observations	985	985	955	955
R-squared	0.420	0.314	0.476	0.557

Robust standard errors in parentheses, clustered by province. *** p<0.01, ** p<0.05, * p<0.1. All regressions include province dummies and the same controls as the ines in Table 1


Atkinson05 non linearities
Marginals effects of
Atkinson05" with 95%"
resistance_total
recoverability_total
resistance_self
recoverability_self
Effects on linear prediction
Atkinson05
20 40 60 80 100
0 -1 -2 -3 -4
1 0 -1 -2 -3 -4
0 -2 -4 -6
0 -2 -4 -6 -8 -10


Atkinson05 - Income non linearities
Marginals effects of Gini with 95%
resistance_total
recoverability_total
resistance_self
recoverability_self
Effects on linear prediction
Average Income


Atkinson05 - Population non linearities
Marginals effects of Gini with 95%
resistance_total
recoverability_total
resistance_self
recoverability_self
Effects on linear prediction
log Population