

ΠΑΝΤΕΙΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΚΟΙΝΩΝΙΚΩΝ ΚΑΙ ΠΟΛΙΤΙΚΩΝ ΕΠΙΣΤΗΜΩΝ

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Three essays on the geography of income inequality in Greece

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**ΣΧΟΛΗ ΕΠΙΣΤΗΜΩΝ ΟΙΚΟΝΟΜΙΑΣ ΚΑΙ ΔΗΜΟΣΙΑΣ ΔΙΟΙΚΗΣΗΣ
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ΔΙΔΑΚΤΟΡΙΚΗ ΔΙΑΤΡΙΒΗ

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**Τρεις πραγματείες για τη γεωγραφία της εισοδηματικής ανισότητας
στην Ελλάδα**

Αθήνα, Δεκέμβριος 2023

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Με επιφύλαξη παντός δικαιώματος.

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Abstract

The subject of this PhD thesis is the study of the spatial dimension of income inequality in Greece. The dissertation is based on declared income data and covers the period 2002-2019. The spatial unit of analysis includes both territorial spatial units of the statistical classification of the European Union, NUTS I, NUTS II and NUTS III, as well as smaller territorial units such as Regional Units and Municipalities. This thesis provides empirical analysis of income inequality in Greece using a sample of statistical data on the tax declarations of individuals over a long period of time. For the first time in the literature, it is possible to measure and change income inequality in Greece intraregionally. The research is currently at the heart of the literature because it has been observed that the increase of inequality is one of the major problems of our time with strong economic and social side effects, while it is also a factor of dissatisfaction expressed in antisystemic electoral behavior. The analysis of income inequality at various geographical scales, such as Municipalities and Regional Units, the analysis of income inequality before and after the economic crisis and the examination of the role of income inequality during the pandemic are additional elements of originality deriving from the main innovation of the thesis, which is the analysis of income inequality based on individual tax data. The conclusions constitute original contributions to the scientific literature and are important inputs for the formulation of spatially and socially focused policy.

The doctoral dissertation consists of three modules.

The first section concerns the analysis of the geographical distribution of declared income and income inequality in Greece by Municipality during the period 2002-2014, which is analyzed in two sub-periods 2002-2011 and 2012-2014. The time span of the analysis allows for a comparative investigation of changes in inequality before and after the financial crisis. The analysis methodology includes statistical, cartographic and econometric analysis using the most appropriate analysis methods used in the international bibliography. The results of the analysis substantiate two main conclusions: first, the economic crisis constitutes a turning point for the form of income inequality in Greece, and second, that there are many geographies of income inequality that differ based on the time period of the analysis, the geographical level of the analysis and the level of income per geographical unit. Finally, education is a very key determinant of income inequality. These results provide for the first time such a scientifically substantiated analysis of income inequality at the spatial level in Greece.

The second section provides a clustering of municipalities based on income and income inequality. The results of the analysis highlighted that the geographical dimension of income distribution and income inequality exceeds the schemes Center - Region, North - South or Island - Mainland. High-income areas are located within metropolitan areas, on some islands and scattered in different regions of the country. At the same time, low-income areas are located both in metropolitan areas, as well as on mainland and islands. It is worth noting that the geography of interregional income inequality differs from the geography of intraregional inequality within municipalities. Finally, it is found that there is a positive and statistically significant self-correlation in space for both declared income and income inequality, i.e. low-income areas also affect the income of neighboring areas, just as high-income areas affect the level of income of their neighboring areas. Similarly, it is observed that income inequality also affects the inequality of neighboring municipalities.

The third part analyzes the spatiotemporal variations of COVID-19 mortality in Greece, by age category of cases / deaths for six waves of the pandemic. In particular, the analysis investigates the geographical differences in mortality due to COVID-19 in Greece, using statistical data classified by seventy-four Regional Administrative Units, ten-year age groups, and six waves of the pandemic, covering forty-two weeks of the pandemic covering the period 26-10-2020 to 22-3-2022. The analysis of this phenomenon lies at the intersection of scientific fields, such as Spatial Economics, Demography, Spatial Planning and Geography, and is therefore based on a combination of disciplines and empirical analysis methods. The estimation of Standardized by ten-year age group Case-Fatality Ratios (SFR), as well as the application of Spatial Durbin Econometric Model (SDEM), offer statistically strong evidence for the influence of socioeconomic, demographic and geographical factors on the mortality rate from COVID-19. The innovative database created provided the appropriate background for estimating age-adjusted SFR and for applying statistical analyses and econometric techniques, which allows for a very structured approach to the geographical dimension of COVID-19 mortality.

Keywords: *income inequality, economic crisis, geography of income inequality, austerity, spatial dependence, spatial analysis of COVID-19, Age-Standardized Fatality Ratio (SFR), Spatial Durbin Error Model (SDEM), spatial health inequalities, Municipalities, Regions, Regional Units, Greece*

Περίληψη

Αντικείμενο της παρούσας διδακτορικής διατριβής είναι η μελέτη της χωρικής διάστασης της εισοδηματικής ανισότητας στην Ελλάδα. Η διπλωματική εργασία βασίζεται σε στοιχεία δηλωθέντων εισοδημάτων και καλύπτει την περίοδο 2002-2019. Η χωρική κλίμακα ανάλυσης περιλαμβάνει τόσο εδαφικές χωρικές ενότητες της στατιστικής ταξινόμησης της Ευρωπαϊκής Ένωσης, NUTS I, NUTS II και NUTS III, όσο και μικρότερες εδαφικές ενότητες όπως Περιφερειακές Ενότητες και Δήμους. Η παρούσα διπλωματική εργασία παρέχει εμπειρική ανάλυση της εισοδηματικής ανισότητας στην Ελλάδα χρησιμοποιώντας δείγμα στατιστικών στοιχείων για τις φορολογικές δηλώσεις φυσικών προσώπων για μεγάλο χρονικό διάστημα. Για πρώτη φορά στη βιβλιογραφία, είναι δυνατή η μέτρηση και η δυναμική της εισοδηματικής ανισότητας στην Ελλάδα ενδοπεριφερειακά. Η έρευνα βρίσκεται επί του παρόντος στο επίκεντρο της βιβλιογραφίας γιατί έχει παρατηρηθεί ότι η αύξηση της ανισότητας είναι ένα από τα μεγαλύτερα προβλήματα της εποχής μας με έντονες οικονομικές και κοινωνικές παρενέργειες, ενώ είναι και παράγοντας δυσαρέσκειας που εκφράζεται στην αντισυστημική εκλογική συμπεριφορά. . Η ανάλυση της εισοδηματικής ανισότητας σε διάφορες γεωγραφικές κλίμακες, η ανάλυση της εισοδηματικής ανισότητας πριν και μετά την οικονομική κρίση και η εξέταση του ρόλου της εισοδηματικής ανισότητας κατά την πανδημία είναι πρόσθετα στοιχεία πρωτοτυπίας που απορρέουν από την κύρια καινοτομία. της διπλωματικής εργασίας, που είναι η ανάλυση της εισοδηματικής ανισότητας με βάση τα ατομικά φορολογικά στοιχεία. Τα συμπεράσματα αποτελούν πρωτότυπες συνεισφορές στην επιστημονική βιβλιογραφία και αποτελούν σημαντικές εισροές για τη διαμόρφωση χωρικά και κοινωνικά εστιασμένης πολιτικής.

Η διδακτορική διατριβή αποτελείται από τρεις ενότητες.

Η πρώτη ενότητα αφορά την ανάλυση της γεωγραφικής κατανομής των δηλωθέντων εισοδημάτων και της εισοδηματικής ανισότητας στην Ελλάδα κατά Δήμο κατά την περίοδο 2002-2014, η οποία αναλύεται σε δύο υποπεριόδους 2002-2011 και 2012-2014. Το χρονικό διάστημα της ανάλυσης επιτρέπει τη συγκριτική διερεύνηση των αλλαγών στην ανισότητα πριν και μετά την οικονομική κρίση. Η μεθοδολογία ανάλυσης περιλαμβάνει περιγραφική στατιστική, χαρτογραφική και οικονομετρική ανάλυση χρησιμοποιώντας τις καταλληλότερες μεθόδους ανάλυσης από τη διεθνή βιβλιογραφία. Τα αποτελέσματα της ανάλυσης τεκμηριώνουν δύο βασικά συμπεράσματα: πρώτον, η οικονομική κρίση αποτελεί σημείο καμπής για τη μορφή εισοδηματικής ανισότητας στην Ελλάδα και δεύτερον, ότι υπάρχουν πολλές γεωγραφίες εισοδηματικής ανισότητας που διαφέρουν ανάλογα με τη χρονική περίοδο της ανάλυσης. το γεωγραφικό επίπεδο της ανάλυσης και το επίπεδο

εισοδήματος ανά γεωγραφική ενότητα. Τέλος, η εκπαίδευση είναι ένας πολύ βασικός καθοριστικός παράγοντας της εισοδηματικής ανισότητας. Τα αποτελέσματα αυτά παρέχουν για πρώτη φορά τεκμηριωμένη ανάλυση της εισοδηματικής ανισότητας σε χωρικό επίπεδο στην χώρα.

Η δεύτερη ενότητα παρέχει μια ομαδοποίηση των δήμων με βάση την εισοδηματική και εισοδηματική ανισότητα. Τα αποτελέσματα της ανάλυσης υπογραμμίζουν ότι η γεωγραφική διάσταση της κατανομής του εισοδήματος και της εισοδηματικής ανισότητας υπερβαίνει τα σχήματα Κέντρο - Περιφέρεια, Βορράς - Νότος ή Νησιωτική - Ηπειρωτική χώρα. Οι περιοχές υψηλού εισοδήματος βρίσκονται εντός μητροπολιτικών περιοχών, σε ορισμένα νησιά και διάσπαρτες σε διάφορες περιοχές της χώρας. Παράλληλα, περιοχές με χαμηλό εισόδημα βρίσκονται τόσο σε μητροπολιτικές περιοχές, όσο και σε ηπειρωτικές και νησιωτικές ενότητες. Αξίζει να σημειωθεί ότι η γεωγραφία της διαπεριφερειακής εισοδηματικής ανισότητας διαφέρει από τη γεωγραφία της ενδοπεριφερειακής ανισότητας εντός των δήμων. Τέλος, διαπιστώθηκε ότι υπάρχει θετική και στατιστικά σημαντική χωρική αυτοσυσχέτιση τόσο για το δηλωμένο εισόδημα όσο και για την εισοδηματική ανισότητα.

Στο τρίτο μέρος αναλύονται οι χωροχρονικές διακυμάνσεις της θνησιμότητας από τον COVID-19 στην Ελλάδα, ανά ηλικιακή κατηγορία κρουσμάτων/θανάτων για έξι κύματα της πανδημίας. Ειδικότερα, η ανάλυση διερευνά τις γεωγραφικές διαφορές στη θνησιμότητα λόγω COVID-19 στην Ελλάδα, χρησιμοποιώντας στατιστικά στοιχεία ταξινομημένα στις Περιφερειακές Ενότητες, δεκαετείς ηλικιακές ομάδες και έξι κύματα της πανδημίας, που καλύπτει την περίοδο 26-10-2020 έως 22-3-2022. Η ανάλυση βασίζεται σε έναν συνδυασμό επιστημονικών κλάδων και μεθόδων εμπειρικής ανάλυσης όπως η χωρική οικονομετρία, η δημογραφία, ο χωροταξικός σχεδιασμός και η γεωγραφία. Η εκτίμηση των τυποποιημένων κατά δεκαετή ηλικιακή ομάδα δεικτών θνησιμότητας (Case-Fatality Ratios-SFR), καθώς και η εφαρμογή του χωρικού οικονομετρικού υποδείγματος Durbin (Spatial Durbin Econometric Model-SDEM)), προσφέρουν στατιστικά ισχυρές ενδείξεις για την επίδραση κοινωνικοοικονομικών, δημογραφικών και γεωγραφικών παραγόντων στο ποσοστό θνησιμότητας από τον COVID-19. Η βάση δεδομένων που δημιουργήθηκε παρείχε το κατάλληλο υπόβαθρο για την εκτίμηση του δείκτη του σταθμισμένου δείκτη SFR και για την εφαρμογή στατιστικών αναλύσεων και οικονομετρικών τεχνικών, γεγονός που επιτρέπει μια συγκροτημένη προσέγγιση στη γεωγραφική διάσταση της θνησιμότητας από COVID-19.

***Λέξεις κλειδιά:** εισοδηματική ανισότητα, οικονομική κρίση, γεωγραφία, γεωγραφία εισοδηματικής ανισότητας, λιτότητα, χωρική εξάρτηση, χωρική ανάλυση του COVID-19, τυποποιημένη αναλογία θνητότητας ηλικίας (SFR), χωρικό υπόδειγμα Durbin (SDEM), χωρική ανισότητα υγείας, Δήμοι, Περιφερειακές Ενότητες, Περιφέρειες, Ελλάδα*

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Chapter I

Introduction

“We should prioritize the reduction of inequalities over the pursuit of endless economic growth.”

Thomas Piketty, Professor of Economics

“It amazes me how people are often more willing to act based on little or no data than to use data that is a challenge to assemble”.

Robert J. Shiller, Nobel laureate 2013, Sterling Professor of Economics

I.1 Motivation

Income inequality has been risen in historically high levels. This observation, along with the empirical evidence that inequality matters for the growth potential of nations and for the wellbeing and prosperity of citizens, has placed this issue at the core of scientific investigation (Piketty & Saez, 2003; Dorling, 2015; Atkinson & Piketty, 2010; Atkinson, Piketty & Saez 2011; Bourguignon, 2015). Robert Shiller, recipient of the Nobel Prize in Economics (2013) declared that the most important problem we are facing today is the rising inequality.

Although income inequality has been a longstanding issue in economics (Kuznets, 1955), this renewed attention is arguably, at least in a large part, attributable to the work of Piketty (2014), which provided evidence that income and wealth inequality has risen considerably and that inequality levels are today comparable with these that before the outbreak of the World War I. The work of Piketty has triggered a voluminous number of publications providing insights from different countries across the globe.

International organisations are aware of the importance of this issue. The OECD, for example, provides empirically supported evidence that income inequality in OECD countries is at the highest level for the past half century. The average income of the richest 10% of the population is about nine times that of the poorest 10%, up from seven times 25 years ago (OECD, 2017). Furthermore, OECD data show that, the economic crisis has intensified income inequality and thus income remains significantly more unequally distributed today than it was before the economic crisis (OECD, 2014). Finally, OECD has placed income inequalities at the top of research and policy agenda (OECD, 2017).

In September 2015, the United Nations (UN) introduced the 2030 Agenda for Sustainable Development. Within this new framework, issues such as environmental and social inclusion seem to maintain a prominent role towards achieving sustainability, whereas additional dimensions have been added, focusing on economic growth, innovation and sustainable urban development.

In the case of the European Union (EU), inclusive and sustainable development is mainstreamed through the EU Cohesion policy framework, targeting to reduce disparities between and within EU regions through investing in a smart, sustainable and inclusive growth model. Under this scope, the Europe 2020 strategy contributes to the achievement of the overall 2030 Agenda, by investing on reducing inter- and intra-regional inequalities.

In terms of strategic planning, the adoption of the Europe 2020 strategy introduced an extended set of indicators, signalling a shift towards a more quantitative-oriented approach of policy-design. This eventually prompted the use of data-driven solutions and open data as facilitators for collecting and processing information, regarding the measurement of indicators related to inclusiveness. This new policy-design approach, characterized by the quantification of inter- and intra-regional inequalities, offers novel opportunities to decision-makers, as they can now expand the analytical framework involved in the strategic planning process. Spatio-temporal analysis, microsimulation models and methods of cartographic representation are tools that can expand the existing knowledge-base for data-driven policies, as they enable a place-based and people-based approach to inclusion and income inequality reduction policies, strongly related to the local context, people and societies.

However, while empirical studies of income inequality at the country level have dominated the scientific literature, the geography of income inequality has become a distinct and rapidly accelerated strand of scientific research. Empirical evidence is increasingly being generated in Europe, the USA and other countries in the world.

Within the European experience, the works by Moser and Schnetzer (2017) and Lee, Sissons & Jones (2015) are most relevant to our research proposal. Both papers are based on sample income data utilizing administrative records for Austria and the UK respectively. Dickey (2007) and Duranton & Monastiriotis (2002) are among scholars who have studied the earnings inequality in the UK. With regard European Union, Rodríguez-Pose and Tselios (2009) and Perugini & Martino (2008) examined the relationship between income inequality, education and regional growth across European regions. In another study, Tselios (2008) find that the relationship between income and educational inequalities has evolved differently across welfare regimes and both spatial autocorrelation and spatial heterogeneity matter for income inequalities.

The geographical aspect of income and earnings inequality is a flourishing area of research in the US. The seminal work of Bennet (1980) for Canada, USA and UK will be a standard point of reference for our work. Furthermore, there has been a flourishing member of publications focusing on income inequality across US cities. Morrill (2000) work on the geographic variation of income inequality across states from 1970 to 1990 offers one of the most representative examples of the relevant studies. Partridge, Rickman & Levernier (1996) and Levernier, Partridge & Rickman (1998) examined variations in U.S examining family income inequality for 3.109 counties and independent cities in 48 contiguous states. Gleaser, Lesseger & Tobio (2009) examined income inequality in US cities. Another work, relevant to our research proposal, is that of Florida &

Mellander (2016) which examines the geographic variation in wage inequality and income inequality across US metropolitan areas.

Other relevant works provide important insights regarding the income-inequality nexus in many other countries. These include Paderes, Iturra & Lufin (2016) for Chile, Mello (2017) for Scotland, Rios & Hortas-Rico (2016) for Spain, Acciari & Mocetti (2013) for Italy and Cynthia & Guadalupe (2016) for Argentina, just to mention a few.

With regard to Greece, recent studies (Andriopoulou *et al.*, 2017; Kaplanoglou & Rapanos 2016; Mitrakos, 2014) focusing in the levels of inequality and poverty in Greece during the recent crisis and compared their distributions before and close to the peak of the crisis, using information from EU-SILC database and Household Expenditure Surveys (HES) and by the Hellenic Statistical Authority (EL.STAT.). The research on the geographical aspects of income inequality is very limited. Kalogirou (2011) and Prodromidis (2006), Maloutas (2018) are among these works while Psycharis and Pantazis (2016) examine declared income and social segregation in Athens. All these works utilize postal code data.

However, the present work will be based on individual data, which constitutes a novelty since this will be the first time that inequalities in income and polarization trends will be measured with individual micro-data. The use of income data to calculate a set of inequality indexes, such as the Gini index, the Theil index at a municipal level of analysis is a key part of this effort.

I.2 Methods and models of spatial analysis

The research design of this effort is quantitative analysis. We apply statistical and econometric techniques to urban and regional data in order to generate and test hypothesis about the underlying dynamics of the interregional and intra-regional income inequalities in Greece. We will use panel data which will allow us to put emphasis not only on the evolution of income inequalities over the 2000-2015 period and on the differences in inequalities between and after the economic crisis period but also on the differences across space (i.e. between regions and between municipalities).

We will use panel data analytical techniques because they control for regional heterogeneity, give more informative data and variability along with a greater degree of freedom and efficiency, and facilitate the study of the dynamics of adjustment (e.g. to estimate what proportion of income inequality with a region is one period may remain over another period) (Baltagi, 2005).

The panel data analysis is divided into two categories: a) descriptive analysis and b) econometric analysis.

A. Descriptive analysis: After the construction of the databases, we will start the initial examination of the variables through histograms (e.g. to represent the distribution of net personal income in Greece, between regions and within regions), through boxplots to identify outliers and extreme cases (e.g. to identify households with very high income levels), through visualisations (e.g. to identify clusters of high income inequality regions mapping income inequality indexes) and through correlation indices (e.g. to see whether the income per capita of a region is correlated with the income inequality within the region using the Pearson correlation index between the regional income per capita and the regional interpersonal income inequality). We will also apply Exploratory Spatial Data Analysis to explore regional and urban clusters and patterns of income inequality. We will initial create different spatial weights schemes (e.g. the k-nearest neighbours) and then we will apply global and local spatial autocorrelation statistics such as the global and local Moran's I to test for spatial dependence (Anselin, 1995). Hence, we will examine whether spatial data are random or there are similarities between neighbours.

B. Regression analysis: We will use static regressions (e.g. spatial econometric techniques) and dynamic regressions (e.g. generalised method of moments econometric techniques) in order to identify the economic, social, political, institutional and geographical determinants of income inequality. The selection of the determinants of income inequality is based not only on the theoretical background but also on the availability of the different data sources. In the econometric analysis will also consider and control for causality, heteroscedasticity and autocorrelation. We will use many estimators (such as ordinary least squares, fixed effects, random effects, instrumental variables) and will use statistical tests (e.g. Hausman test) for the appropriateness of these estimators.

We apply spatial analytical techniques at different spatial levels. As we will use spatially aggregated data, we will consider the 'modifiable area unit problem' (Openshaw, 1983) which implies that spatially aggregated data contain a higher degree of uncertainty than the individual components undergoing aggregation and thus some observed patterns could be a result of the aggregation level (Fotheringham, Brunson & Charlton 2000). This is very important because it is possible for spatial autocorrelation to appear at the local level, but to disappear at a larger spatial level due to the 'modifiable area unit problem'.

I.2.1 Random sample of statements by natural persons (microdata)

The database that has been constructed includes a random sample of 10% of the annual declarations of natural persons for the period 2002-2019. Based on the principle of confidentiality, this anonymous data has been provided with special permission for scientific purposes by the Ministry of Finance. Based on the main source of income, these declarations are grouped into six main categories: *Owners, Traders, Farmers, Workers, Self-employed* and *Pensioners*. In addition, this dataset includes information about household characteristics. These include marital status and age, family size, number of children, single-parent families, number and cubic capacity of privately owned cars.

There are two variables available for income: **declared and imputed (taxed)**. The first is based on gross income derived from various sources (real estate, interest/dividends/royalties, capital transfer goodwill, entrepreneurial activity, agricultural business, salaried work and pensions). Taxable income is calculated using the declared sources of income; however, it could be increased, based on "objective criteria" applied to calculate imputed income subject to tax, and It is used as the basis -by definition- for calculating the tax burden. Taxable income could also be lower than declared income if there are special tax exemptions. In addition to these two variables, the overall tax burden is also included.

Equivalent declared and taxable income was used for the purpose of the analysis. Based on the declared income of households, the equivalent declared income is estimated that takes into account family income and the specific characteristics of households and their members. More specifically, equivalent income is the total income of a tax return, divided by the number of household members converted into equivalent adults based on the modified OECD (Organisation for Economic Co-operation and Development) equivalence scale: the first member of the adults counts as 1 person, the remaining adult members of the household are counted as 0.5 persons, Each household member is declared as a "child" aged 14 and over counts as 0.5 persons, each household member is referred as a "child" aged 13 or less counts as 0.3 persons. For the construction of the database, the random sample was used, which includes 10% of the declarations of natural persons per year (period 2002-2019) with approximately 500,000 records per year (**Table I-1**).

In the first step, a normalisation process (stratified weighting procedure) of the data was carried out based on the total (national) distribution of declared revenues by geographical stratum [Prefectures (NUTSIII-2010) -51 modules] and fixed income brackets (10 groups).

Table I-1. Sample size of individual tax declarations by year and level of spatial analysis

Year	Records	Spatial reference
2002	472.329	PC/Municipality
2003	498.135	PC/Municipality
2004	529.804	PC/Municipality
2005	563.997	PC/Municipality
2006	556.252	PC/Municipality
2007	561.096	PC/Municipality
2008	567.853	PC/Municipality
2009	573.703	PC/Municipality
2010	575.928	PC/Municipality
2011	572.664	PC/Municipality
2012	446.134	PC/Municipality
2013	579.237	PC/Municipality
2014	600.089	PC/Municipality
2015	606.179	PC/Municipality
2016	621.298	PC/Municipality
2017	629.886	PC/Municipality
2018	635.658	PC/Municipality
2019	643.648	PC/Municipality

At a later stage, data selection (non-zero declaration selection) and spatial smoothing for aggregated data at the lowest spatial scale (325 units - Municipalities) were carried out in order to reduce sampling error, especially in sparsely populated areas. The unit geographical reference refers to Postal Codes (PC) as recorded by the information system of the Ministry of Finance. A logical check of code mapping was performed over time. Initially, the codes of the GSIS files were checked in relation to those of ELTA based on the correspondence file of Postal codes provided by the GSIS. Subsequently, the geographical reference of each postal code of ELTA at the level of the Municipality was investigated. Greek municipalities constitute the basic geographical level of the analysis (Local administrative units --level LAU 1, formerly NUTS level 4) in Eurostat terminology. According to the existing administrative system, the 325 municipalities constitute the first tier of local government in Greece (Law 3852/2010). Income inequality variables are planned to be estimated at 4 spatial reference levels:

1. at municipal level of 325 municipalities for the entire period of our analysis. In addition, according to Law 4555/2018 (Kleisthenis) Greek Municipalities have been grouped into six

categories based on population and geographical characteristics and are planned to be used to analyze income and income inequality in Greece:

- [K1] Municipalities belonging to metropolitan areas [*Metropolitan district*],
 - [K2] large municipalities and capitals of the mainland [*Mainland large*],
 - [K3] medium-sized municipalities [*Mainland medium-size*],
 - [K4] small continental and small mountain municipalities [*Mainland small & mountainous*],
 - [K5] municipalities of large and medium-sized islands [*Island large & medium-size*] and
 - [K6] municipalities of small islands [*Island small*].
2. Geographical level of Regional units and/or NUTSIII (*aka* Nomoi in previous years)
 3. geographical level of regions (NUTSII)
 4. The whole country.

I.3 Statistical description and spatial distribution of declared income for the period 2002-2019

This chapter provides a basic descriptive and cartographic presentation of the equivalent declared income - which is the main variable of analysis in this work – at the lowest available geographic scale (municipalities) – for the period 2002-2019.

I.3.1 Declared income distributions and trends at national level

Figure I-1 **Figure I-2** and **Figure I-3** present the evolution of the equivalent declared income at the national level over time. Based on the distribution of the weighted average and weighted median we observe that after 2011 the declared and taxable income decreased significantly (**Figure I-1** and **Figure I-2**). This was the result of the cascading effect of factors such as rising unemployment, reductions in wages and pensions, and rising taxes. From 2016 a stabilization at low levels is observed, while from 2018 a small recovery trend appears. These figures clearly show the severe decrease in incomes and the sharp increase in taxes. This is the result of the fiscal adjustment program implemented in the country after the implementation of the First Economic Adjustment Program for Greece that started in 2010. Until 2015, no significant differentiation is observed in the income of employees compared to the entire sample, in contrast to the period 2015-2019 where a gradual trend of deviation above the national average is observed.

Figure I-1. Weighted mean declared income equivalent, Greece, st. prices 2015, period 2002-2019

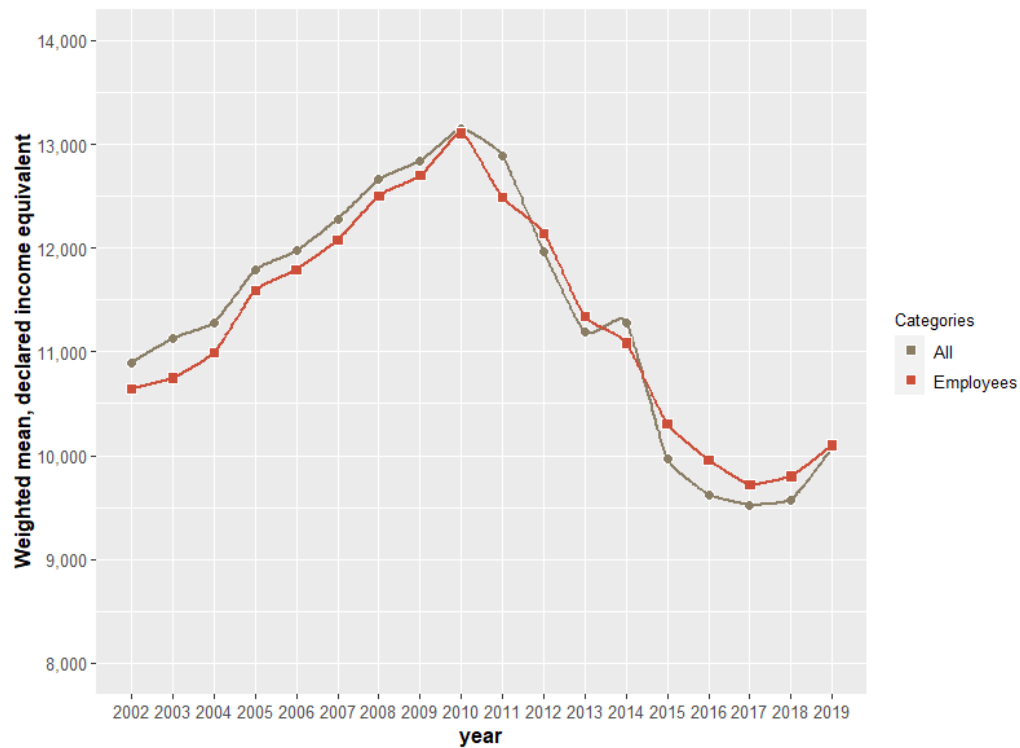
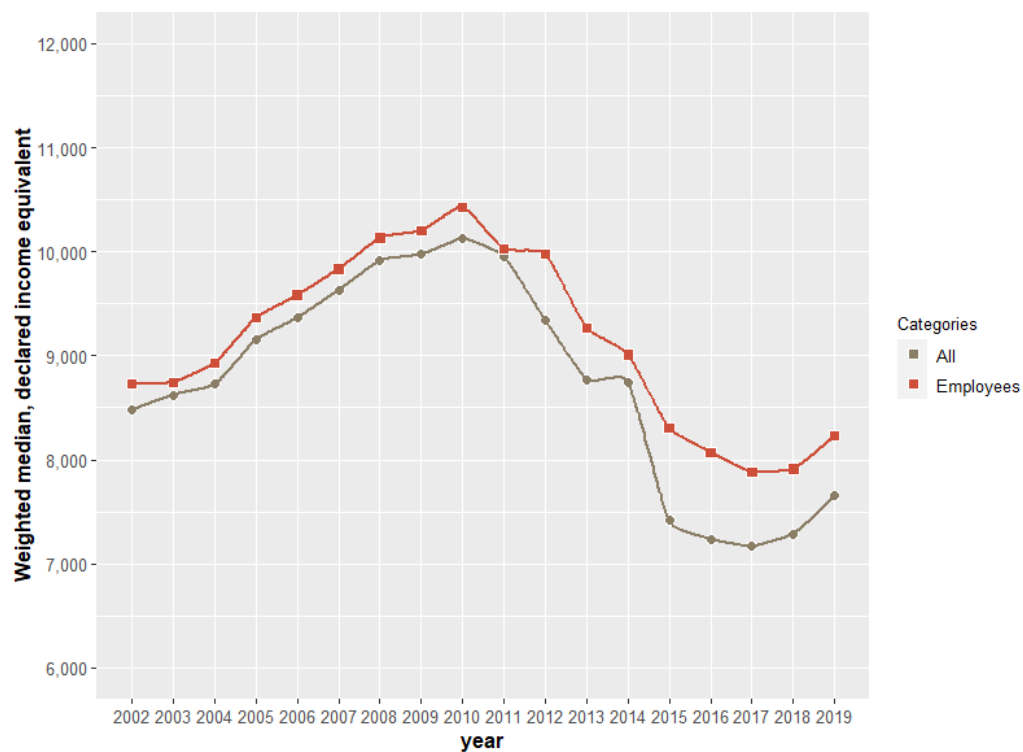
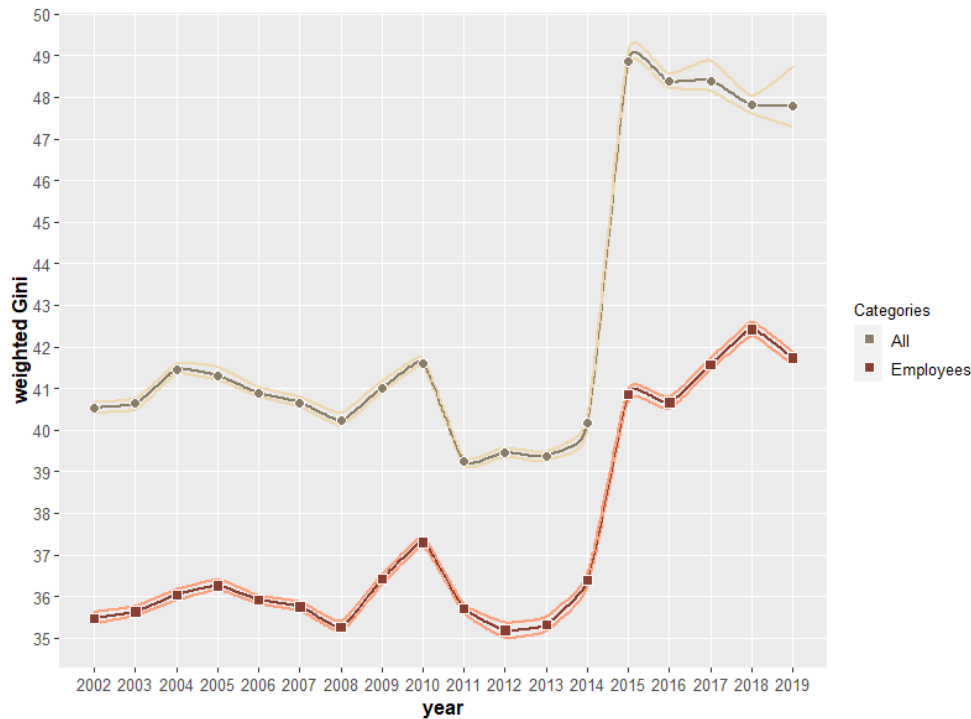


Figure I-2. Weighted median declared income equivalent, Greece, st. prices 2015, period 2002-2019



Income inequality shows relative stability with a slight downward trend until 2008, relative increase in the period 2009-2010, decrease until 2013, sharp increase in the period 2014-2015 and finally relative stability at high levels in the period 2015-2019 (**Figure I-3**). In every case, in terms of income inequality, the category of employees (wage earners) shows a similar picture to the whole sample but with clearly lower values of the Gini index throughout the period 2002-2019 and a differentiated trend after 2015.

Figure I-3. Weighted Gini of declared income equivalent, Greece, period 2002-2019



I.3.2 Declared income distributions and trends at regional and sub-regional level

From **Figure I-4** and **Figure I-5** which include the statistical distribution of spatial units at sub-regional level (regional units) and **Table I-2-Table I-3** with selected indicators of descriptive statistics based on the weighted average and median equivalent declared income, the first conclusions concerning the relatively greater for greater dispersion in the period 2009 to 2011, as well as a shift of the curve of employees to a higher level compared to the total sample, beginning from the year 2015. At the regional level, no significant differences were identified (**Figure I-7**, **Figure I-8**, **Table I-4** and **Table I-5**). In terms of income inequality (**Figure I-6** and **Table I-4**), the findings are compatible with their counterparts at the national level, with the year 2015 being a turning point and the dispersion of prices increasing over time, especially for the entire sample. Correspondingly, at the regional level the distribution is very similar (**Figure I-9** and **Table I-7**).

Figure I-4. Weighted mean declared income equivalent distribution by Regional Units, st. prices 2015, period 2002-2019

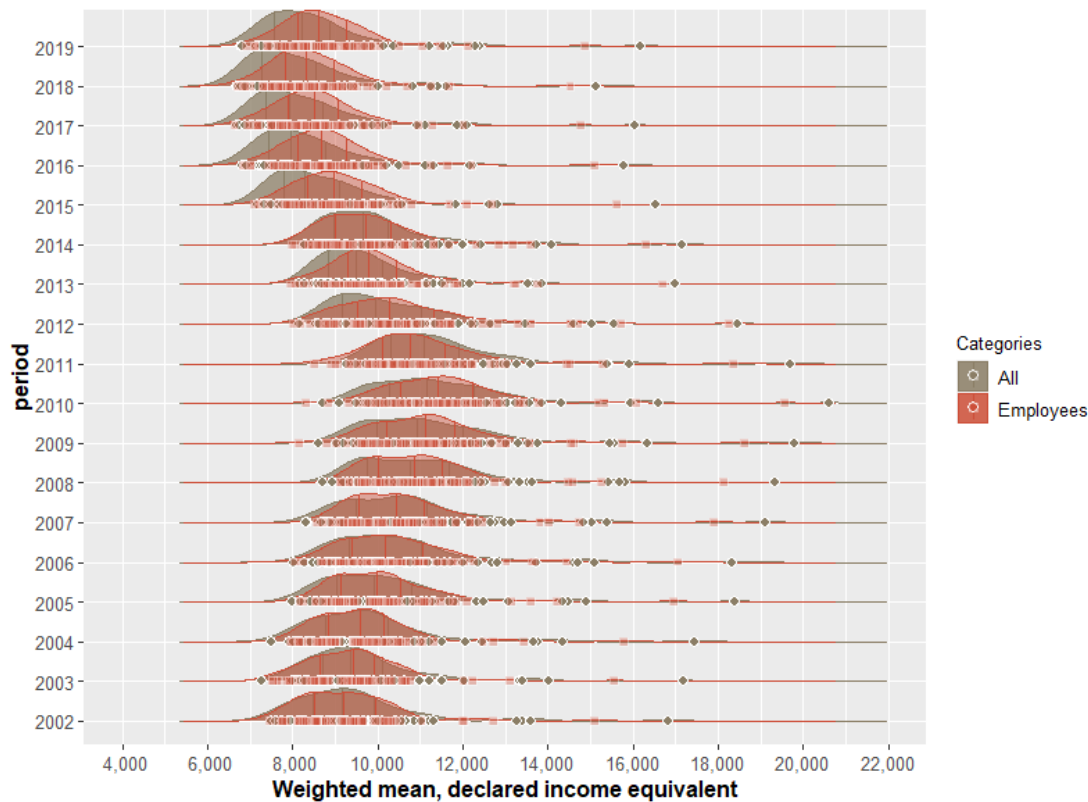


Table I-2. Descriptive statistics for weighted mean of declared income equivalent distribution by Regional Units, st. prices 2015, period 2002-2019

Year	All								Employees							
	count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
2002	74	9.172,8	9.430,5	1.526,9	0,162	1.435,7	7.495,8	16.827,2	74	9.210,5	9.310,2	1.246,3	0,134	1.413,8	7.466,9	15.105,1
2003	74	9.361,9	9.649,0	1.543,1	0,160	1.388,0	7.283,6	17.199,0	74	9.428,1	9.472,1	1.278,6	0,135	1.287,8	7.536,5	15.566,3
2004	74	9.593,8	9.779,1	1.602,6	0,164	1.466,7	7.495,9	17.453,2	74	9.587,6	9.669,4	1.269,3	0,131	1.305,2	7.955,9	15.776,1
2005	74	9.899,9	10.194,7	1.724,9	0,169	1.767,5	8.001,0	18.406,6	74	9.985,9	10.160,6	1.416,9	0,139	1.422,5	8.170,3	16.944,4
2006	74	10.178,7	10.472,8	1.738,6	0,166	1.687,5	8.022,9	18.333,3	74	10.170,6	10.415,4	1.478,6	0,142	1.642,4	8.044,4	17.041,0
2007	74	10.420,4	10.667,5	1.779,2	0,167	1.672,2	8.331,1	19.115,5	74	10.430,3	10.571,1	1.469,5	0,139	1.504,7	8.566,6	17.897,2
2008	74	10.771,5	11.083,2	1.791,8	0,162	1.934,9	8.691,7	19.335,7	74	10.859,1	11.007,9	1.474,6	0,134	1.502,4	9.124,5	18.131,9
2009	74	10.908,4	11.223,0	1.823,6	0,162	2.029,4	8.608,9	19.794,3	74	11.128,6	11.207,7	1.587,5	0,142	1.597,7	8.144,6	18.629,7
2010	74	11.152,1	11.513,8	1.896,4	0,165	1.999,5	8.691,6	20.618,1	74	11.429,1	11.575,4	1.665,5	0,144	1.680,5	8.328,2	19.562,4
2011	74	11.090,0	11.408,2	1.645,3	0,144	1.576,6	9.263,8	19.685,5	74	10.771,3	11.038,4	1.515,0	0,137	1.448,4	8.501,8	18.367,5
2012	74	9.952,0	10.350,3	1.767,7	0,171	1.888,1	8.143,9	18.459,1	74	10.262,0	10.591,2	1.758,5	0,166	1.782,0	8.018,9	18.269,3
2013	74	9.501,0	9.864,9	1.477,4	0,150	1.276,3	8.149,4	16.997,1	74	9.791,0	10.023,7	1.366,9	0,136	1.140,0	7.965,4	16.703,9
2014	74	9.667,7	9.958,6	1.506,3	0,151	1.284,4	8.285,9	17.163,5	74	9.730,5	9.849,6	1.364,5	0,139	1.307,4	7.998,9	16.305,3
2015	74	8.297,0	8.718,9	1.475,7	0,169	1.279,9	7.175,2	16.532,3	74	8.970,2	9.142,2	1.288,8	0,141	1.270,4	7.113,6	15.616,3
2016	74	7.954,4	8.416,8	1.454,6	0,173	1.333,3	6.807,6	15.784,4	74	8.675,1	8.840,2	1.230,0	0,139	1.140,3	6.857,4	15.089,2
2017	74	7.930,8	8.341,3	1.511,6	0,181	1.364,3	6.701,7	16.033,3	74	8.507,2	8.625,9	1.215,8	0,141	1.161,7	6.637,6	14.761,0

Figure I-5. Weighted median declared income equivalent distribution by Regional Units, st. prices 2015, period 2002-2019

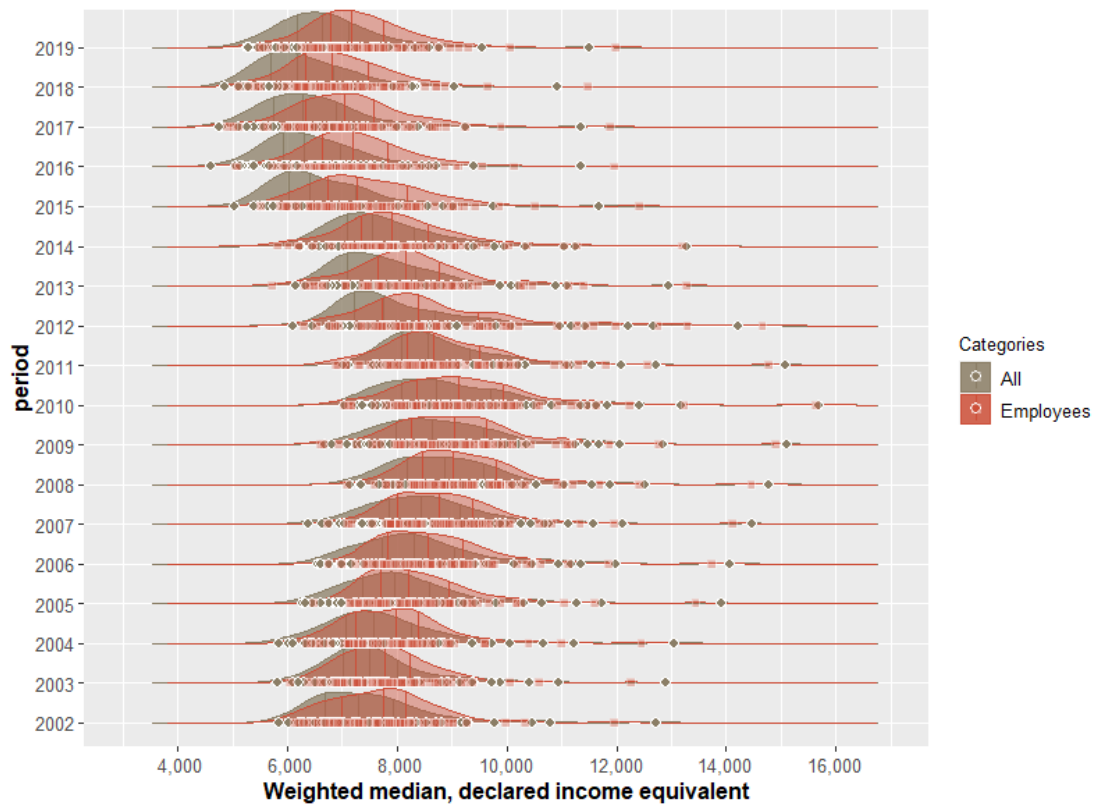


Table I-3. Descriptive statistics for weighted median of declared income equivalent distribution by Regional Units, st. prices 2015, period 2002-2019

Year	All								Employees							
	count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
2002	74	7.307,7	7.531,2	1.159,8	0,154	1.222,1	5.851,8	12.709,5	74	7.755,1	7.743,7	1.010,3	0,130	1.176,4	6.138,2	15.087,3
2003	74	7.492,2	7.691,8	1.145,4	0,149	998,1	5.831,5	11.952,3	74	7.788,4	7.848,0	979,2	0,125	990,8	6.045,6	14.773,3
2004	74	7.564,5	7.786,7	1.203,2	0,155	1.186,6	5.840,8	12.891,8	74	7.984,4	7.988,0	1.023,9	0,128	1.153,7	6.364,7	14.207,3
2005	74	7.948,7	8.178,4	1.287,5	0,157	1.221,2	6.275,0	12.274,2	74	8.217,4	8.407,9	1.110,2	0,132	1.238,5	6.492,1	14.662,9
2006	74	8.298,1	8.482,1	1.316,7	0,155	1.318,5	6.566,3	13.057,8	74	8.560,5	8.675,3	1.130,6	0,130	1.375,1	6.751,1	12.956,8
2007	74	8.442,4	8.649,1	1.317,0	0,152	1.285,5	6.374,7	12.456,6	74	8.775,3	8.855,0	1.152,2	0,130	1.373,4	6.741,6	13.287,4
2008	74	8.870,8	9.000,1	1.262,4	0,140	1.386,8	7.140,4	13.908,4	74	9.030,7	9.221,9	1.124,7	0,122	1.333,5	7.084,0	13.268,4
2009	74	8.650,2	8.944,5	1.439,4	0,161	1.597,6	6.681,5	13.445,8	74	9.054,5	9.130,2	1.330,3	0,146	1.381,1	6.609,9	13.195,7
2010	74	8.724,0	9.045,9	1.485,1	0,164	1.617,9	7.035,7	14.062,5	74	9.123,7	9.287,6	1.399,3	0,151	1.581,0	7.037,2	11.677,2
2011	74	8.560,6	8.911,9	1.341,0	0,150	1.251,0	7.025,4	13.744,6	74	8.661,7	8.932,1	1.313,0	0,147	1.321,8	6.895,9	12.413,0
2012	74	7.749,2	8.199,5	1.474,8	0,180	1.477,8	6.096,3	14.463,7	74	8.381,1	8.740,2	1.558,8	0,178	1.753,3	6.313,4	11.342,8
2013	74	7.653,8	7.911,4	1.196,1	0,151	1.263,3	6.161,2	14.115,0	74	8.166,7	8.286,7	1.213,4	0,146	1.122,3	5.729,7	11.962,6
2014	74	7.549,7	7.859,3	1.223,1	0,156	1.197,2	6.227,7	14.766,4	74	7.916,0	8.078,2	1.224,0	0,152	1.232,3	5.828,2	11.359,6
2015	74	6.402,5	6.705,6	1.085,5	0,162	1.230,3	5.048,3	14.460,8	74	7.278,5	7.515,4	1.158,4	0,154	1.447,9	5.521,6	11.896,2
2016	74	6.316,0	6.548,0	1.068,0	0,163	1.044,0	4.597,8	15.101,6	74	7.196,6	7.302,5	1.086,6	0,149	1.188,2	5.058,9	10.913,4
2017	74	6.292,0	6.484,9	1.055,9	0,163	1.136,3	4.750,0	14.906,6	74	7.041,3	7.136,3	1.109,7	0,156	1.231,2	4.913,8	11.473,5

Figure I-6. Weighted Gini of declared income equivalent distribution by Regional Units, period 2002-2019

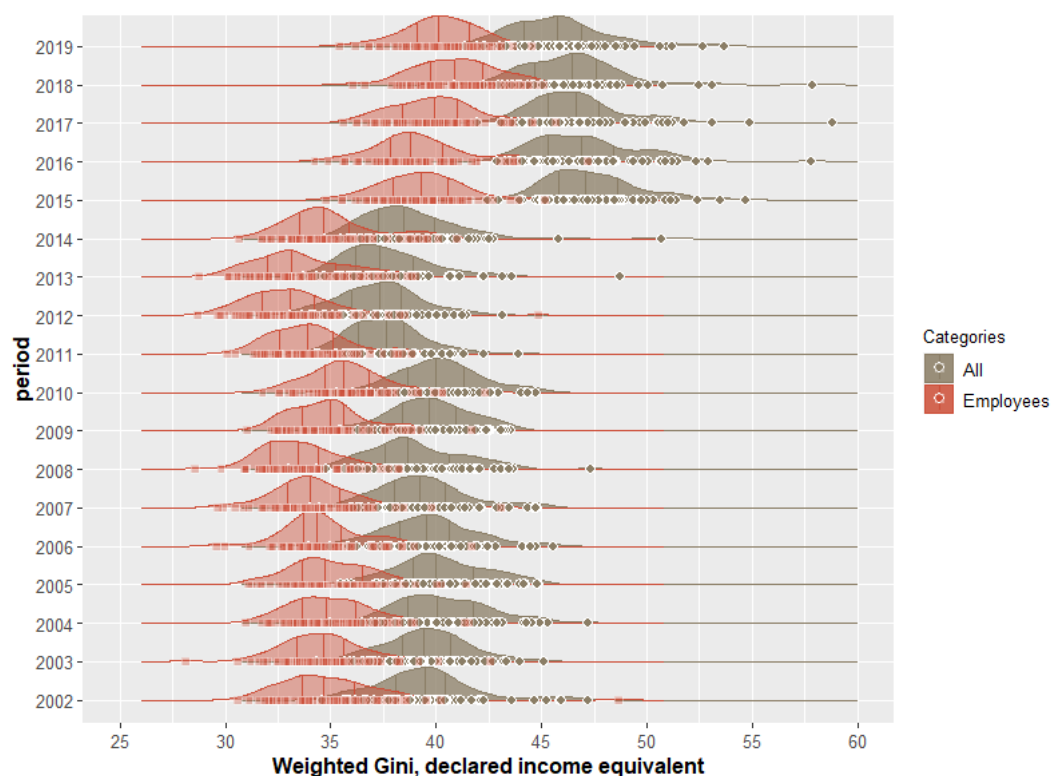


Table I-4. Descriptive statistics for weighted Gini of declared income equivalent distribution by Regional Units, period 2002-2019

Year	All								Employees							
	count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
2002	74	39,47	39,52	2,46	0,062	2,34	34,6	47,2	74	34,65	34,97	2,63	0,075	2,53	30,61	48,69
2003	74	39,41	39,51	2,02	0,051	2,31	34,3	45,1	74	34,65	34,70	2,21	0,064	2,27	28,11	42,59
2003	74	40,05	40,37	2,29	0,057	3,15	35,0	47,2	74	34,78	35,05	2,08	0,059	2,57	30,98	41,57
2004	74	39,98	40,18	2,21	0,055	2,91	35,5	44,9	74	34,69	35,12	2,14	0,061	2,84	31,11	41,46
2005	74	39,56	39,61	2,24	0,057	2,34	34,0	45,6	74	34,36	34,68	2,01	0,058	1,82	29,57	41,71
2007	74	39,22	39,29	2,25	0,057	2,42	34,0	44,8	74	34,04	34,24	2,15	0,063	2,46	29,65	43,07
2008	74	38,68	38,96	2,46	0,063	2,99	33,0	47,3	74	33,45	33,53	1,91	0,057	2,28	28,58	38,25
2009	74	39,67	39,68	1,91	0,048	2,53	35,4	43,5	74	34,95	34,93	1,97	0,057	1,97	31,03	41,70
2010	74	40,02	40,14	1,96	0,049	2,67	35,3	44,7	74	35,59	35,82	1,97	0,055	2,10	31,77	42,36
2011	74	37,61	37,66	1,79	0,048	2,12	34,3	43,9	74	33,93	34,00	1,89	0,056	2,53	30,11	38,84
2012	74	37,35	37,34	1,99	0,053	2,34	33,0	43,2	74	33,08	33,19	2,47	0,074	2,46	28,71	44,85
2013	74	37,31	37,79	2,43	0,064	2,69	33,7	48,7	74	33,11	33,64	2,32	0,069	3,19	28,74	39,04
2014	74	38,45	38,75	2,45	0,063	2,63	34,7	50,7	74	34,64	34,99	2,20	0,063	2,40	30,64	41,00
2015	74	47,07	47,39	2,31	0,049	2,73	42,5	54,7	74	39,29	39,28	1,97	0,050	2,60	34,76	45,17
2016	74	46,91	47,16	2,64	0,056	3,11	42,9	57,8	74	38,80	39,22	2,32	0,059	2,47	34,25	47,19
2017	74	46,65	46,93	2,75	0,059	2,45	41,9	58,8	74	39,90	39,93	2,11	0,053	2,59	35,64	45,69
2018	74	46,43	46,47	2,55	0,055	2,92	40,9	57,9	74	40,88	40,96	1,94	0,047	2,47	36,04	45,10
2019	74	45,75	45,85	2,45	0,053	2,77	41,4	53,7	74	40,13	40,21	1,77	0,044	2,47	35,42	44,57

Figure I-7. Weighted mean declared income equivalent distribution by regions, st. prices 2015, period 2002-2019

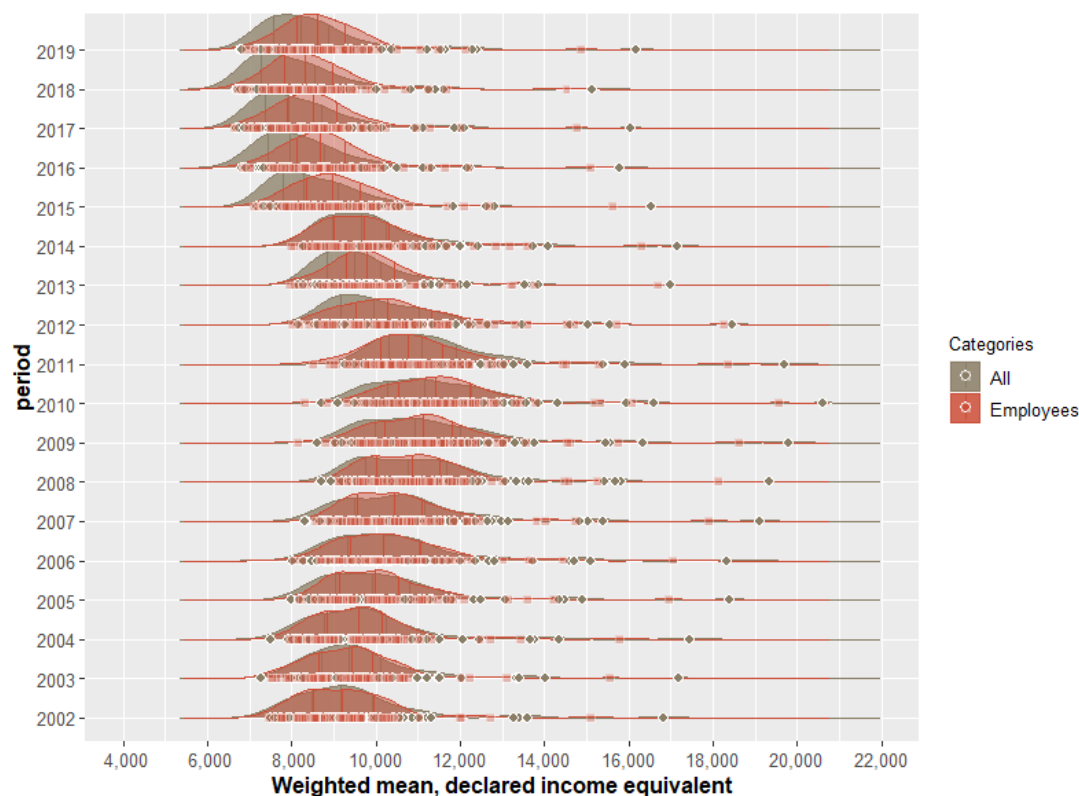


Table I-5. Descriptive statistics for weighted mean of declared income equivalent distribution by regions, st. prices 2015, period 2002-2019

Year	All								Employees							
	count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
2002	13	9.370,4	9.593,7	1.146,6	0,120	663,7	8.655,6	13.200,6	13	9.417,4	9.565,3	804,4	0,084	582,5	8.877,8	12.023,9
2003	13	9.627,2	9.856,2	1.117,0	0,113	621,2	8.919,5	13.361,8	13	9.659,3	9.751,8	830,8	0,085	490,2	8.956,9	12.276,6
2004	13	9.564,6	9.920,3	1.192,8	0,120	527,5	8.931,4	13.698,2	13	9.795,9	9.927,7	869,4	0,088	433,5	9.246,4	12.658,6
2006	13	10.029,3	10.313,0	1.291,3	0,125	575,2	9.254,4	14.396,9	13	10.335,2	10.437,5	973,8	0,093	444,1	9.568,4	13.489,2
2007	13	10.475,5	10.589,7	1.247,2	0,118	477,6	9.436,0	14.543,1	13	10.533,2	10.675,4	964,2	0,090	515,6	9.801,9	13.676,0
2008	13	10.719,6	10.838,8	1.295,6	0,120	566,6	9.700,4	14.943,9	13	10.719,3	10.906,5	1.008,5	0,092	494,2	10.076,5	14.068,5
2009	13	10.903,4	11.209,4	1.304,6	0,116	510,9	10.086,9	15.369,0	13	11.175,5	11.307,1	1.010,8	0,089	425,9	10.577,4	14.535,5
2010	13	11.227,2	11.397,7	1.307,0	0,115	647,9	10.276,9	15.558,2	13	11.367,3	11.523,3	1.032,4	0,090	414,8	10.710,9	14.742,5
2011	13	11.437,7	11.665,4	1.369,5	0,117	499,4	10.412,6	16.001,5	13	11.689,9	11.870,9	1.108,0	0,093	553,2	10.939,0	15.316,4
2013	13	11.376,3	11.624,3	1.215,7	0,105	457,0	10.607,5	15.474,7	13	11.254,0	11.351,5	1.046,9	0,092	444,0	10.224,1	14.583,3
2014	13	10.322,1	10.552,4	1.364,6	0,129	751,3	9.565,2	14.885,1	13	10.558,9	10.822,5	1.266,0	0,117	623,0	9.671,9	14.760,2
2015	13	9.831,8	10.064,0	1.090,5	0,108	537,7	9.203,1	13.534,9	13	10.090,9	10.311,2	963,7	0,093	318,1	9.399,0	13.273,6
2016	13	9.879,8	10.175,6	1.087,1	0,107	367,5	9.411,3	13.662,4	13	9.922,6	10.118,3	941,2	0,093	474,2	9.335,6	13.023,9
2017	13	8.488,4	8.642,5	1.069,1	0,124	412,8	7.578,7	12.010,7	13	9.239,6	9.373,5	900,5	0,096	455,8	8.212,4	12.057,9
2018	13	8.138,0	8.375,0	1.028,9	0,123	428,4	7.434,7	11.612,5	13	8.855,1	9.055,2	850,1	0,094	512,4	8.089,5	11.655,7
2019	13	8.035,4	8.314,2	1.024,3	0,123	543,8	7.372,4	11.414,3	13	8.605,4	8.840,6	831,1	0,094	513,8	7.799,6	11.344,1

Figure I-8. Weighted median declared income equivalent distribution by regions, Units, st. prices 2015, period 2002-2019

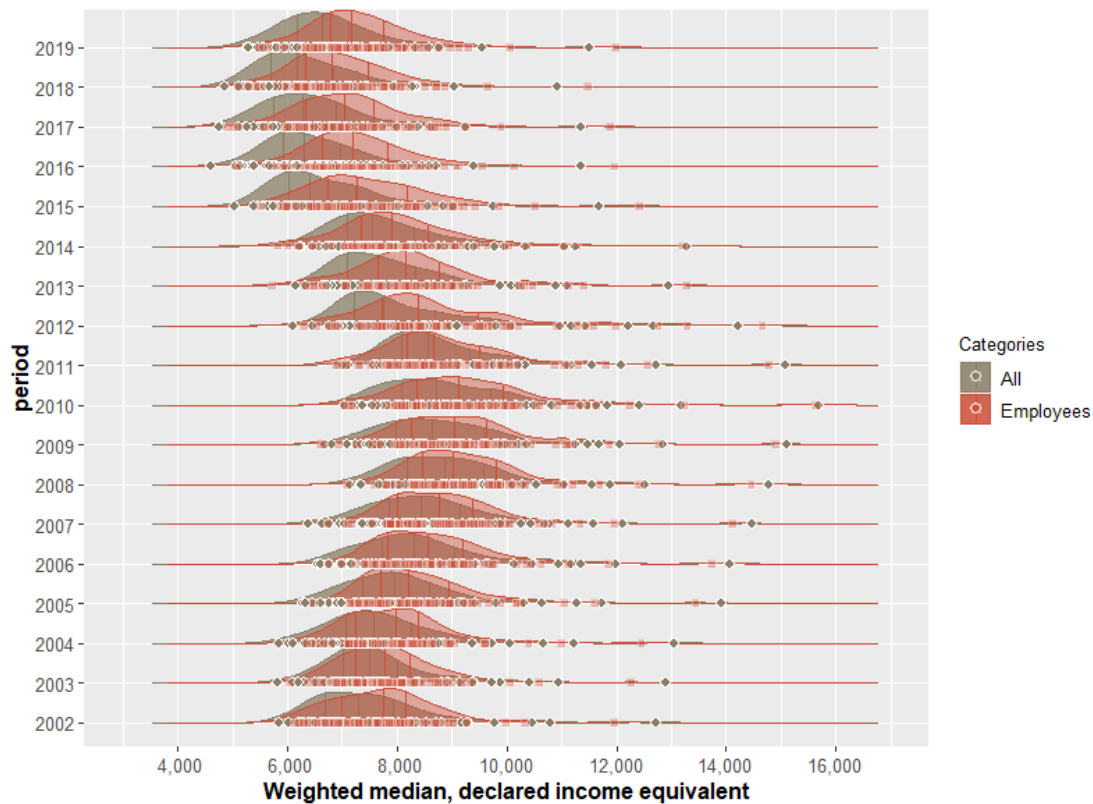


Table I-6. Descriptive statistics for weighted median of declared income equivalent distribution by regions, st. prices 2015, period 2002-2019

Year	All								Employees							
	count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
2002	13	7.445,0	7.698,3	813,3	0,106	519,2	6.996,9	10.192,9	13	7.920,9	8.007,1	616,2	0,077	418,1	7.346,8	9.767,5
2003	13	7.628,3	7.863,6	786,8	0,100	559,3	7.194,2	10.269,2	13	7.959,9	8.098,7	628,5	0,078	453,3	7.377,4	9.932,5
2004	13	7.700,9	7.921,2	840,2	0,106	490,3	7.224,4	10.511,6	13	8.104,4	8.240,3	665,6	0,081	518,4	7.555,1	10.255,4
2006	13	8.040,6	8.275,0	903,6	0,109	518,7	7.575,0	11.086,4	13	8.414,1	8.606,7	746,8	0,087	454,7	7.767,2	10.880,2
2007	13	8.313,3	8.546,1	888,4	0,104	630,5	7.775,8	11.292,1	13	8.620,2	8.863,5	727,7	0,082	396,6	8.150,3	11.102,7
2008	13	8.632,6	8.792,8	885,6	0,101	471,5	7.962,3	11.531,7	13	8.957,8	9.102,3	722,6	0,079	449,7	8.493,2	11.321,6
2009	13	8.869,5	9.111,2	880,5	0,097	534,3	8.399,9	11.854,8	13	9.310,5	9.430,9	730,2	0,077	316,6	8.735,5	11.682,2
2010	13	8.823,6	9.023,4	978,6	0,108	568,8	8.203,9	12.048,0	13	9.205,9	9.354,7	829,5	0,089	400,0	8.477,1	11.870,6
2011	13	8.880,2	9.108,7	1.066,7	0,117	638,8	8.165,2	12.385,9	13	9.375,8	9.495,5	923,4	0,097	497,2	8.370,3	12.282,3
2013	13	8.897,1	9.065,9	978,7	0,108	451,3	7.944,7	12.050,2	13	9.102,1	9.162,8	900,0	0,098	567,0	7.858,3	11.809,2
2014	13	8.022,4	8.336,6	1.147,6	0,138	544,7	7.234,1	11.924,3	13	8.683,5	8.893,0	1.171,6	0,132	727,8	7.530,0	12.430,6
2015	13	8.024,3	8.086,8	881,6	0,109	545,5	7.080,6	10.724,3	13	8.465,9	8.528,6	843,2	0,099	429,2	7.388,6	10.958,9
2016	13	7.819,0	8.025,7	897,4	0,112	483,9	7.201,0	10.833,4	13	8.143,9	8.282,5	852,5	0,103	541,7	7.345,4	10.873,4
2017	13	6.530,8	6.613,9	792,1	0,120	460,9	5.609,2	8.934,4	13	7.558,2	7.657,8	808,8	0,106	486,4	6.470,3	9.921,4
2018	13	6.382,7	6.487,1	763,6	0,118	399,9	5.472,2	8.731,9	13	7.349,4	7.453,7	771,3	0,103	492,5	6.301,4	9.613,8
2019	13	6.232,2	6.429,9	733,2	0,114	362,4	5.421,9	8.557,2	13	7.111,4	7.289,5	734,1	0,101	527,9	6.094,6	9.303,5

Figure I-9. Weighted Gini of declared income equivalent distribution by regions, period 2002-2019

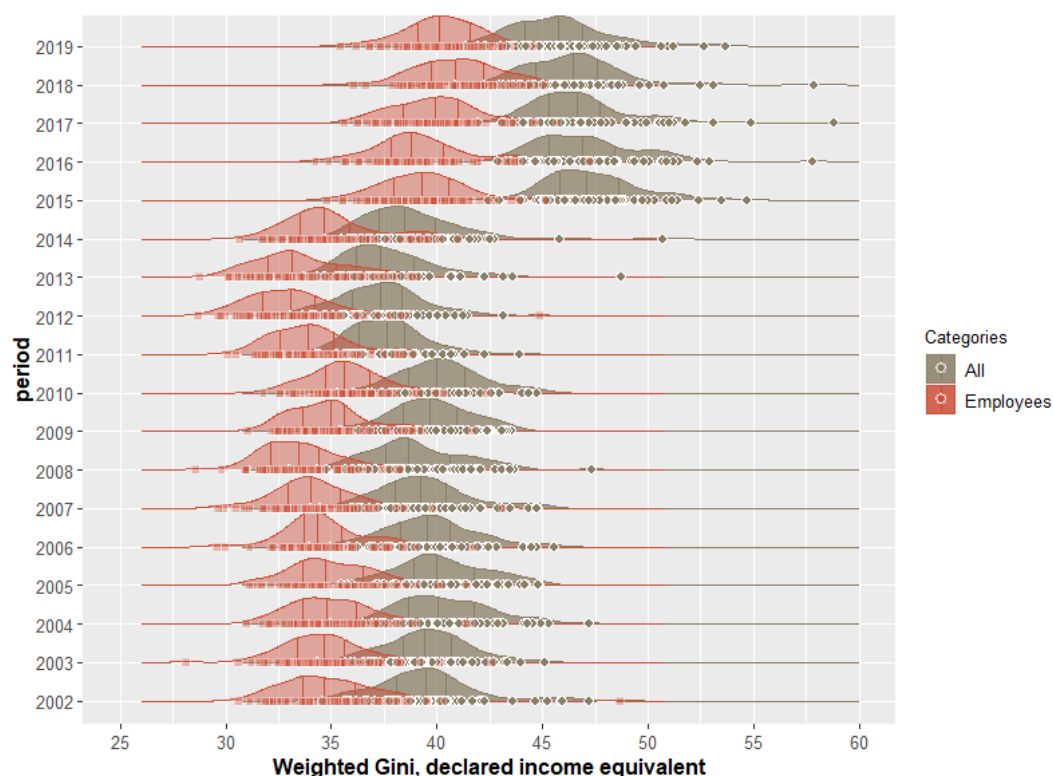


Table I-7. Descriptive statistics for weighted Gini of declared income equivalent distribution by regions, period 2002-2019

Year	All								Employees							
	count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
2002	13	39,89	39,75	1,21	0,031	0,66	36,58	41,39	13	34,71	34,69	1,27	0,037	1,46	32,69	37,00
2003	13	40,17	39,91	1,12	0,028	1,02	36,86	41,34	13	34,81	34,68	1,03	0,030	1,34	32,47	36,03
2003	13	41,19	40,88	1,20	0,029	1,02	37,85	42,59	13	35,02	35,03	1,08	0,031	1,33	32,88	36,54
2004	13	41,00	40,85	1,33	0,033	1,28	37,70	43,01	13	35,69	35,31	1,09	0,031	1,29	32,90	36,97
2005	13	40,31	40,35	1,37	0,034	1,79	37,22	42,06	13	35,31	34,87	1,09	0,031	0,94	32,35	36,20
2007	13	40,17	39,94	1,32	0,033	1,29	36,63	41,46	13	34,39	34,46	1,19	0,034	1,15	31,70	36,04
2008	13	39,87	39,54	1,38	0,035	0,99	36,10	41,48	13	33,74	33,76	1,28	0,038	1,33	31,34	35,82
2009	13	40,66	40,45	1,30	0,032	1,08	37,43	42,04	13	34,97	35,21	1,23	0,035	1,35	32,94	36,95
2010	13	41,05	40,95	1,35	0,033	1,21	37,57	42,86	13	36,36	36,05	1,33	0,037	1,42	33,59	37,68
2011	13	38,06	37,88	0,99	0,026	0,89	35,66	39,39	13	34,41	34,29	1,18	0,035	1,09	32,34	36,32
2012	13	37,86	37,76	0,98	0,026	0,76	35,92	39,17	13	33,68	33,50	1,31	0,039	0,97	31,41	35,74
2013	13	38,16	37,89	1,37	0,036	2,02	35,72	39,92	13	33,63	33,75	1,59	0,047	2,66	31,65	36,36
2014	13	39,33	38,84	1,36	0,035	1,80	36,24	40,54	13	35,26	35,07	1,30	0,037	2,05	33,35	37,06
2015	13	49,21	48,91	1,15	0,023	1,35	46,54	50,17	13	39,68	39,48	1,30	0,033	1,77	36,99	41,61
2016	13	48,73	48,37	1,44	0,030	1,92	45,37	50,02	13	39,32	39,30	1,38	0,035	1,83	37,06	41,50
2017	13	48,20	48,28	2,08	0,043	1,33	45,09	53,57	13	39,96	40,11	1,30	0,032	1,72	38,12	42,37
2018	13	48,12	47,67	1,51	0,032	1,92	44,64	49,27	13	41,28	41,03	1,35	0,033	2,15	38,54	42,85
2019	13	47,26	47,22	1,46	0,031	1,44	43,92	49,52	13	40,49	40,33	1,19	0,029	1,77	38,02	42,13

I.3.3 Declared income distributions and trends at local level

Figure I-10, Figure I-11 Table I-8 and Table I-9 present the weighted mean and weighted median of the equivalent of the declared income at municipal level and **Figure I-12 and Table I-10** describe the distribution of the gini index as a proxy variable of structural inequality.

The the conclusions regarding the distribution of the aforementioned indicators at the municipal level are similar to the previous geographical levels of analysis.

In order to better determine the geographic dimension of income and income inequality, we examined the diversification of income level and income inequality for the six categories of municipalities mentioned at chapter **I.2.1** (Kleisthenis Classification) (**Figure I-13, Figure I-14 and Figure I-15** as well and **Table I-11, Table I-12 and Table I-13**).

The document the positive relationship between income levels and income inequality for metropolitan municipalities. For municipalities in metropolitan areas, income growth is followed by income inequality growth. This is also true in most cases in large mainland administrative units and county capitals. However, the opposite is true in the case of medium and small mainland and island municipalities. For these cases, an increase in income is followed by a decrease in income inequality. These findings provide the first evidence that income inequality is higher in the most urban areas of the country. The evolution and level of distribution of declared income by category of municipality reveal that municipalities belonging to metropolitan areas are placed at the upper end of the distribution curve and have a large dispersion. However, island and small mainland municipalities that belong to the lower part of the distribution curve and show relatively less dispersion.

Figure I-10. Weighted mean declared income equivalent distribution by municipalities, st. prices 2015, period 2002-2019

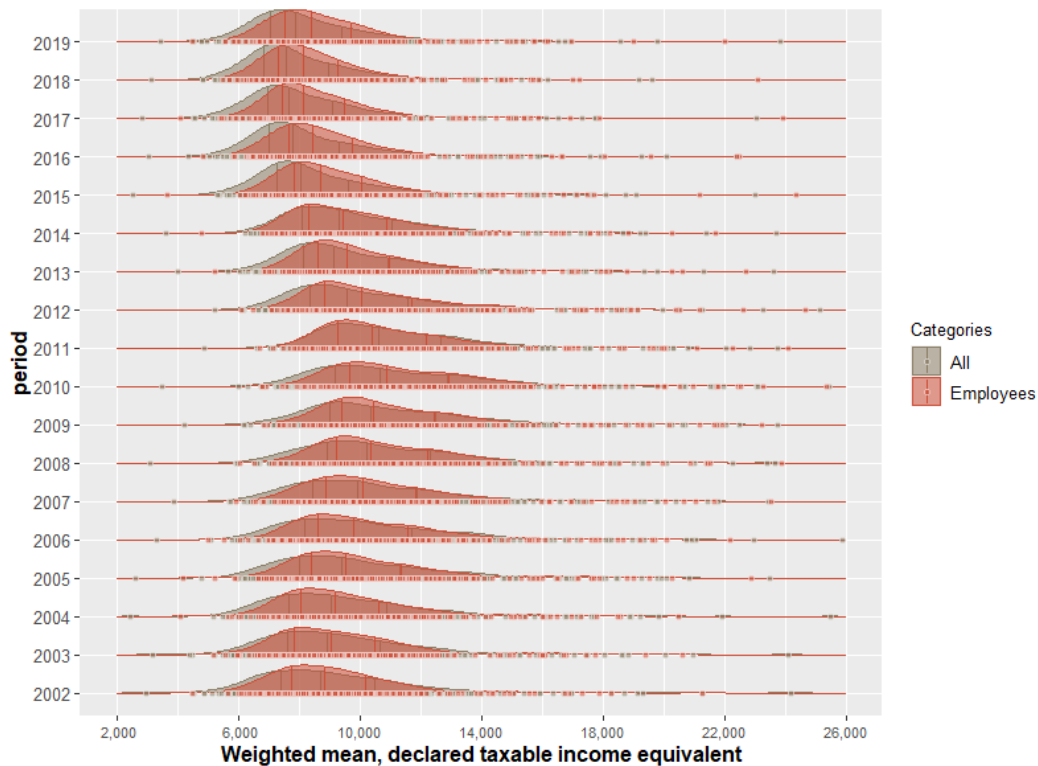


Table I-8. Descriptive statistics for weighted mean of declared income equivalent distribution by municipalities, st. prices 2015, period 2002-2019

Year	All								Employees							
	count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
2002	318	8.695,8	9.243,4	2.764,3	0,299	3.116,0	2.956,1	24.178,0	312	8.832,5	9.234,4	2.233,4	0,242	2.451,9	4.504,8	21.286,8
2003	319	8.935,6	9.479,3	2.804,2	0,296	3.025,5	3.211,1	24.079,8	314	9.073,7	9.458,0	2.313,6	0,245	2.642,6	5.200,2	20.630,2
2004	319	9.039,8	9.609,5	2.854,1	0,297	3.199,0	2.464,9	25.470,3	317	9.203,9	9.615,6	2.315,0	0,241	2.561,1	4.112,0	20.473,5
2005	321	9.417,4	10.056,0	3.051,9	0,303	3.354,1	2.611,8	26.167,3	315	9.531,4	10.165,9	2.584,3	0,254	2.930,8	4.183,7	22.903,0
2006	320	9.777,1	10.292,1	3.032,2	0,295	3.500,9	3.312,2	25.887,0	316	9.785,4	10.370,7	2.601,1	0,251	2.951,0	5.030,0	22.184,8
2007	318	9.917,4	10.549,7	3.110,2	0,295	3.447,7	3.887,0	27.770,1	316	10.107,3	10.645,0	2.671,4	0,251	2.922,8	5.924,6	23.540,5
2008	320	10.279,1	10.906,0	3.108,2	0,285	3.394,2	3.097,4	26.453,8	317	10.362,6	11.036,6	2.672,9	0,242	2.997,3	6.062,3	23.862,0
2009	320	10.382,4	11.128,0	3.152,7	0,283	3.492,1	4.212,9	27.455,3	316	10.460,8	11.227,5	2.731,4	0,243	3.040,9	6.847,5	23.242,6
2010	319	10.649,3	11.389,1	3.276,4	0,288	3.723,6	3.478,7	28.593,8	317	10.868,0	11.616,3	2.887,2	0,249	3.237,1	6.790,0	25.370,0
2011	320	10.607,7	11.338,6	2.923,7	0,258	3.389,2	4.885,8	26.875,7	317	10.397,2	11.084,2	2.607,7	0,235	2.895,8	6.725,2	24.117,3
2012	320	9.559,9	10.370,4	2.930,1	0,283	3.195,5	5.218,3	25.134,2	316	10.072,5	10.747,3	2.812,5	0,262	2.853,7	6.122,6	24.671,1
2013	319	9.135,5	9.811,4	2.579,9	0,263	2.811,6	4.018,8	23.641,1	316	9.573,2	10.152,9	2.380,8	0,234	2.360,0	5.219,6	22.719,6
2014	321	9.337,8	9.918,6	2.589,1	0,261	2.934,4	3.618,2	23.731,2	317	9.448,3	9.922,0	2.360,4	0,238	2.593,1	4.779,2	21.708,5
2015	320	8.053,7	8.790,3	2.697,6	0,307	2.349,5	2.542,9	30.377,0	318	8.706,5	9.249,9	2.282,0	0,247	2.221,7	3.689,3	24.361,9
2016	321	7.822,3	8.486,9	2.637,8	0,311	2.296,0	3.068,9	28.022,1	319	8.466,1	8.990,1	2.272,9	0,253	2.074,7	4.845,9	22.497,1
2017	321	7.681,5	8.370,6	2.577,2	0,308	2.131,3	2.823,3	27.966,1	318	8.159,0	8.739,6	2.117,1	0,242	2.039,3	4.106,9	23.935,3
2018	320	7.608,5	8.205,3	2.440,3	0,297	2.154,1	3.160,8	28.426,7	319	8.164,7	8.641,0	2.081,8	0,241	1.956,9	5.500,4	23.120,5
2019	320	7.889,8	8.585,4	2.740,7	0,319	2.347,6	3.437,5	31.490,1	317	8.407,3	8.907,7	2.174,6	0,244	2.147,9	4.490,3	22.006,0

Figure I-11. Weighted median declared income equivalent distribution by municipalities, st. prices 2015, period 2002-2019

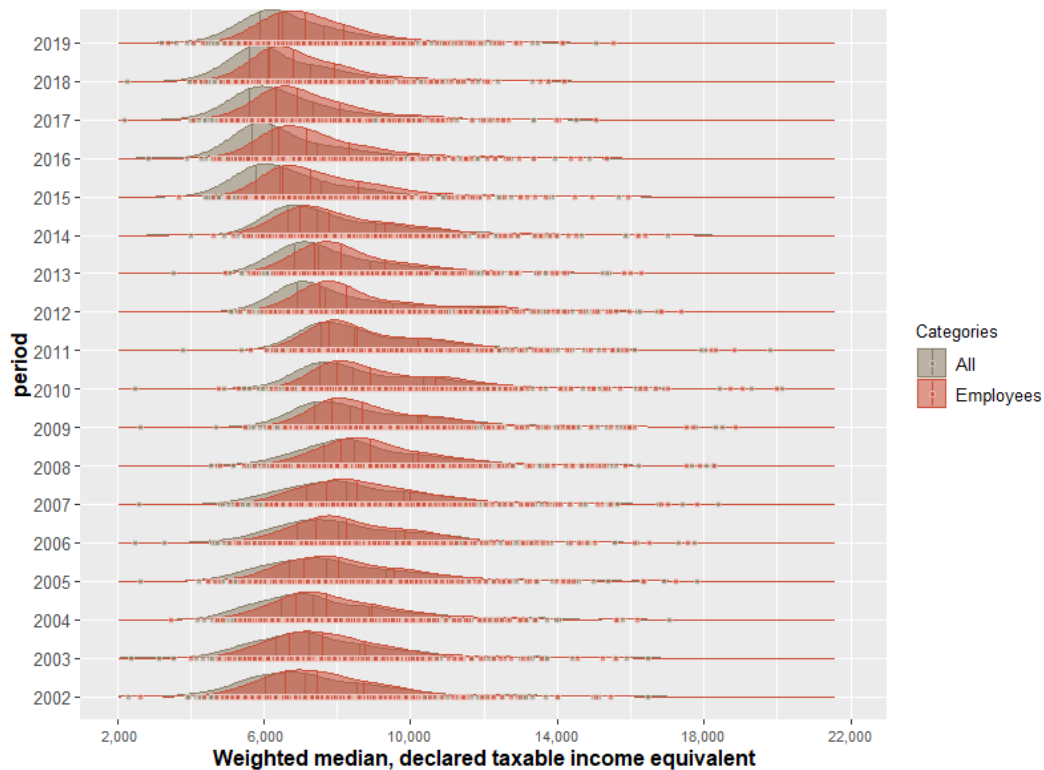


Table I-9. Descriptive statistics for weighted median of declared income equivalent distribution by municipalities, st. prices 2015, period 2002-2019

Year	All								Employees							
	count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
2002	318	7.138,5	7.479,8	2.067,8	0,276	2.515,8	2.295,5	16.456,8	312	7.458,3	7.711,4	1.757,9	0,228	2.126,9	2.638,3	15.443,2
2003	319	7.229,2	7.653,6	2.075,1	0,271	2.295,6	2.360,3	16.473,8	314	7.610,3	7.886,4	1.787,6	0,227	2.045,2	4.021,3	15.582,3
2004	319	7.317,7	7.789,2	2.108,9	0,271	2.404,9	1.788,2	17.031,1	317	7.693,6	8.079,1	1.872,8	0,232	2.090,7	3.470,2	16.173,8
2005	321	7.718,7	8.164,5	2.254,4	0,276	2.634,2	2.625,6	17.800,7	315	8.016,4	8.460,2	2.042,2	0,241	2.475,3	4.462,9	17.226,3
2006	320	8.027,1	8.435,0	2.259,1	0,268	2.682,7	2.487,0	17.731,7	316	8.240,9	8.731,4	2.012,9	0,231	2.398,6	5.064,0	17.551,7
2007	318	8.259,5	8.692,1	2.268,8	0,261	2.647,1	2.584,3	18.382,7	316	8.542,1	8.985,4	2.023,1	0,225	2.292,2	5.257,3	17.802,9
2008	320	8.467,5	9.003,3	2.249,3	0,250	2.427,9	1.872,7	18.239,8	317	8.880,4	9.326,3	2.006,4	0,215	2.097,1	4.786,6	18.271,1
2009	320	8.365,7	9.045,2	2.348,5	0,260	2.811,5	2.645,9	18.497,6	316	8.682,7	9.308,1	2.147,8	0,231	2.431,0	5.485,9	18.871,9
2010	319	8.434,0	9.185,5	2.431,9	0,265	2.847,8	2.475,8	20.125,6	317	8.882,2	9.522,4	2.269,4	0,238	2.708,2	4.769,6	19.968,8
2011	320	8.459,9	9.096,2	2.248,7	0,247	2.674,0	3.777,9	19.814,3	317	8.548,1	9.198,4	2.115,9	0,230	2.427,8	5.638,3	18.829,7
2012	320	7.675,9	8.437,0	2.258,0	0,268	2.585,4	5.100,3	16.733,1	316	8.256,3	9.049,0	2.289,2	0,253	2.561,2	5.355,1	17.364,7
2013	319	7.499,7	8.079,3	1.881,9	0,233	2.076,4	3.543,8	15.426,3	316	8.098,4	8.565,3	1.854,4	0,217	1.911,6	4.950,6	16.275,3
2014	321	7.460,5	8.047,7	2.022,7	0,251	2.394,8	4.009,1	17.028,8	317	7.783,8	8.288,9	1.940,6	0,234	2.309,2	4.622,0	16.393,6
2015	320	6.420,9	6.892,3	1.779,1	0,258	1.811,5	1.382,4	15.661,9	318	7.279,0	7.729,5	1.772,3	0,229	2.046,4	3.664,2	15.929,5
2016	321	6.228,9	6.735,4	1.711,2	0,254	1.772,3	1.762,9	14.876,0	319	7.158,8	7.553,7	1.717,6	0,227	1.909,4	4.625,0	15.334,6
2017	321	6.328,5	6.694,1	1.672,7	0,250	1.736,7	2.203,6	14.523,9	318	6.919,8	7.355,8	1.651,0	0,224	1.735,2	4.072,8	15.063,7
2018	320	6.091,7	6.563,8	1.579,4	0,241	1.684,3	2.266,5	13.744,7	319	6.812,5	7.210,7	1.589,6	0,220	1.771,0	4.101,7	14.186,2
2019	320	6.490,2	6.929,8	1.736,7	0,251	1.755,3	1.731,3	15.062,4	317	7.114,7	7.523,9	1.718,8	0,228	1.760,8	3.373,5	15.524,5

Figure I-12. Weighted Gini of declared income equivalent by municipalities, period 2002-2019

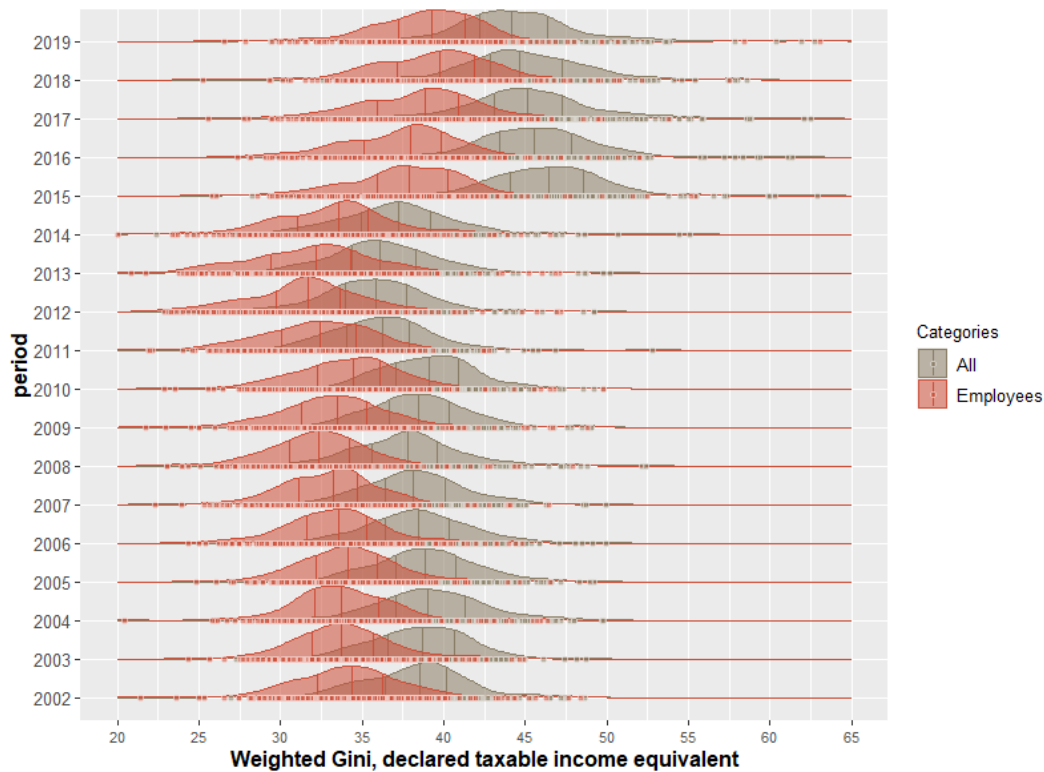


Table I-10. Descriptive statistics for weighted Gini of declared income equivalent distribution by municipalities, st. prices 2015, period 2002-2019

Year	All								Employees							
	count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
2002	318	38,54	38,37	3,18	0,083	3,80	26,94	48,66	312	34,34	34,44	3,74	0,108	4,01	21,39	48,43
2003	319	38,66	38,56	3,01	0,078	4,07	27,28	48,73	314	33,75	34,00	3,16	0,093	3,74	24,33	44,91
2003	319	39,04	39,25	3,37	0,086	4,28	29,03	49,81	317	33,74	34,08	3,42	0,100	3,93	20,44	46,37
2004	321	38,88	39,00	3,11	0,080	3,66	30,87	49,22	315	34,11	34,13	3,12	0,092	3,76	19,14	46,52
2005	320	38,45	38,52	3,27	0,085	3,97	29,23	49,94	316	33,54	33,53	3,28	0,098	3,65	24,32	44,79
2007	318	38,13	38,24	3,21	0,084	3,66	25,86	49,99	316	33,26	33,11	3,30	0,100	3,57	19,36	46,41
2008	320	37,80	37,83	3,61	0,095	4,02	27,78	52,38	317	32,35	32,51	3,39	0,104	3,75	23,02	47,87
2009	320	38,41	38,40	3,25	0,085	3,68	28,52	49,08	316	33,49	33,46	3,63	0,108	4,00	21,71	48,81
2010	319	39,09	39,01	3,14	0,081	3,83	28,44	49,78	317	34,46	34,32	3,60	0,105	3,89	22,89	49,79
2011	320	36,28	36,18	3,23	0,089	3,83	26,32	52,82	317	32,44	32,33	3,50	0,108	4,55	21,91	42,74
2012	320	35,86	35,94	3,37	0,094	3,72	27,39	49,23	316	31,67	31,76	3,86	0,122	4,07	18,56	47,14
2013	319	36,10	36,35	3,54	0,097	3,97	24,71	50,18	316	32,17	32,04	4,14	0,129	4,97	18,80	47,09
2014	321	37,24	37,21	3,92	0,105	4,30	22,41	55,09	317	33,57	33,33	3,88	0,116	4,29	17,84	46,50
2015	320	46,47	46,44	3,91	0,084	4,43	28,23	62,88	318	37,89	37,92	3,90	0,103	4,32	25,85	55,37
2016	321	45,58	45,86	3,83	0,084	4,38	32,34	61,32	319	37,96	37,67	3,84	0,102	4,67	27,36	51,99
2017	321	45,16	45,39	4,14	0,091	4,18	31,67	62,54	318	38,90	38,52	3,86	0,100	4,92	25,60	53,82
2018	320	44,69	45,15	4,06	0,090	4,41	32,62	65,51	319	39,77	39,62	3,90	0,098	4,74	25,26	57,52
2019	320	44,20	44,67	4,25	0,095	4,18	29,42	68,77	317	39,27	39,20	3,84	0,098	4,08	26,57	63,04

Figure I-13. Weighted mean declared income equivalent distribution by municipality types, st. prices 2015, period 2002-2019

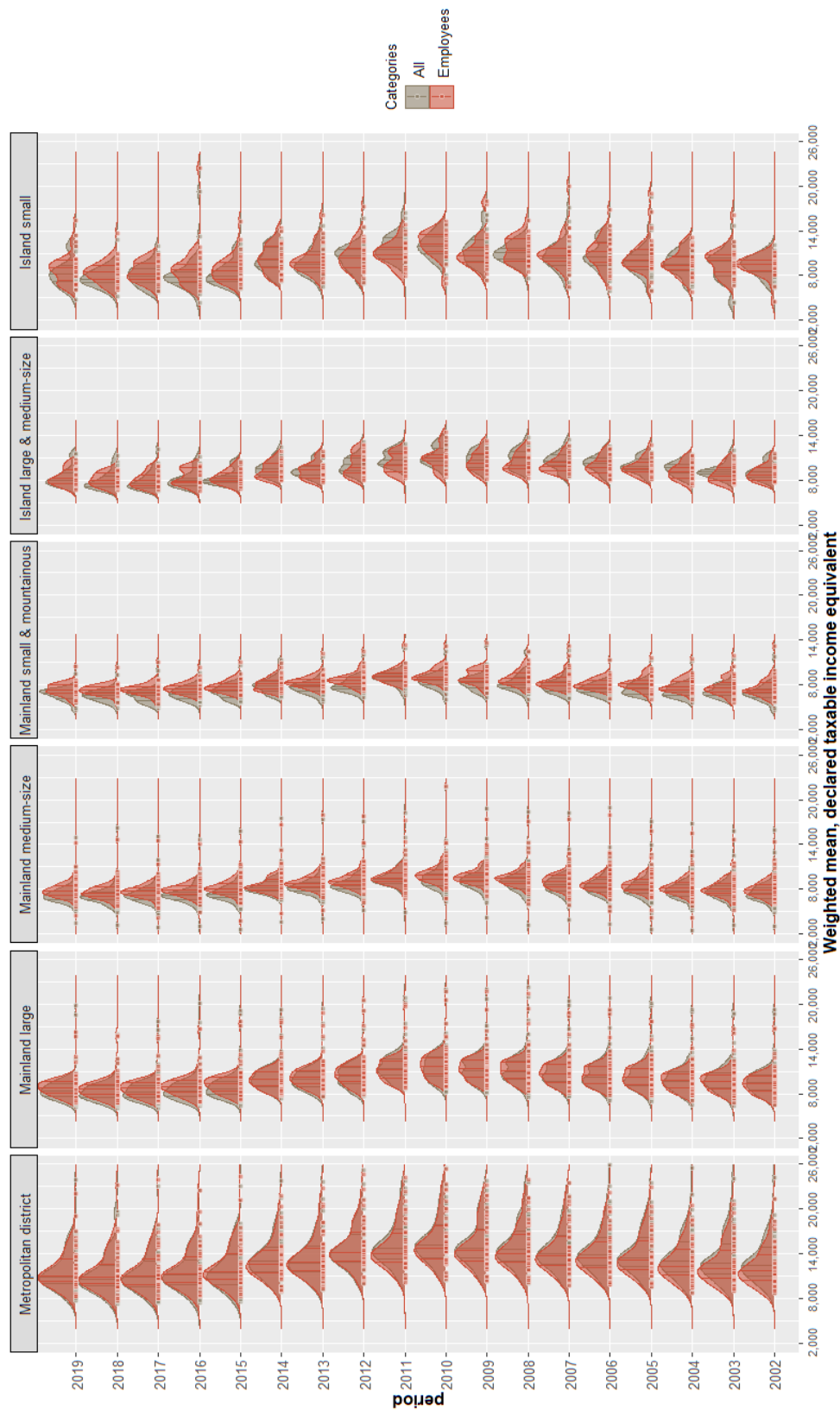


Table I-11. Descriptive statistics for weighted mean of declared income equivalent distribution by municipality type, st. prices 2015, period 2002-2019

Type of Municipality	Year	All								Employees							
		count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
Metropolitan district	2002	47	12.376,5	13.250,6	3.166,2	0,239	3.821,2	8.634,4	24.178,0	47	11.679,7	12.329,7	2.696,5	0,219	3.505,9	8.617,6	21.286,8
	2003	47	12.747,0	13.571,7	3.245,6	0,239	4.025,1	9.138,6	24.079,8	47	12.009,5	12.702,0	2.745,1	0,216	3.757,5	8.916,7	20.630,2
	2004	47	12.938,9	13.829,3	3.319,1	0,240	4.067,7	8.797,9	25.470,3	47	12.281,0	12.991,5	2.635,2	0,203	3.495,0	8.673,9	20.473,5
	2005	47	13.475,8	14.515,6	3.446,3	0,237	4.065,0	9.556,9	26.167,3	47	13.094,9	13.840,2	2.913,1	0,210	3.857,1	9.518,8	22.903,0
	2006	47	13.809,2	14.649,8	3.359,5	0,229	3.815,3	9.970,2	25.887,0	47	13.388,9	14.034,7	2.836,9	0,202	3.542,1	9.820,7	22.184,8
	2007	47	14.086,0	15.080,1	3.621,8	0,240	4.083,6	9.781,3	27.770,1	47	13.712,9	14.475,3	3.133,8	0,216	3.839,9	9.751,6	23.540,5
	2008	47	14.531,1	15.477,0	3.533,0	0,228	4.090,7	10.007,4	26.453,8	47	13.948,8	14.927,7	3.106,5	0,208	3.801,0	10.084,4	23.862,0
	2009	47	14.760,5	15.733,7	3.633,4	0,231	4.484,3	10.212,9	27.455,3	47	14.420,0	15.189,0	3.200,9	0,211	4.176,9	10.322,3	23.242,6
	2010	47	15.211,2	16.182,8	3.824,7	0,236	4.698,3	10.414,5	28.593,8	47	14.757,9	15.735,2	3.405,0	0,216	4.484,7	10.546,8	25.370,0
	2011	47	14.694,2	15.640,2	3.525,4	0,225	4.288,6	10.445,6	26.875,7	47	14.026,8	14.993,3	3.119,2	0,208	3.934,2	10.163,9	24.117,3
	2012	47	14.100,0	14.923,5	3.222,9	0,216	3.725,1	9.941,9	25.134,2	47	14.196,8	15.062,9	3.138,7	0,208	3.915,4	9.997,3	24.671,1
	2013	47	12.775,0	13.585,5	3.031,6	0,223	3.455,5	9.135,5	23.641,1	47	12.885,5	13.569,1	2.906,3	0,214	3.129,0	9.297,7	22.719,6
	2014	47	12.922,6	13.611,3	3.111,6	0,229	3.238,9	8.868,4	23.731,2	47	12.615,5	13.241,0	2.802,0	0,212	2.963,3	8.946,2	21.708,5
	2015	47	11.405,7	12.486,9	4.034,3	0,323	4.000,2	7.520,8	30.377,0	47	11.559,3	12.441,9	3.128,2	0,251	3.404,2	8.209,7	24.361,9
	2016	47	11.110,0	12.031,9	3.691,5	0,307	3.782,7	7.414,6	28.022,1	47	11.223,1	12.057,1	2.898,2	0,240	3.397,0	8.235,2	22.497,1
	2017	47	10.817,0	11.916,5	3.834,1	0,322	3.596,9	7.387,8	27.966,1	47	11.028,9	11.772,3	2.954,5	0,251	3.359,5	7.941,2	23.935,3
	2018	47	10.515,6	11.623,6	3.642,6	0,313	2.888,9	7.285,2	28.426,7	47	10.845,4	11.611,8	2.844,4	0,245	2.597,9	7.746,2	23.120,5
	2019	47	10.869,9	12.205,6	4.131,9	0,339	3.460,7	7.704,3	31.490,1	47	10.969,3	11.922,9	2.796,6	0,235	3.082,5	8.192,3	22.006,0
Mainland large	2002	92	9.491,7	9.719,6	2.025,5	0,208	2.070,1	6.513,0	19.322,6	92	9.341,8	9.480,5	1.675,5	0,177	1.897,1	6.486,1	16.887,8
	2003	92	9.629,5	9.987,9	2.001,6	0,200	1.985,1	6.302,2	18.836,2	92	9.638,3	9.745,5	1.591,8	0,163	1.799,9	6.856,6	16.693,6
	2004	92	9.703,6	10.064,8	2.052,4	0,204	2.110,6	6.546,1	19.216,8	92	9.753,1	9.918,0	1.659,7	0,167	1.932,5	7.074,2	17.279,8
	2005	92	10.167,9	10.537,4	2.179,8	0,207	2.336,9	6.932,4	20.105,5	92	10.281,0	10.444,2	1.763,2	0,169	2.241,6	7.720,9	17.715,0
	2006	92	10.260,5	10.746,8	2.188,4	0,204	2.369,4	7.020,2	20.919,2	92	10.452,6	10.686,2	1.860,1	0,174	2.241,9	7.731,1	19.219,5
	2007	92	10.598,1	11.020,8	2.156,5	0,196	2.338,7	7.575,4	20.405,1	92	10.713,6	10.923,3	1.818,4	0,166	2.314,1	8.138,8	18.785,5
	2008	92	10.967,6	11.415,1	2.354,9	0,206	2.433,0	7.484,9	22.286,8	92	11.112,6	11.372,5	2.032,4	0,179	2.180,2	8.335,7	21.454,8
	2009	92	11.135,2	11.590,6	2.245,2	0,194	2.316,2	8.104,1	22.051,1	92	11.355,8	11.586,4	1.973,4	0,170	2.280,1	8.785,9	21.651,0
	2010	92	11.611,1	11.807,1	2.350,8	0,199	2.637,1	8.185,5	21.965,3	92	11.691,0	11.913,4	2.113,5	0,177	2.130,3	8.963,7	21.754,1
	2011	92	11.403,6	11.710,1	2.091,8	0,179	2.247,2	8.637,8	20.798,4	92	11.218,6	11.428,8	1.915,5	0,168	2.264,3	8.731,0	19.994,8
	2012	92	10.394,0	10.669,0	2.160,1	0,202	2.220,6	7.651,0	20.484,6	92	10.581,5	10.937,4	2.082,0	0,190	1.940,7	7.903,6	20.556,7
	2013	92	9.915,9	10.150,2	1.859,4	0,183	1.983,9	7.469,6	19.381,6	92	10.204,4	10.414,7	1.717,2	0,165	1.749,7	7.634,0	18.801,8
	2014	92	9.937,2	10.210,9	1.884,1	0,185	2.027,1	7.414,9	19.232,8	92	9.892,7	10.164,9	1.733,0	0,170	1.793,2	7.842,4	17.841,3
	2015	92	8.644,8	9.024,5	1.962,4	0,217	1.674,6	6.393,2	19.080,1	92	9.336,5	9.456,5	1.643,3	0,174	1.764,1	7.189,4	17.701,7
	2016	92	8.326,6	8.702,8	1.956,1	0,225	1.664,6	6.384,8	20.100,3	92	8.928,2	9.128,2	1.572,4	0,172	1.569,8	6.914,6	16.666,5
	2017	92	8.246,4	8.584,0	1.785,4	0,208	1.591,9	6.068,0	17.752,5	92	8.772,4	8.878,1	1.459,8	0,164	1.520,6	6.933,3	15.616,3
	2018	92	7.950,9	8.386,8	1.612,9	0,192	1.537,0	6.037,5	15.929,2	92	8.581,5	8.768,9	1.510,6	0,172	1.426,0	6.756,2	15.873,8
	2019	92	8.398,4	8.769,2	1.968,7	0,225	1.639,0	6.178,1	19.806,5	92	8.862,1	9.021,2	1.497,6	0,166	1.460,7	6.726,0	16.201,2
Mainland medium-size	2002	96	7.408,7	7.632,5	1.613,1	0,211	1.447,9	2.956,1	15.932,9	95	7.933,6	8.111,2	1.312,6	0,162	1.383,8	6.033,9	14.425,0
	2003	96	7.683,8	7.893,4	1.534,9	0,194	1.364,2	3.211,1	15.798,5	96	7.999,9	8.205,7	1.292,7	0,158	1.230,7	5.200,2	14.608,3
	2004	96	7.823,0	7.965,7	1.655,8	0,208	1.553,8	2.464,9	16.784,7	96	8.122,9	8.341,6	1.397,1	0,167	1.234,1	4.112,0	15.463,9
	2005	96	8.027,6	8.283,9	1.748,2	0,211	1.541,9	2.611,8	17.066,3	96	8.675,7	8.727,1	1.424,6	0,163	1.453,8	4.183,7	15.856,4
	2006	96	8.372,1	8.576,3	1.836,0	0,214	1.686,8	3.312,2	18.984,4	96	8.721,2	8.977,9	1.581,0	0,176	1.470,5	5.030,0	17.874,6
	2007	96	8.656,8	8.741,5	1.730,0	0,198	1.746,5	3.887,0	18.166,6	96	9.100,9	9.192,0	1.460,7	0,159	1.514,8	5.924,6	17.350,6
	2008	96	9.055,8	9.084,1	1.800,1	0,198	1.556,4	3.097,4	18.426,6	96	9.444,5	9.579,5	1.443,9	0,151	1.327,9	6.062,3	17.139,1
	2009	96	9.153,6	9.367,1	1.812,7	0,194	1.480,5	4.212,9	18.847,0	96	9.614,1	9.860,7	1.414,2	0,143	1.085,5	6.976,1	17.419,0
	2010	96	9.278,8	9.523,7	1.978,1	0,208	1.540,2	3.478,7	21.615,6	96	9.954,7	10.131,2	1.736,6	0,171	1.267,1	6.790,0	21.781,7
	2011	96	9.285,3	9.616,8	1.593,1	0,166	1.420,6	4.885,8	18.208,6	96	9.493,7	9.702,4	1.393,1	0,144	1.114,7	6.725,2	17.188,2
	2012	96	8.478,9	8.737,5	1.550,7	0,177	1.136,5	5.218,3	17.124,2	96	9.083,2	9.313,6	1.503,5	0,161	1.264,8	6.122,6	17.808,4
	2013	96	8.218,9	8.452,4	1.458,9	0,173	1.127,8	4.018,8	17.372,9	96	8.797,8	9.006,5	1.350,4	0,150	1.254,1	5.219,6	17.943,6
	2014	96	8.144,4	8.453,8	1.528,8	0,181	1.272,2	3.618,2	17.490,4	96	8.411,0	8.701,7	1.403,6	0,161	1.371,3	4.779,2	16.691,7
	2015	96	7.385,0	7.567,8	1.441,2	0,190	1.215,2	2.542,9	15.792,0	96	8.106,2	8.247,2	1.232,5	0,149	1.125,0	3.689,3	14.353,7
	2016	96	7.163,4	7.258,0	1.294,8	0,178	1.034,2	3.068,9	14.624,4	96	7.875,3	7.951,0	1.088,5	0,137	1.081,2	4.845,9	14.083,0
	2017	96	7.138,2	7.241,9	1.402,5	0,194	1.237,3	2.823,3	15.054,5	96	7.692,6	7.796,8	1.193,1	0,153	997,6	4.106,9	14.503,6
	2018	96	6.983,2	7.105,1	1.356,9	0,191	939,5	3.160,8	16.175,5	96	7.533,5	7.673,3	1.126,1	0,147	1.208,9	5.693,8	14.663,7
	2019	96	7.123,7	7.317,3	1.342,1	0,183	1.166,5	3.437,5	14.904,9	96	7.748,3	7.898,6	1.199,3	0,152	1.253,5	4.490,3	14.183,7

Table I-11. (continued) Descriptive statistics for weighted mean of declared income equivalent distribution by municipality type, st. prices 2015, period 2002-2019

Type of Municipality	Year	All								Employees							
		count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
Mainland small & mountainous	2002	34	6.790,5	6.898,6	1.236,5	0,179	1.187,2	4.554,0	11.677,9	34	7.232,4	7.637,9	1.384,5	0,181	1.315,0	5.672,9	13.225,9
	2003	34	6.935,1	7.245,8	1.119,6	0,155	1.416,5	5.659,3	11.460,1	34	7.521,1	7.779,7	1.297,0	0,167	1.329,8	5.562,0	11.833,4
	2004	34	7.064,4	7.201,0	1.013,9	0,141	1.181,2	5.581,3	11.138,2	34	7.724,8	7.960,0	1.025,8	0,129	1.135,7	6.023,6	11.494,4
	2005	34	7.392,0	7.554,7	1.014,1	0,134	1.303,9	6.248,2	11.362,2	34	8.078,0	8.232,7	1.128,1	0,137	1.021,6	5.942,0	11.537,0
	2006	34	7.377,4	7.482,3	967,3	0,129	1.006,1	5.962,7	11.356,7	34	7.945,5	8.138,5	905,3	0,111	1.021,2	6.077,5	11.287,9
	2007	34	7.798,7	7.965,4	1.211,5	0,152	1.329,3	6.184,6	12.532,5	34	8.240,1	8.630,8	1.301,6	0,151	1.237,7	7.205,9	13.105,4
	2008	34	8.034,9	8.347,3	1.380,3	0,165	1.470,1	5.943,4	12.473,5	34	8.814,4	8.977,8	1.174,9	0,131	1.383,5	7.096,2	12.425,4
	2009	34	8.312,9	8.382,7	1.277,5	0,152	1.326,6	6.218,1	13.241,2	34	8.846,6	9.124,1	1.234,2	0,135	1.456,6	6.847,5	13.655,8
	2010	34	8.548,3	8.560,7	1.114,8	0,130	1.033,2	6.031,4	12.397,6	34	9.066,5	9.311,8	1.063,1	0,114	1.096,5	7.449,1	13.224,8
	2011	34	8.976,0	8.971,9	1.106,5	0,123	1.073,5	6.620,8	12.924,2	34	9.128,9	9.247,5	1.034,9	0,112	1.091,2	7.832,8	13.311,3
	2012	34	7.768,4	7.992,7	1.050,4	0,131	1.148,1	6.208,5	11.976,0	34	8.620,5	8.782,8	1.052,1	0,120	801,1	7.084,6	12.498,8
	2013	34	7.691,5	7.678,1	1.059,2	0,138	927,5	5.655,2	11.787,6	34	8.306,0	8.409,8	937,5	0,111	827,8	7.033,2	12.146,8
	2014	34	7.891,0	7.958,6	1.159,3	0,146	1.403,3	6.223,3	11.295,6	34	8.130,5	8.155,7	984,0	0,121	1.218,5	6.792,0	10.855,1
	2015	34	7.087,8	7.130,7	998,7	0,140	1.397,1	5.603,4	10.585,7	34	7.749,3	7.821,0	901,5	0,115	864,7	6.514,2	11.030,1
	2016	34	6.778,1	6.864,6	881,0	0,128	1.259,6	5.214,6	9.598,7	34	7.465,3	7.601,4	818,4	0,108	877,5	6.255,5	10.345,4
	2017	34	6.614,6	6.564,5	985,1	0,150	1.189,3	4.870,9	9.936,8	34	7.315,1	7.400,5	956,2	0,129	823,9	5.440,2	11.036,2
	2018	34	6.522,8	6.591,2	832,1	0,126	877,6	4.828,7	9.342,1	34	7.308,6	7.347,0	781,6	0,106	838,8	5.500,4	10.313,2
	2019	34	6.900,5	6.764,8	940,1	0,139	1.097,8	4.546,2	9.480,4	34	7.350,5	7.394,1	929,1	0,126	1.081,5	5.565,4	10.415,2
Island large & medium-size	2002	21	9.123,4	9.274,8	1.099,5	0,119	1.229,1	7.620,2	11.345,6	21	8.651,8	8.929,1	1.080,1	0,121	1.669,0	7.635,5	11.579,0
	2003	21	9.051,8	9.259,7	1.012,2	0,109	666,2	7.756,7	11.920,9	21	8.564,6	8.867,9	1.159,4	0,131	1.727,3	7.344,4	11.210,3
	2004	21	9.693,3	9.569,3	961,9	0,101	1.277,8	7.933,6	11.431,5	21	9.120,4	9.189,3	1.161,9	0,126	1.378,0	7.281,4	11.297,5
	2005	21	9.477,6	9.732,4	1.156,8	0,119	1.270,6	8.170,3	12.642,4	21	10.287,5	10.295,0	1.138,6	0,111	1.257,5	8.294,6	12.493,8
	2006	21	10.287,5	10.295,0	1.138,6	0,111	1.257,5	8.294,6	12.493,8	21	9.696,9	9.891,8	1.236,2	0,125	1.558,1	7.966,8	12.296,1
	2007	21	10.522,1	10.575,2	1.298,1	0,123	1.380,1	8.342,2	13.350,5	21	9.786,7	10.080,8	1.074,4	0,107	1.170,2	8.566,6	12.559,5
	2008	21	11.041,8	10.863,9	1.317,2	0,121	2.288,6	8.859,6	13.637,0	21	9.981,9	10.310,0	1.256,4	0,122	1.683,0	8.291,5	12.932,2
	2009	21	10.679,4	10.720,5	1.171,2	0,109	1.788,8	8.608,9	12.549,8	21	10.286,8	10.457,5	1.432,1	0,137	2.196,8	8.144,6	13.260,1
	2010	21	10.931,5	11.214,6	1.360,2	0,121	1.817,8	8.691,6	13.738,9	21	11.002,8	10.930,1	1.639,8	0,150	1.472,0	8.328,2	14.461,3
	2011	21	10.727,5	10.948,9	1.006,1	0,092	1.757,5	9.263,8	12.812,3	21	10.042,0	10.224,4	1.298,9	0,127	2.477,0	8.285,2	12.294,8
	2012	21	9.685,6	10.045,8	1.551,9	0,154	2.360,9	8.018,9	12.671,0	21	9.355,9	9.451,2	1.029,6	0,109	1.156,3	7.800,4	11.510,4
	2013	21	9.355,9	9.451,2	1.029,6	0,109	1.156,3	7.800,4	11.510,4	21	9.438,5	9.295,1	1.165,8	0,125	1.706,9	7.684,6	11.815,9
	2014	21	9.516,3	9.695,9	1.131,4	0,117	1.591,7	8.249,7	12.436,0	21	9.067,3	9.343,8	1.117,9	0,120	1.851,2	8.019,4	11.769,3
	2015	21	7.934,0	8.361,7	1.065,4	0,127	783,5	7.108,0	10.575,6	21	8.252,7	8.416,7	956,7	0,114	1.205,5	6.864,3	10.456,2
	2016	21	8.005,3	8.142,2	1.178,3	0,145	1.026,8	6.908,2	11.125,8	21	7.818,2	8.406,6	1.106,6	0,132	2.017,9	6.484,9	10.031,1
	2017	21	7.578,9	8.028,1	1.392,5	0,173	1.653,6	6.560,5	12.090,6	21	7.986,7	8.078,9	1.010,7	0,125	1.474,5	6.695,3	9.945,4
	2018	21	7.462,8	7.979,0	1.272,3	0,159	1.356,3	6.676,1	11.262,1	21	8.005,3	8.078,5	859,0	0,106	1.392,9	6.716,4	9.355,5
	2019	21	8.031,9	8.485,2	1.354,0	0,160	1.428,9	6.781,4	11.537,1	21	8.217,5	8.433,8	1.156,4	0,137	1.966,9	6.672,5	10.657,6
Island small	2002	28	9.517,4	9.298,5	1.417,4	0,152	1.643,5	6.341,7	12.060,6	23	9.507,8	9.202,7	1.484,9	0,161	1.461,9	4.504,8	11.088,5
	2003	29	9.907,0	9.260,6	2.247,7	0,243	2.473,9	4.390,3	14.695,1	24	10.046,4	9.906,1	2.047,1	0,207	2.385,3	6.615,4	16.077,1
	2004	29	9.550,5	9.620,2	1.634,8	0,170	1.962,9	6.500,9	12.583,1	27	9.372,1	9.655,4	1.746,7	0,181	1.768,0	5.814,8	13.075,6
	2005	31	9.892,0	10.134,6	2.486,9	0,245	1.989,3	5.966,9	18.485,1	25	10.087,4	10.751,8	2.755,9	0,256	2.315,4	5.867,8	19.033,4
	2006	30	10.537,7	10.743,1	2.135,9	0,199	3.161,8	5.978,1	14.738,4	26	11.216,1	11.079,9	2.343,6	0,212	2.529,2	6.341,3	16.895,9
	2007	28	10.318,5	10.716,0	2.329,4	0,217	2.273,2	6.329,8	17.149,4	26	10.720,2	11.190,5	2.545,1	0,227	1.821,8	6.503,9	20.051,9
	2008	30	11.059,6	10.943,5	1.319,4	0,121	1.436,2	7.656,5	13.269,0	27	11.392,1	11.457,3	1.718,6	0,150	2.940,9	8.559,0	15.440,1
	2009	30	11.384,0	11.525,3	2.137,8	0,185	2.871,5	7.351,3	16.296,2	26	10.682,5	11.215,7	2.461,4	0,219	2.067,1	7.347,2	17.947,8
	2010	29	11.879,3	11.911,6	1.663,1	0,140	2.255,4	8.113,4	14.938,4	27	12.285,9	12.150,0	1.974,8	0,163	2.416,2	6.908,8	15.210,4
	2011	30	11.453,2	11.924,8	1.705,2	0,143	2.231,9	9.275,9	16.379,2	27	10.860,3	10.999,4	1.653,1	0,150	1.529,6	7.894,1	14.886,2
	2012	30	10.657,2	10.456,7	1.933,8	0,185	2.391,0	6.871,2	15.617,2	26	10.362,7	10.702,6	2.254,3	0,211	2.532,7	7.090,9	17.310,7
	2013	29	9.577,8	9.880,4	1.926,3	0,195	2.729,1	6.531,5	14.726,1	26	9.729,4	10.256,3	1.990,9	0,194	1.757,0	7.030,5	16.042,7
	2014	31	10.150,8	10.289,1	1.770,8	0,172	2.556,1	7.231,7	13.977,9	27	10.162,2	10.329,4	1.945,5	0,188	2.911,3	7.400,2	14.442,1
	2015	30	7.864,9	8.373,2	1.617,5	0,193	2.005,5	6.204,1	12.284,0	28	8.708,2	9.010,9	1.930,4	0,214	2.342,1	6.355,3	15.203,0
	2016	31	7.834,9	8.290,3	2.619,2	0,316	1.489,9	4.377,9	19.283,8	29	8.843,7	9.071,2	2.999,2	0,331	2.167,8	5.881,7	22.395,6
	2017	31	7.910,0	8.069,5	1.503,9	0,186	1.834,0	5.820,0	11.973,1	28	8.230,1	8.548,2	1.346,9	0,158	2.190,8	5.895,5	10.832,8
	2018	30	7.429,9	7.801,4	1.432,7	0,184	1.448,7	5.252,7	12.805,3	29	8.436,8	8.548,4	1.614,7	0,189	1.765,3	6.113,3	13.695,0
	2019	30	8.270,2	8.541,5	2.155,6	0,252	2.142,6	4.777,4	13.430,9	27	9.069,6	9.134,2	2.221,3	0,243	2.608,3	6.036,7	15.342,6

Figure I-14. Weighted median declared income equivalent distribution by municipality types, st. prices 2015, period 2002-2019

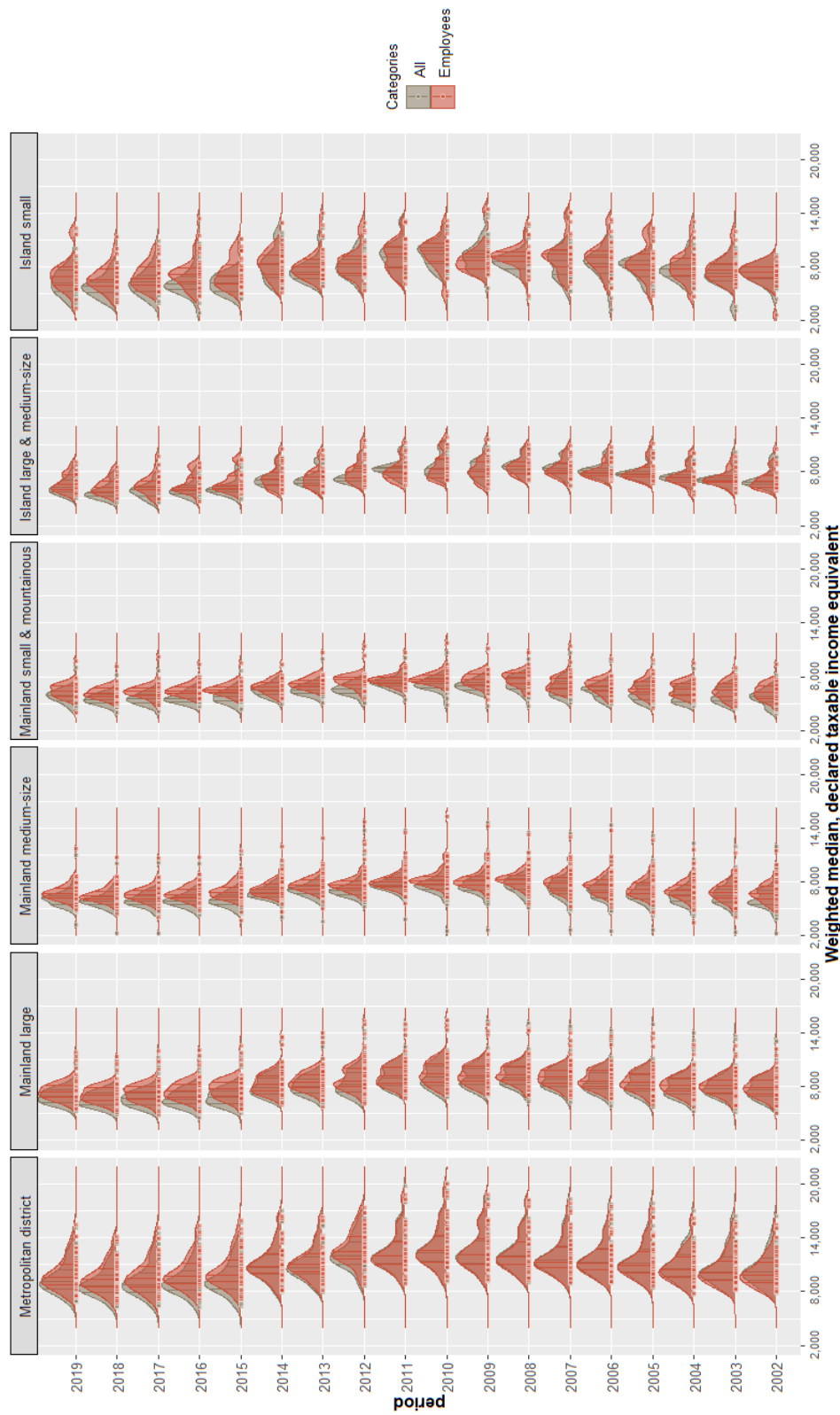


Table I-12. Descriptive statistics for weighted median of declared income equivalent distribution by municipality type, st. prices 2015, period 2002-2019

Type of Municipality	Year	All								Employees							
		count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
Mainland small & mountainous	2002	47	10.223,0	10.698,1	1.993,8	0,186	2.448,5	7.769,1	16.456,8	47	9.874,8	10.304,9	1.772,9	0,172	2.320,5	7.873,3	15.443,2
	2003	47	10.264,4	10.856,1	2.072,2	0,191	2.494,9	8.123,4	16.473,8	47	10.052,5	10.546,6	1.832,3	0,174	2.215,3	8.113,7	15.582,3
	2004	47	10.599,9	11.095,6	2.021,9	0,182	2.404,8	7.746,8	17.031,1	47	10.463,5	10.881,1	1.872,3	0,172	2.287,7	7.847,5	16.173,8
	2005	47	11.110,5	11.678,9	2.154,9	0,185	2.533,2	8.439,5	17.800,7	47	10.981,6	11.546,1	2.027,3	0,176	2.390,5	8.646,6	17.226,3
	2006	47	11.323,6	11.897,1	2.114,0	0,178	2.330,3	8.999,2	17.731,7	47	11.198,2	11.783,2	2.017,3	0,171	2.305,2	9.042,4	17.551,7
	2007	47	11.461,4	12.136,3	2.193,4	0,181	2.346,3	8.903,3	18.382,7	47	11.338,3	12.012,2	2.079,0	0,173	2.263,8	8.978,4	17.802,9
	2008	47	12.023,3	12.525,0	2.257,5	0,180	2.516,7	9.044,0	18.239,8	47	11.877,6	12.439,5	2.204,6	0,177	2.528,9	9.195,9	18.271,1
	2009	47	12.142,4	12.736,3	2.317,2	0,182	2.594,9	9.091,8	18.497,6	47	12.167,6	12.726,2	2.306,6	0,181	2.776,4	9.290,0	18.871,9
	2010	47	12.408,6	13.080,7	2.512,3	0,192	2.821,1	9.121,7	20.125,6	47	12.591,5	13.109,6	2.486,5	0,190	2.926,2	9.237,9	19.968,8
	2011	47	11.979,3	12.683,3	2.380,9	0,188	2.536,5	8.971,7	19.814,3	47	11.991,4	12.559,1	2.308,0	0,184	2.499,9	8.941,5	18.829,7
	2012	47	11.987,8	12.323,2	1.910,5	0,155	2.547,3	8.664,6	16.733,1	47	12.467,5	12.893,4	1.970,0	0,153	2.547,7	8.892,5	17.364,7
	2013	47	10.696,9	11.066,5	1.810,1	0,164	1.899,0	7.936,8	15.426,3	47	10.996,3	11.403,8	1.907,6	0,167	2.079,3	8.126,7	16.275,3
	2014	47	10.721,9	11.175,2	2.080,5	0,186	2.233,7	7.890,4	17.028,8	47	10.835,7	11.276,6	2.020,4	0,179	2.223,3	8.011,5	16.393,6
	2015	47	9.108,3	9.634,8	1.997,5	0,207	2.453,9	6.383,0	15.661,9	47	9.843,1	10.447,1	1.982,7	0,190	2.427,6	7.178,5	15.929,5
	2016	47	9.000,5	9.418,2	1.862,4	0,198	2.139,8	6.283,5	14.876,0	47	9.715,7	10.161,7	1.857,1	0,183	2.214,0	7.216,3	15.334,6
	2017	47	8.807,5	9.288,3	1.860,5	0,200	2.107,8	6.338,1	14.523,9	47	9.538,2	9.988,1	1.874,4	0,189	2.256,4	7.060,8	15.063,7
	2018	47	8.656,9	9.074,0	1.704,6	0,188	1.834,9	6.226,3	13.744,7	47	9.347,5	9.675,7	1.739,7	0,180	1.974,6	6.792,8	14.186,2
	2019	47	9.112,8	9.568,3	1.845,4	0,193	2.166,4	6.861,7	15.062,4	47	9.601,2	10.082,7	1.894,8	0,188	2.226,6	7.351,7	15.524,5
Island large & medium-size	2002	92	7.653,9	7.845,7	1.391,0	0,177	1.804,5	5.065,2	13.133,9	92	7.867,4	7.970,4	1.197,2	0,150	1.668,2	4.992,9	12.248,9
	2003	92	7.741,3	8.041,3	1.396,4	0,174	1.597,8	5.131,0	13.628,2	92	8.187,7	8.168,8	1.175,4	0,144	1.447,5	5.828,3	12.568,1
	2004	92	7.819,7	8.073,6	1.456,6	0,180	1.756,2	5.302,6	13.986,0	92	8.174,4	8.279,8	1.203,9	0,145	1.453,2	5.769,3	12.693,9
	2005	92	8.191,8	8.491,8	1.543,0	0,182	1.881,1	5.697,2	14.965,7	92	8.516,6	8.715,3	1.326,8	0,152	1.686,8	6.044,7	13.968,4
	2006	92	8.389,4	8.731,0	1.491,3	0,171	1.807,8	5.892,5	14.279,1	92	8.641,9	8.936,4	1.269,1	0,142	1.760,6	6.665,0	13.600,7
	2007	92	8.800,7	9.008,7	1.473,6	0,164	1.807,6	6.270,9	14.753,3	92	9.052,5	9.186,3	1.235,9	0,135	1.501,9	6.841,7	13.999,9
	2008	92	9.028,1	9.339,6	1.552,9	0,166	1.939,9	6.369,1	15.114,2	92	9.314,0	9.576,5	1.364,3	0,142	1.642,5	7.084,0	14.424,0
	2009	92	8.974,8	9.287,3	1.576,3	0,170	1.890,2	6.965,3	15.356,9	92	9.255,7	9.512,4	1.381,3	0,145	1.692,1	7.193,1	14.910,1
	2010	92	9.124,3	9.397,6	1.674,7	0,178	2.163,3	6.828,0	15.416,0	92	9.487,2	9.692,0	1.522,8	0,157	2.021,6	7.173,8	15.382,5
	2011	92	8.999,3	9.282,3	1.545,9	0,167	2.037,7	6.719,5	15.133,0	92	9.166,8	9.370,6	1.436,0	0,153	1.800,8	6.685,7	14.923,4
	2012	92	8.291,2	8.546,8	1.633,8	0,191	2.207,1	6.070,5	14.897,7	92	8.676,9	9.117,6	1.659,0	0,182	2.056,9	6.135,6	15.360,7
	2013	92	8.022,2	8.270,5	1.334,2	0,161	1.534,1	5.905,4	13.438,3	92	8.528,5	8.720,1	1.320,4	0,151	1.469,3	5.794,3	13.945,2
	2014	92	7.923,6	8.213,2	1.397,4	0,170	1.783,5	6.176,8	13.640,7	92	8.304,3	8.479,5	1.367,7	0,161	1.688,8	5.951,5	13.565,4
	2015	92	6.843,2	7.005,0	1.217,7	0,174	1.436,5	5.048,3	11.849,9	92	7.791,7	7.830,2	1.214,3	0,155	1.625,1	5.482,1	12.541,3
	2016	92	6.639,8	6.847,1	1.174,3	0,172	1.344,6	4.597,8	11.358,7	92	7.516,1	7.619,9	1.173,6	0,154	1.466,4	5.102,4	12.084,0
	2017	92	6.669,0	6.780,5	1.097,5	0,162	1.322,5	4.814,5	11.260,8	92	7.463,1	7.430,8	1.143,8	0,154	1.502,0	4.913,8	11.989,7
	2018	92	6.457,5	6.710,6	1.072,6	0,160	1.281,5	4.862,1	10.896,3	92	7.106,9	7.287,9	1.076,0	0,148	1.456,3	5.123,6	11.415,7
	2019	92	6.907,9	7.059,7	1.115,3	0,158	1.331,6	5.293,2	11.440,8	92	7.464,4	7.593,4	1.105,3	0,146	1.296,1	5.504,6	11.885,6
Island small	2002	96	6.037,2	6.270,2	1.328,9	0,212	1.491,5	2.295,5	11.979,4	95	6.697,6	6.879,0	1.168,6	0,170	1.398,3	4.695,0	11.471,0
	2003	96	6.428,2	6.487,5	1.261,9	0,195	1.482,3	2.360,3	11.931,7	96	6.841,6	6.912,6	1.107,2	0,160	1.358,6	4.021,3	11.176,1
	2004	96	6.498,9	6.559,5	1.333,3	0,203	1.342,9	1.788,2	12.273,3	96	6.986,5	7.088,7	1.149,1	0,162	1.248,8	3.470,2	11.583,6
	2005	96	6.709,2	6.846,9	1.372,9	0,201	1.509,6	2.625,6	13.147,8	96	7.173,5	7.322,2	1.165,2	0,159	1.223,2	4.482,7	12.671,3
	2006	96	7.013,9	7.181,8	1.459,6	0,203	1.527,4	2.487,0	14.278,0	96	7.600,6	7.664,7	1.224,6	0,160	1.371,9	5.064,0	13.722,5
	2007	96	7.325,5	7.387,3	1.386,7	0,188	1.513,9	2.584,3	13.313,6	96	7.833,4	7.904,4	1.158,4	0,147	1.368,9	5.257,3	12.986,5
	2008	96	7.738,8	7.772,0	1.411,1	0,182	1.263,6	1.872,7	13.536,8	96	8.253,3	8.305,4	1.080,4	0,130	1.016,0	5.437,5	13.198,4
	2009	96	7.578,4	7.781,7	1.408,0	0,181	1.193,9	2.645,9	14.563,3	96	8.050,2	8.299,7	1.122,5	0,135	910,4	6.141,1	14.150,8
	2010	96	7.628,3	7.810,2	1.400,7	0,179	1.022,7	2.475,8	15.250,4	96	8.151,0	8.382,4	1.172,0	0,140	858,3	6.221,2	15.296,0
	2011	96	7.679,9	7.857,7	1.180,3	0,150	933,9	3.777,9	13.725,5	96	7.969,0	8.110,6	1.051,2	0,130	888,2	5.638,3	13.538,5
	2012	96	7.066,3	7.286,1	1.272,7	0,175	995,7	5.277,1	13.683,9	96	7.680,9	7.913,0	1.298,4	0,164	913,5	5.949,4	14.682,1
	2013	96	7.095,2	7.172,4	1.085,0	0,151	899,9	3.543,8	12.714,8	96	7.619,0	7.742,7	980,4	0,127	978,1	4.950,6	12.919,4
	2014	96	6.832,0	6.956,7	1.040,9	0,150	1.002,3	4.009,1	11.956,2	96	7.176,1	7.285,2	1.014,1	0,139	1.113,0	4.622,0	11.971,9
	2015	96	5.977,0	6.086,6	1.103,9	0,181	1.056,4	1.382,4	11.087,0	96	6.845,2	6.954,1	1.010,8	0,145	1.099,1	3.664,2	11.437,8
	2016	96	5.803,8	5.924,2	948,6	0,160	945,1	1.762,9	9.980,9	96	6.567,7	6.742,1	860,4	0,128	971,6	4.702,4	10.745,2
	2017	96	5.866,3	5.965,5	961,3	0,161	974,7	2.203,6	10.095,6	96	6.559,7	6.600,3	866,1	0,131	930,5	4.072,8	10.616,5
	2018	96	5.855,1	5.942,0	950,9	0,160	821,7	2.266,5	10.046,7	96	6.410,5	6.550,5	880,2	0,134	889,4	4.392,3	10.701,9
	2019	96	6.159,1	6.157,1	989,7	0,161	975,8	3.200,7	10.963,0	96	6.678,3	6.786,8	926,9	0,137	1.086,0	4.920,5	11.694,4

Table I-12. (continued) Descriptive statistics for weighted median of declared income equivalent distribution by municipality type, st. prices 2015, period 2002-2019

Type of Municipality	Year	All								Employees							
		count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
Mainland small & mountainous	2002	34	5.802,6	5.738,4	945,5	0,165	1.013,3	3.940,7	8.242,3	34	6.326,0	6.381,5	987,9	0,155	1.405,2	4.364,0	9.343,8
	2003	34	5.789,3	6.013,0	952,9	0,158	1.499,5	4.517,3	8.815,1	34	6.498,8	6.543,0	994,9	0,152	1.409,8	4.777,6	9.055,6
	2004	34	6.013,6	6.089,1	926,2	0,152	1.609,3	4.727,5	8.974,4	34	6.689,7	6.718,0	893,4	0,133	1.247,9	5.358,2	9.523,0
	2005	34	6.045,4	6.240,5	1.016,4	0,163	1.554,3	4.736,9	9.562,6	34	6.588,1	6.836,6	1.083,4	0,158	1.221,1	4.462,9	9.860,1
	2006	34	6.557,9	6.473,0	940,3	0,145	1.039,1	4.928,6	9.770,1	34	7.053,1	7.031,4	933,3	0,133	1.119,7	5.231,3	10.022,7
	2007	34	6.791,0	6.855,4	1.122,1	0,164	1.527,9	5.140,7	10.741,6	34	7.205,9	7.384,9	1.110,8	0,150	1.211,4	6.065,2	11.380,1
	2008	34	7.250,9	7.217,9	1.003,6	0,139	1.282,2	4.717,8	10.026,0	34	7.894,9	7.851,5	931,6	0,119	1.139,0	5.994,9	10.663,3
	2009	34	7.039,4	7.081,6	987,3	0,139	791,0	4.702,3	11.102,3	34	7.695,9	7.730,8	973,5	0,126	1.141,6	5.485,9	11.135,8
	2010	34	7.200,7	7.247,7	959,3	0,132	1.029,1	4.895,5	10.760,5	34	7.682,2	7.938,2	889,1	0,112	748,6	6.615,6	11.845,1
	2011	34	7.339,4	7.349,0	837,1	0,114	633,6	5.398,4	10.142,3	34	7.634,6	7.757,8	810,1	0,104	692,8	6.513,8	10.756,8
	2012	34	6.597,9	6.703,2	918,5	0,137	904,2	5.100,3	10.438,1	34	7.707,1	7.672,2	1.043,7	0,136	909,1	5.595,3	11.400,7
	2013	34	6.580,3	6.657,5	842,4	0,127	879,4	5.056,5	10.006,0	34	7.226,3	7.381,6	816,1	0,111	736,4	6.257,9	10.707,9
	2014	34	6.474,9	6.522,7	829,5	0,127	792,9	4.916,7	9.267,9	34	6.890,4	6.934,1	803,4	0,116	897,3	5.577,7	9.352,2
	2015	34	5.786,8	5.847,7	856,3	0,146	852,0	4.410,0	8.709,7	34	6.568,6	6.644,0	750,0	0,113	665,3	5.426,8	9.526,1
	2016	34	5.602,1	5.733,8	718,9	0,125	924,1	4.598,8	8.047,3	34	6.452,2	6.572,1	766,4	0,117	773,0	5.501,7	9.416,7
	2017	34	5.593,2	5.681,6	875,8	0,154	1.008,1	4.072,8	8.721,9	34	6.348,5	6.444,8	912,0	0,142	805,8	4.842,7	10.235,5
	2018	34	5.475,7	5.560,4	748,9	0,135	860,7	3.983,6	8.141,3	34	6.143,5	6.276,7	764,9	0,122	905,6	4.993,3	9.115,0
	2019	34	5.910,3	5.902,4	901,6	0,153	1.048,1	4.070,4	8.986,4	34	6.407,7	6.493,5	971,7	0,150	1.138,7	4.071,3	9.801,0
Island large & medium-size	2002	21	6.891,0	7.307,9	1.078,9	0,148	995,4	5.975,0	9.759,4	21	6.945,8	7.230,1	1.204,8	0,167	1.341,8	5.899,1	10.518,6
	2003	21	7.081,3	7.348,3	1.007,5	0,137	496,3	5.788,2	10.201,1	21	7.013,0	7.333,3	977,9	0,133	690,3	5.703,4	9.735,9
	2004	21	7.405,7	7.556,3	892,3	0,118	589,9	5.653,2	9.411,2	21	7.354,9	7.577,0	1.214,3	0,160	1.236,6	5.461,9	10.089,3
	2005	21	7.830,7	8.080,4	945,3	0,117	439,3	6.721,1	10.275,1	21	7.682,4	8.122,7	1.164,5	0,143	1.009,9	6.762,4	11.097,2
	2006	21	8.148,3	8.347,6	940,7	0,113	668,2	7.118,2	10.535,7	21	7.949,2	8.245,5	1.043,2	0,127	1.428,5	6.982,0	10.823,5
	2007	21	8.358,8	8.482,4	998,5	0,118	975,6	6.374,7	10.168,6	21	8.176,3	8.408,3	1.094,1	0,130	1.175,6	6.546,6	10.859,4
	2008	21	8.610,5	8.702,7	989,3	0,114	879,7	6.951,0	10.547,5	21	8.646,3	8.666,0	1.092,0	0,126	1.303,3	7.131,4	11.091,9
	2009	21	8.253,0	8.391,2	1.137,1	0,136	1.657,9	6.628,9	10.815,6	21	8.050,9	8.219,7	1.353,1	0,165	1.689,6	6.187,2	11.592,7
	2010	21	8.350,6	8.718,0	1.223,6	0,140	1.605,9	7.301,0	11.006,9	21	8.241,5	8.651,5	1.483,8	0,172	2.069,3	7.058,3	11.820,7
	2011	21	8.382,3	8.446,7	983,0	0,116	410,8	7.110,6	10.674,0	21	7.901,7	8.209,0	1.267,5	0,154	1.347,9	6.501,5	11.282,8
	2012	21	7.381,3	7.764,4	1.049,1	0,135	1.418,7	6.457,4	10.098,5	21	8.050,6	8.193,8	1.406,7	0,172	1.366,1	6.220,4	11.480,4
	2013	21	7.040,6	7.324,9	1.063,2	0,145	767,3	5.855,3	9.571,6	21	7.434,6	7.449,9	1.286,5	0,173	1.575,7	5.609,6	10.405,2
	2014	21	7.117,5	7.340,9	1.030,8	0,140	932,7	5.972,8	9.634,3	21	7.252,1	7.409,7	1.315,4	0,178	1.450,8	5.626,9	10.527,0
	2015	21	6.051,1	6.358,3	1.044,2	0,164	682,0	4.971,5	8.948,0	21	6.529,5	6.945,1	1.191,1	0,172	1.365,2	5.509,3	9.519,9
	2016	21	5.922,9	6.154,2	979,4	0,159	998,5	4.672,9	8.402,3	21	6.205,1	6.857,0	1.199,5	0,175	1.315,8	4.754,7	9.046,4
	2017	21	5.989,7	5.993,7	1.028,3	0,172	913,2	4.599,7	8.896,0	21	6.401,8	6.642,9	1.196,1	0,180	971,5	4.957,1	9.754,7
	2018	21	5.662,7	5.843,7	880,1	0,151	988,5	4.600,1	7.749,8	21	6.293,5	6.420,9	928,3	0,145	1.095,2	5.016,0	8.466,5
	2019	21	6.252,5	6.435,5	988,8	0,154	1.340,6	5.094,7	8.899,4	21	6.624,0	6.848,6	1.064,8	0,155	1.678,0	5.421,6	9.100,5
Island small	2002	28	7.399,7	7.266,3	1.077,7	0,148	1.418,1	4.383,4	9.378,8	23	7.471,4	7.219,9	1.309,8	0,181	1.307,8	2.638,3	9.097,2
	2003	29	7.271,7	7.237,7	1.558,3	0,215	1.727,4	3.148,5	10.194,1	24	7.666,8	7.876,4	1.518,3	0,193	1.472,2	5.755,4	11.984,7
	2004	29	7.739,4	7.760,5	1.391,0	0,179	1.347,2	5.528,5	11.195,5	27	7.821,0	8.143,1	1.948,1	0,239	1.944,2	4.713,9	12.992,2
	2005	31	8.310,8	8.111,8	1.652,6	0,204	1.800,1	5.387,8	12.270,9	25	8.290,1	8.581,6	1.992,1	0,232	1.749,1	4.765,6	12.272,6
	2006	30	8.407,8	8.398,8	2.012,6	0,240	2.042,8	3.271,6	12.980,2	26	9.054,9	9.044,0	1.929,1	0,213	1.858,0	5.577,8	13.283,1
	2007	28	8.712,1	8.731,7	2.132,5	0,244	2.678,9	5.251,0	14.068,0	26	9.418,7	9.353,2	2.147,1	0,230	1.961,5	6.044,2	14.068,0
	2008	30	8.623,7	8.628,8	1.493,4	0,173	1.397,0	4.531,6	12.571,8	27	9.189,8	9.054,7	1.633,6	0,180	1.026,2	4.786,6	12.772,1
	2009	30	9.097,8	9.246,9	1.854,0	0,200	2.103,0	5.614,1	13.930,7	26	8.679,4	9.071,9	1.851,1	0,204	1.690,3	7.086,8	14.433,3
	2010	29	9.477,5	9.362,5	1.419,8	0,152	1.763,1	6.845,9	12.539,1	27	9.847,7	9.425,1	1.938,5	0,206	2.036,2	4.769,6	13.179,3
	2011	30	9.141,9	9.303,3	1.771,1	0,190	2.223,0	6.547,3	13.142,3	27	9.395,7	9.212,8	1.808,6	0,196	2.403,0	6.073,0	13.024,8
	2012	30	8.045,3	8.130,8	1.430,0	0,176	1.787,9	5.355,1	11.034,9	26	8.331,1	8.542,2	1.796,7	0,210	1.886,2	5.355,1	12.967,6
	2013	29	7.439,9	7.847,2	1.600,4	0,204	1.665,3	5.914,0	12.355,9	26	7.974,7	8.373,0	1.899,5	0,227	1.720,9	5.855,3	13.984,6
	2014	31	8.249,1	8.344,7	1.972,4	0,236	2.555,7	5.489,8	12.905,3	27	8.415,7	8.397,6	1.753,2	0,209	2.101,2	5.182,5	12.905,3
	2015	30	6.168,0	6.386,5	1.458,1	0,228	1.755,3	4.405,2	11.167,4	28	6.988,7	7.401,8	1.666,5	0,225	2.168,5	5.014,0	11.133,7
	2016	31	6.134,4	6.340,8	1.649,1	0,260	1.440,9	2.834,4	10.637,2	29	7.238,1	7.458,8	1.974,1	0,265	1.584,7	4.625,0	13.346,1
	2017	31	6.342,9	6.346,0	1.584,7	0,250	1.889,4	3.989,2	10.864,4	28	6.728,5	7.073,9	1.439,0	0,203	2.050,4	5.109,3	10.248,1
	2018	30	5.826,4	5.812,5	1.177,8	0,203	1.165,0	3.962,0	8.464,8	29	6.573,7	6.823,5	1.622,3	0,238	1.923,2	4.101,7	11.373,4
	2019	30	6.127,7	6.381,1	2.006,4	0,314	2.326,5	1.731,3	11.999,8	27	6.959,8	7.276,4	2.095,3	0,288	1.993,4	3.373,5	12.284,0

Figure I-15. Weighted Gini of declared income equivalent distribution by municipality types, period 2002-2019

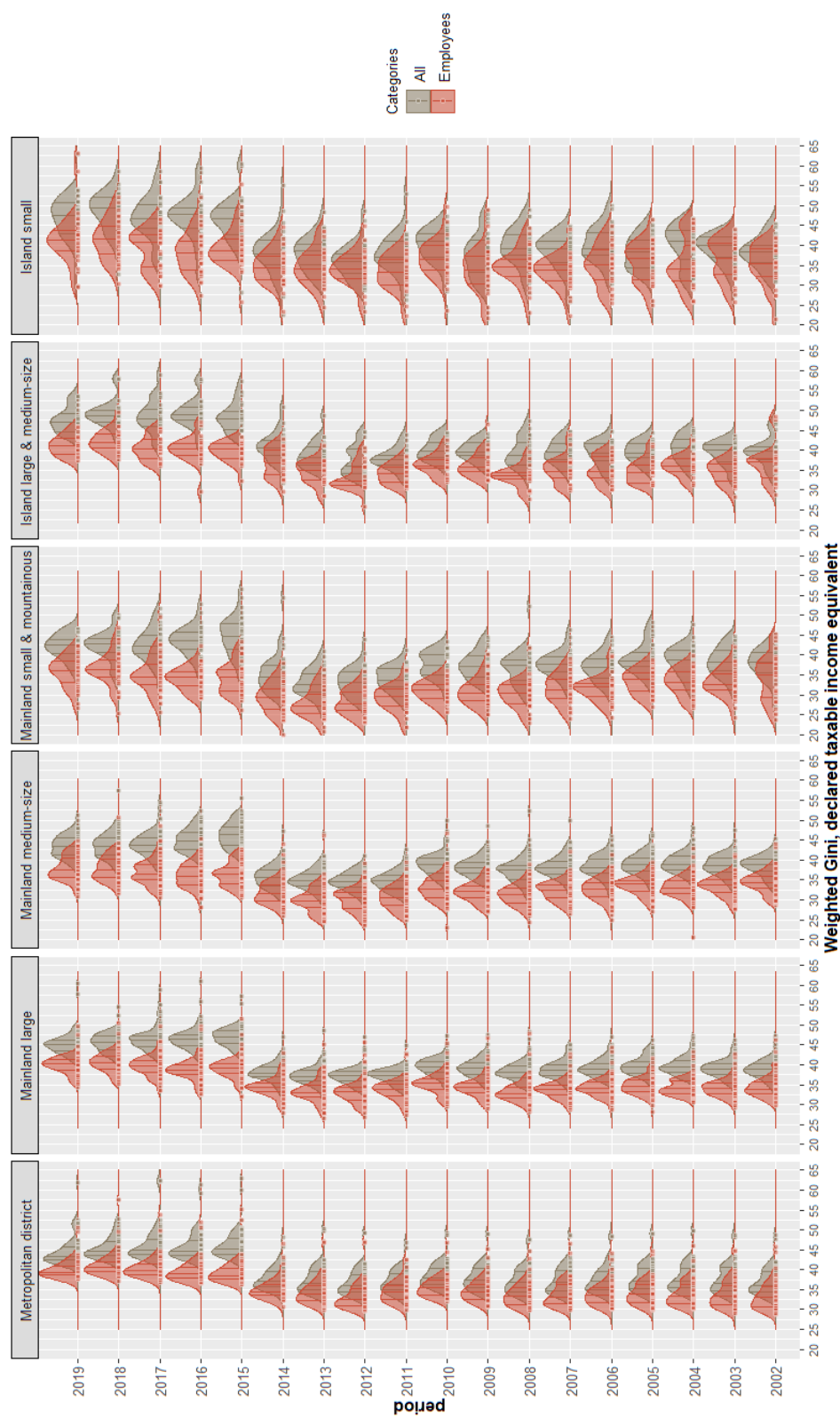


Table I-13. Descriptive statistics for weighted Gini of declared income equivalent distribution by municipality type, period 2002-2019

Type of Municipality	Year	All								Employees							
		count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
Metropolitan district	2002	47	36,12	37,11	3,55	0,096	4,95	32,71	48,66	47	32,95	33,50	3,71	0,111	5,05	28,74	45,59
	2003	47	36,71	37,64	3,65	0,097	5,89	33,02	48,73	47	33,29	33,88	3,63	0,107	4,90	28,94	44,91
	2004	47	37,05	38,12	3,74	0,098	5,07	33,84	49,81	47	33,42	34,04	3,34	0,098	4,74	30,25	45,89
	2005	47	37,07	37,99	3,63	0,095	5,12	33,53	49,22	47	33,75	34,25	3,21	0,094	4,68	29,87	44,65
	2006	47	37,06	37,62	3,52	0,093	4,33	33,26	48,46	47	33,69	33,92	3,05	0,090	3,80	30,16	44,03
	2007	47	36,82	37,46	3,71	0,099	4,96	32,35	48,72	47	33,15	34,02	3,51	0,103	4,84	29,80	46,41
	2008	47	36,72	37,33	3,50	0,094	5,13	33,12	47,64	47	33,29	33,85	3,22	0,095	4,25	29,85	44,56
	2009	47	37,29	38,12	3,49	0,091	4,74	33,44	49,08	47	34,47	34,89	3,03	0,087	3,87	30,70	45,14
	2010	47	38,03	38,76	3,14	0,081	4,03	35,23	49,22	47	35,37	35,69	2,84	0,080	3,75	32,10	46,76
	2011	47	36,38	37,17	3,12	0,084	4,15	32,83	46,87	47	34,45	34,56	2,91	0,084	3,51	29,89	42,51
	2012	47	36,00	36,93	3,66	0,099	4,40	32,79	49,23	47	32,48	33,39	3,73	0,112	4,35	29,61	47,14
	2013	47	36,66	37,58	3,68	0,098	4,76	33,34	50,18	47	34,01	34,54	3,55	0,103	3,76	29,92	47,09
	2014	47	37,11	37,91	3,06	0,081	3,82	32,72	48,22	47	34,53	35,20	2,91	0,083	2,68	30,64	46,50
	2015	47	45,24	46,49	4,03	0,087	3,97	41,82	62,88	47	38,50	39,64	3,55	0,090	2,68	36,27	55,17
	2016	47	44,72	46,05	3,89	0,085	3,78	42,17	61,32	47	38,86	39,69	3,07	0,077	2,78	36,45	51,99
	2017	47	44,88	46,25	4,26	0,092	3,86	42,04	62,54	47	39,84	40,53	2,97	0,073	2,47	36,92	53,82
	2018	47	44,60	45,95	4,25	0,093	3,52	41,52	65,51	47	40,51	41,22	3,30	0,080	2,60	37,17	57,52
	2019	47	43,20	45,25	4,95	0,109	3,67	41,48	65,81	47	39,35	40,20	2,65	0,066	2,37	37,52	50,70
Mainland large	2002	92	38,86	38,86	2,55	0,066	2,82	33,24	47,36	92	33,90	34,40	2,74	0,080	2,86	29,66	46,25
	2003	92	38,86	38,95	2,26	0,058	2,68	34,03	46,09	92	34,06	34,21	2,34	0,068	2,71	29,33	42,60
	2004	92	39,36	39,68	2,41	0,061	2,80	34,59	47,19	92	34,07	34,50	2,37	0,069	3,38	30,60	43,14
	2005	92	39,36	39,65	2,33	0,059	2,86	34,75	46,32	92	34,52	34,66	2,29	0,066	2,87	28,17	41,56
	2006	92	38,89	39,14	2,39	0,061	2,75	32,93	47,12	92	34,14	34,28	2,46	0,072	2,57	28,64	44,44
	2007	92	38,64	38,72	2,41	0,062	2,82	33,30	45,04	92	33,88	33,82	2,40	0,071	2,62	28,82	42,79
	2008	92	38,11	38,28	2,55	0,067	2,85	32,23	48,42	92	32,81	33,18	2,74	0,083	2,80	28,05	47,87
	2009	92	39,08	39,15	2,42	0,062	3,02	33,64	47,54	92	34,30	34,43	2,75	0,080	2,40	28,98	46,66
	2010	92	39,59	39,55	2,33	0,059	2,80	34,18	47,26	92	35,36	35,26	2,65	0,075	2,61	29,55	45,51
	2011	92	37,36	37,18	2,09	0,056	2,50	31,62	44,87	92	33,76	33,62	2,54	0,076	2,89	27,23	42,74
	2012	92	37,27	37,25	2,34	0,063	2,47	32,57	46,93	92	33,14	33,12	3,01	0,091	3,17	26,83	45,72
	2013	92	37,06	37,27	2,45	0,066	2,64	31,55	48,64	92	33,08	33,30	2,91	0,087	2,95	26,52	45,24
	2014	92	37,82	38,04	2,44	0,064	2,34	31,80	46,96	92	34,41	34,39	2,55	0,074	2,30	28,01	43,06
	2015	92	47,01	46,99	2,51	0,053	3,15	41,92	57,34	92	39,18	39,07	2,88	0,074	2,60	32,05	51,59
	2016	92	46,41	46,47	2,86	0,061	2,79	41,28	61,10	92	38,70	38,84	2,80	0,072	2,31	32,48	49,58
	2017	92	46,06	46,34	3,05	0,066	2,80	40,82	58,77	92	39,84	39,79	2,63	0,066	2,93	33,54	49,58
	2018	92	45,73	45,61	2,48	0,054	3,49	40,24	54,61	92	40,63	40,65	2,62	0,065	3,18	35,04	50,44
	2019	92	45,16	45,17	2,98	0,066	2,82	38,85	60,40	92	40,18	40,04	2,42	0,061	2,71	34,30	49,71
Mainland medium-size	2002	96	38,80	38,50	2,63	0,068	2,97	32,09	45,26	95	34,42	34,45	2,80	0,081	3,03	28,68	43,95
	2003	96	38,46	38,52	2,69	0,070	3,63	31,35	47,39	96	33,72	33,55	2,55	0,076	3,21	27,65	41,33
	2004	96	38,94	39,28	2,92	0,074	3,28	31,38	47,97	96	32,93	33,18	2,90	0,087	3,27	20,44	42,99
	2005	96	38,83	38,95	2,78	0,071	3,37	31,90	46,58	96	33,91	33,36	2,82	0,084	2,85	19,14	39,32
	2006	96	38,18	38,26	2,91	0,076	3,63	30,49	45,86	96	32,67	32,59	2,79	0,086	3,48	24,98	41,21
	2007	96	38,03	38,13	2,94	0,077	3,14	30,73	49,99	96	32,51	32,19	2,55	0,079	3,37	26,43	41,99
	2008	96	37,59	37,22	3,33	0,089	3,48	28,55	52,38	96	31,31	31,20	2,65	0,085	3,59	24,32	38,79
	2009	96	37,98	38,14	2,69	0,070	2,78	29,83	48,44	96	32,02	31,98	2,50	0,078	3,14	26,88	37,62
	2010	96	38,85	38,67	3,16	0,082	3,90	29,54	49,78	96	32,77	32,81	3,17	0,097	4,21	22,89	46,53
	2011	96	34,87	34,67	2,44	0,070	3,04	30,02	42,57	96	30,43	30,53	2,88	0,094	4,06	24,75	39,34
	2012	96	34,58	34,65	2,33	0,067	2,94	28,96	41,10	96	30,50	30,06	2,91	0,097	4,01	23,59	39,25
	2013	96	34,75	35,03	2,71	0,077	2,98	29,43	46,59	96	29,84	29,98	3,25	0,108	3,42	24,21	46,03
	2014	96	35,69	35,78	2,89	0,081	3,98	30,20	47,26	96	31,53	31,76	3,41	0,107	4,15	17,84	43,93
	2015	96	46,29	46,10	3,36	0,073	4,70	36,10	55,51	96	36,46	36,41	2,96	0,081	4,10	30,63	42,56
	2016	96	44,89	44,98	2,91	0,065	4,19	39,46	52,26	96	35,92	36,01	3,17	0,088	4,48	28,12	45,27
	2017	96	43,81	43,97	3,18	0,072	3,48	37,41	54,39	96	36,51	36,92	3,21	0,087	3,84	30,43	48,58
	2018	96	43,44	43,55	3,25	0,075	4,30	36,78	57,43	96	37,51	37,85	3,21	0,085	4,50	31,49	50,62
	2019	96	43,41	43,33	2,87	0,066	4,26	36,35	51,13	96	37,48	37,93	3,05	0,080	4,75	30,85	44,83

Table I-13. (continued) Descriptive statistics for weighted Gini of declared income equivalent distribution by municipality type, period 2002-2019

Type of Municipality	Year	All								Employees							
		count	median	mean	sd	CV	IQR	min	max	count	median	mean	sd	CV	IQR	min	max
Mainland small & mountainous	2002	34	38,13	37,88	4,04	0,107	5,29	26,94	45,30	34	34,97	34,17	5,70	0,167	8,59	23,65	45,24
	2003	34	38,36	38,22	3,62	0,095	5,14	30,47	44,84	34	32,47	33,13	3,62	0,109	3,96	24,33	42,04
	2004	34	38,74	38,56	3,88	0,101	5,51	30,28	47,73	34	33,27	33,22	3,38	0,102	4,63	26,72	39,82
	2005	34	38,54	39,11	3,89	0,099	3,51	31,94	48,34	34	34,04	33,25	3,15	0,095	4,71	26,92	38,74
	2006	34	36,88	36,87	3,56	0,097	4,84	29,23	44,51	34	32,19	31,44	3,25	0,103	3,24	24,32	39,81
	2007	34	37,64	37,59	3,40	0,091	3,70	30,26	46,31	34	31,32	31,60	3,85	0,122	4,87	23,91	39,12
	2008	34	37,33	36,64	4,55	0,124	4,93	28,90	52,14	34	30,49	30,22	3,67	0,121	4,94	23,02	41,63
	2009	34	37,18	37,50	3,39	0,091	5,29	32,27	44,53	34	30,53	30,87	3,56	0,115	4,09	24,98	40,20
	2010	34	37,43	37,45	3,45	0,092	5,18	28,73	43,29	34	31,16	30,99	2,68	0,086	3,62	25,58	36,18
	2011	34	33,80	34,02	3,15	0,092	4,61	27,63	41,14	34	29,66	29,22	3,35	0,115	4,26	21,91	36,42
	2012	34	33,15	33,42	3,69	0,110	5,14	27,39	43,81	34	27,59	28,02	3,65	0,130	4,82	18,56	35,88
	2013	34	32,52	32,97	3,59	0,109	4,65	24,71	41,06	34	27,08	27,65	3,94	0,142	4,76	18,80	36,39
	2014	34	34,43	35,15	5,38	0,153	6,12	24,69	54,42	34	29,32	29,30	3,97	0,136	5,10	20,00	37,89
	2015	34	44,75	44,72	5,14	0,115	6,42	34,20	56,58	34	34,54	34,27	4,14	0,121	5,39	26,07	43,35
	2016	34	43,53	43,49	3,74	0,086	4,22	35,10	52,69	34	34,49	34,18	3,04	0,089	3,69	29,09	42,26
	2017	34	42,16	42,47	4,37	0,103	4,68	31,67	51,78	34	34,56	35,13	4,86	0,138	4,97	25,60	49,43
	2018	34	42,88	42,23	4,02	0,095	3,54	32,62	50,17	34	36,25	36,45	4,49	0,123	4,20	25,26	46,73
	2019	34	42,46	42,03	3,16	0,075	3,42	34,25	46,63	34	36,07	35,80	3,96	0,111	5,35	26,57	42,33
Island large & medium-size	2002	21	39,67	39,56	3,77	0,095	3,12	32,27	47,18	21	37,02	36,51	4,84	0,132	4,90	28,72	48,43
	2003	21	40,06	39,26	2,97	0,076	4,21	32,89	43,45	21	34,66	34,41	2,94	0,086	4,35	28,11	39,31
	2004	21	40,64	40,22	3,30	0,082	4,63	34,23	45,48	21	36,09	35,99	2,73	0,076	3,08	31,21	42,59
	2005	21	39,23	39,52	2,63	0,067	3,66	34,41	44,24	21	34,46	34,74	3,02	0,087	4,59	31,10	41,34
	2006	21	39,32	39,24	3,16	0,081	4,34	33,20	44,75	21	34,73	35,14	3,31	0,094	5,54	29,97	40,55
	2007	21	39,50	39,46	3,09	0,078	4,14	33,38	44,71	21	34,72	35,12	3,53	0,101	3,86	29,89	43,88
	2008	21	38,75	39,22	3,92	0,100	5,61	32,15	47,32	21	33,70	33,42	2,79	0,084	1,54	27,71	39,58
	2009	21	39,53	39,82	2,44	0,061	3,25	35,40	44,22	21	35,72	36,47	3,47	0,095	3,60	32,24	46,56
	2010	21	39,82	40,01	2,69	0,067	3,74	35,14	44,39	21	36,07	36,38	2,73	0,075	2,21	32,00	42,53
	2011	21	37,57	37,81	2,73	0,072	2,29	32,76	43,94	21	34,19	34,05	2,44	0,072	3,80	30,33	38,49
	2012	21	36,13	37,52	3,80	0,101	6,05	32,67	44,72	21	32,24	33,30	3,53	0,106	4,51	25,85	40,66
	2013	21	38,21	38,89	3,46	0,089	4,45	34,52	48,71	21	34,98	34,54	3,11	0,090	4,33	28,44	41,02
	2014	21	40,72	40,72	4,07	0,100	3,82	31,78	50,72	21	36,88	36,68	3,69	0,101	6,27	29,64	42,80
	2015	21	47,89	48,37	3,82	0,079	4,61	42,97	57,21	21	40,38	39,58	2,62	0,066	3,78	32,34	43,28
	2016	21	48,91	49,10	3,94	0,080	3,42	40,95	57,82	21	40,34	40,29	3,59	0,089	2,87	29,50	47,19
	2017	21	47,92	48,45	4,47	0,092	4,27	40,29	58,84	21	40,39	40,55	2,98	0,073	4,76	36,12	45,39
	2018	21	48,80	49,22	3,66	0,074	2,82	42,53	57,99	21	41,87	42,34	2,86	0,067	3,52	37,56	49,42
	2019	21	47,17	47,60	3,19	0,067	4,47	43,32	53,65	21	41,15	41,28	2,55	0,062	3,98	37,33	46,03
Island small	2002	28	38,44	38,13	3,90	0,102	4,37	30,75	45,35	23	35,43	35,00	5,26	0,150	6,96	21,39	41,93
	2003	29	40,04	38,90	3,93	0,101	5,17	27,28	43,87	24	36,77	36,13	5,30	0,147	7,64	25,69	44,16
	2004	29	41,20	39,70	5,37	0,135	7,25	29,03	46,83	27	34,09	35,53	6,46	0,182	8,71	25,84	46,37
	2005	31	38,30	38,34	4,19	0,109	7,00	30,87	46,59	25	36,76	35,56	5,31	0,149	7,87	24,81	46,52
	2006	30	39,31	40,23	4,66	0,116	5,78	30,22	49,94	26	35,19	35,02	5,29	0,151	7,79	25,41	44,79
	2007	28	39,29	38,22	4,80	0,126	5,18	25,86	44,94	26	33,68	32,71	5,09	0,156	4,49	19,36	44,05
	2008	30	39,08	39,55	4,98	0,126	5,26	27,78	48,77	27	34,72	34,67	4,73	0,136	4,39	23,04	44,36
	2009	30	37,30	37,40	5,64	0,151	7,99	28,52	48,88	26	33,68	33,84	6,22	0,184	7,21	21,71	48,81
	2010	29	40,95	39,91	4,39	0,110	5,95	28,44	47,37	27	36,57	36,65	5,32	0,145	6,18	23,54	49,79
	2011	30	37,07	37,74	5,24	0,139	5,38	26,32	52,82	27	33,25	33,09	4,42	0,133	6,51	22,12	40,64
	2012	30	35,98	36,23	4,58	0,127	4,96	28,71	48,57	26	34,16	33,91	4,60	0,136	4,95	23,31	44,85
	2013	29	38,68	37,91	4,38	0,115	5,15	30,13	48,26	26	33,98	34,41	4,78	0,139	6,37	24,30	43,59
	2014	31	37,88	37,99	6,23	0,164	6,18	22,41	55,09	27	34,23	34,49	4,58	0,133	5,93	23,36	44,70
	2015	30	46,84	46,35	6,20	0,134	6,61	28,23	60,32	28	38,70	39,61	5,70	0,144	5,43	25,85	55,37
	2016	31	47,82	46,89	6,14	0,131	5,05	32,34	59,41	29	38,23	38,32	5,57	0,145	7,10	27,36	51,99
	2017	31	46,61	46,81	5,62	0,120	5,96	34,84	58,56	28	40,93	39,01	5,01	0,128	8,04	29,84	46,64
	2018	30	49,47	48,05	5,50	0,114	7,22	32,81	58,58	29	41,61	41,42	5,32	0,128	6,96	30,44	52,17
	2019	30	47,74	47,44	7,55	0,159	7,72	29,42	68,77	27	41,29	41,75	7,21	0,173	5,13	29,48	63,04

I.3.4 Geography of declared income

In this subsection, in order to capture the geographical dimension of income inequality, the thematic mapping of the analysis variables (weighted mean value, weighted median and inequality index-Gini) presented in the previous subsections was chosen for selected years (2004, 2009, 2012, 2015, 2019) at the lowest available spatial reference level (municipalities).

More specifically, **Figure I-16-Figure I-25** present the weighted mean of the equivalent of the declared income for total sample tax of declarations as well as those with a basic source of income of salaried service in the municipalities of Greece, **Figure I-26- Figure I-35** depict the weighted median of the equivalent of the declared income for both of previous stratum, and **Figure I-36-Figure I-45** describe the geographical distribution of the gini index as a proxy variable of structural inequality.

Regarding the spatial distribution of income at municipal level, we observe that the geography of declared income is highly polarized between the two main urban agglomerations of Athens and Thessaloniki and the rest of the country. Second, the spatial pattern of income inequality remains fairly stable over time.

Finally, income inequalities appear to persist in metropolitan areas. However, polarization and segregation in large urban agglomerations is a separate subject of study that could provide an avenue for further and thoughtful future research. It also finds that income inequality is high and affects a large number of municipalities across the country. This gives us a first indication that income inequalities have narrowed during the economic crisis due to the decrease in income and the increase in taxes. However, this fall in inequalities is unacceptable, as it is accompanied by high levels of poverty and a decline in household income.

Figure I-16. Spatial distribution of weighted mean of declared income equivalent, municipalities, 2004

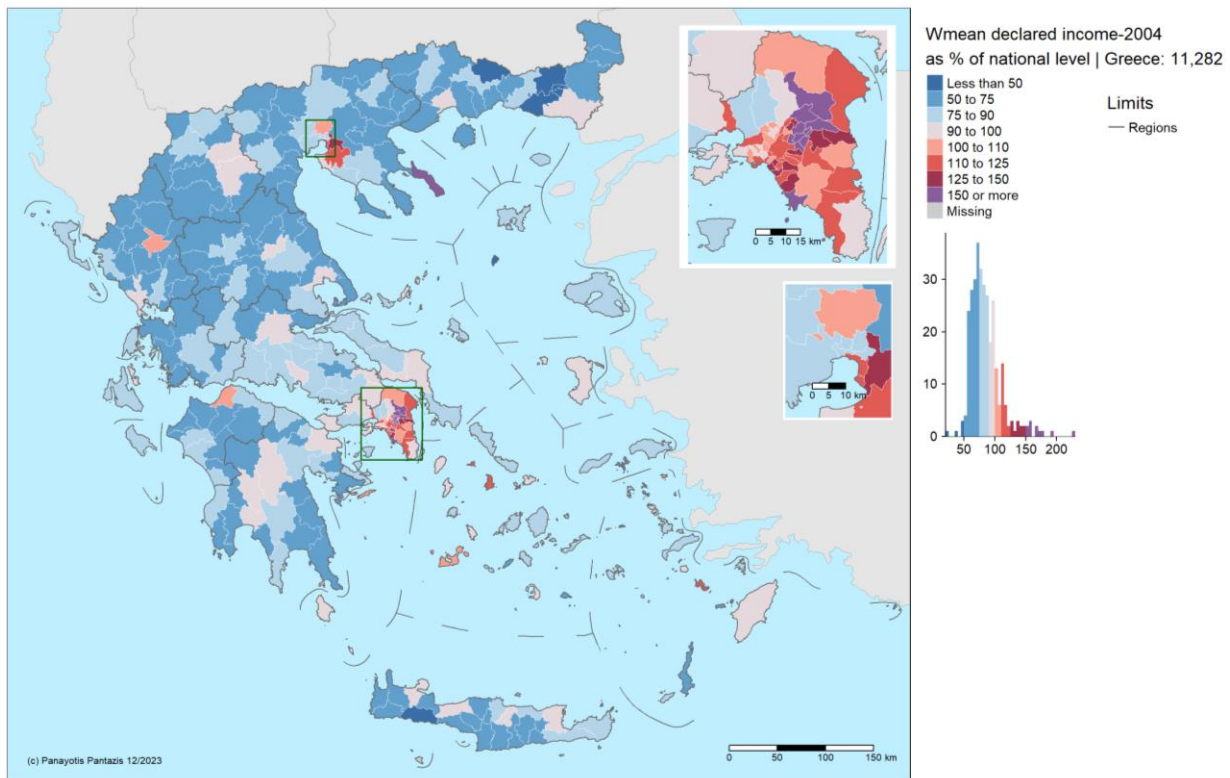


Figure I-17. Spatial distribution of weighted mean of declared income equivalent for employees, municipalities, 2004

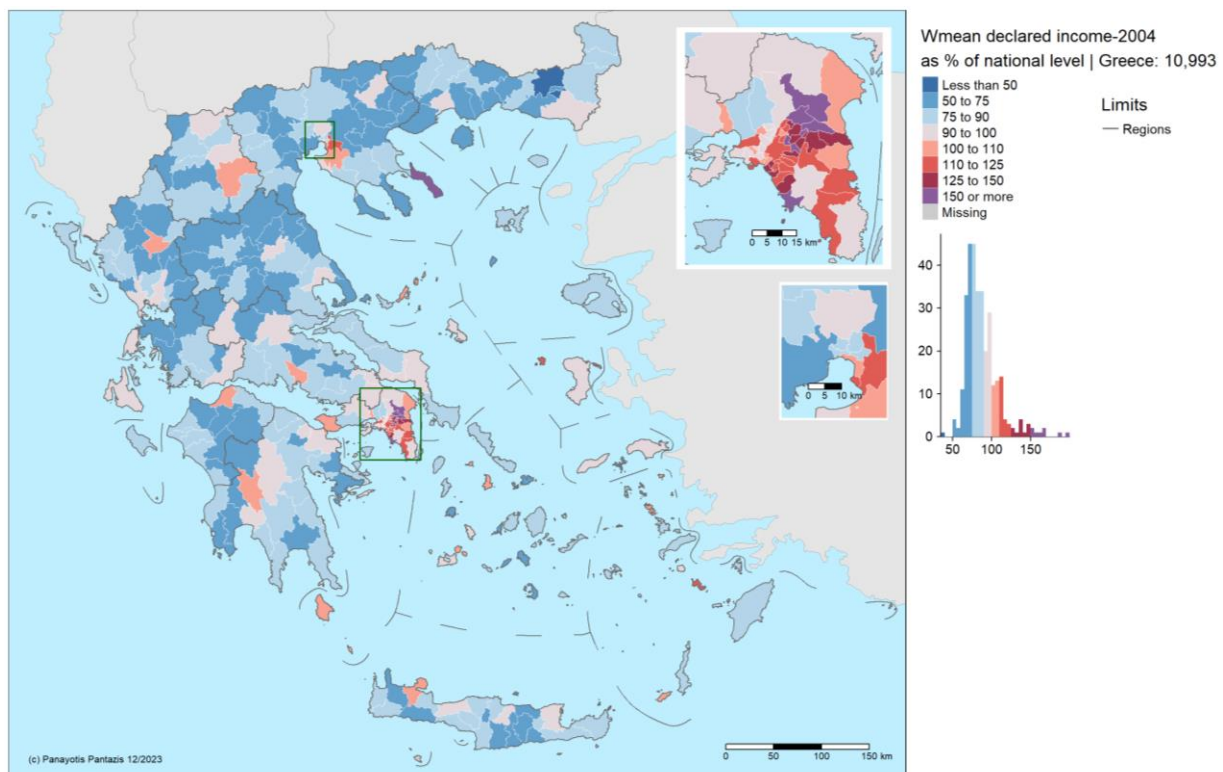


Figure I-18. Spatial distribution of weighted mean of declared income equivalent, municipalities, 2008

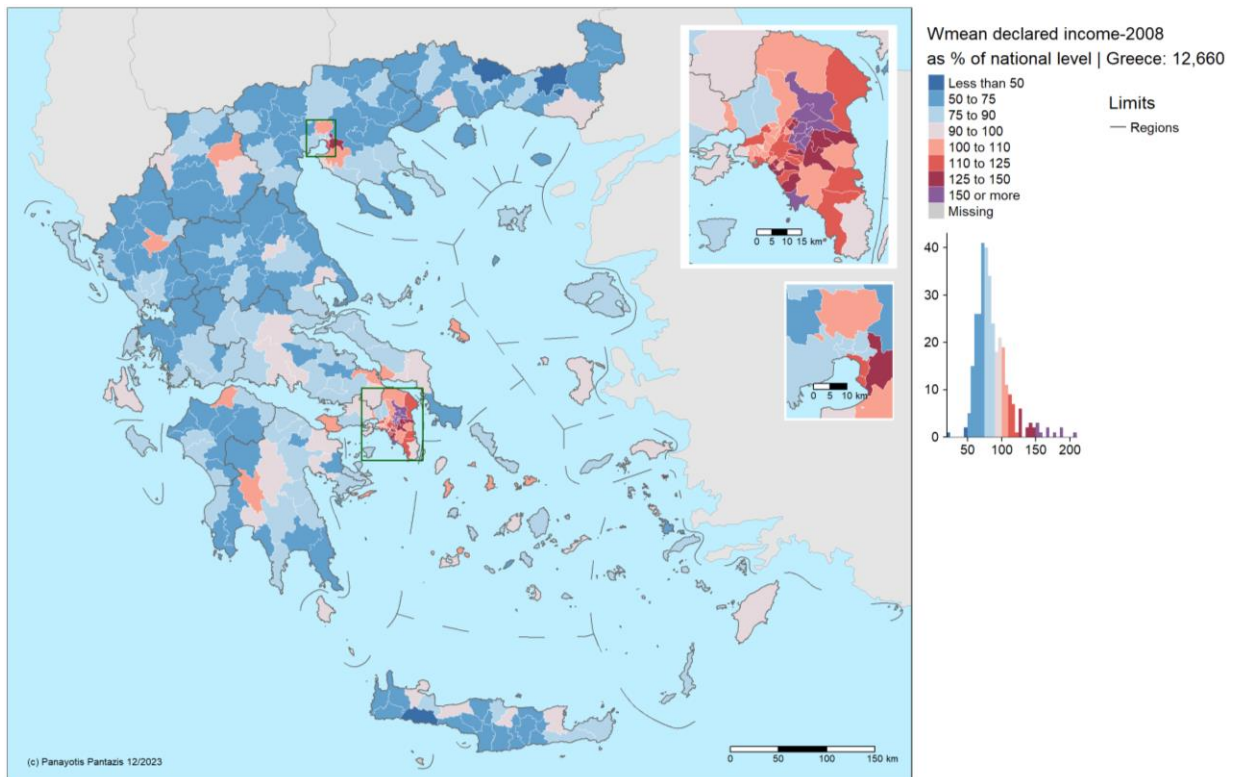


Figure I-19. Spatial distribution of weighted mean of declared income equivalent for employees, municipalities, 2008

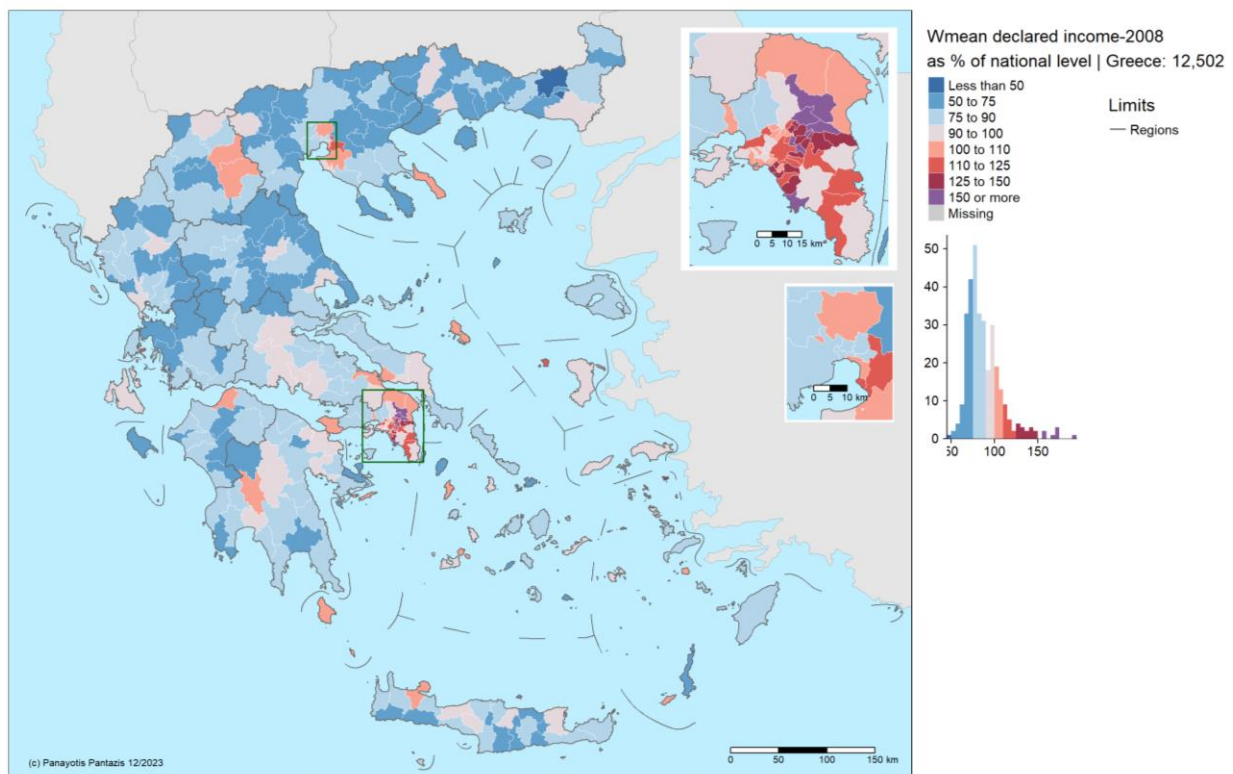


Figure I-20. Spatial distribution of weighted mean of declared income equivalent, municipalities, 2012

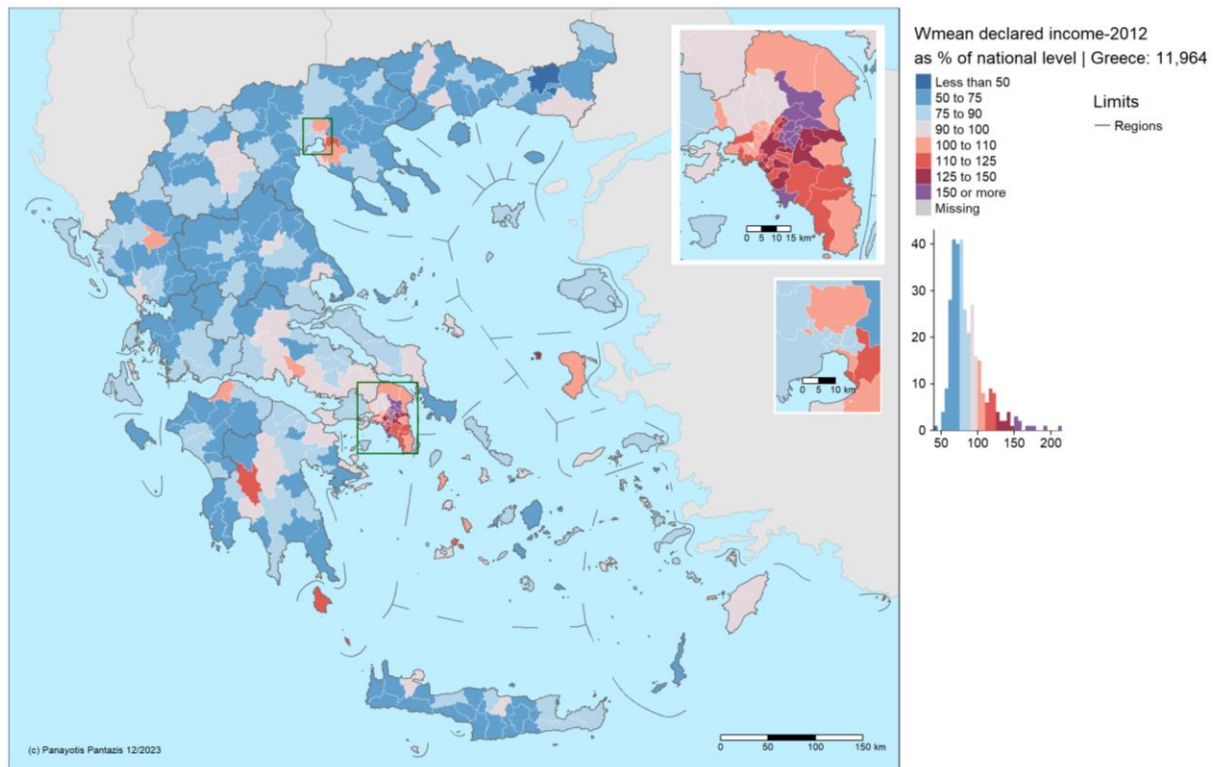


Figure I-21. Spatial distribution of weighted mean of declared income equivalent for employees, municipalities, 2012

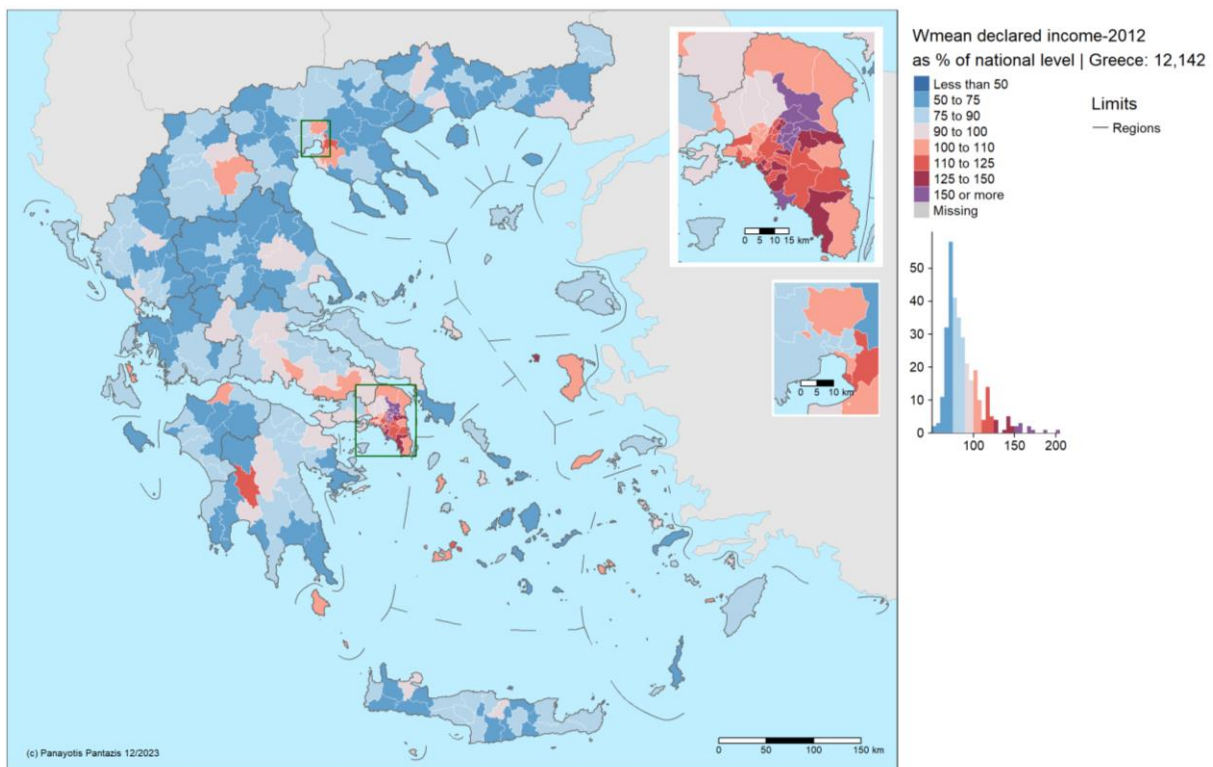


Figure I-22. Spatial distribution of weighted mean of declared income equivalent, municipalities, 2015

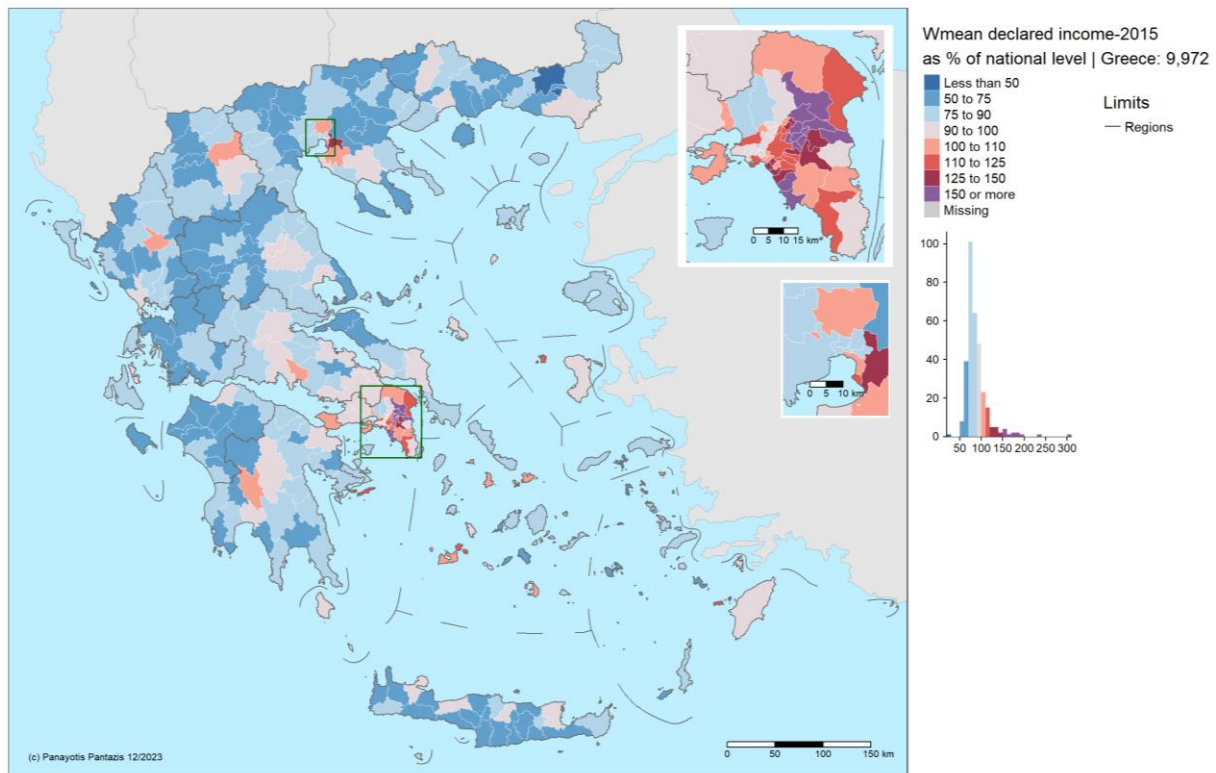


Figure I-23. Spatial distribution of weighted mean of declared income equivalent for employees, municipalities, 2015

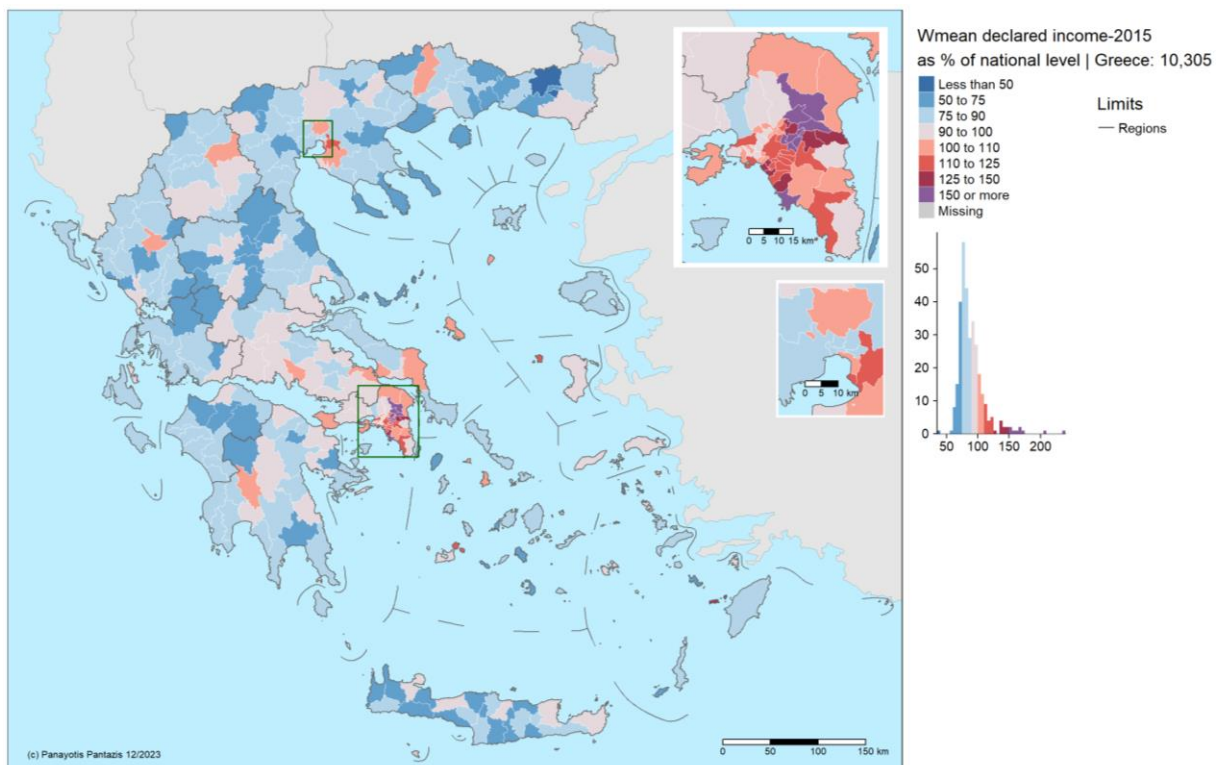


Figure I-24. Spatial distribution of weighted mean of declared income equivalent, municipalities, 2019

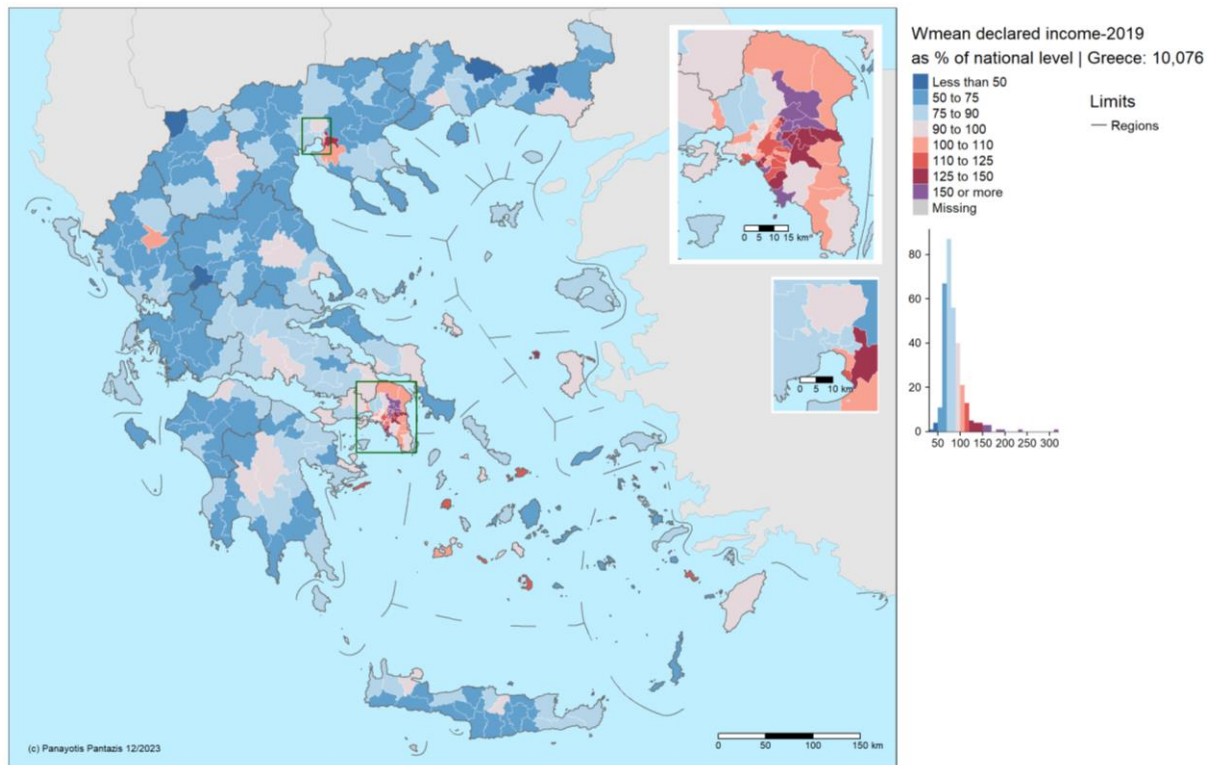


Figure I-25. Spatial distribution of weighted mean of declared income equivalent for employees, municipalities, 2019

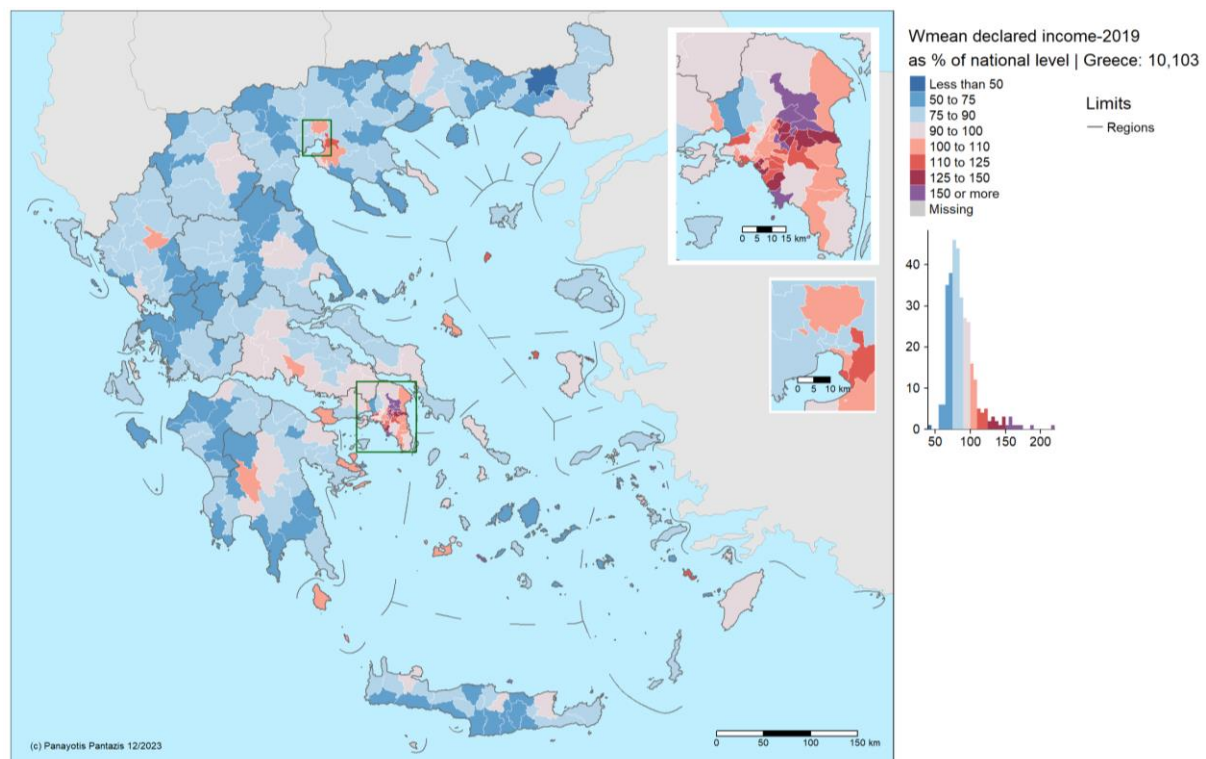


Figure I-26. Spatial distribution of weighted median of declared income equivalent, municipalities, 2004

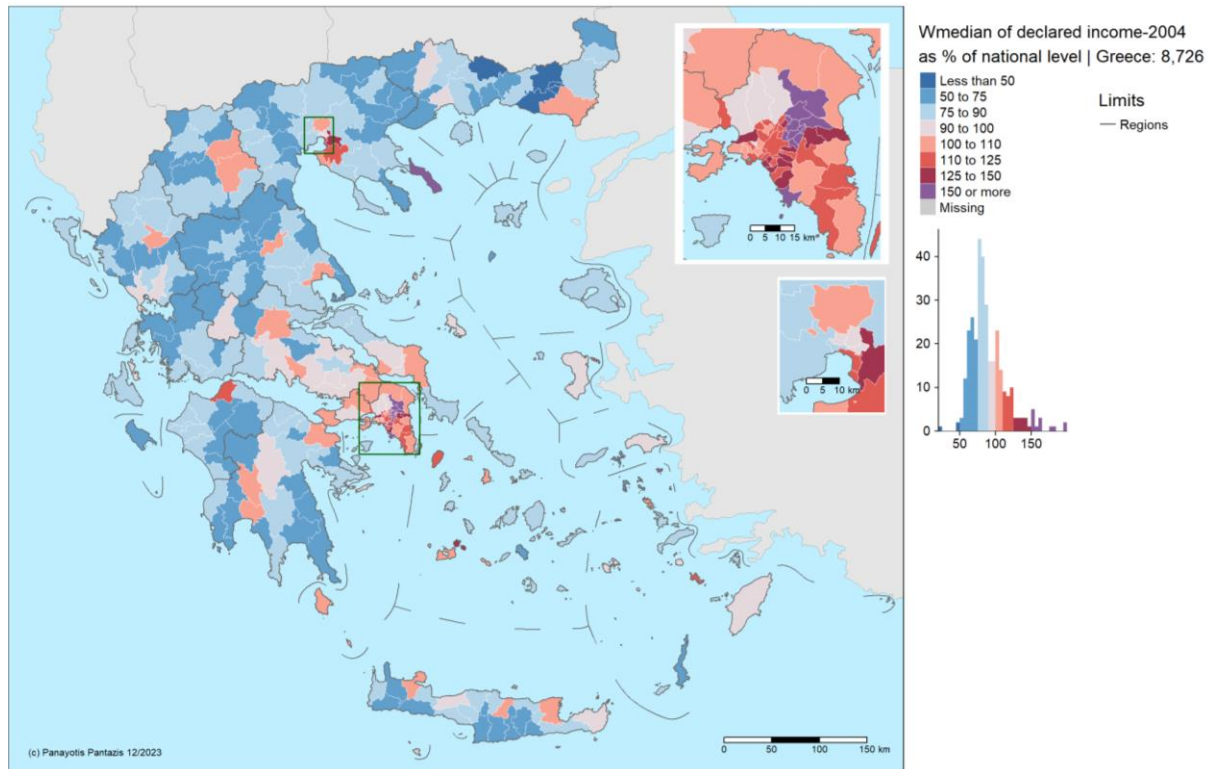


Figure I-27. Spatial distribution of weighted median of declared income equivalent for employees, municipalities, 2004

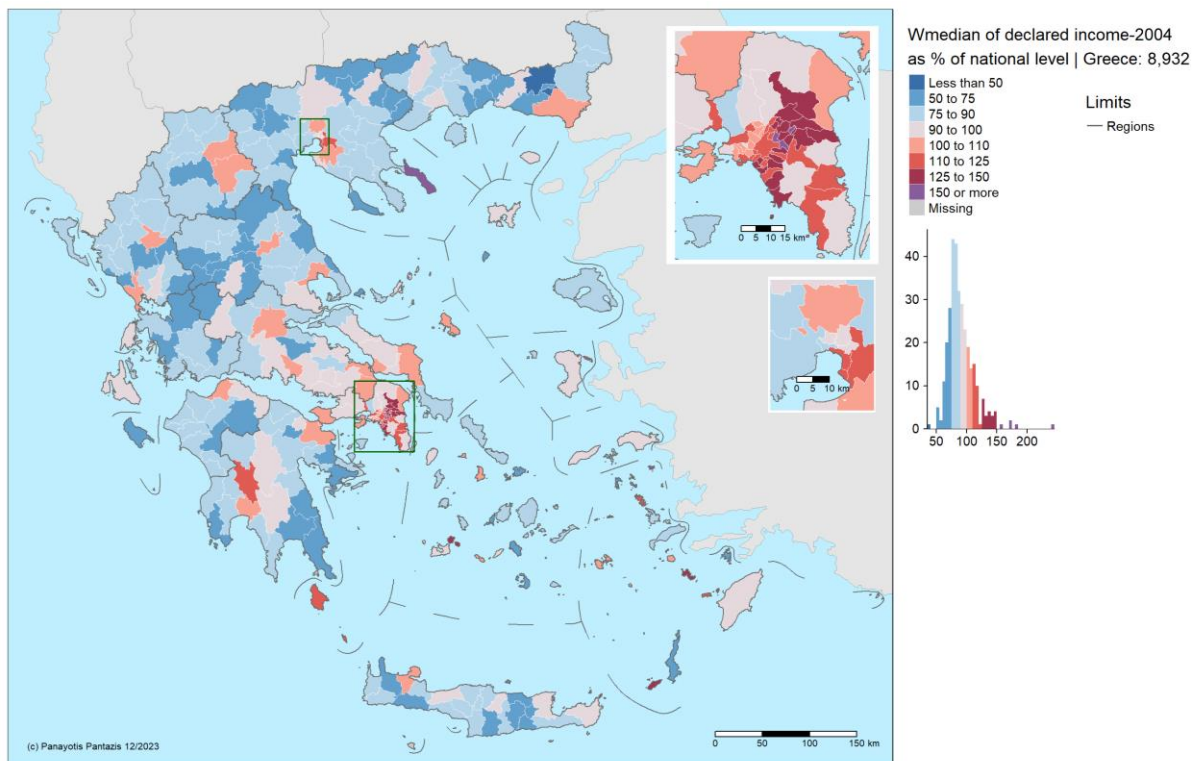


Figure I-28. Spatial distribution of weighted median of declared income equivalent, municipalities, 2008

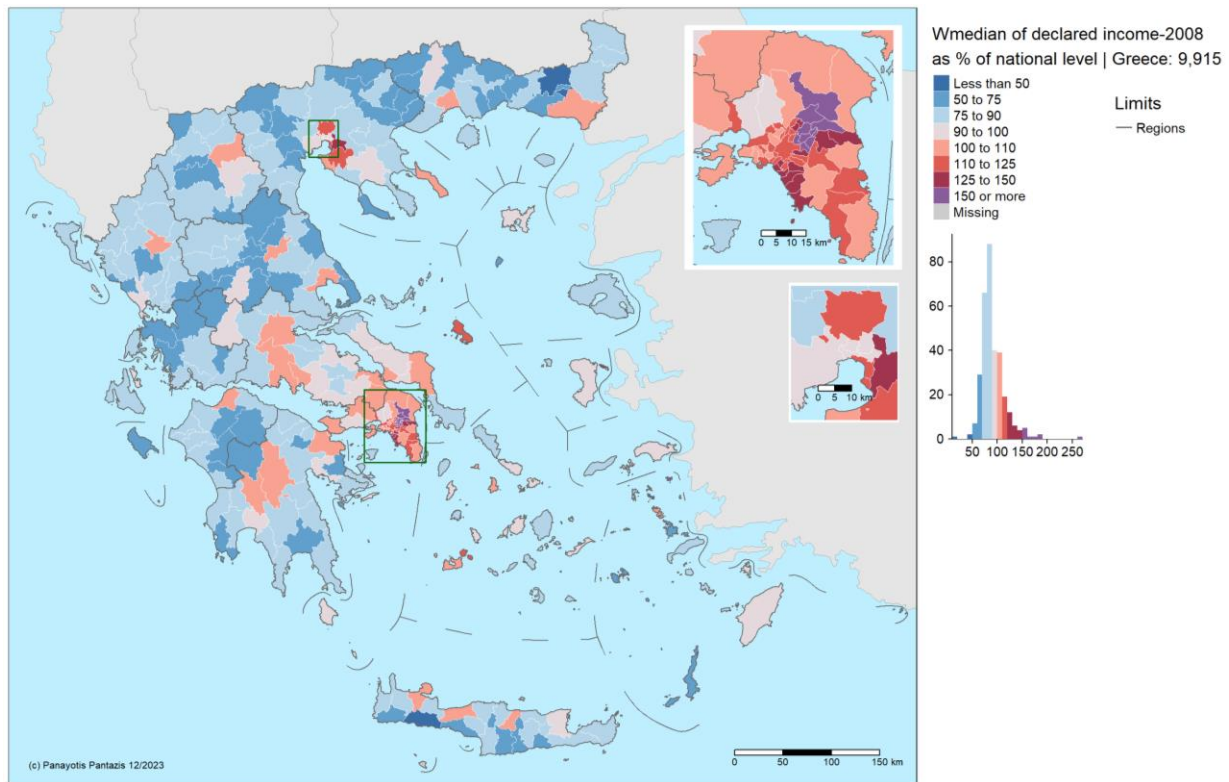


Figure I-29. Spatial distribution of weighted median of declared income equivalent for employees, municipalities, 2008

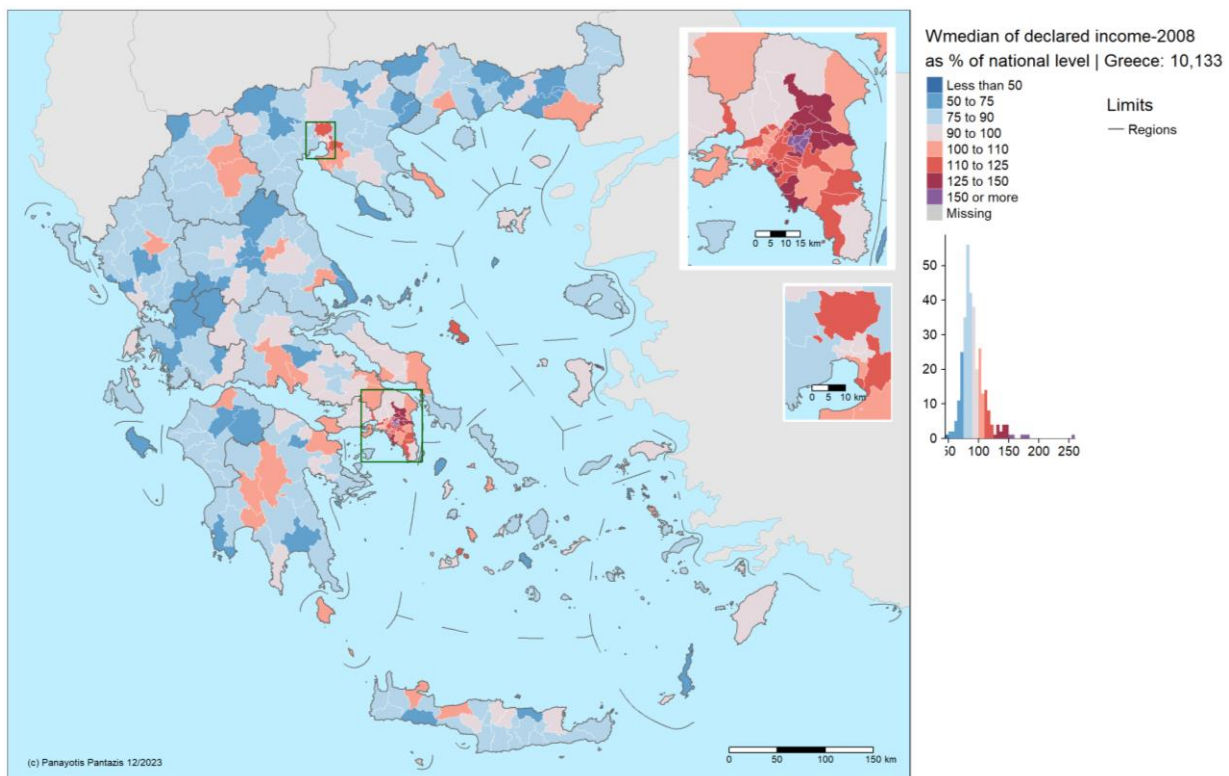


Figure I-30. Spatial distribution of weighted median of declared income equivalent, municipalities, 2012

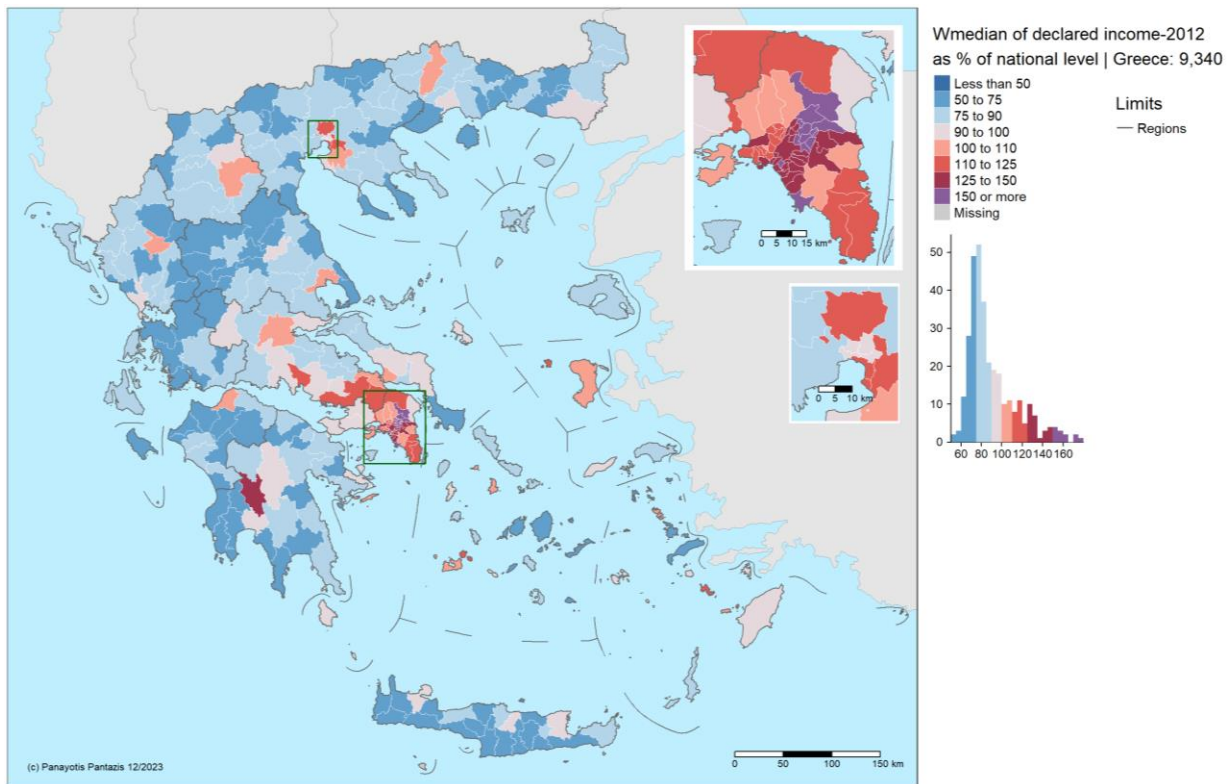


Figure I-31. Spatial distribution of weighted median of declared income equivalent for employees, municipalities, 2012

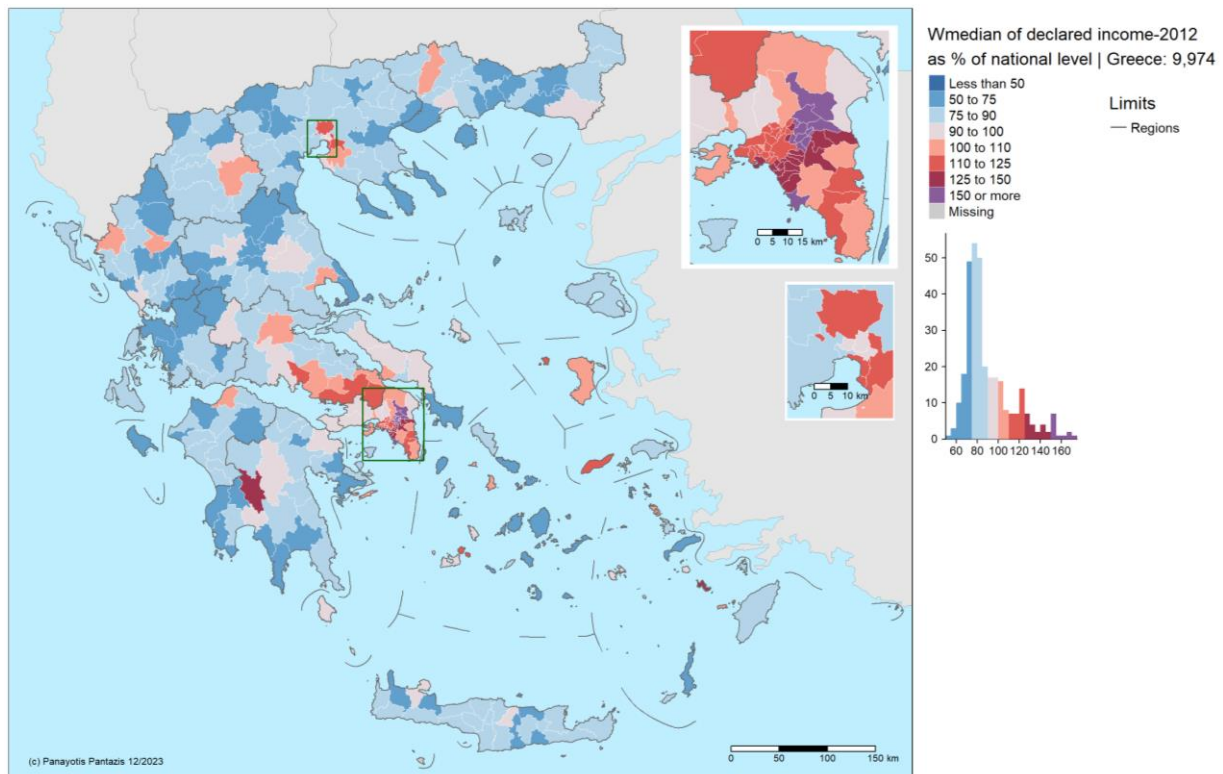


Figure I-32. Spatial distribution of weighted median of declared income equivalent, municipalities, 2015

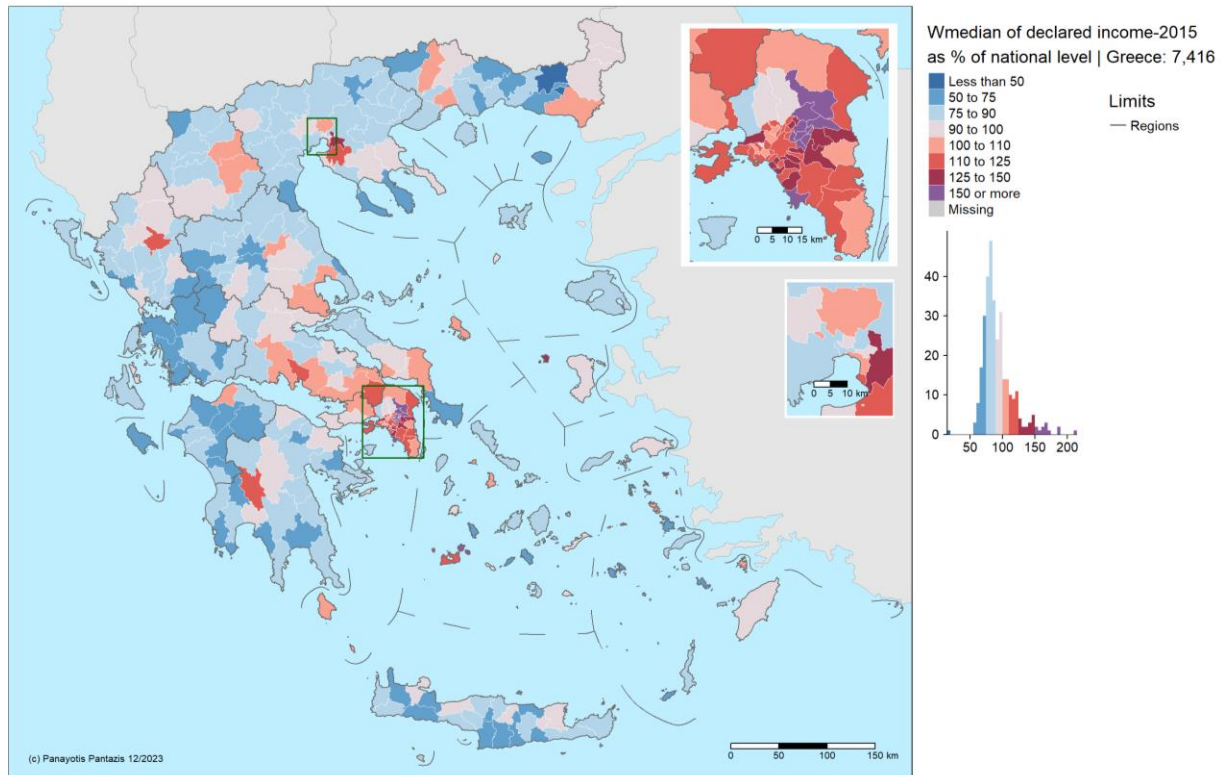


Figure I-33. Spatial distribution of weighted median of declared income equivalent for employees, municipalities, 2015

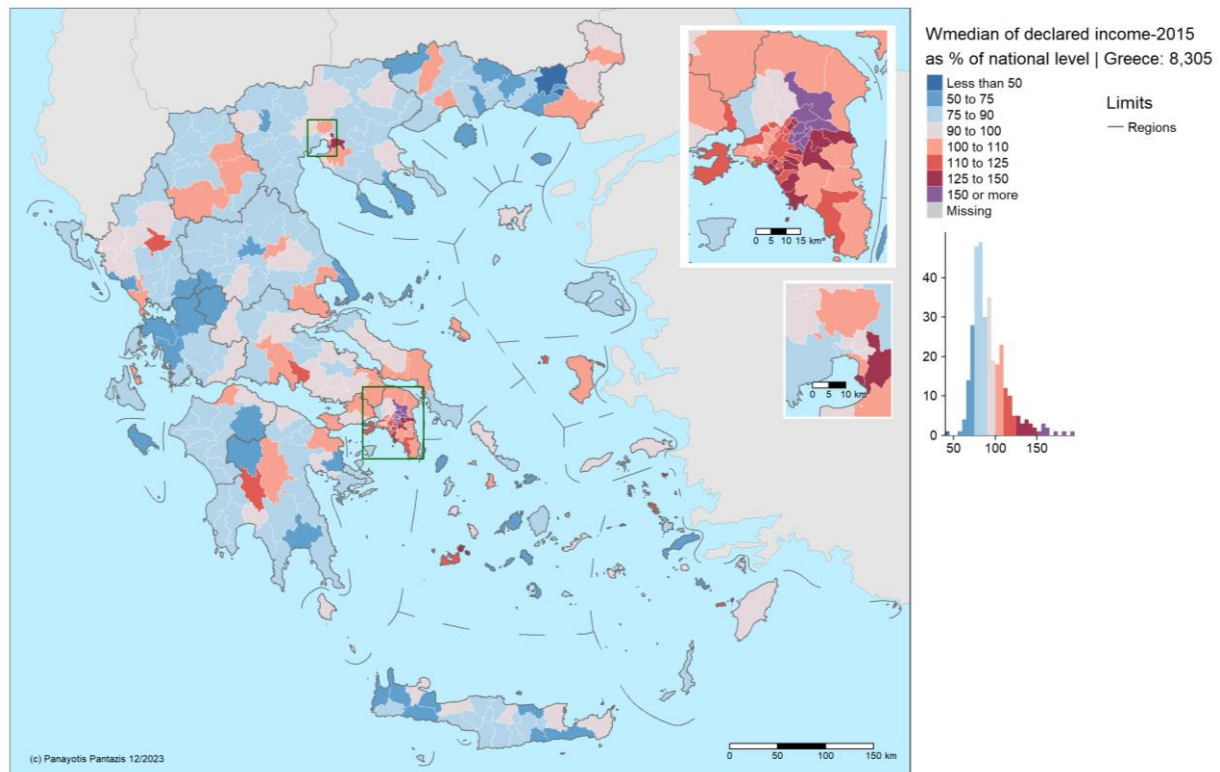


Figure I-34. Spatial distribution of weighted median of declared income equivalent, municipalities, 2019

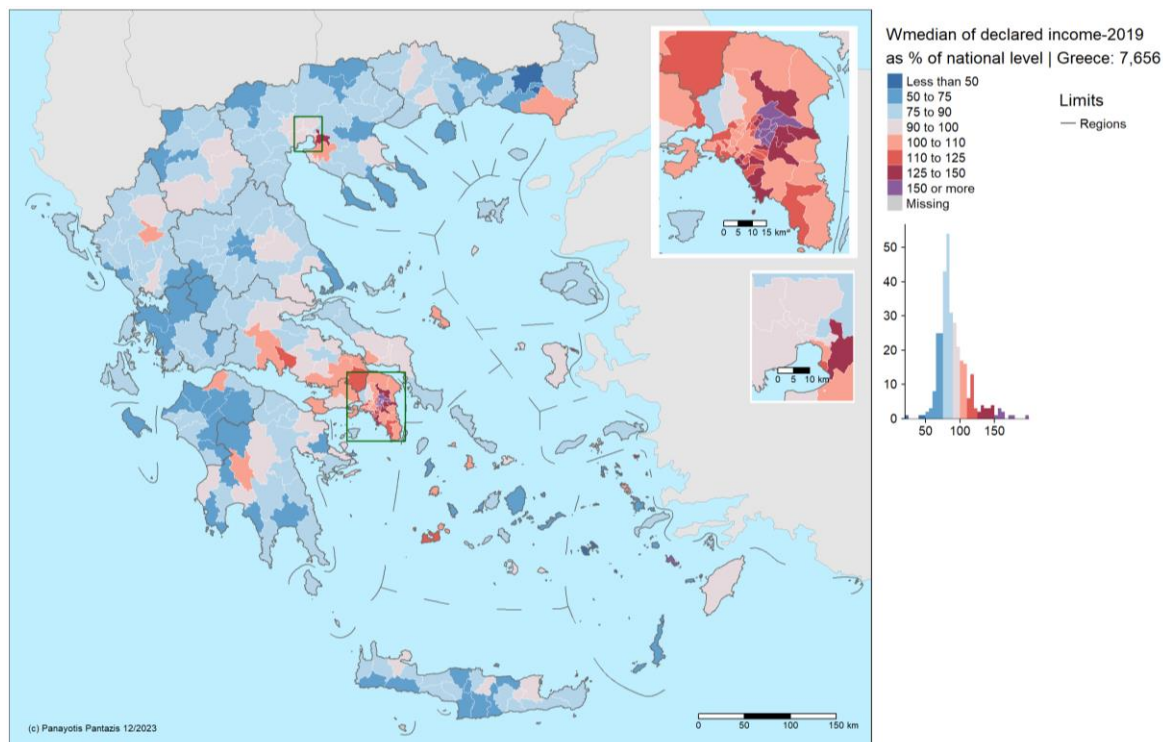


Figure I-35. Spatial distribution of weighted median of declared income equivalent for employees, municipalities, 2019

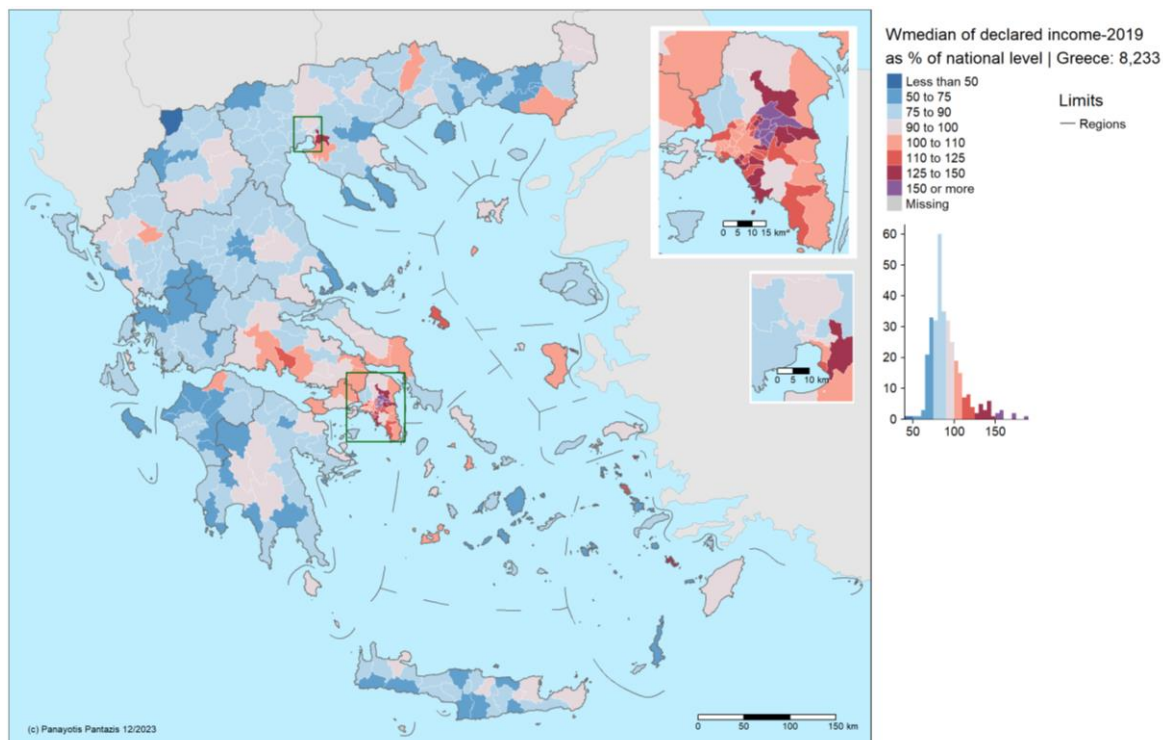


Figure I-36. Spatial distribution of weighted Gini of declared income equivalent, municipalities, 2004

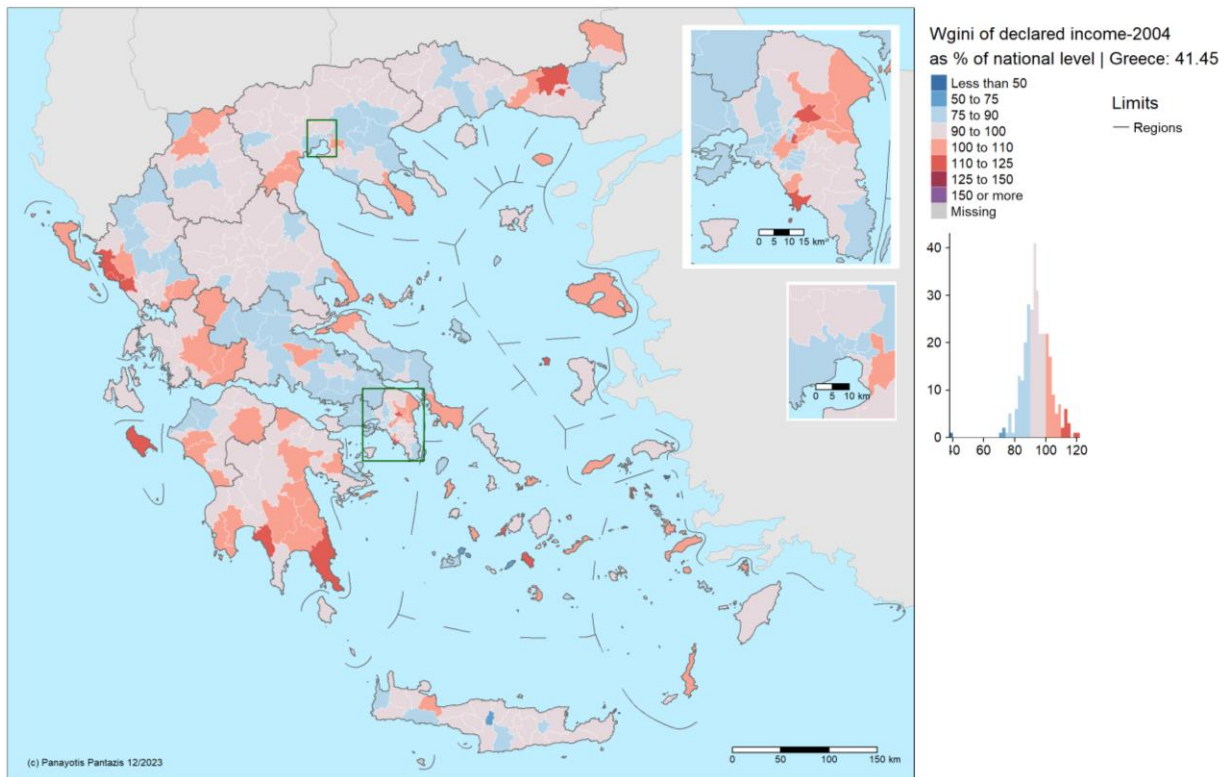


Figure I-37. Spatial distribution of weighted Gini of declared income equivalent for employees, municipalities, 2004

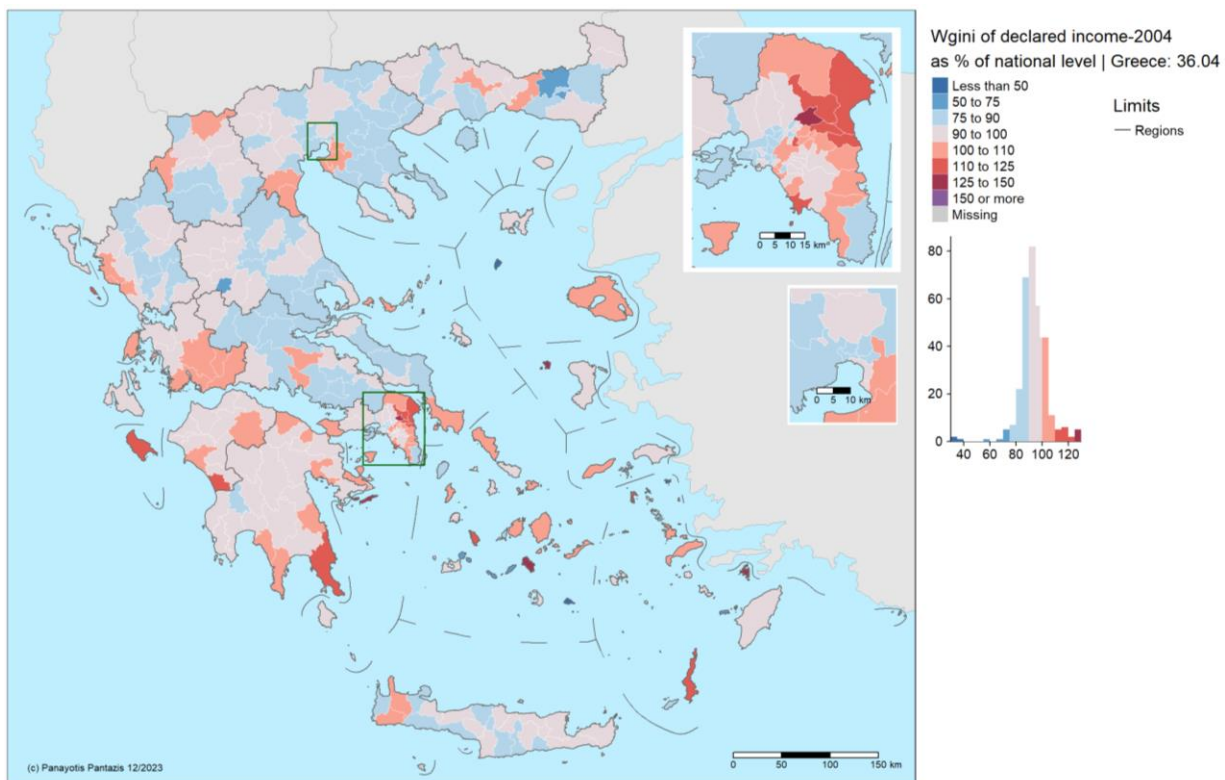


Figure I-38. Spatial distribution of weighted Gini of declared income equivalent, municipalities, 2008

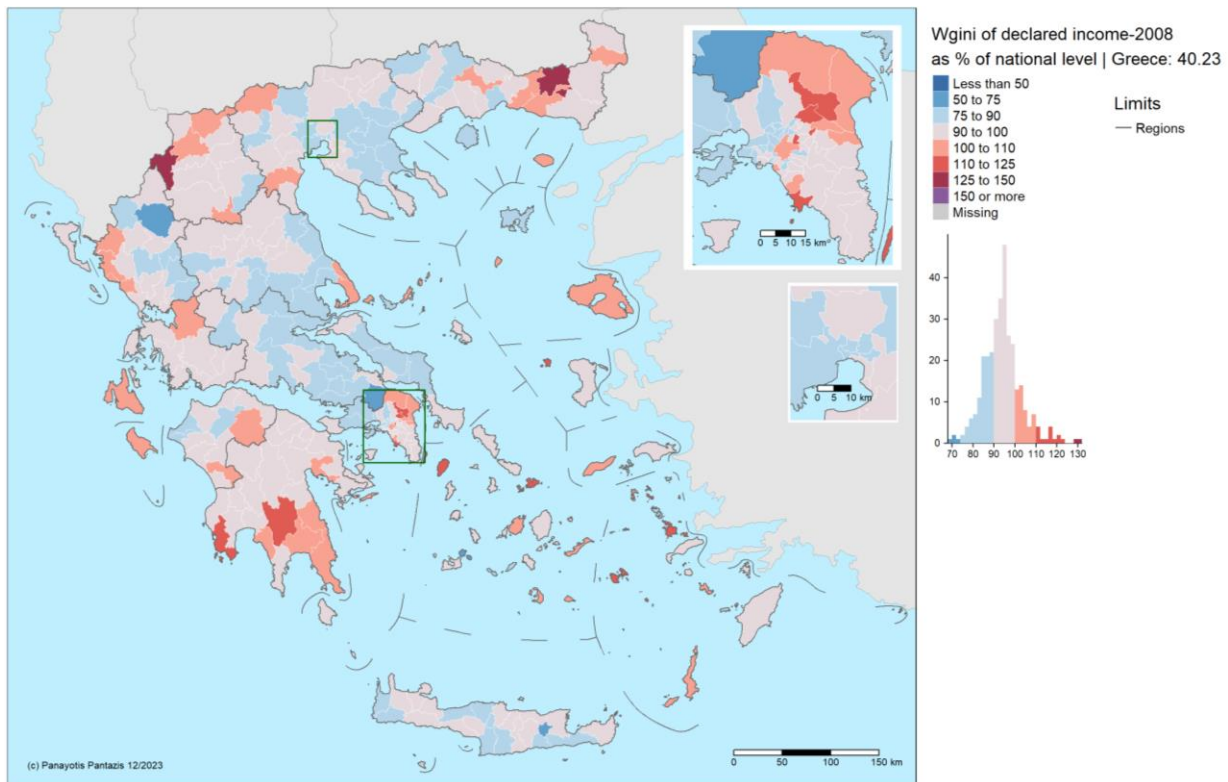


Figure I-39. Spatial distribution of weighted Gini of declared income equivalent for employees, municipalities, 2008

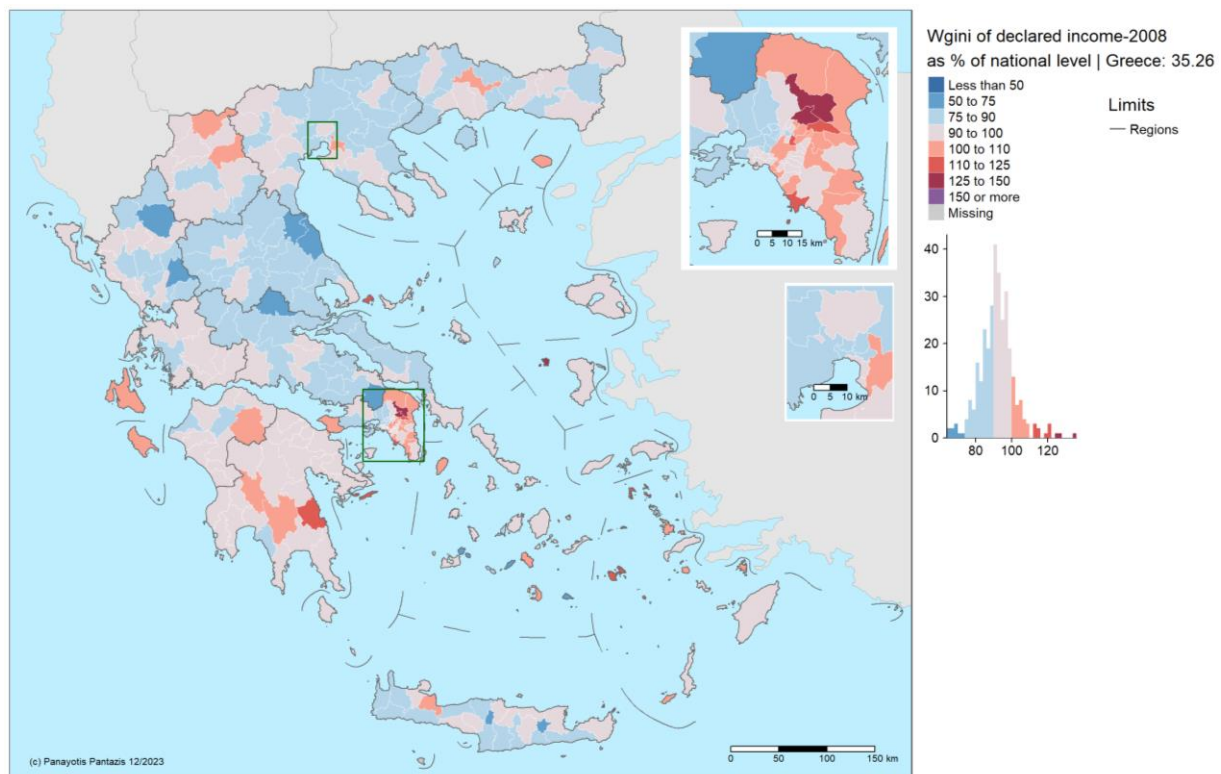


Figure I-40. Spatial distribution of weighted Gini of declared income equivalent, municipalities, 2012

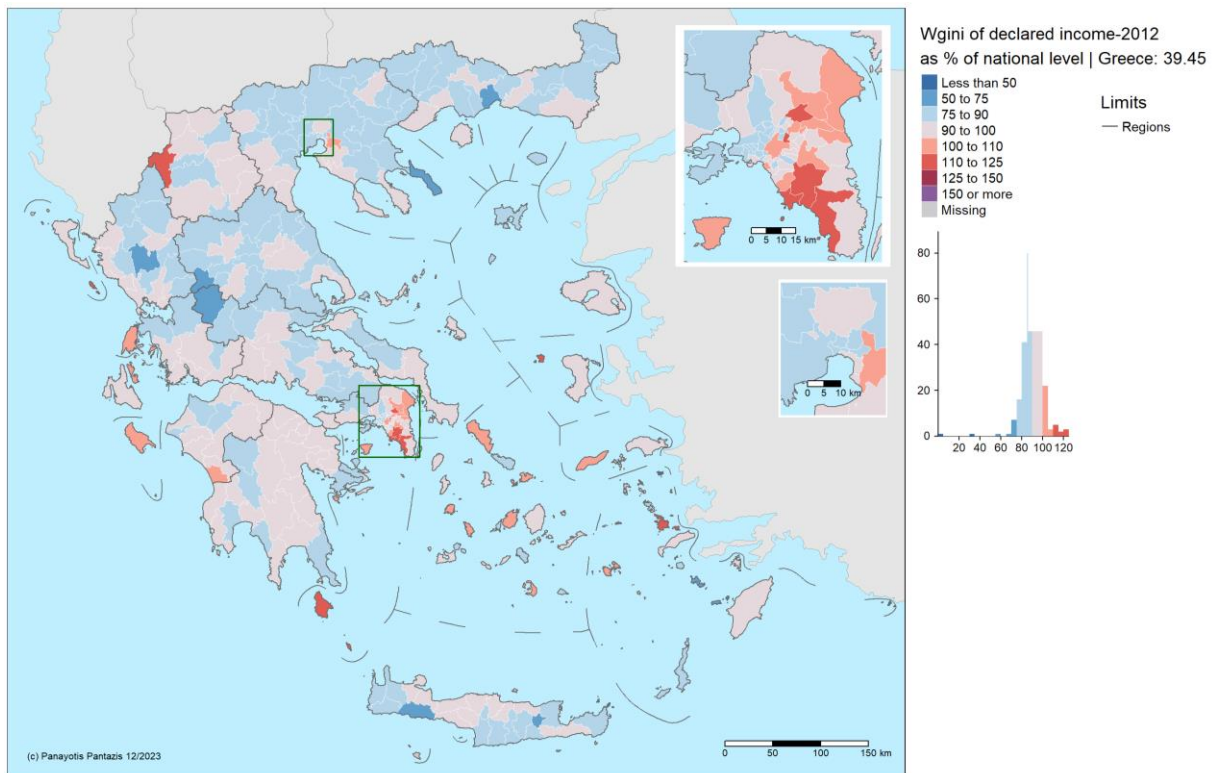


Figure I-41. Spatial distribution of weighted Gini of declared income equivalent for employees, municipalities, 2012

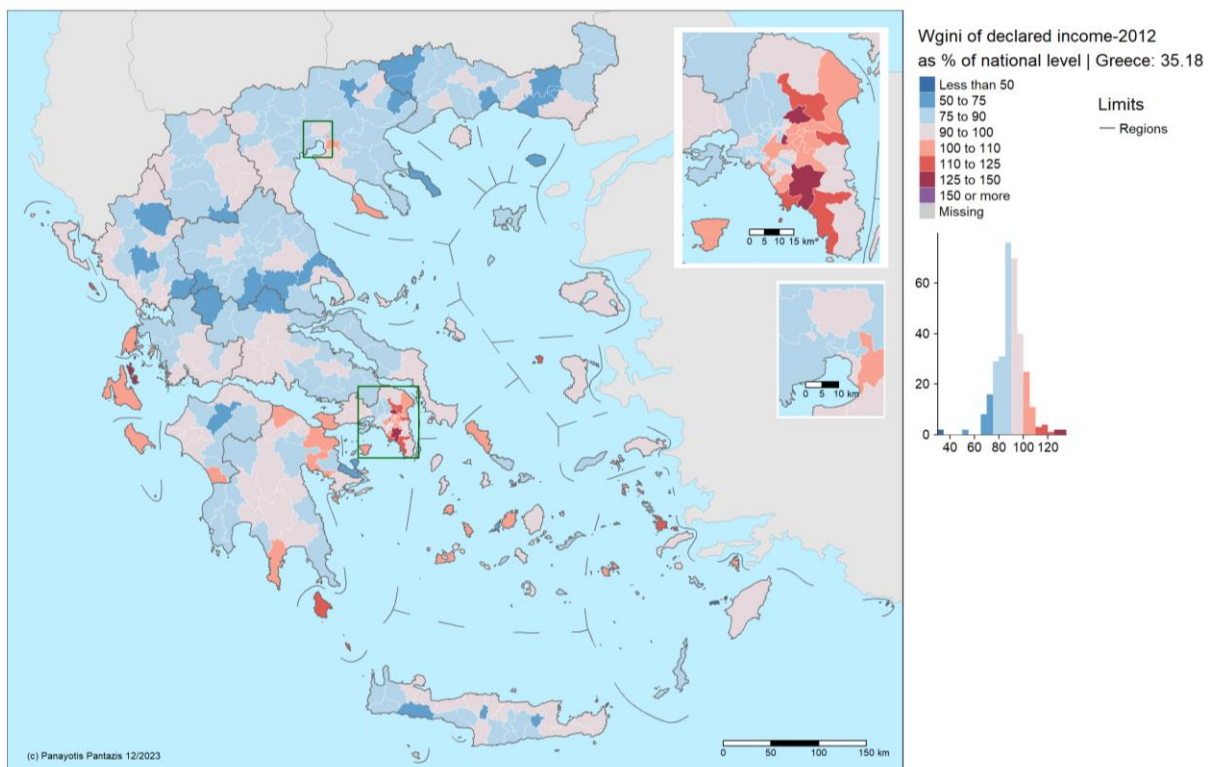


Figure I-42. Spatial distribution of weighted Gini of declared income equivalent, municipalities, 2015

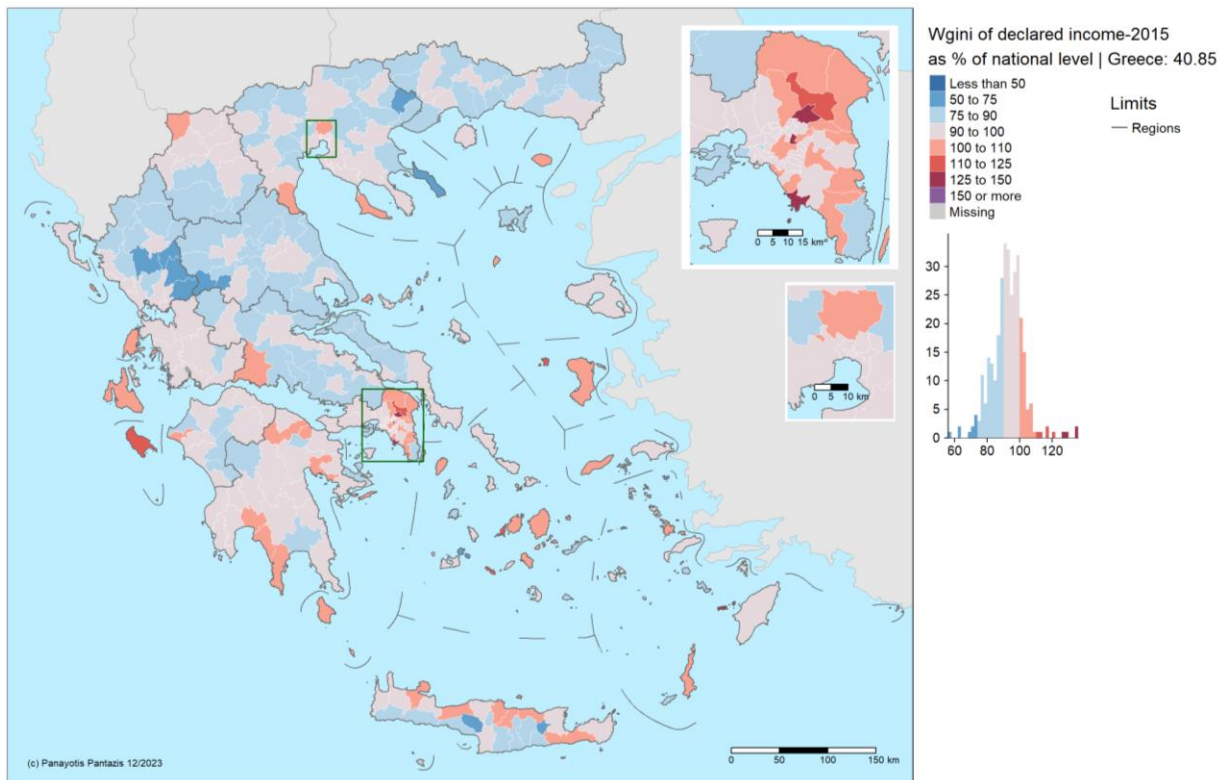


Figure I-43. Spatial distribution of weighted Gini of declared income equivalent for employees, municipalities, 2015

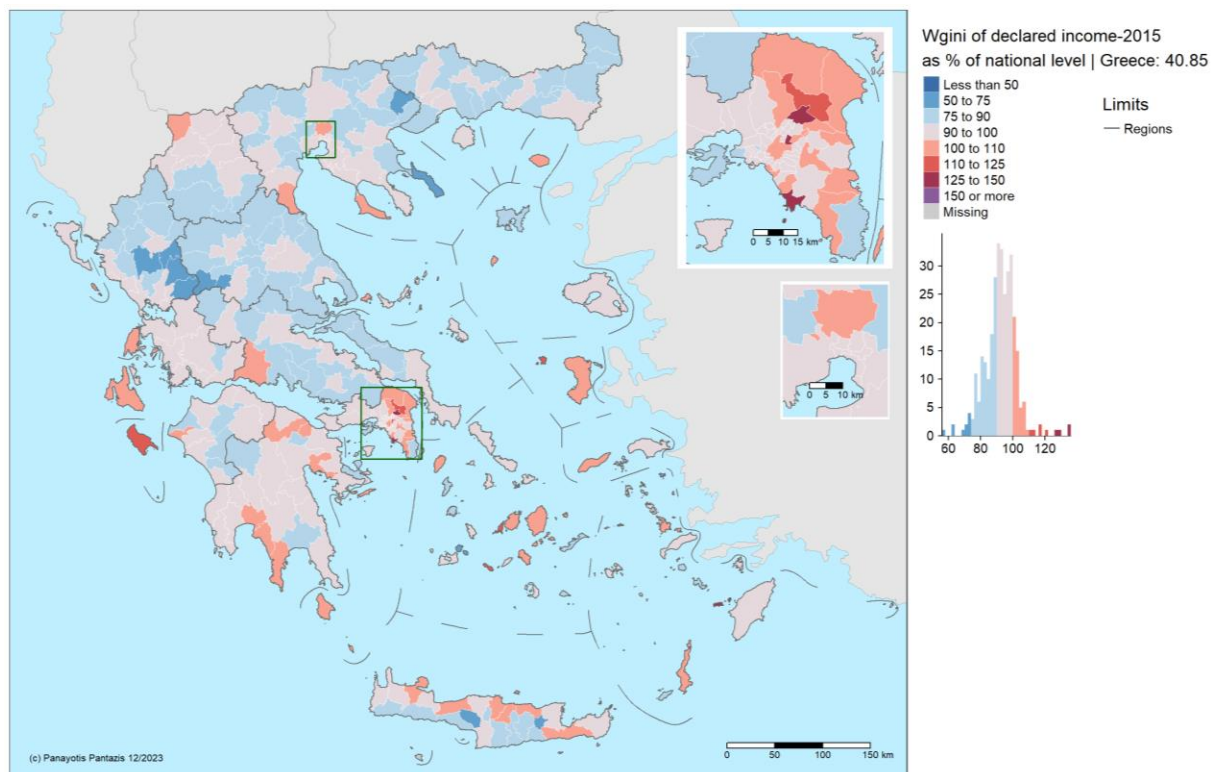


Figure I-44. Spatial distribution of weighted Gini of declared income equivalent, municipalities, 2019

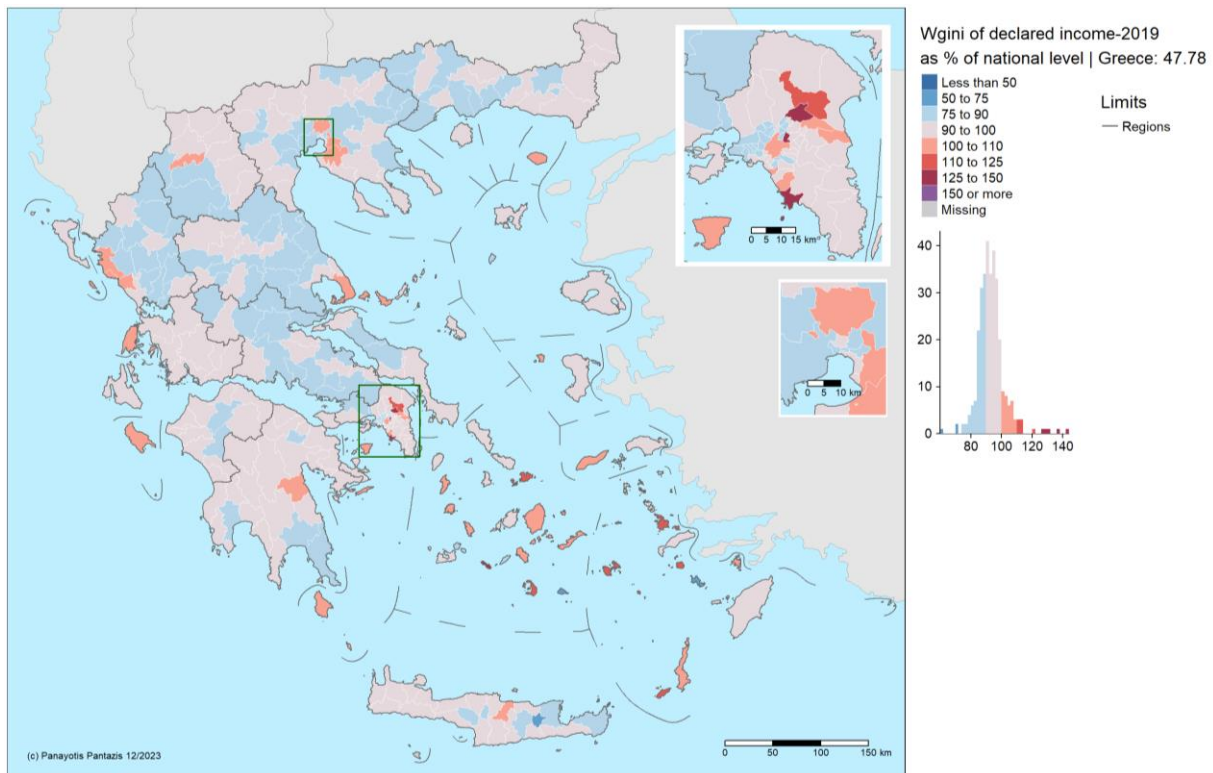
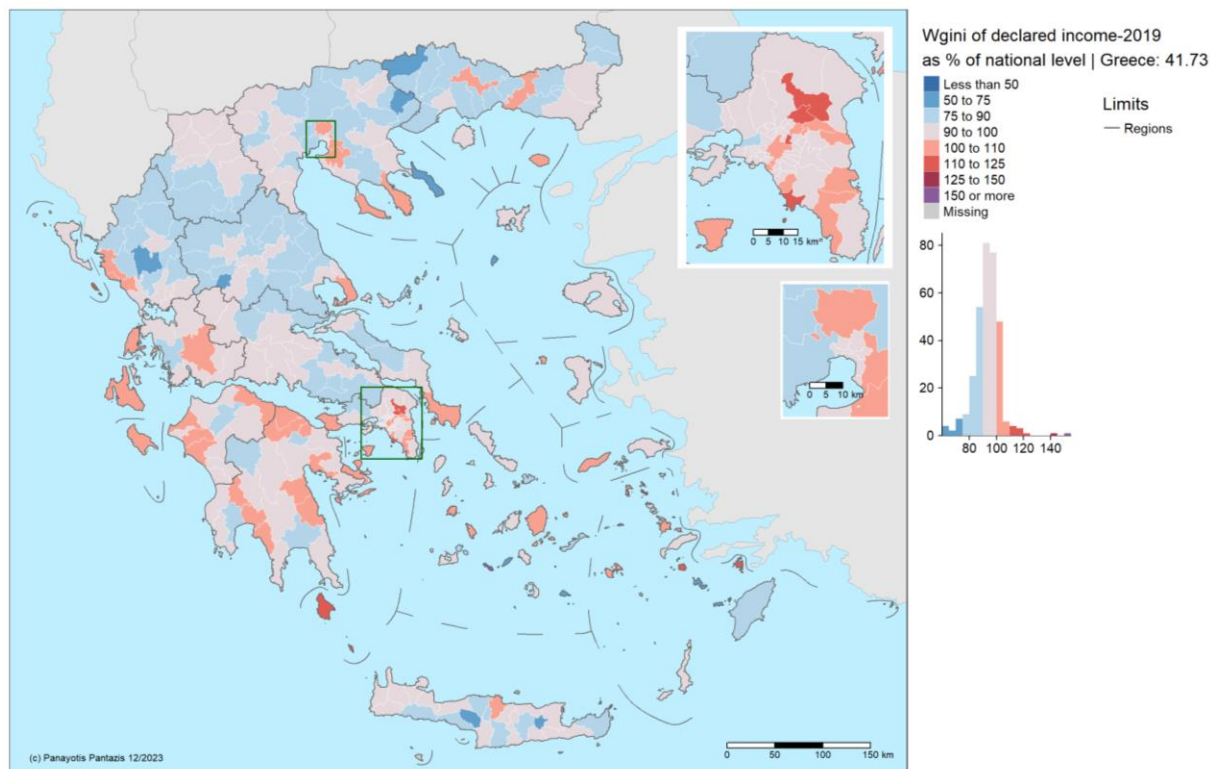


Figure I-45. Spatial distribution of weighted Gini of declared income equivalent for employees, municipalities, 2019



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Chapter II

The geographical dimension of income inequality in Greece: Evolution and the ‘turning point’ after the economic crisis

In this chapter, we unveil the geographical variations in income level and income inequality in Greece over a long time period allowing comparisons between pre and during the economic and fiscal crisis time periods. The analysis is based on a novel database which includes individual micro-data of declared and taxable income aggregated at municipal level over the period 2002-2014. Results indicate that economic crisis and fiscal reforms changed substantially both inter-municipal and intra-municipal / interpersonal income inequalities. The geographies of income inequality are subject to time-period of analysis, type of municipality, and level of income. The geographies of inequality question the fairness and inclusiveness of the implemented reforms during the recession.

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Disclaimer

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II.1 Introduction

Income inequality has risen to historically high levels. Robert Shiller, recipient of the Nobel Memorial Prize in Economics (2013), declared that the most important problem we are facing today is rising inequality. This observation, along with the empirical evidence that inequality matters for the economic performance of nations and for the wellbeing and prosperity of citizens and territories, has placed the issue at the core of scientific investigation (Piketty and Saez, 2003; Dorling, 2015; Atkinson and Piketty, 2010; Atkinson *et al.* 2011; Bourguignon 2015).

Although income inequality has been a longstanding issue in economics (Kuznets, 1955), this renewed attention is arguably, at least in large part, attributable to the work of Atkinson (1997). Subsequently, the works of Piketty (2014), gave further impetus and triggered a voluminous number of publications providing insights from different countries across the globe. Cavanaugh and Breau (2018) show that the rate of increase in papers on inequality was more than twice as fast as and greater than several other major research themes in the social sciences.

International organisations are aware of the importance of this issue. Income inequality in OECD countries is at its highest level of the past half century; the average income of the richest 10 per cent of the population is about nine times that of the poorest 10 per cent, compared to seven times, 25 years ago (OECD, 2019). Furthermore, the economic crisis has intensified income inequality as income is significantly more unequally distributed today than it was before the economic crisis (OECD 2014). Reducing inequalities and eliminating poverty are among the policy priorities of the 2030 Agenda for Sustainable Development (United Nations, 2015). Inclusive and sustainable development constitute strategic priorities of the EU cohesion policy (European Commission 2014, 2022). IMF report claims that widening income inequality has been regarded as the defining challenge of our time (Dabla-Norris *et al.*, 2015; International Monetary Fund, 2015).

Given the intensity and the consequences of income inequality for economic development and social wellbeing, tackling income inequality has been placed at the forefront of academic discussions and policy practices.

However, while income inequality reflects the prosperity and welfare conditions that prevail in an economy over a certain period of time, the geography of income and income inequality provides additional evidence on the variations in wealth and the wellbeing of people within a country across space (Wei, 2015). The geography of income level and income inequality becomes a particularly significant subject of study in times of economic crisis with soaring unemployment rates and severe

cuts in wages and pensions. Nowhere in Europe were these conditions more evident than in Greece during the period of the Great Recession that began in 2008 and the implementation of the strict fiscal adjustment programs after 2010.¹

This paper aims at analysing the geographical aspects of declared income and income inequality in Greece during the period 2002-2014. In addition, this paper focuses on the impact of the economic crisis and tax reforms in the evolution of income per capita and income inequality across Greek municipalities. The analysis is based on individual micro-data, which constitute a random sample of 10 per cent of the annual income tax declarations. Seven and a half 7.5 million observations, about five hundred thousand declarations per year, are included in the analysis with information regarding declared and taxable income as well as important attributes of households and tax incidence.

Despite the above-mentioned advantages, this dataset has some important limitations. The variable ‘declared income’ captures the income received by households during the preceding calendar year which are submitted to tax authorities with the tax declarations in the following year. This data includes income that is submitted by six categories of taxpayers: proprietors, traders, farmers, employees, self-employed, and retired. However, this data cannot capture other types of income such as fiscal transfers to individuals of places. In addition, this dataset does not include income from shadow/hidden economy, a chronic problem for the Greek economy (IOBE, 2018). Although ‘taxable’ income, an induced estimation of income based on objective criteria, which is also included in the dataset complements the information regarding declared income, this dataset still cannot capture the net/ real income level and income inequality in the country.

Contrary to these limitations, the quality, consistency, length, and accuracy of the tax data provide well-grounded conditions to analyse the spatial and temporal evolution of income and income inequality and their association focusing on changes due to the economic crisis and tax reforms. In addition, following Piketty (2014), tax data offer the advantage that they refer to registered incomes and tax incidences and are usually considered more suitable for the estimation of short-term changes in inequality.

¹ The First Economic Adjustment Programme for Greece, ‘the first Memorandum’, was signed in 2010 by the Greek Government, the European Commission and the International Monetary Fund (IMF), The Second Economic Adjustment Programme for Greece, ‘the second Memorandum’, was signed in 2012. The Third Memorandum signed in 2015 is outside the time frame of the analysis in this paper.

The analysis is anticipated to meet a multiplicity of objectives. First, it provides a comprehensive overview of the taxation system and tax incidence by income group and by municipality in Greece. This research complements existing knowledge about inter-regional and intra-regional inequality and welfare in the country by focusing on municipalities. Second, it analyses the association between income level and income inequality over a long time-period which, to the best of our knowledge, is the longest period for which such research has ever been conducted for Greece. The time length of the analysis allows for comparison before and during the economic crisis and the implementation of the Memorandums and the fiscal adjustments programs. Third, the analysis is based on individual tax declarations data which allow an estimation of the Gini index of income inequality. We trust that, this is also the first time that such research has been conducted on the estimation of income inequality with individual declared income data for Greece over such a long time period. Fourth, the analysis pays specific attention to the geographical dimensions of income and income inequality at a small geographical/municipal level. The geographical attributes of taxation and the analysis of dynamics of income change at a small geographical level is an important issue for understanding the wealth conditions across the country and an important element for the evaluation of regional and fiscal policy. Finally, this research employs a combination of analytical tools in order to provide multi-dimensional statistical, cartographical and econometric evidence from a country that was hit severely by the economic crisis and was subject to the implementation of austerity policies and fiscal reforms. Austerity policy, with a huge decrease in public investment, had been a detrimental factor to the regional resilience, accelerated economic recession and widened geographical and income inequalities in the country (Psycharis *et al.*, 2014; Psycharis *et al.*, 2022).

This paper is organised as follows. After this short introduction, Section 2 provides a concise literature review regarding the geographical aspects of income inequality. Section 3 discusses about the dataset and provides information about tax reforms along with a descriptive analysis of declared income in Greece during the period under study. Section 4 analyses the geographical attributes of income and income inequality in Greece before and during the economic crisis. Section 5 presents the econometric specifications for the association between income level and income inequality at municipal level before and during the economic crisis. Section 6 presents and discusses the econometric results. Finally, Section 7 summarises the key findings and sketches the framework and trajectories for further research.

II.2 Income inequality: space matters

Income inequality is a key issue in economic analysis as well as in social and welfare policy (Atkinson, 2015; Stiglitz, 2012; Galbraith, 2012). While empirical studies of income inequality at the national level have dominated the scientific literature, the geography of income inequality has become a distinct and rapidly accelerating strand of scientific research (Wei, 2015).

But, why income inequality matters across space? First, local-level income inequality (e.g., income inequality at municipality level) is likely to be different from national-level income inequality, as it neither responds to the same factors, nor creates the same policy implications (Glaeser *et al.*, 2009; Florida and Mellander, 2016).

Second, there is likely to be an association between the geography of income inequality and the geography of income per capita. This association is addressed by the Kuznets (1955) curve which shows that income per capita has an inverted U-curve effect on income inequality. According to this curve, income inequality increases as regions move to higher welfare levels and then, declines at the mature stages of development. In the early stages of economic development, workers are likely to move from the low-paid sectors, such as the large primary sector, to the high-paid sectors, such as the secondary and tertiary sector. This movement boosts further income inequality (Firebaugh 2003). In the latter stages of economic development, as the low-paid sectors shrink and the high-paid sectors increase in size, further movement decreases income inequality. The investigation of the inverted U-turn hypothesis at local level constitutes an interesting and timely research area. As an example, exploring a unique panel dataset of Canadian regions Breau and Lee (2023) test whether inter-personal income inequality increases once the initial inverted-U pattern is completed. Analysis supports the notion of a sideways S-shaped curve describing a wavelike decrease to increase shift, with a turning point in the late-1990s/early-2000s.

Third, the geography of income inequality depends not only on the geography of income per capita, but also on a series of other factors, such as the previous levels of wealth and inequality, human capital, agglomeration economies, economic structure, and quality of institutions, which also vary across space (Quito *et. al.*, 2023; Hortas-Rico & Rios 2019)). The previous levels of both income per capita and inequality affect the geography of income distribution because history matters. Moreover, changes in income distribution take place at a very slow pace because, for example, people are often reluctant to change jobs and to migrate for psychological and institutional reasons (Gujarati, 2003; Rodríguez-Pose and Tselios 2009a). A higher level of education is likely to increase the earning opportunity of the lowest strata and the social and job

opportunities of the poor, reducing income inequality (Checchi, 2000, Rodríguez-Pose and Tselios, 2009). The concentration of population in particular areas generates spillover effects upsurging the economic activities in these areas, which, in turn, affect income distribution (Iqbal *et al.*, 2018). The sectoral composition of an area affects its income inequality because the added value of each sector to GDP differs. Since the sectoral composition varies across space, this variation affects the geography of income inequality. Using the case study of Indonesia, González Gordón and Resosudarmo (2019) find a positive impact of both manufacturing and services shares of GDP on income inequality, but a negative impact of agriculture share of GDP on inequality. The quality of institutions shapes the distribution of income inequality. In economies with relatively high governance quality, such as in economies with high levels of voice and accountability, political stability, government effectiveness, regulatory quality, rule of law and control of corruption, is expected a lower income inequality than in economies with low governance quality (Tselios, 2023).

Fourth, an economic and financial crisis impacts the geographical dimension of income inequality because the austerity measures affect not only the geography of welfare, but also all determinants of income inequality. For instance, it is quite usual for wages to fall during a crisis. However, wages differ across space making the impact of crisis on areas heterogeneous. Moreover, some sectors, such as manufacturing and tourism, suffer more in an economic crisis than others. Since the sector composition varies between regions, the impact of crisis is unequal. Overall, the sign and the significance of the determinants of income inequality may differ between the pro-crisis period and the after-crisis time-period. Recent advances in research underlie the significance of the intraregional/ interpersonal inequality (Moretti, 2022). More precisely, place-based policies are not sufficient *per se* in promoting growth *and* inclusiveness. The benefits of an area are not necessarily trickled down in the same vain to all members of the area for many reasons. First, because the gains of capital are disproportionally higher comparing to the gains of labor. Furthermore, the benefits of political interventions are not distributed evenly among income groups. Usually, the most educated and higher income workers or citizens can grasp easier the benefits of policy interventions than the less educated. In addition, the less well-off segments of population lack in skills and expertise to utilize in disproportional manner the gains from the policy. As a result, interpersonal income inequalities may still continue to grow even if place-targeted policy are in action. This has been considered as a course of increasing populism and discontent (Rodríguez-Pose *et al.*, 2023).

While inequality constitutes an alarming issue of our times, the spatiality of inequality enhances our understanding regarding the expressions of inequality and trigger further research on this topic.

Literature seems to lean towards two important conclusions. First, the level of urbanization is highly correlated with the level of income inequality. Inequality is higher in large cities and urban agglomerations. Second, the level of education seems to have been one of the most significant factors of interpersonal income inequality across space.

With regards to Greece there is relatively limited research regarding the geographical dimension of income and income inequality (Psycharis & Pantazis, 2016). More recently, Psycharis *et al.*, (2023) find that the Attica Metropolitan Region exhibits a higher degree of income inequality relative to the rest of the country, and the economic crisis increased inequality not only in this Region but also in the rest of the country. Furthermore, Psycharis and Panori (2023) find that segregation trends across municipalities in Athens metropolitan area and high and increasing. These results are in line with Mastronardi and Cavallo (2020) and Moser and Schnetzer (2017) show that interpersonal inequality within urban municipalities are higher in comparison with the rural areas for the Italian and Austrian municipalities respectively. Mussidaa and Parisi (2020) show that inequality appears largely to be a within-region problem across Italian regions, particularly in the South, and the crisis exacerbated this phenomenon while. However, the relationship between income level and income inequality at municipal level still remains a promising and underexploited area of research. This paper is aiming at filling at least in part the existing gap and to trigger further research on this research topic.

II.3 Greek economic crisis and declared income: basic facts and figures

II.3.1 Data on declared income and definition of variables

This paper is based on a purpose-constructed database which includes micro-data for 10 percent of the annual household declarations for the time period 2002-2014.

This dataset includes information about two types of income: declared income and taxable income. The difference is that while the former is based on the gross income that has been generated within a year for each member of the household, and it is submitted to tax authority with the annual tax declarations, the latter is the income that has been estimated either by deducting tax exemptions from the gross income or by taking into consideration different attributes of the individuals, such real estate or car ownership.

The analysis carried out for this research is based on equivalent individual income.² Income inequality has been measured with the estimation of the Gini index (known as Gini coefficient) which summarises the dispersion of income across the entire income distribution and varies between 0 (i.e., everyone has the same income) and 100 (i.e. one person has all the income) The Gini index, which is the most popular measure of income inequality, is easy to interpret and acceptable to test models of income inequality (Rodríguez-Pose and Tselios 2009b). The Gini index allows for comparison among regions with different population sizes. Contrary to much of the literature that the Gini index is more sensitive to changes around the median of the income distribution than to changes among the very rich or the very poor (Allison 1978; Firebaugh 2003), the study by Gastwirth (2017) shows that the Gini index is more sensitive to changes in the lower and upper parts of the distribution than in the middle.

The geographical level of analysis refer to the 325 Municipalities which constitute the first tier of local government in Greece (Law 3852/2010). Municipalities are grouped into six categories based on population and geographical characteristics (Law 4555/2018); *Metropolitan; Large Mainland, Medium Mainland, Small Mainland, Large Islands, and Small Islands*.

II.3.2 The evolution of income inequality

Figure II-1 shows the evolution of declared and taxable income and clearly shows that after 2011, declared and taxable income dropped substantially. The fiscal consolidation reforms was implemented with detrimental effects on economic activity, growth and finally on tax revenues. Between 2008 and 2014 the revenue from personal income tax dropped by 24 percent (EC, 2016). This was the outcome of simultaneous increases in unemployment, cuts in wages and pensions and increases in taxes.

However, as **Figure II-1** shows, income inequality also dropped. This is more pronounced in the case of taxable than in the case of declared income. This drop in inequality in declared income could be primarily attributed to the broadening of the tax base and the increased number of declarations in the low brackets of the income scale.³ Part of the explanation could also be attributed

² Equivalised declared (taxable) income: is the total income of a tax declaration, divided by the number of household members converted into equivalised adults; household members are equivalised or made equivalent by the following so-called modified OECD equivalence scale: the first household “adult” member counts as 1 person, the other adult household members count as 0.5 person, each household member indicated as “child” aged 14 years or more counts as 0.5 person, each household member indicated as “child” aged 13 years or less counts as 0.3 person

³ The lower income taxpayers had an increase in the tax burden by 337.7 percent while those in high income classes an increase of only 9 percent. Or the share of the lower income groups to the tax-led adjustment increased from 2.5

to the drop in high incomes due to the increased tax rate scales, the imposition of the solidarity tax and the cuts in salaries for the high-income earners.

Figure II-1. Evolution of income per capita and income inequality (Gini index)

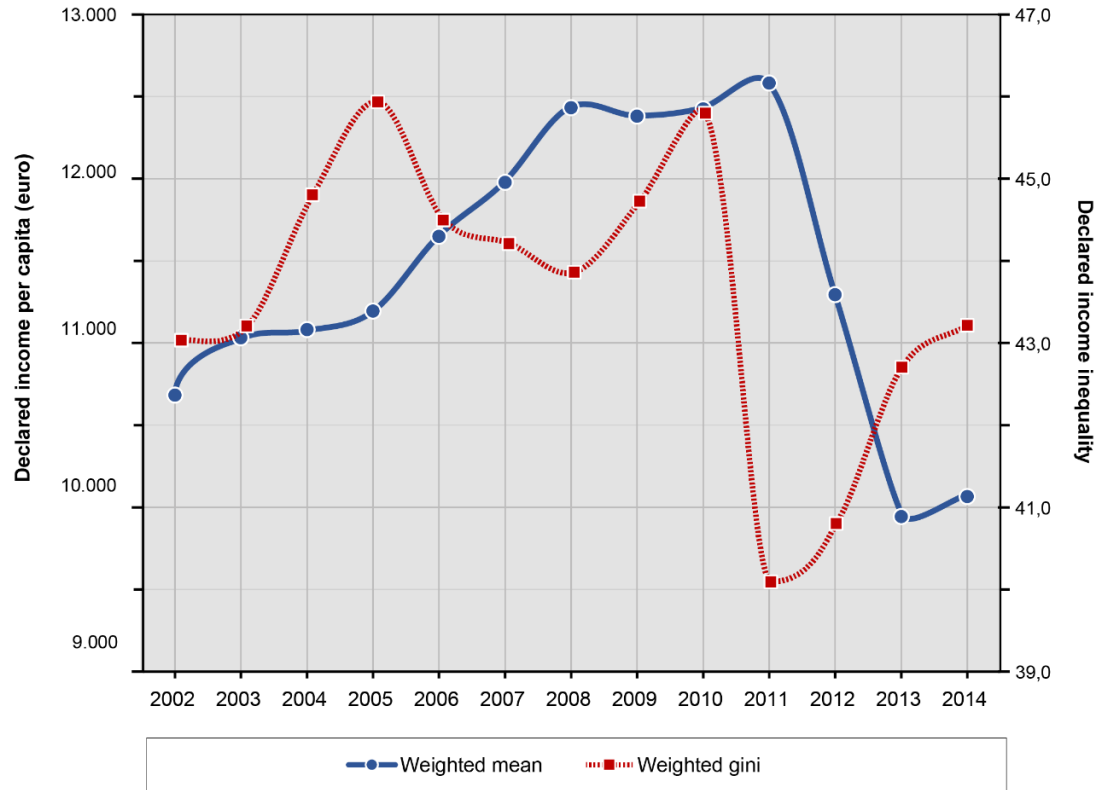


Fig. 1, with two solid lines, shows the evolution of income per capita, (blue line) and income inequality (red line) in Greece over the period 2002–14. Clearly indicates abrupt drop of income after 2011.

II.4 The geographical incidence of declared income

II.4.1 Cartographical representation of income and income inequality

Figure II-2 portrays income level and income inequality at the Municipal level in Greece after the implementation of first Memorandum (2010). More precisely, **Figure II-2** presents the inequalities in declared income at the Municipal level for the periods before and during the economic crisis and the implementation of fiscal reforms. The comparative examination of these maps provides some interesting findings.

percent to 9.4 percent, while that of the higher income groups decreased from 97.5 percent to 90.6 percent. (European Commission, 2016:33).

Figure II-2. The geography of income per capita and income inequality (Gini index)

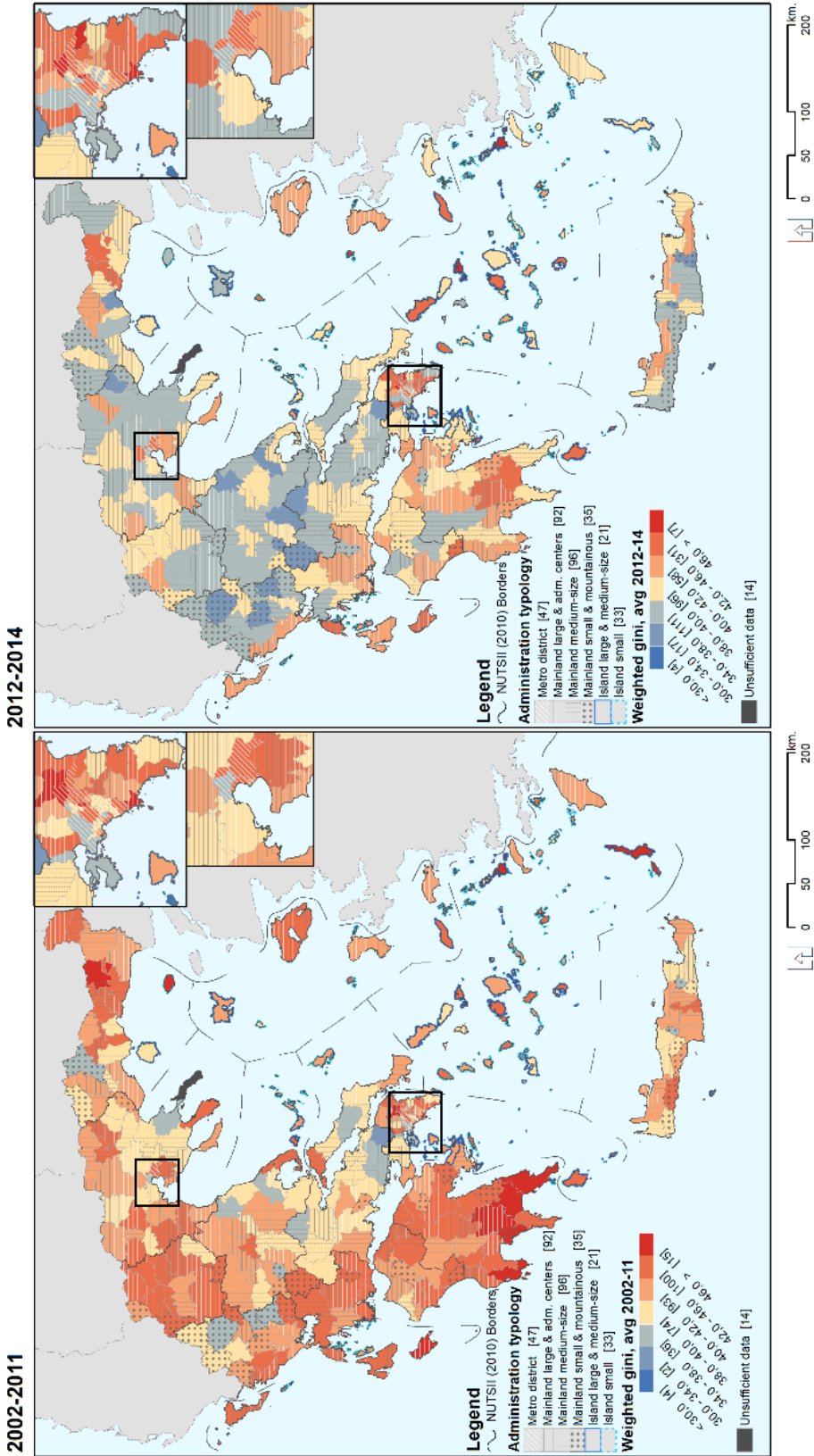
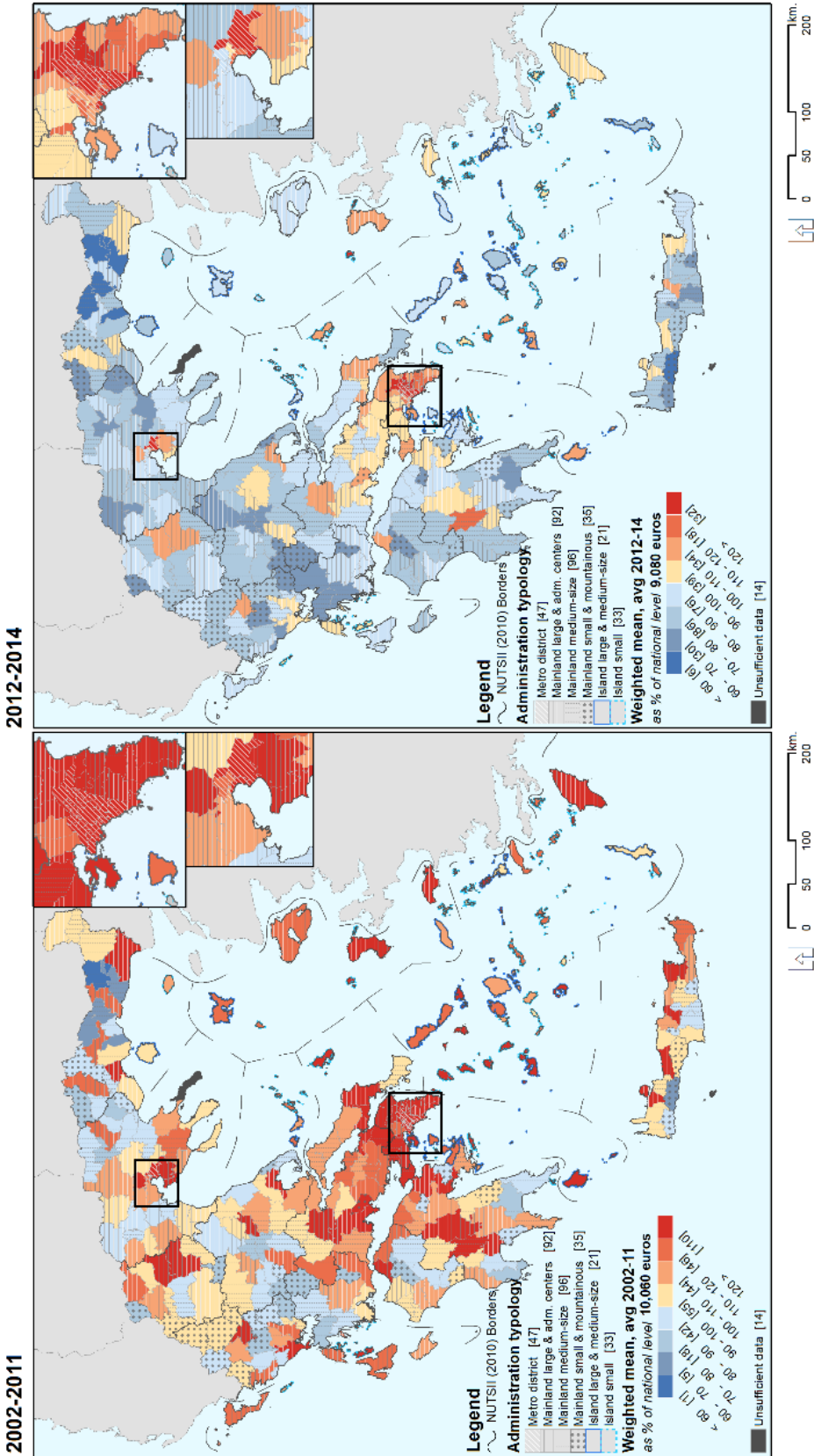


Figure II-3. The geography of income per capita and income inequality (Mean income)



During the period 2002-2011, there are important differences in the levels of income per capita across the Municipalities. The first observation shows that there is a gap between a large number of metropolitan and medium Municipalities and Islands on the one hand, and the most remote, small and mountainous Municipalities on the other hand.

However, during the period 2012-2014 the map changes. First, the average level of declared income during the crisis and the implementation of fiscal adjustment programs has dropped. However, its drop is not geographically uniform. Most Municipalities outside the large metropolitan areas, reveal levels of declared income per capita below the country average. As a result, inequalities in the level of average income per capita between Municipalities during the economic crisis have widened.

Furthermore, the geography of income inequality among individuals within Municipalities is portrayed on the two maps **Figure II-3**. Comparing these maps, with those in **Figure II-2**, it can be observed that they contradict each other in many ways. The most striking observation is that during the period of economic crisis interpersonal income inequality declined. This is more pronounced in Municipalities outside the large metropolitan areas.

The decrease in interpersonal income inequality in the Municipalities outside the large urban agglomerations can be attributed to two simultaneous factors. First, there is the widespread obligation for a vast number of people across country to submit declarations. The number of people obligated to make a tax declaration increased and crosses all the income groups, especially the lower income groups, across the country. At the same time, the drop in incomes due to the economic recession and wage and salary cuts has led to the reduction in incomes relative to the pre-crisis period. The combined effects of these two trends, namely the increase of low-income tax declarations across space, along with the further decrease in - the relatively lower incomes - outside the urban agglomerations, has led to the decrease of interpersonal income inequality in areas outside the large cities and urban agglomerations. The interpretation of inequality questions the inclusiveness of the tax policy since the drop in inequality is achieved primarily with the increase in tax of the low-income taxpayers.

II.4.2 The evolution in income level and income inequality

These results can be further scrutinized by type of Municipality. **Figure II-4** clearly shows that the level of income and the dispersion of inequality varies significantly by type of Municipality.

More precisely, the dispersion of income for the most urbanized Municipalities are found at the upper end of the scale and the dispersion is higher compared to with the small mainland Municipalities. This documents that average declared income in Metropolitan Municipalities is higher than the average declared income in the small mainland Municipalities. In addition, interpersonal inequalities within metropolitan Municipalities are higher compared to the interpersonal income inequality within small mainland Municipalities. This trend is more pronounced than it was in the past and has further intensified during the years of economic crisis and the implementation of fiscal adjustment programs.

These findings document that geography matters in terms of income inequality. The type of interpersonal income inequality it is not at all neutral regarding the type of Municipality.

Figure II-4. The evolution income and of the dispersion of income inequality (Gini index) by category of municipality (constant price, 2015=100)

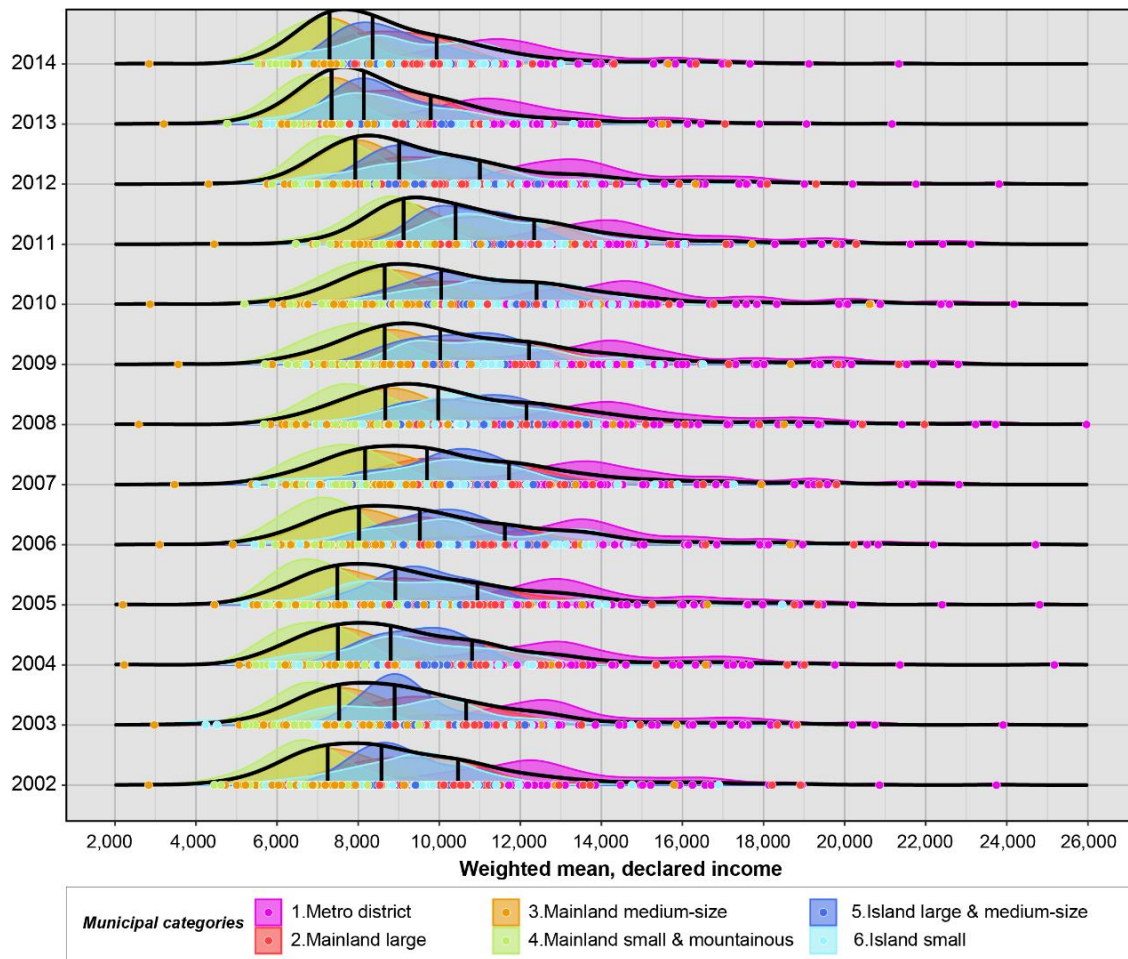


Fig. 3 shows the dispersion of per capita income and Gini index of income inequality by year and category of municipality (Metro, Large, Medium and Small mainland, Large and medium, and small islands). Clearly indicates that after 2011, the mean per capita income has been reduced and the dispersion of income has been reduced especially on the higher tail of the distribution.

II.4.3 The dispersion of income by type of Municipality

Figure II-5 goes a step further in order to examine more precisely how interpersonal income inequality is related with the type of Municipality. More precisely, it presents the relationship between income levels and income inequality for the six categories of municipalities.

Figure II-5. The evolution of the relationship between income and income inequality (Gini index) by category/ group of Municipalities (constant price, 2015=100)

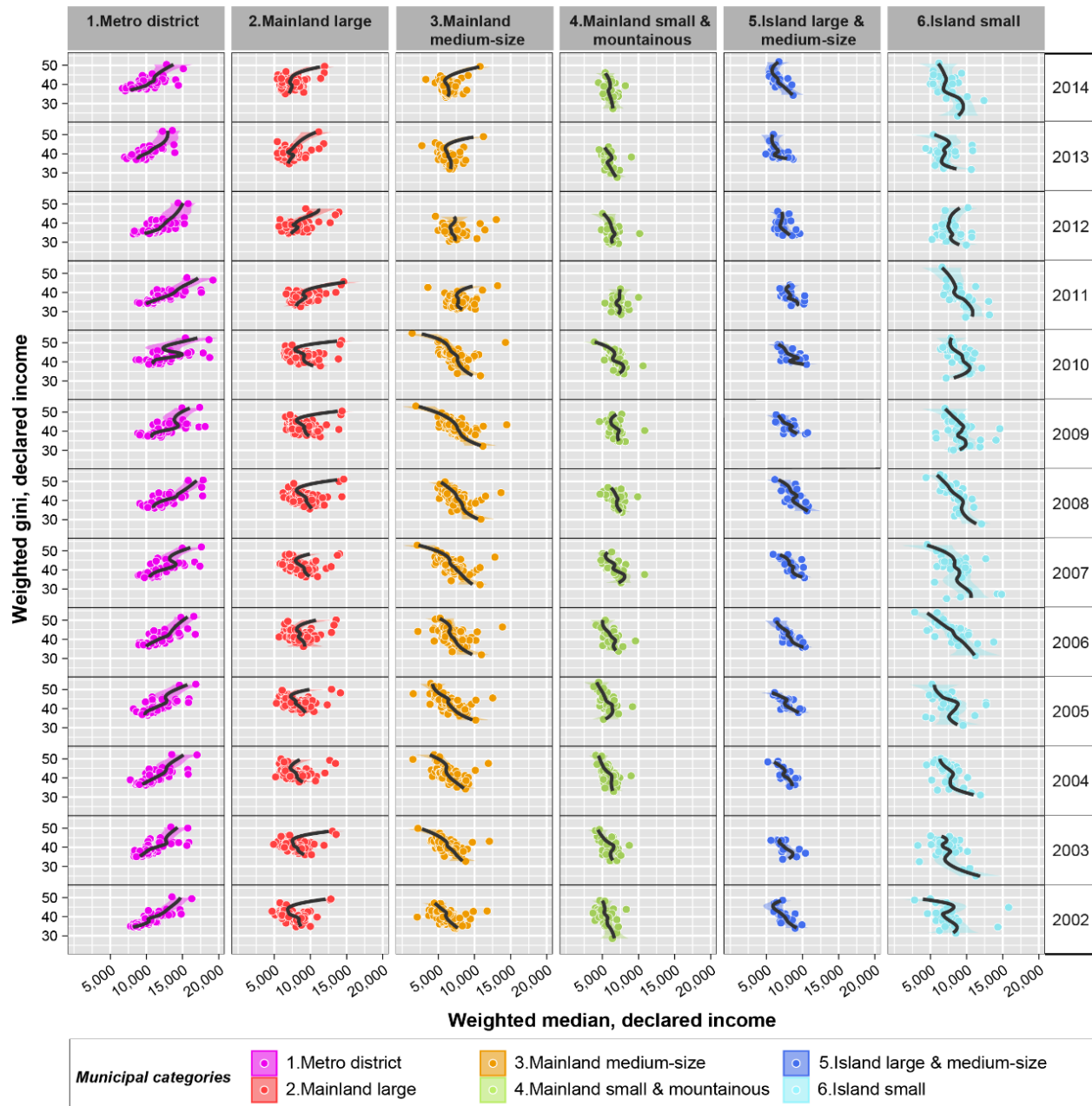


Fig. 4 with small graphs shows the relationship between income per capita and income inequality by type of municipality and year during the period 2002–12. The visualisation of results shows a clear positive relationship between income per capita and income inequality in Metro districts.

This Scatterplot documents the positive relationship between income levels and income inequality for metropolitan municipalities. For the Municipalities in Metropolitan areas, an increase in income is followed by an increase in income inequality. This also applies to the majority of cases in the large Mainland Municipalities and Capital cities.

However, the opposite applies in the case of the medium and small mainland and island Municipalities. In these cases, an increase in income is followed by a decrease in income inequality. These findings provide initial evidence that income inequalities are higher in more urbanized areas of the country.

Summing up it can be stated that geography matters both for inequalities in wealth across space as well as inequalities in wealth within Municipalities. This relationship brings an interesting feature to the discussion of income inequalities. These findings will be further examined with the use of an econometric model.

II.5 The association between income per capita and income inequality

We then examine the relationship between income per capita and income inequality at the municipality level for two periods: a) between 2002 and 2011 (before economic crisis) and, b) between 2012 and 2014 (within the economic crisis). The relationship between income per capita and income inequality is not presumed to be linear, but is configured using a stepwise approach, i.e., we initially start with a linear income per capita variable and then add its square term. The explorative analysis shows a non-linear relationship between income per capita and income inequality. Therefore, we estimate the income inequality of a municipality as a function of a municipality's per-capita income and its square term and a set of control municipality characteristics. Taking into account that, in theory, many socioeconomic factors are correlated with income inequality, the selection of control variables draws on the microeconomic data availability. Hence, we use the following empirical specification.

$$IncIneq_{it} = \beta_0 + \beta_1 IncPerCapita_{it} + \beta_2 IncPerCapita_{it}^2 + \beta_3 Controls_{it} + \omega_i + \varphi_t + \varepsilon_{it} \quad (1)$$

where,

- $IncIneq_{it}$ is inequality in declared or taxable income for municipality i in year t ,
- $IncPerCapita_{it}$ is declared or taxable income per capita, respectively, for municipality i in year t ,
- $Controls_{it}$ is a vector of control variables for municipality i in year t , ω_i is unobserved municipality-specific characteristics which denotes spatial fixed effects and represents the effect

of the omitted variables that are peculiar to each municipality such as the geographical characteristics of the municipalities, φ_t is the unobserved time effect characteristics (i.e. time-period fixed effects) which controls for all time-specific spatial-invariant variables such as the business cycle, and

- ε_{it} is the disturbance term.

We run this econometric specification for both periods.

For the estimation of **equation 1**, we use Fixed Effects (FEs), because these effects allow for unobserved heterogeneity in the time-invariant geographical characteristics of the Greek municipalities. Even if we use observed time-invariant municipality-specific characteristics (such as dummies for island or mountainous municipalities), the FEs estimator cannot estimate the effect of these time-invariant variables because the within transformation wipes out those variables (Baltagi, 2005). Thus, the spatial FEs allow for both observed and unobserved heterogeneity in the time-invariant geographical characteristics. We also use time dummies, because if these dummies are statistically significant, the one-way FEs estimator will suffer from omission bias (Baltagi, 2005). Therefore, our econometric specification is a two-way FEs model. In our empirical specification, β_0 is a constant, β_1 and β_2 are coefficients on income per capita and its square term, respectively, and β_3 is a vector of coefficients on controls. It should be clarified here that the effect of a change in per-capita income on income inequality depends on the level of per-capita income of the municipality. Therefore, the marginal effect of per-capita income on income inequality is:

$$\frac{\partial IncIneq}{\partial IncPerCapita} = \beta_1 + \beta_2 IncPerCapita \text{ (Brambor, Clark, and Golder, 2006).}$$

Finally, we use cluster-robust standard errors in order to control for arbitrary heteroscedasticity and autocorrelation.

This empirical specification allows us to examine whether income distribution across people and within municipalities is associated with the wealth level of municipalities (i.e. income-per capita) after controlling for some time-variant characteristics of municipalities ($Controls_{it}$) as well as the spatial and time-period fixed effects (ω_i and φ_t , respectively). The time-variant control variables are drawn from the microeconomic database. These variables are:

- a) the number of population samplings of a municipality divided by the size of the municipality (in km²) which is a proxy for population density,

- b) the mean number of children within a family which is a proxy for family size⁴,
- c) the mean number of cars of a family which is a proxy for family life-style,
- d) the percentage of married people within a municipality which is a proxy for family status, and
- e) the percentage of people within a municipality based on their main income source (i.e. proprietors, traders, farmers, employees, self-employed, and retired).

We then examine whether the association between income per capita and income inequality differs by municipality type, which is a time-invariant categorical variable. Thus, we run equation 1: a) for large and medium-size islands, b) for small islands, c) for large mainland, d) for medium-size mainland, e) for small and mountainous mainland and f) for metro district municipalities, for both periods.

Table II-1 presents the descriptive statistics of the variables for municipalities with population samples (*sample*) greater than or equal to 50 people, for the two periods: 2002-2011 and 20012-14. Income inequality within a municipality is measured by the Gini index which is 0 for perfect equality and 100 for perfect inequality. We consider both declared and taxable income distribution. Despite the conceptual differences between the declared and the taxable income distribution, the correlation coefficients between the declared and taxable income per capita, as well as between inequality in the declared and taxable income, is very high (0.9960 and 0.8985, respectively for the whole period of analysis). The average mean of the declared income inequality index between 2002 and 2011 is 41,175 while between 2012 and 2014 is 38,829. Declared income inequality decreased by 5.68 percent. The average mean of the taxable income inequality index, which is lower than that of the declared income inequality, decreased as well (from 40,194 to 33,391), but this reduction is much higher (20.37 percent). The descriptive statistics for the declared and taxable income per capita show that declare income per capita decreased by 10.76 percent while taxable income per capita 5.39 percent.

Regarding the control variables population density, the mean number of cars and the percentage of married people have decreased and are likely to be result of the economic crisis, while the mean

⁴ This variable is highly correlated with the mean number of members within a family which is a better proxy for family size (correlation coefficient=0.8897). However, we do not use this variable in our analysis because it is highly correlated with the percentage of married people within a municipality, which is another control (correlation coefficient=0.7242).

number of children has not changed. Finally, the main sources of income are salaries and pensions for both periods.

Table II-1. Descriptive statistics

Variable	Year	Obs	Mean	Std. Dev.	Min	Max
Inequality in declared income	2002-2011	3,088	41.175	3.703	27.218	55.772
	2012-2014	924	38.829	3.498	27.291	55.799
Inequality in taxable income	2002-2011	3,088	40.194	4.163	25.704	55.772
	2012-2014	924	33.391	4.047	21.449	52.636
Declared income per capita	2002-2011	3,088	10.147	3.100	2.192	27.457
	2012-2014	924	9.161	2.554	2.845	23.811
Taxable income per capita	2002-2011	3,088	10.299	3.094	2.229	27.771
	2012-2014	924	9.771	2.451	3.951	24.255
Population density	2002-2011	3,087	73.454	197.594	0.074	1258.2
	2012-2014	924	66.163	177.876	0.068	1174.9
Mean number of kids	2002-2011	3,088	0.444	0.089	0.129	0.912
	2012-2014	924	0.444	0.100	0.118	0.844
Mean number of cars	2002-2011	3,088	0.631	0.182	0.013	1.223
	2012-2014	924	0.525	0.276	0.015	1.221
Percentage of married	2002-2011	3,088	0.536	0.062	0.352	0.859
	2012-2014	924	0.511	0.053	0.347	0.823
Rent	2002-2011	3,087	0.054	0.027	0.000	0.174
	2012-2014	924	0.068	0.030	0.000	0.214
Manufacturing	2002-2011	3,087	0.137	0.043	0.000	0.426
	2012-2014	924	0.117	0.054	0.013	0.369
Farming	2002-2011	3,087	0.143	0.112	0.005	0.797
	2012-2014	924	0.123	0.086	0.001	0.542
Salary	2002-2011	3,087	0.315	0.106	0.039	0.641
	2012-2014	924	0.298	0.100	0.027	0.615
Freelance	2002-2011	3,087	0.048	0.029	0.000	0.214
	2012-2014	924	0.043	0.027	0.000	0.197
Pension	2002-2011	3,087	0.302	0.081	0.044	0.652
	2012-2014	924	0.351	0.086	0.109	0.688

Note: Income per capita is divided by 1,000

II.6 Regression results

The empirical analysis exploits the panel structure of the dataset for 311 Greek municipalities (i.e., municipalities with population samples (*sample*) greater than or equal to 50 declarations) from 2002-2011 (before crisis) and from 2012-2014 (within crisis), by FEs estimation taking into account unobserved municipality specific effects. To evaluate the robustness of the results in terms of the population size of the municipalities, we experimented with different sizes of population

samples. We start with $sample \geq 50$, and then $sample \geq 100$ (297 municipalities), $sample \geq 500$ (229 municipalities), $sample \geq 1,000$ (154 municipalities), $sample \geq 2,000$ (84 municipalities) and $sample \geq 3,000$ (54 municipalities). We also checked whether municipalities with very small population samples ($sample < 50$), which represent the very small populated municipalities (11 municipalities), are important for the estimation results, but omitting these observations has almost no effect.⁵ Finally, we used populated weighed regressions to further explore the robustness of the results in terms of the population size. However, the differences between unweighted and weighted regressions should be mentioned here (Tselios *et al.* 2012; Sala-i-Martin 2003). In the unweighted regressions, each Greek municipality is weighted the same, and thus the emphasis of analysis and policy is on Greek municipalities, while in the weighted regressions, highly populated municipalities have more weight than lower-populated ones, because each Greek citizen should be weighted the same, and therefore the emphasis is on Greek citizens. In this section, we initially examine the relationship between income per capita and income inequality before and within crisis, and then, whether this association differs by municipality type.

Table II-2 displays the FEs regression results when the dependent variable is the declared income inequality for the two periods of analysis: a) 2002-2011 (Regressions 1-7) and b) 2012-2014 (Regressions 8-14). The R-within confirms the overall goodness-of-fit of all the regressions presented and the F-statistics probability lets us reject the null hypothesis that all coefficients are zero. The performance of the regressions is in general satisfactory, because our specifications account for more than half of the variance in income inequality across the sample for both periods. Moreover, there is a gradual increase in the R-within as the population size of the municipalities increases, (from Regression 1 to Regression 6, and from Regression 8 to Regression 13) e.g., the R-within in Regression 1 is 0. 5412 while in Regression 6 is 0. 7904.

The period 2002-2011: Regressions 1-3 show that there is a strong U-shape relationship between declared income per capita and declared income inequality, but this association weakens as the population size of the municipality increases (for the marginal effects see Appendix 1). Therefore, there is evidence that an increase in municipal welfare levels -measured by the declared income per capita- is associated a) with a reduction in income inequality for low-income municipalities, b) with a lower reduction or a very low increase in inequality for middle-income municipalities, and c) with an increase in inequality for high-income municipalities (Regressions 1-3). This finding is not robust for all regions, as there is no evidence of a U-shape welfare-inequality relationship for

⁵ These results can be provided upon request.

municipalities with relatively large populations (Regressions 4-6). The non-linear association between income per capita and income inequality (U-shaped) is also confirmed by the population weighted regression (Regression 7 – for the marginal effects *see* **Appendix: Figure A-II-7**).

In the period 2012-2014, the association between income per capita and income inequality within the crisis is different than it is before the crisis. For the period 2012-2014, there is evidence that an increase (decrease) in income per capita is related with an increase (decrease) in income inequality (Regressions 8-11 and 14). This finding is also confirmed by examining the linear association between income per capita and income inequality (*see* **Appendix: Table A-II-4**). The welfare-inequality relationship is moderated by the welfare level of municipalities only for the large-populated ones, as for these municipalities, there is an inverted U-shape relationship between income per capita and income inequality (Regression 13 – for the marginal effects *see* **Appendix: Figure A-II-7**).

As for the controls, there is weak evidence for the within-crisis period that an increase in the population density, in the average number of children, or in the mean number of cars increases income inequality, but that increase in the percentage of married people reduces inequality. The results for both periods show that rise in the percentage of people whose main source of income is renting increases income inequality. Once more, the results show that income inequality increased from 2002 to 2011, it decreased drastically in 2011 and then it increased from 2012 to 2014.

But, are there differences in the relationship between income per capita and income inequality between different types of municipalities? **Table II-3** shows that the U-shape relationship between income per capita and income inequality from 2002-2011 holds for large and medium-size islands (Regression 1) and for the mainland (Regressions 3-5). And the magnitude of the coefficients is higher for the small and mountainous islands (Regression 5). However, this is not the picture for the metro district municipalities (47 municipalities), because there is strong evidence that there is an inverted U-shape relationship between income per capita and income inequality (Regression 6). Hence, a rise in welfare for the relatively less-wealthy metropolitan areas increases income inequality, but a rise in welfare for the relatively more-wealthy metropolitan areas reduces inequality. **Table II-3** also shows that the positive association between income per capita and income inequality over 2012-2014 is more profound for the large and medium-size mainland (Regressions 9 and 10, respectively).

Table II-2. Regression results for inequality in declared income

	Sample ≥ 50	Sample ≥ 100	Sample ≥ 500	Sample ≥ 1,000	Sample ≥ 2,000	Sample ≥ 3,000	Sample ≥ 50 Weighted by population
Before crisis: 2002-2011	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Declared income pc	-1.1308***	-1.1139***	-0.8954***	-0.4264	0.0142	0.1548	-1.1888***
Declared income pc square	0.0384***	0.0388***	0.0294***	0.0155	-0.0012	-0.0037	0.0357***
Population density	-0.0022	-0.0010	-0.0010	0.0000	0.0017	0.0014	-0.0018
Mean number of kids	-2.0799*	-1.2282	0.0342	-1.7231	-2.9301	-2.9196	-1.6068
Mean number of cars	-1.2264	-1.5942	-3.9931**	-1.6395	0.6912	2.8546	-1.8056
Percentage of married	-2.7331	-1.2290	1.3377	1.0549	3.4207	4.1182	1.3186
Proprietors	base	base	base	base	base	base	base
Traders	-0.0353***	-0.0374***	-0.0317***	-0.0248***	-0.0185*	-0.0075	-0.0391***
Farmers	-0.0379***	-0.0395***	-0.0348***	-0.0296***	-0.0275***	-0.0137	-0.0423***
Employees	-0.0402***	-0.0409***	-0.0370***	-0.0319***	-0.0271***	-0.0137	-0.0449***
Self-Employed	-0.0401***	-0.0411***	-0.0358***	-0.0251***	-0.0214*	-0.0138	-0.0405***
Retired	-0.0466***	-0.0469***	-0.0417***	-0.0350***	-0.0352***	-0.0208*	-0.0496***
2002	base	base	base	base	base	base	base
2003	1.1565***	0.9308***	0.9328***	0.7951***	0.6012***	0.4855**	1.0070***
2004	2.6717***	2.5009***	2.3998***	2.0726***	1.8758***	1.8250***	2.5031***
2005	3.5452***	3.3865***	3.3290***	3.0558***	2.8290***	2.6276***	3.4250***
2006	2.4466***	2.2211***	2.4785***	2.1095***	1.8172***	1.5945***	2.5807***
2007	2.4821***	2.2804***	2.4574***	1.9097***	1.7290***	1.4154***	2.6493***
2008	2.3024***	2.0226***	2.3117***	1.7275***	1.5016***	1.2671*	2.5261***
2009	3.2260***	3.0987***	3.4056***	2.7239***	2.5782***	2.3130***	3.6005***
2010	4.0012***	3.8429***	4.3146***	3.6521***	3.5783***	3.1926***	4.4466***
2011	-2.0048***	-2.2278***	-2.0306***	-1.8424***	-0.9998	-0.8248	-1.3764***
FEs	yes	yes	yes	yes	yes	yes	yes
Constant	88.5941***	88.4459***	82.3959***	72.9154***	64.1328***	48.8299***	91.4403***
Municipalities	311	297	229	154	84	54	311
Observations	3,087	2,905	2,194	1,464	779	498	3,087
R-within	0.5412	0.5887	0.6439	0.6897	0.7607	0.7904	0.6553
Within crisis: 2012-2014	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Declared income pc	2.2980**	1.0445*	1.4339***	1.5829*	0.9249	2.0262**	1.5865***
Declared income pc square	-0.0242	0.0062	-0.0044	-0.0186	0.0011	-0.0710**	-0.0122
Population density	0.0070***	0.0052***	0.0043**	0.0034	0.0033*	0.0009	0.0039**
Mean number of kids	4.3853	7.7093***	5.5024**	11.5173***	4.7527	1.6235	3.8390*
Mean number of cars	1.3287	2.3237***	1.9526**	2.0231**	1.7959	1.6457	1.7546**
Percentage of married	-2.3518	-4.7010	-14.9986***	-20.4275***	-10.0259	-14.9558*	-7.4401*
Proprietors	base	base	base	base	base	base	base
Traders	-0.0516***	-0.0435***	-0.0388***	-0.0226*	-0.0157	-0.0184	-0.0403***
Farmers	-0.0436***	-0.0264**	-0.0139	-0.0130	-0.0252	-0.0103	-0.0329***
Employees	-0.0530***	-0.0456***	-0.0382***	-0.0315**	-0.0325**	-0.0374**	-0.0481***
Self-Employed	-0.0604***	-0.0437***	-0.0359**	-0.0046	-0.0098	0.0018	-0.0408***
Retired	-0.0585***	-0.0476***	-0.0373***	-0.0188	-0.0197	-0.0309*	-0.0454***
2012	base	base	base	base	base	base	base
2013	2.8674***	1.8813***	1.5649***	1.3131**	1.2350	1.0619	1.7491***
2014	3.3614***	2.5610***	1.8892***	1.8394***	2.0622**	2.1106	2.4114***
FEs	yes	yes	yes	yes	yes	yes	yes
Constant	66.2827***	65.0759***	60.7996***	48.4270***	51.4165***	57.1196***	64.7860***
Municipalities	311	297	229	154	84	54	311
Observations	924	868	648	421	220	129	924
R-within	0.5077	0.5713	0.6811	0.6982	0.8144	0.8810	0.6665

Note: *** p<0.01, ** p<0.05, * p<0.1

Table II-3. Regression results for inequality in declared income by municipality type

	Sample ≥ 50 Island: large & medium-size	Sample ≥ 50 Island: small	Sample ≥ 50 Mainland: large	Sample ≥ 50 Mainland: medium-size	Sample ≥ 50 Mainland: small & mountainous	Sample ≥ 50 Metro district
Before crisis: 2002-2011	(1)	(2)	(3)	(4)	(5)	(6)
Declared income pc	-3.2353*	-0.0634	-1.3654***	-2.1450***	-5.0872*	2.1780***
Declared income pc square	0.1679*	-0.0231	0.0651***	0.0781***	0.3343*	-0.0398***
Population density	0.7252	1.4786	-0.1732***	-0.3615	-4.4312**	0.0017
Mean number of kids	0.8756	-4.0420	-1.8955	-0.4275	-3.8703*	2.6756
Mean number of cars	-11.9180**	1.6196	-2.3719	-0.1920	4.4436	-2.3890
Percentage of married	-0.9341	-8.6127	-0.3711	-3.0122	-3.7938	-13.8329***
Proprietors	base	base	base	base	base	base
Traders	-0.0340*	-0.0184	-0.0121	-0.0321***	-0.0583***	-0.0043
Farmers	-0.0412**	-0.0184	-0.0195***	-0.0358***	-0.0550***	0.0089
Employees	-0.0424**	-0.0135	-0.0197***	-0.0382***	-0.0647***	-0.0244**
Self-Employed	-0.0426	-0.0177	-0.0137*	-0.0371***	-0.0655***	-0.0134
Retired	-0.0467**	-0.0257**	-0.0263***	-0.0437***	-0.0668***	-0.0277***
2002	base	base	base	base	base	base
2003	-0.0562	1.1600	0.8620***	1.5003***	2.2027**	1.1518***
2004	1.9092*	3.0649***	2.3320***	3.0438***	4.1477***	1.9295***
2005	2.2861**	3.6414**	3.3850***	4.0411***	5.4239***	2.2191***
2006	1.2721	3.5254***	2.3139***	2.9862***	3.0070***	1.1683**
2007	1.8942	2.0542**	2.0671***	3.2015***	3.5420***	0.6631
2008	1.6260	3.9213***	1.7761***	2.8210***	2.5215**	0.0309
2009	2.7067*	2.4013*	2.9041***	4.0430***	3.8421***	0.9498
2010	3.4757**	3.9228**	3.8197***	4.8621***	3.6433***	2.3677***
2011	-4.0669***	-0.4254	-1.9851***	-2.0654***	-2.8476**	-2.5261***
FEs	yes	yes	yes	yes	yes	yes
Constant	99.0511***	64.7290***	69.9360***	90.4505***	121.5848***	42.7155***
Municipalities	21	21	92	96	34	47
Observations	210	188	920	960	339	470
R-within	0.4392	0.3554	0.7093	0.6577	0.5731	0.7409
Within crisis: 2012-2014	(7)	(8)	(9)	(10)	(11)	(12)
Declared income pc	-0.4392	0.0053	1.6968*	1.5229*	-2.1727	-0.4375
Declared income pc square	0.1261	0.1392	0.0014	-0.0098	0.3863	0.0285
Population density	0.3671	-0.0615	0.1842***	0.6261***	4.0482	0.0003
Mean number of kids	-0.9438	-5.3132	7.0312*	3.4991	13.9997**	4.5078
Mean number of cars	1.1241	-6.1853	0.6730	1.2903	3.4774	3.2549*
Percentage of married	-0.8220	-4.6258	-24.8375***	-6.4546	-6.6187	-13.4496
Proprietors	base	base	base	base	base	base
Traders	-0.0386**	-0.0302	-0.0351***	-0.0497***	-0.0778**	-0.0066
Farmers	-0.0316	-0.0129	-0.0291**	-0.0376***	-0.0760**	-0.0055
Employees	-0.0279	-0.0312	-0.0378***	-0.0558***	-0.0916***	-0.0011
Self-Employed	-0.0444*	-0.0722	-0.0266	-0.0599***	-0.0894**	0.0192
Retired	-0.0537**	-0.0348	-0.0359***	-0.0629***	-0.0969***	0.0006
2012	base	base	base	base	base	base
2013	3.9172	7.4206***	2.0240***	2.2971***	2.1593	0.6655
2014	5.5733**	5.2037**	2.3445***	2.9569***	3.4577*	0.7980
FEs	yes	yes	yes	yes	yes	yes
Constant	66.7552***	59.3933*	62.4802***	76.5187***	108.4048**	41.3665*
Municipalities	21	20	92	96	34	47
Observations	62	55	276	288	102	141
R-within	0.8077	0.3914	0.7263	0.6829	0.5523	0.7660

Note: *** p<0.01, ** p<0.05, * p<0.1

The findings when the dependent variable is inequality in taxable income are similar to the findings when the dependent variable is inequality in declared income (see **Appendix Table A-II-5, Figure II-8, Table II-6**).⁶

Overall, there is strong evidence that the association between declared or taxable income per capita and inequality in declared or taxable income, respectively, differs between the period 2002-2011 and the period 2012-2014, as well as between the metro district municipalities and the other municipalities. Economic crisis and tax reforms highlight a ‘turning point’ for the geography on income inequality across Greek municipalities.

- For the period before the crisis, there is a U-shape relationship between (either declared or taxable) income per capita and income inequality for non-metro-district municipalities (i.e., islands and mainland). An increase in the income of non-metropolitan municipalities is likely to be associated with a decrease in income inequality within the municipality, but this negative association is lower as income (welfare) increases and then becomes positive for relatively rich municipalities. For the very high economic welfare municipalities, an increase in welfare may be linked with a rise in income inequality. In other words, the benefits of economic growth for a poor municipality (i.e. an increase in income per capita), as a result of lower taxes, are likely to trickled down gradually to all members of the municipality by raising low incomes and subsequently narrowing the income gap. However, this reduction in income inequality is lower as income increases, and for the rich, but non-metro-district, municipalities a further increase in wealth is linked with an increase in inequality.
- The picture for the metro-district municipalities is different, as the welfare-inequality relationship is an inverted U-shape, i.e., an increase in welfare for metropolitan areas increases inequality, but for the relatively rich urban areas, a welfare increase reduces inequality. These finding are robust to changing the definition of income inequality, but the welfare-inequality association is much stronger for taxable than for declared income distribution.
- For the period within the crisis, an increase (decrease) in either declared or taxable income per capita is associated with an increase (decrease) in income inequality, especially for the

⁶ Moreover, the findings are robust the measurement of income inequality. This is hardly surprising, because the Gini index is highly correlated with the other indices of measuring income inequality, such as the Theil index and the squared coefficient of variation.

large or medium-size mainland municipalities. However, further increases (decreases) in taxable income per capita are likely to reduce (increase) income inequality.

Summing up it could be said that there is a very specific type of income inequality in Greece which is determined by factors such as time (before and during the economic crisis), geography (type of Municipality), and level of wealth (per capita income). The combination of these factors provide different “Geographies of Inequality”. These findings are sketched and summarized in **Figure II-6**.

Figure II-6. Types of income inequality at the municipal level in Greece

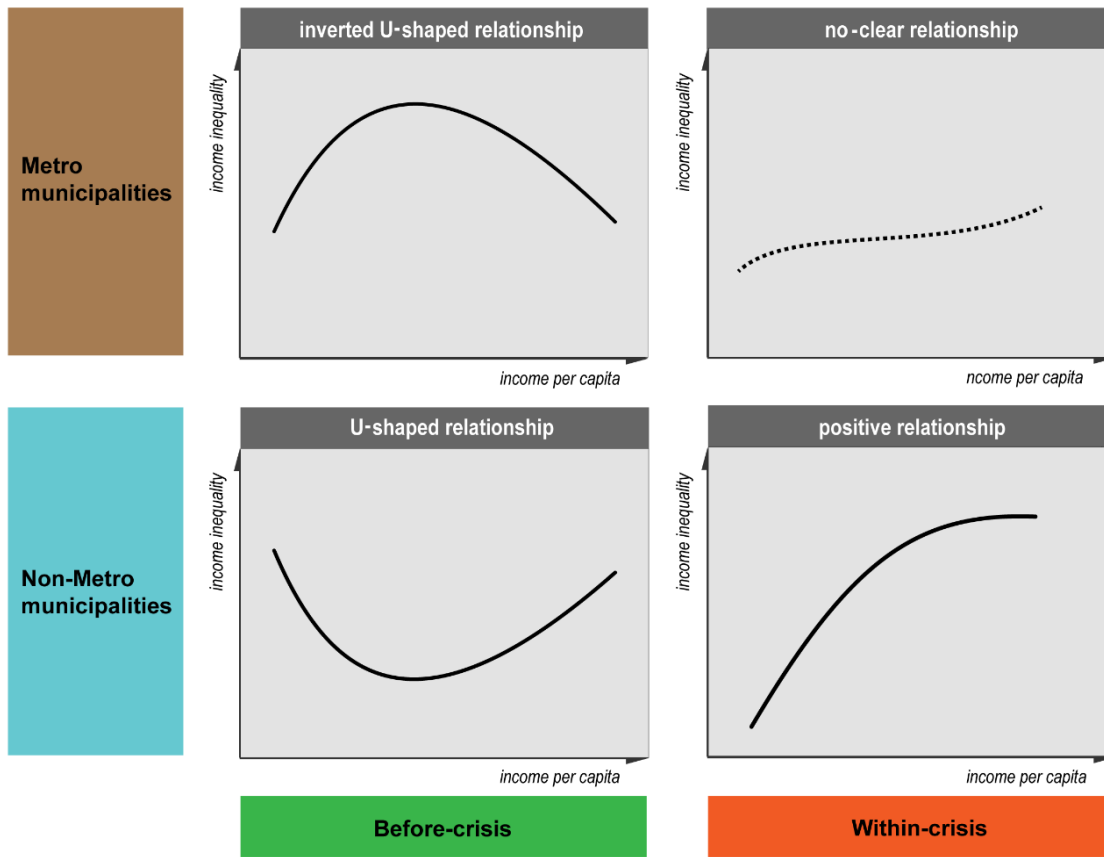


Fig. 5 provides a relationship between income per capita and income inequality for Metro and Non-metro municipalities before and during the economic crisis. Four types of correlation are evident (inverted U-turn relationship -Kuznets' like, U-shape relationship, linear and unclear).

II.7 Conclusions and discussion

The main goal of this paper has been to explore the evolution and relationship between income per capita and income inequality at municipal level in Greece before and during the economic crisis. Analysis has provided different ‘geographies of inequality’. Economic crisis signifies a ‘turning point’ in the geographies of inequality.

The obtained results are sensitive to time period of analysis (before and during the crisis), type of municipality (metropolitan, urban, large and medium and small mainland, and small and large islands), and income level (better-off and less well-off).

Regarding the evolution of income per capita, economic crisis and fiscal consolidation reforms dropped substantially income level across municipalities. However, the income drop had not been homogenous across municipalities. The geography of changes in income per capita across municipalities shows that mainland middle and small municipalities lost more while islands lost less. Within cities drop of income had been spatially uneven.

Regarding intraregional/interpersonal income inequality analysis provides evidence that economic crisis resulted in a decrease of interpersonal inequality at relatively less well-off municipalities and increase of interpersonal inequality in the relatively well-off municipalities of the country. Interpersonal income inequalities in cities and large agglomerations have been higher relative to the municipalities outside the urban areas. Economic crisis has increased income inequalities in cities and decreased income inequalities in rural areas.

Finally, the existence of a Kuznets inverted U-shaped relationship between income per capita and income inequality is not at all a case of ‘one size fits all’.

The association between income per capita and income inequality is in accordance with the predictions of Kuznets inverted U-turn for the cases of metro-municipalities before the economic crisis. However, analysis shows that there exists an U-turned relationship between income per capita and income inequality for the non-metro municipalities before the crisis.

Conversantly, economic crisis reveals a positive association of income per capital and income inequality for the relatively more well-off municipalities in cities and metropolitan areas.

These differentiated geographies of income per capital and income inequality call for different policy responses combining place-based along with people-centred policies in achieving territorially balanced and inclusive development for all the people.

This work offered some initial insights regarding the geographical dimension of income inequality in Greece. However, much work remains to be done. The geography of inequality constitutes a long range issue. Future research will built on a continuously updated, enriched and expanded database which could serve as a main source of analysis. Income inequalities in cities and large metropolitan areas and the association between income inequalities, voting patterns and political discontent are among the next trajectories of our research.

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Appendix

Figure A-II-7. Marginal effects for inequality in declare income

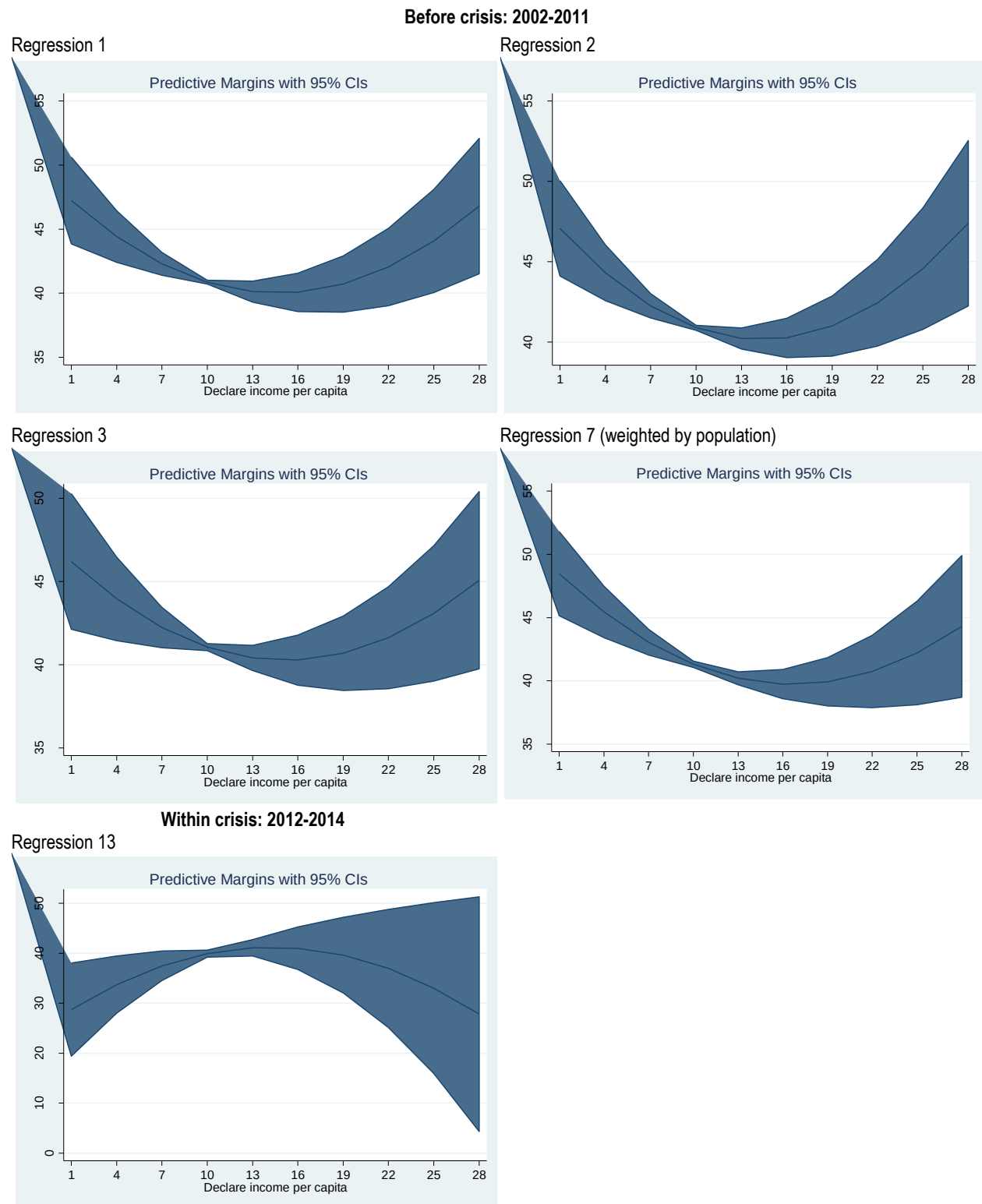


Table A-II-4. The linear association between declare income per capita and income inequality: 2012-2014

	Sample $\geq$ 50	Sample $\geq$ 100	Sample $\geq$ 500	Sample $\geq$ 1,000	Sample $\geq$ 2,000	Sample $\geq$ 3,000	Sample $\geq$ 50 Weighted by population
Within crisis: 2012-2014	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Declare income pc	1.7666***	1.1881***	1.3192***	1.0261***	0.9611***	0.3742	1.2824***
Population density	0.0080***	0.0050**	0.0044**	0.0035	0.0033**	0.0008	0.0041**
Mean number of kids	4.0256	7.8043***	5.4246**	11.4827***	4.7766	2.6536	3.7151
Mean number of cars	1.7466**	2.2034***	2.0301**	2.2885***	1.7902	2.8585	1.9704***
Percentage of married	-1.8723	-4.8456	-14.7220***	-18.7213***	-10.1443	-14.7884*	-6.8820*
Proprietors	base	base	base	base	base	base	base
Traders	-0.0520***	-0.0434***	-0.0389***	-0.0239**	-0.0157	-0.0208	-0.0406***
Farmers	-0.0448***	-0.0262**	-0.0142	-0.0150	-0.0252	-0.0120	-0.0339***
Employees	-0.0534***	-0.0456***	-0.0383***	-0.0318**	-0.0325**	-0.0417***	-0.0485***
Self-Employed	-0.0628***	-0.0432***	-0.0366***	-0.0105	-0.0094	-0.0197	-0.0431***
Retired	-0.0590***	-0.0475***	-0.0375***	-0.0200*	-0.0197	-0.0306*	-0.0458***
2012	base	base	base	base	base	base	base
2013	2.5692***	1.9701***	1.5011***	1.0274**	1.2493	-0.2620	1.5668***
2014	3.0708***	2.6478***	1.8303***	1.5435***	2.0759**	0.7070	2.2350***
FEs	yes	yes	yes	yes	yes	yes	yes
Constant	69.3819***	64.2740***	61.5255***	52.3617***	51.1274***	69.3048***	66.7926***
Municipalities	311	297	229	154	84	54	311
Observations	924	868	648	421	220	129	924
R-within	0.5059	0.5711	0.6810	0.6958	0.8144	0.8731	0.6659

Note: *** p<0.01, ** p<0.05, * p<0.1

Table A-II-5.Econometric analysis for Taxable income. Regression results for inequality

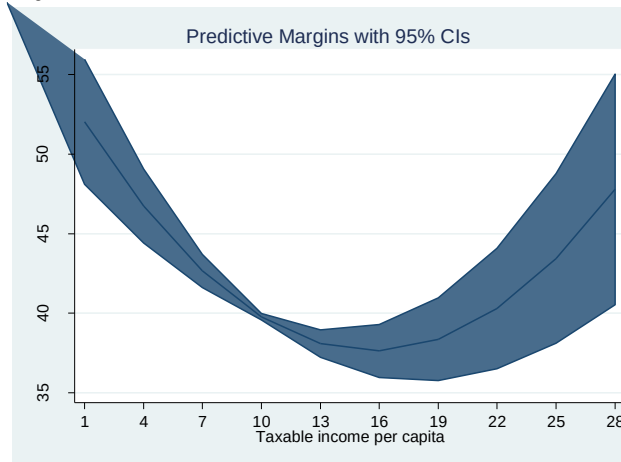
	Sample ≥ 50	Sample ≥ 100	Sample ≥ 500	Sample ≥ 1,000	Sample ≥ 2,000	Sample ≥ 3,000	Sample ≥ 50 Weighted by population
Before crisis: 2002-2011	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Taxable income pc	-2.0982***	-2.1194***	-2.2603***	-2.0214***	-1.5733***	-1.6825**	-2.5947***
Taxable income pc square	0.0669***	0.0663***	0.0614***	0.0502***	0.0336**	0.0353	0.0705***
Population density	-0.0059*	-0.0051	-0.0044	-0.0016	0.0011	0.0022	-0.0052
Mean number of kids	-1.9705*	-1.3797	-0.8665	-3.2235*	-4.4870	-4.3318	-2.2777*
Mean number of cars	-1.1988	-1.4278	-3.3045*	0.6591	3.5210	6.9389*	-0.6996
Percentage of married	-2.7578	-0.2583	1.3186	0.7427	1.2605	0.4292	1.6623
Proprietors	base	base	base	base	base	base	base
Traders	-0.0336***	-0.0336***	-0.0269***	-0.0212**	-0.0123	0.0014	-0.0351***
Farmers	-0.0372***	-0.0366***	-0.0332***	-0.0284***	-0.0227**	-0.0072	-0.0399***
Employees	-0.0379***	-0.0369***	-0.0346***	-0.0301***	-0.0205**	-0.0058	-0.0414***
Self-Employed	-0.0388***	-0.0383***	-0.0322***	-0.0246***	-0.0150	-0.0055	-0.0364***
Retired	-0.0441***	-0.0422***	-0.0383***	-0.0327***	-0.0308***	-0.0143	-0.0460***
2002	base	base	base	base	base	base	base
2003	0.9545***	0.8142***	0.9762***	0.8525***	0.6672***	0.5735**	1.0373***
2004	3.8875***	3.8127***	3.7937***	3.4570***	3.1752***	3.0929***	3.8085***
2005	4.7673***	4.7191***	4.7648***	4.5024***	4.1829***	3.9592***	4.7899***
2006	3.8440***	3.7560***	4.2282***	3.8254***	3.4380***	3.1837***	4.2074***
2007	3.9693***	3.9264***	4.3464***	3.7905***	3.4830***	3.1345***	4.4134***
2008	3.9456***	3.8565***	4.4627***	3.9014***	3.5048***	3.2362***	4.5340***
2009	4.8831***	4.9359***	5.5628***	4.8834***	4.5335***	4.2277***	5.6004***
2010	5.6581***	5.6818***	6.4693***	5.7709***	5.6035***	5.1986***	6.4525***
2011	-2.7789***	-2.7203***	-1.8799***	-1.1764*	-0.0775	0.3961	-1.1229***
FEs	yes	yes	yes	yes	yes	yes	yes
Constant	91.7498***	89.6194***	88.4021***	81.8037***	70.5751***	55.5352***	97.1297***
Municipalities	311	297	229	154	84	54	311
Observations	3,087	2,905	2,194	1,464	779	498	3,087
R-within	0.7037	0.7403	0.7795	0.8061	0.8480	0.8644	0.7857
Within crisis: 2012-2014	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Taxable income pc	4.2627***	2.8739***	2.4858***	2.2791***	1.7328***	2.9839***	2.7026***
Taxable income pc square	-0.0842***	-0.0491***	-0.0375***	-0.0380**	-0.0182	-0.0837***	-0.0460***
Population density	0.0085***	0.0067***	0.0053***	0.0042*	0.0030	0.0029	0.0051***
Mean number of kids	3.5327*	5.1653**	6.0919**	11.4399***	2.8060	-0.0133	3.6865*
Mean number of cars	1.1508	2.3384***	2.5511***	2.1236**	1.7980	3.0138	1.9424***
Percentage of married	-5.3490	-7.2734**	-15.9419***	-17.9427**	-10.3006	-17.5612**	-8.3071**
Proprietors	base	base	base	base	base	base	base
Traders	-0.0425***	-0.0364***	-0.0320***	-0.0195*	-0.0144	-0.0083	-0.0313***
Farmers	-0.0365***	-0.0222**	-0.0137*	-0.0134	-0.0277	-0.0119	-0.0291***
Employees	-0.0372***	-0.0321***	-0.0248***	-0.0198*	-0.0260**	-0.0239*	-0.0330***
Self-Employed	-0.0346***	-0.0254**	-0.0177	-0.0016	-0.0078	0.0069	-0.0232***
Retired	-0.0375***	-0.0308***	-0.0196**	-0.0059	-0.0100	-0.0144	-0.0269***
2012	base	base	base	base	base	base	base
2013	1.6443**	0.5465	-0.1112	0.0812	0.0427	-0.7131	0.4598
2014	2.5874***	1.5795***	0.6560	0.9100*	1.1244	0.5938	1.5152***
FEs	yes	yes	yes	yes	yes	yes	yes
Constant	34.0563***	37.6843***	36.5544***	28.5079***	36.3590***	33.7498**	38.7799***
Municipalities	311	297	229	154	84	54	311
Observations	924	868	648	421	220	129	924
R-within	0.4922	0.4714	0.5675	0.5716	0.7319	0.8233	0.5566

Nore: *** p<0.01, ** p<0.05, * p<0.1

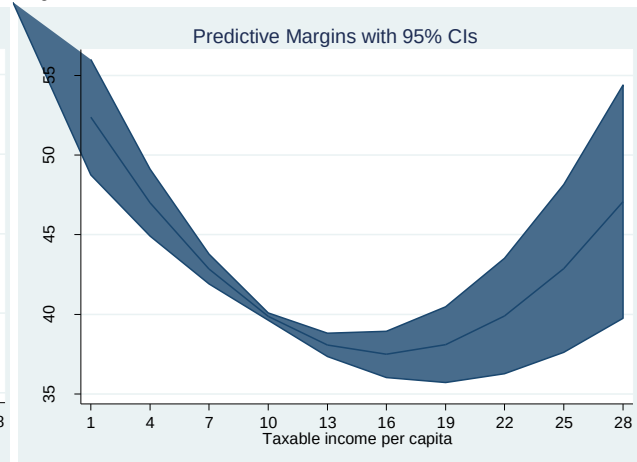
Figure II-8. Econometric analysis for Taxable income. Marginal effects for inequality

Before crisis: 2002-2011

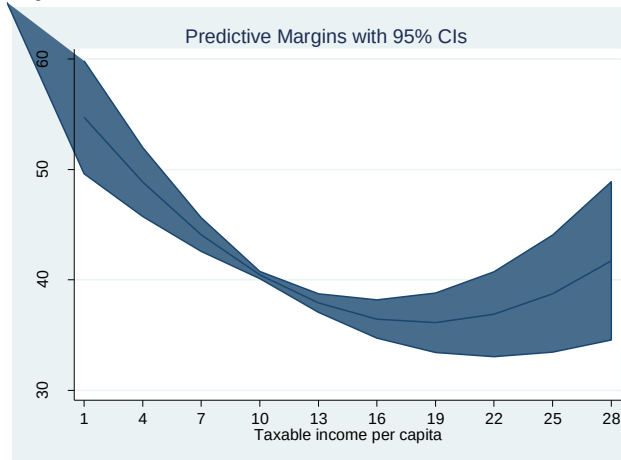
Regression 1



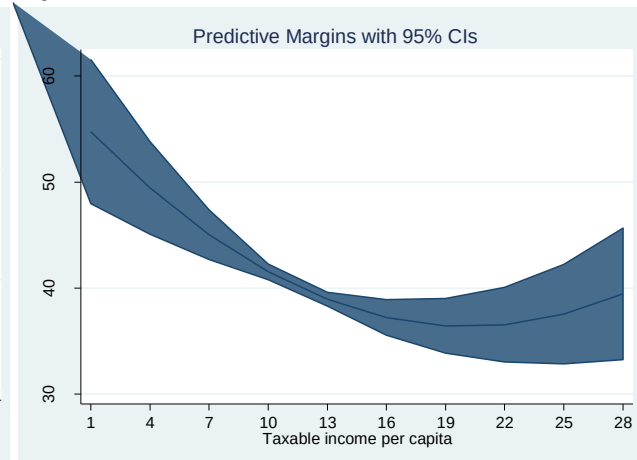
Regression 2



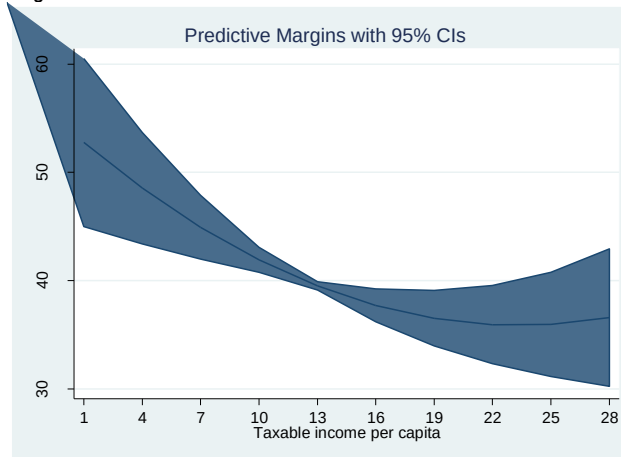
Regression 3



Regression 4



Regression 5



Regression 7 (weighted by population)

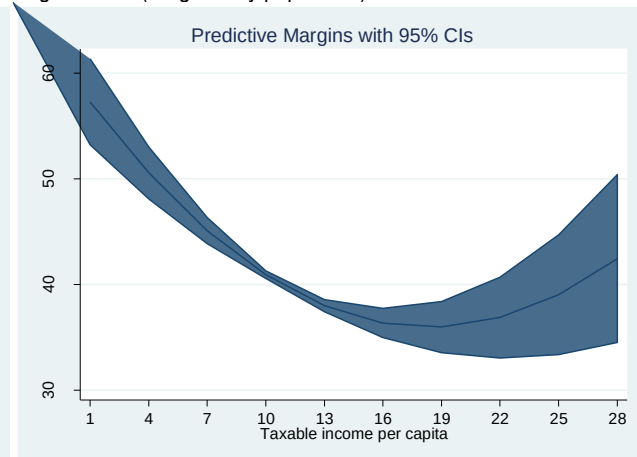
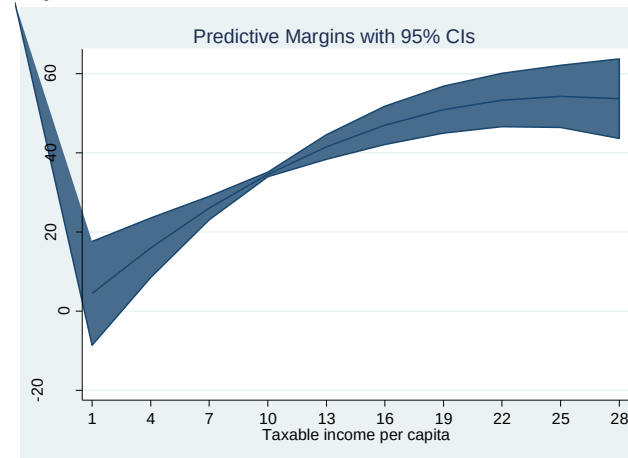


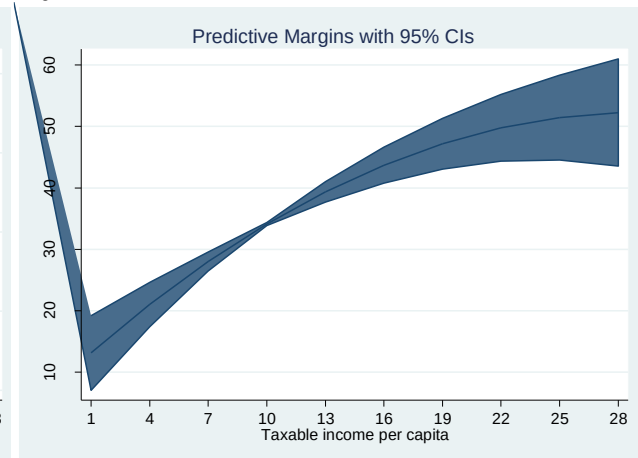
Figure II-2. (Continued) Econometric analysis for Taxable income. Marginal effects for inequality

Before crisis: 2002-2011

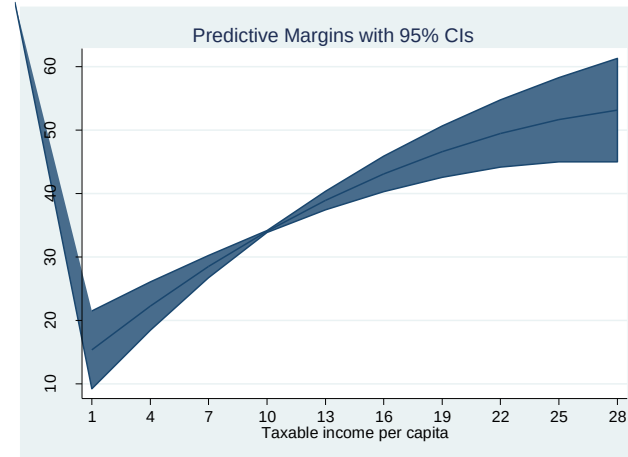
Regression 8



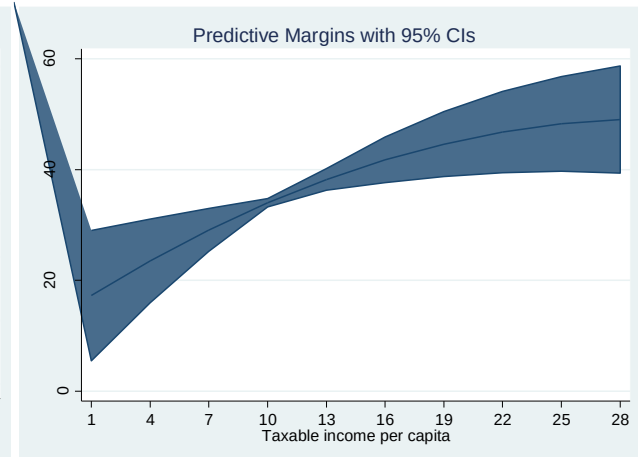
Regression 9



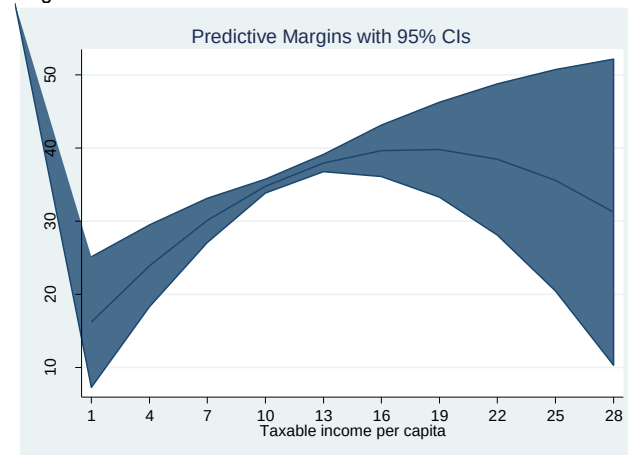
Regression 10



Regression 11



Regression13



Regression 14 (weighted by population)

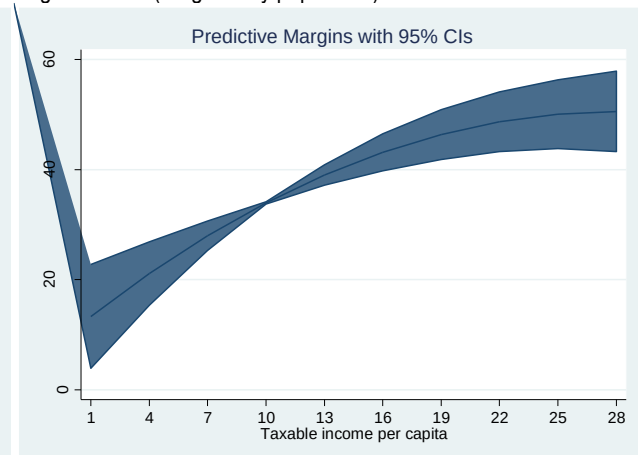


Table II-6. Econometric analysis for Taxable income. Regression results for inequality by municipality type

	Sample ≥ 50 Island: large & medium- size	Sample ≥ 50 Island: small	Sample ≥ 50 Mainland: large	Sample ≥ 50 Mainland: medium-size	Sample ≥ 50 Mainland: small & mountainous	Sample ≥ 50 Metro district
Before crisis: 2002-2011	(1)	(2)	(3)	(4)	(5)	(6)
Taxable income pc	-4.7687**	-0.6616	-2.6278***	-3.6966***	-6.1420**	1.9070***
Taxable income pc square	0.2375**	0.0009	0.1019***	0.1397***	0.3977**	-0.0349***
Population density	0.8030*	1.2342	-0.2206***	-0.7435***	-4.5668**	0.0018
Mean number of kids	-0.0559	-3.6527	-2.4173	-1.4488	-2.3645	0.6195
Mean number of cars	-12.1773**	1.1732	-1.9630	-0.1907	3.0650	0.6891
Percentage of married	-2.2508	-10.0341	-0.5094	-1.9355	-4.7866	-14.8840***
Proprietors	base	base	base	base	base	base
Traders	-0.0317*	-0.0196*	-0.0081	-0.0248***	-0.0554***	-0.0006
Farmers	-0.0367*	-0.0205	-0.0177**	-0.0303***	-0.0529***	0.0179
Employees	-0.0395**	-0.0143	-0.0176**	-0.0306***	-0.0607***	-0.0182*
Self-Employed	-0.0463*	-0.0224*	-0.0144*	-0.0280***	-0.0609***	-0.0078
Retired	-0.0431*	-0.0260**	-0.0237***	-0.0377***	-0.0622***	-0.0208**
2002	base	base	base	base	base	base
2003	-0.1508	0.5870	0.8502***	1.5016***	1.4804*	1.1017***
2004	3.2982***	3.6448***	3.8918***	4.5267***	5.0540***	3.1816***
2005	3.5364***	4.1713***	4.9809***	5.5597***	6.3181***	3.3919***
2006	2.7025**	4.1044***	4.0913***	4.7664***	3.8813***	2.3610***
2007	3.1521**	2.5327**	3.9891***	5.0567***	4.5419***	1.8172***
2008	2.9608*	4.6497***	3.8845***	4.8603***	3.5372***	1.1939
2009	4.1357**	3.1577**	5.0420***	6.0998***	4.8823***	2.1226***
2010	4.9388***	4.5012***	5.9466***	6.9135***	4.6674***	3.5423***
2011	-5.4865***	-1.8860	-2.2870***	-2.7096***	-6.3937***	-2.3486***
FEs	yes	yes	yes	yes	yes	yes
Constant	103.7684***	69.6022***	75.0189***	90.9513***	121.6499***	37.2560***
Municipalities	21	21	92	96	34	47
Observations	210	188	920	960	339	470
R-within	0.6422	0.4707	0.8413	0.8006	0.7213	0.8356
Within crisis: 2012-2014	(7)	(8)	(9)	(10)	(11)	(12)
Taxable income pc	-0.7803	7.1309*	2.9302***	2.6077*	9.0600	0.3460
Taxable income pc square	0.1443	-0.1628	-0.0408	-0.0593	-0.2438	0.0083
Population density	0.7278**	0.6233	0.1494***	0.8230***	0.1131	0.0002
Mean number of kids	-1.8141	1.7077	8.8144**	2.9600	9.5995*	4.1298
Mean number of cars	-1.5038	-2.1887	0.5590	0.2888	-3.1410	3.8271**
Percentage of married	0.6482	-6.0726	-24.0255***	-7.5615*	-10.7061	-15.2648
Proprietors	base	base	base	base	base	base
Traders	-0.0340*	-0.0362*	-0.0343***	-0.0301**	-0.0695**	-0.0048
Farmers	-0.0275	-0.0195	-0.0272**	-0.0262**	-0.0623**	0.0187
Employees	-0.0302	-0.0232	-0.0270***	-0.0301***	-0.0685***	0.0068
Self-Employed	-0.0106	-0.0358	-0.0237	-0.0241	-0.0843***	0.0213
Retired	-0.0480**	-0.0236	-0.0238**	-0.0374***	-0.0690**	0.0117
2012	base	base	base	base	base	base
2013	3.7338	4.9625**	0.9303*	1.4958*	3.7091	-0.8123
2014	5.7043**	4.4997**	1.6155***	2.6705***	4.5333**	-0.5149
FEs	yes	yes	yes	yes	yes	yes
Constant	57.9949**	3.8932	39.8905***	43.4990***	38.6479	25.9962
Municipalities	21	20	92	96	34	47
Observations	62	55	276	288	102	141
R-within	0.7496	0.5916	0.6484	0.5296	0.6580	0.6570

Chapter III

The geographical dimension of income inequality: empirical evidence from the Greek municipalities

The aim of this chapter is to explore the geographical pattern of income per capita and income inequality at the municipal level in Greece before and during the economic crisis. Analysis is based on a 10 percent sample of annual income declarations over the period 2002-2014. Results show that geography plays a critical role in shaping wealth and income inequalities across the country. Education constitutes the key determinant of income per capita and income inequality. With regards to policy implications, more place-based and inclusive policies are necessary for social and economic welfare and prosperity across localities.

Additional information

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Disclaimer

This paper, co-authored with Yannis Psycharis (Professor – Department of Economics and Regional Development, Panteion University) and Vassilis Tselios (Associate Professor – Department of Economics and Regional Development, Panteion University), is currently under review at Journal *Regional Studies*.

III.1 Introduction

If an economist were asked to summarise in one word what constitutes the main economic problem of our times, the most probable answer someone would get is growing *inequality*. Income inequality has risen to historically unprecedented levels. Academics and international organizations are aware of the significance of this issue.

Indeed, Robert Shiller, recipient of the Nobel Memorial Prize in Economics (2013), declared that the most important problem we are facing today is rising inequality. The inequality of the top 1 per cent has reached historically unprecedented levels. Joseph Stiglitz, Nobel Prize-winning economist (2001) documents the rising income inequality in the USA between the upper 1 per cent of the top earners vis-à-vis all other income groups (Stiglitz, 2012). Dorling (2015b) documents the recent trends in accumulation of wealth for the upper 1 per cent income earners in the UK.

Income inequality in the OECD countries is at its highest level of the past half century; the average income of the richest 10 per cent of the population is about nine times that of the poorest 10 per cent. This same figure was seven times, 25 years ago (OECD, 2019). Furthermore, the 2008 economic crisis has intensified inequality as income is significantly more unequally distributed today than it was before the economic crisis (OECD, 2014). Reducing inequalities is among the policy priorities of the 2030 Agenda for Sustainable Development (UN, 2015). Inclusive and sustainable development constitute one of the priorities of the EU cohesion policy (EC, 2014). An IMF report claims that widening income inequality is regarded as the defining challenge of our time (IMF, 2015).

These observations, along with the empirical evidence that inequality matters for the economic performance of nations and for the wellbeing and prosperity of citizens and territories, has placed the issue at the core of scientific investigation (Piketty and Saez, 2003; Atkinson and Piketty, 2010; Atkinson *et al.*, 2011; Bourguignon, 2015). Given the intensity and the consequences of income inequality for economic development and social wellbeing, tackling income inequality has been placed at the forefront of academic discussions and political practices (Atkinson, 2015; OECD 2015; Dijkstra *et al.*, 2019; Rodríguez-Pose, 2018).

Although income inequality has been a longstanding issue in economics (Kuznets, 1955), this renewed attention is arguably, at least in large part, attributable to the work of Atkinson (1997) who brought this issue ‘in from the cold’. Furthermore, the works of Piketty (2014) gave further impetus and triggered a voluminous number of publications providing insights from different countries across the globe. Cavanaugh and Breau (2018) show that the rate of increase in papers

on inequality was more than twice as fast as and greater than several other major research themes in the social sciences.

However, while income inequality reflects the prosperity and welfare conditions that prevail in an economy over a certain period of time, the geography of inequality provides additional evidence on the variations in wealth and the wellbeing of people within a country across space (Wei, 2015).

The aim of this paper is to contribute to the geographical aspects of the income inequality literature by providing empirical evidence from Greece. More precisely the aim of this paper is to identify different geographies of wealth and inequality across space and to highlight the changing geographies of wealth and inequality before and during the economic crisis in Greece. The analysis is based on a purpose constructed database which includes official household tax data over the period 2002-2014. The results are anticipated to provide important insights and to enrich the dialogue and understanding regarding the role of geography in shaping wealth and income inequality. The analysis will also provide important messages for policy formulation at the national and international level. These results could offer important contributions to the formulation of the EU cohesion policy as well as to the recovery policies aimed at addressing the economic impacts of COVID-19 pandemic.

The analysis that has been conducted with this work has important merits.

First, the analysis is based on individual household data that were extracted under specific license from the Greek Ministry of Finance. In total 7.5 million observations have been used for the analysis. Individual data allow the estimation of Gini coefficient for inequality.

Second, the analysis places explicitly specific emphasis on the role of geography by utilizing different sub-divisions of the geographical space. These include: the geographical sub-groups of the Greek municipalities; the classification of space according to the altitude; the divisions of space based on the degree of urbanization; and the land use geographical sub-divisions based on CORINE landcover.

Third, the analysis extends over a long time period, one of the lengthiest ever studied in the literature. This provides the opportunity to examine the impact on welfare and prosperity across space of the economic crisis, the austerity policy and the fiscal consolidation reforms that were implemented in the country following the economic and fiscal crisis. These findings are anticipated to contribute to the reformulation of policies in of post 2020 and post COVID-19 time period.

Despite the above mentioned virtues, this dataset has some important limitations. The variable “declared income” captures the income received by households during the preceding calendar

year which are submitted to tax authorities with the tax declarations in the following year. This data includes income that is submitted by six categories of taxpayers: Proprietors; *Traders (Merchants and Craftsmen)*; *Farmers*; *Employees*; *Self-Employed*; and *Retired*. However, this data cannot capture types of income such as fiscal transfers to individuals or places. In addition, it does not include income from shadow/hidden economy, a chronic problem for the Greek economy (IOBE, 2018). Although ‘taxable’ income, which is included in the dataset complements the information regarding declared income, this dataset still cannot unveil the real conditions of wealth and inequality in the country.

Contrary to these limitations, the quality, consistency, length and accuracy of the data provide well-grounded conditions to analyse the spatio-temporal evolution of income and income inequality focusing on the role of geography. Tax data offer the advantage that they refer to registered incomes and tax incidences and are usually considered more suitable for the estimation of short-term changes in inequality (Piketty, 2014).

This paper proceeds as follows. Section 2 provides a synoptic overview of the literature regarding the geographical aspects and empirical studies on income inequality. Section 3 goes on to analyse and portray temporal and geographical issues of income inequality in Greece. Section 4 proceeds with the presentation of the econometric model. Section 5 presents and discusses the findings from the econometric analysis. Section 6 concludes and discusses the policy implication and sketches the framework for the future extension of this work.

III.2 Geographical aspects of Income distribution

Inequality has become the new nexus of flourishing scientific research in recent decades. The empirical evidence of increasing inequality along with the awareness that inequality is accompanied by growing social, economic and welfare impacts has placed this issue at the core of scientific investigation and political debate in most countries across the globe.

However, income and income inequality has a geographical component. Local-level income inequality is likely to be different from national-level income inequality, as it neither responds to the same factors, nor creates the same policy implications (Glaeser *et al.*, 2009). The geographical component of income inequality broadens and enriches the understanding of inequality and brings new dilemmas and challenges for theory, policy and practice. The geographical dimension of income inequality has become a flourishing and rapidly accelerating body of scientific research in recent decades (Cavanaugh and Breau 2018; Wei 2015).

The results of the empirical analysis in the literature are influenced by the geographical level of analysis, the type of data that are available and the time period of the analysis.

The spatial analysis of income inequality has paid specific attention to the urban context. There seems to be a convergence in the literature that higher income and income inequalities exist in urban areas relative to the non-urban or rural areas.

The OECD (2018) provides an assessment of spatial inequalities and segregation in cities and provides new insights regarding inequalities in cities such as the patterns of segregation across income groups, migrant concentration and diversity across cities of different sizes. These trends could be met in many empirical studies. In a comparative study of cities in 12 countries, Veneri et al (2020) show considerable variation in the levels of income segregation across cities, even within countries, reflecting the diversity within urban systems. Larger, more affluent, productive, and more unequal cities tend to be more segregated.

Florida and Mellander (2016) examined the geographic variation in wage and income inequality across US metropolitan areas and found that these variables follow two different types of inequality which are loosely related to each other and are subject to different determinants. Kane and Hipp (2019) find that income inequality in Superstar cities with high-paying creative-class jobs, venture capital, and innovation are thought to be more unequal. Morrill's (2000) examines geographic variation across the states in income inequality from 1970 to 1990 for family and for non-family households and finds that richer and larger metropolitan states, which had less inequality in 1970, became far more unequal, while many less metropolitan, poorer states in 1970, changed less. Bolton and Breau (2011) investigate changes in the distribution of earnings across 87 metropolitan areas in Canada using micro data taken from the 20 per cent long-form sample of the census for the years 1996, 2001 and 2006. Results point to overall increases in urban inequality and to greater heterogeneity in inequality across the urban hierarchy, with larger cities growing particularly unequal over time. Breau (2015) offers an analysis of rising levels of income inequality in Canadian provinces highlighting that the labor market conditions along with socio-demographic and institutional variables are key factors in explaining differences in regional inequality. Breau *et al.*, (2018) analyse the spatial evolution of neighbourhood income disparities across Canada's largest metropolitan areas and found increasing spatial polarization (or divergence) between higher- and lower-income neighbourhoods.

Lee *et al.* (2015) analyse the wage inequality of UK cities. They utilize the 1 per cent sample of employee data of the Annual Survey of Hours and Earnings which include only employee wages. Results highlight that metropolitan areas and large cities are more unequal. Skills have been found to exert prominent influence and act as a driver of income inequality. Dickey (2001, 2007) are among scholars who have studied earnings inequality in the UK. Data on average regional earnings point to a worsening of U.K. regional inequalities and a rise in the North-

South gap. Hortas-Rico and Rios (2019) study the drivers of local income inequality in Spain by utilizing a novel data set of inequality metrics for a sample of Spanish municipalities over the period 2000–06. The Gini index across Spanish municipalities exhibits considerable spatial variation, ranging from a low of 0.25 to a high of 0.60 which is obviously more than double. Dorling (2015a) has made a comparative investigation of income inequality. This paper concentrates on the richest 1% of households in the UK in a comparison with the other four large Western European countries: Germany, France, Italy and Spain. In the European context, the UK is an outlier of extreme inequality. Rey (2018) analyses interregional inequality patterns across US states from 1929–2012 using exploratory space–time methods and finds that local hot and cold spots are found for the per capita income series, while local spatial outliers are found for state interpersonal inequality.

The industry mix constitutes an important factor in shaping income inequality in Canadian provinces. Marchand, Dubé and Breau (2020) find that the industrial mix of a region plays an important role in shaping its distribution of income: regions with high concentrations of manufacturing activities typically have lower levels of inequality, whereas regions with high concentrations of tertiary services, arts, and entertainment, as well as knowledge-intensive business services tend to have higher levels of inequality. There is another strand that explicitly examines the role of rurality in shaping income inequality. Rodríguez-Pose and Hardy (2015) analyze the range of rural development approaches implemented in recent decades and develop a picture in which territorial approaches have become more mainstream.

Some empirical studies have focused on the municipal level. Mastronardi and Cavallo (2020) highlight the influence of the spatial dimension on income inequality in Italy. Inequality appears to be greater in densely populated urban centers with a strong incidence of tertiary activities and young population. Conversely, in the inner areas, the distribution of income is more balanced due probably to the weakness of the social and economic structure that determines low levels of income and job opportunities mainly in the agricultural sector. Moser and Schnetzer (2017) utilize a novel database with individual wage tax data in order to analyse the spatial association of the relationship between income level and income per capita in Austrian Municipalities. They show that spatial patterns of inequality are particularly distinct in urban areas. The Gini inequality index is between 0.3 and 0.4.

Another convergence in the literature is related with the role of education in shaping income inequalities. Both at the EU level (Rodríguez-Pose and Tselios, 2009) and in individual countries (Glaser et. al., 2009; Duranton and Monastiriotis, 2002) education seems to have been the key determinant in income inequality.

As regards Greece there is a limited number of studies that examine the geographical dimension of income inequality. These include: Kalogirou (2011); Psycharis and Pantazis (2016); and Prodromidis (2008). However, to the best of our knowledge the present paper is a first attempt to analyse the geographical dimension of income inequality with household income data for such diverse geographical sub-sets over a lengthy time-period.

III.3 Income distribution in Greece

III.3.1 Data

This paper is based on a purpose-constructed dataset which includes individual tax data along with socioeconomic, demographic and geographical variables.

One of the virtues of this dataset is the quality, consistency and accuracy of the data which extend over one of the lengthiest time periods that have been analysed in the literature. Analysis is based on micro-data for 10 per cent of the annual household declarations for the time period 2002-2015. In total, 7.5 million individual observations are included in the analysis with information regarding declared and taxable income with important attributes of households as well as tax incidence. In the Greek taxation system, the variable ‘declared income’ captures the income received by households during the preceding calendar year which is submitted to tax authorities with the tax declarations in the following year.

Based on the main source of income these declarations are grouped into six main categories: *Proprietors; Traders* (Merchants and Craftsmen); *Farmers; Employees; Self-Employed; and Pensioners*. In addition, this dataset includes information regarding households’ attributes. These include the marital status and age of the submitters, family size, number of children, single parent families, number of cars and car cubism. It also provides information about the tax incidence

There are two variables for income that are used in this analysis: declared; and taxable. The former is based on the gross income that has been generated from many sources. The latter is the income on which the tax incidence is based/estimated. Taxable income is estimated using declared income, however, it could be augmented, based on ‘objective criteria’ that have been applied in order to estimate the real wealth that is subject to tax. This taxable income could also be lower than the declared income if there apply specific tax exemptions. On the contrary, taxable income could be higher than declared income based on imputed income estimations.

Furthermore, based on declared individual and household income, the equivalised/equivalent individual income has been estimated⁷. The equivalent individual income is personal income that takes into consideration the family income and specific attributes of the household and the individual.

The geographical scale of the analysis is primarily the 325 Greek municipalities. According to the existing administrative system, the 325 Municipalities constitute the first tier of local government in Greece (Law 3852/2010). Furthermore, according to Law 4555/2018, the Greek Municipalities have been grouped into six categories based on population and geographical characteristics: Municipalities belonging to Metropolitan areas; large Mainland Municipalities and Capitals of Counties; Mainland-medium-sized Municipalities; Small Mainland and Small Mountainous Municipalities; Large and Medium Island Municipalities; and Small Island Municipalities. This categorization of Municipalities has also been utilized for the analysis.

The geographical scale has been approached through some other geographical categorisations. In order to analyse different geographical dimensions of wealth and income inequality, this paper utilizes the CORINE landcover and provides information about different geographical units. The level of urbanization constitutes another way of approaching and analyzing the geographical space. Finally, the geophysical characteristics of space constitute further way of approaching and analyzing the geographical landscape. These different approaches to geographical space are important, given the much diversified geography of Greece.

Finally, the database includes a large array of variables that have been selected from a broad spectrum of data sources. This data include demographic variables (such as population), socio-economic variables (such as employment and unemployment), and human capital variables (such as level of education) for the Greek municipalities.

III.3.2 Economic and fiscal crisis and Greek reforms: temporal patterns

The Great Recession that began in 2008 had a tremendous impact on the Greek economy which experienced the most severe drop in economic activity since the end of the World War II. The Greek economy experienced a total drop in GDP by 25 per cent and an increase in unemployment which reached 27 per cent of the labour force. The economic downturn was accompanied by increasing fiscal imbalances. The fiscal deficit of the country in 2010

⁷ Equivalised declared (taxable) income: is the total income of a tax declaration, divided by the number of household members converted into equivalised adults; household members are equivalised or made equivalent by the following so-called modified OECD (Organisation for Economic Co-operation and Development) equivalence scale: the first household “adult” member counts as 1 person, the other adult household members count as 0.5 person, each household member indicated as “child” aged 14 years or more counts as 0.5 person, each household member indicated as “child” aged 13 years or less counts as 0.3 person.

amounted to 15 per cent of GDP while the public debt reached the 146 per cent of GDP. The simultaneous incidence of economic crisis and fiscal imbalance placed the country on the verge of bankruptcy. Following these trends the Greek government signed with the EU, the European Central Bank and the IMF, three consecutive bailout programs⁸ were accompanied and accompanied by the implementation of strict fiscal measures and austerity policy. These policies deepened the economic recession even further and resulted an additional tax burden on households.

The majority of tax reforms that were implemented in Greece following the economic and fiscal crisis were related to reforms in personal income tax. The main purpose of these reforms was a broadening of the tax base and increase in tax revenue (Karavitis, 2013; Karfakis, 2013).

Figure III-1 presents the evolution and the composition of tax declarations and personal income tax by category of taxpayers in Greece allowing comparisons before and during the economic crisis and the implementation of fiscal reforms.

Figure III-1 shows that the number of declarations after 2010 increased significantly. This is the result of the broadening of the tax base for households that were obligated to submit declarations along with the obligation for each individual above 18 years to submit income declaration. Despite the broadening of the number of tax declarations, the total revenue from income tax decreased substantially after 2010. Between 2008 and 2014, the revenue from personal income tax dropped by 24 per cent (EC, 2016). The increase in tax rate scales and the broadening of the tax base during the recession resulted in an outcome opposite to that expected in terms of revenue collection. Fiscal consolidation and austerity policy were attempted with ‘detrimental effects on economic activity, growth and finally on tax revenues’ (Tatsos, 2016: 29). By exerting additional recessionary pressures on the economy, the reforms failed to attain the revenue increase and made the distribution of the tax burden more uneven (Giannitsis and Zografakis, 2015).

Figure III-1 shows that income inequality during this period also dropped. This is more pronounced in the case of taxable than in the case of declared income. This drop in declared income inequality could be attributed to the broadening of the tax base and the widespread obligation to make a tax declaration. Part of the explanation could also be the drop in high incomes due to the increased tax rate scales, the imposition of the solidarity tax and the cuts in salaries for the high income earners. This situation could be considered as the outcome of the

⁸ The First Economic Adjustment Programme for Greece, ‘the first memorandum’, was signed in 2010 by the Greek Government, the European Commission and the International Monetary Fund (IMF), The Second Economic Adjustment Programme for Greece, ‘the second memorandum’, was signed in 2012. The Third Memorandum signed in 2015 is outside the time frame of the analysis in this paper.

fiscal adjustment program that was implemented in the country following the First Economic Adjustment Programme for Greece that began in 2010. The lessening of declared income inequality is the outcome of a simultaneous drop in incomes due to unemployment and wage cuts and the increase in the tax burden, especially among the low income tax payers who constitute the vast majority of tax payers in Greece. This outcome questions the fairness, the inclusiveness and the effectiveness of the fiscal reforms imposed in times of economic recession. The geography of these changes is portrayed in **Figure III-2** and **Figure III-3**.

The brighter colors before the crisis show high levels of income and income inequality. The fading colors during the crisis show the drop in incomes and inequality across most geographical areas.

Figure III-1. Evolution of declared and taxable income per capita and income inequality

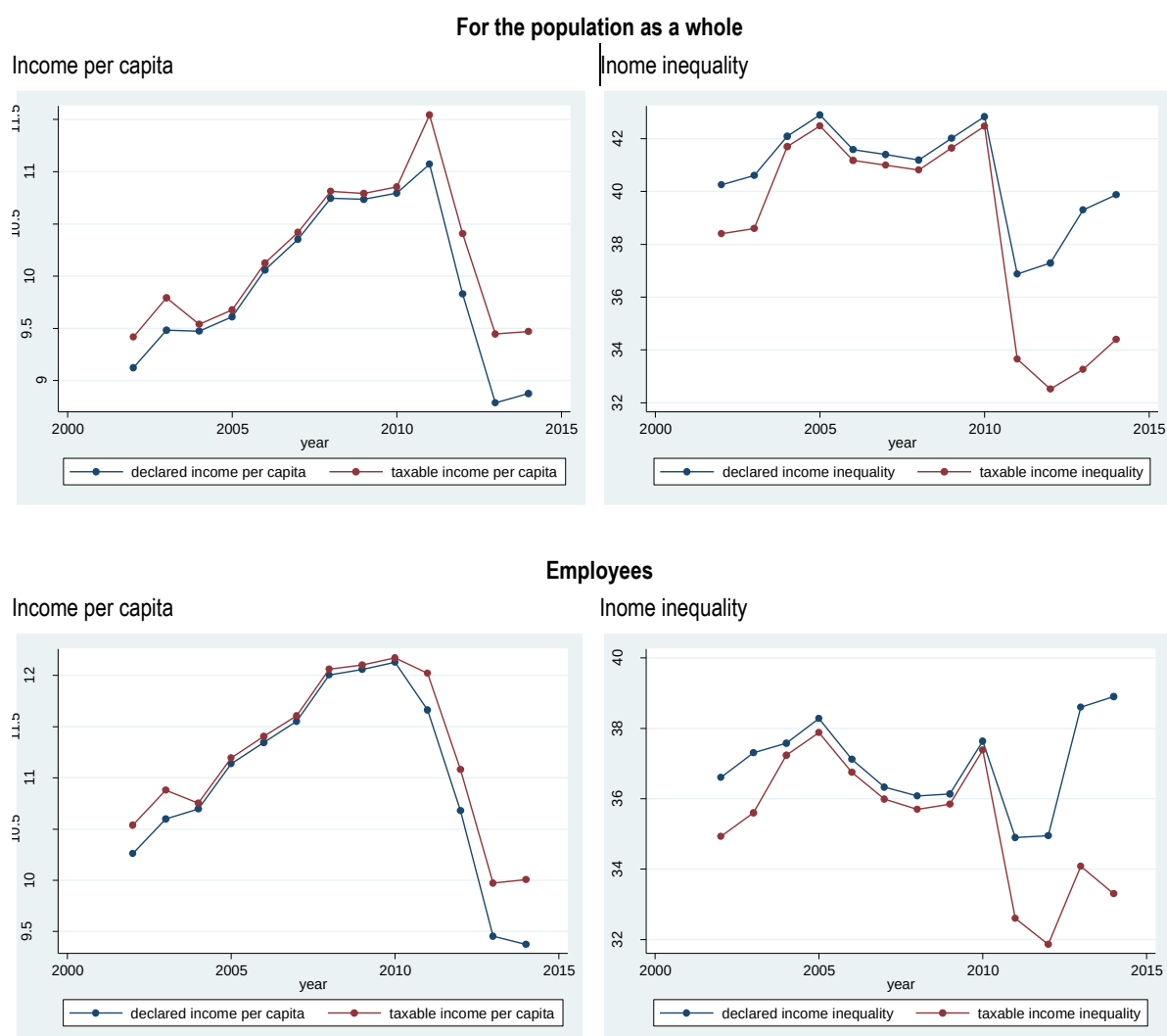
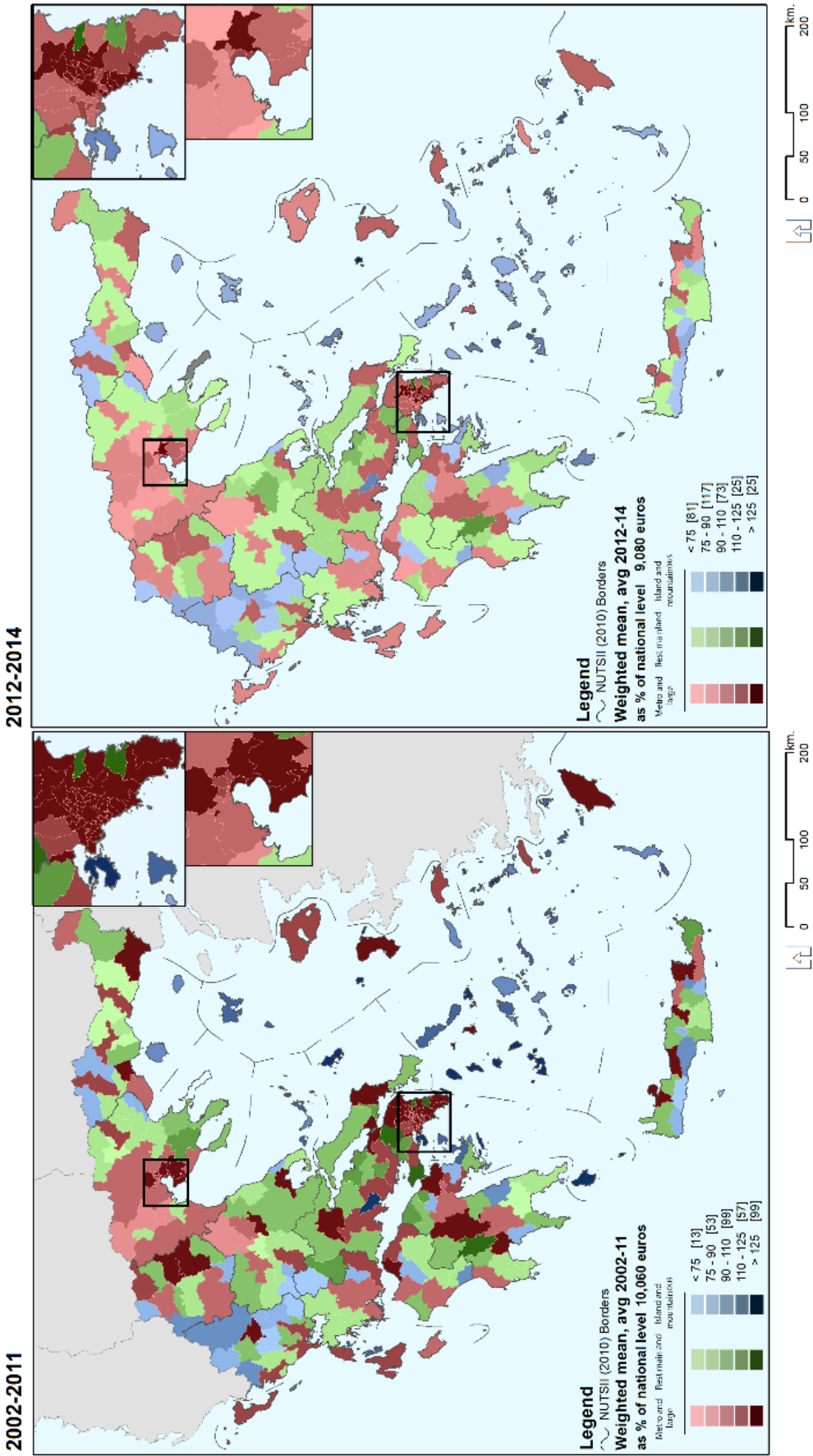
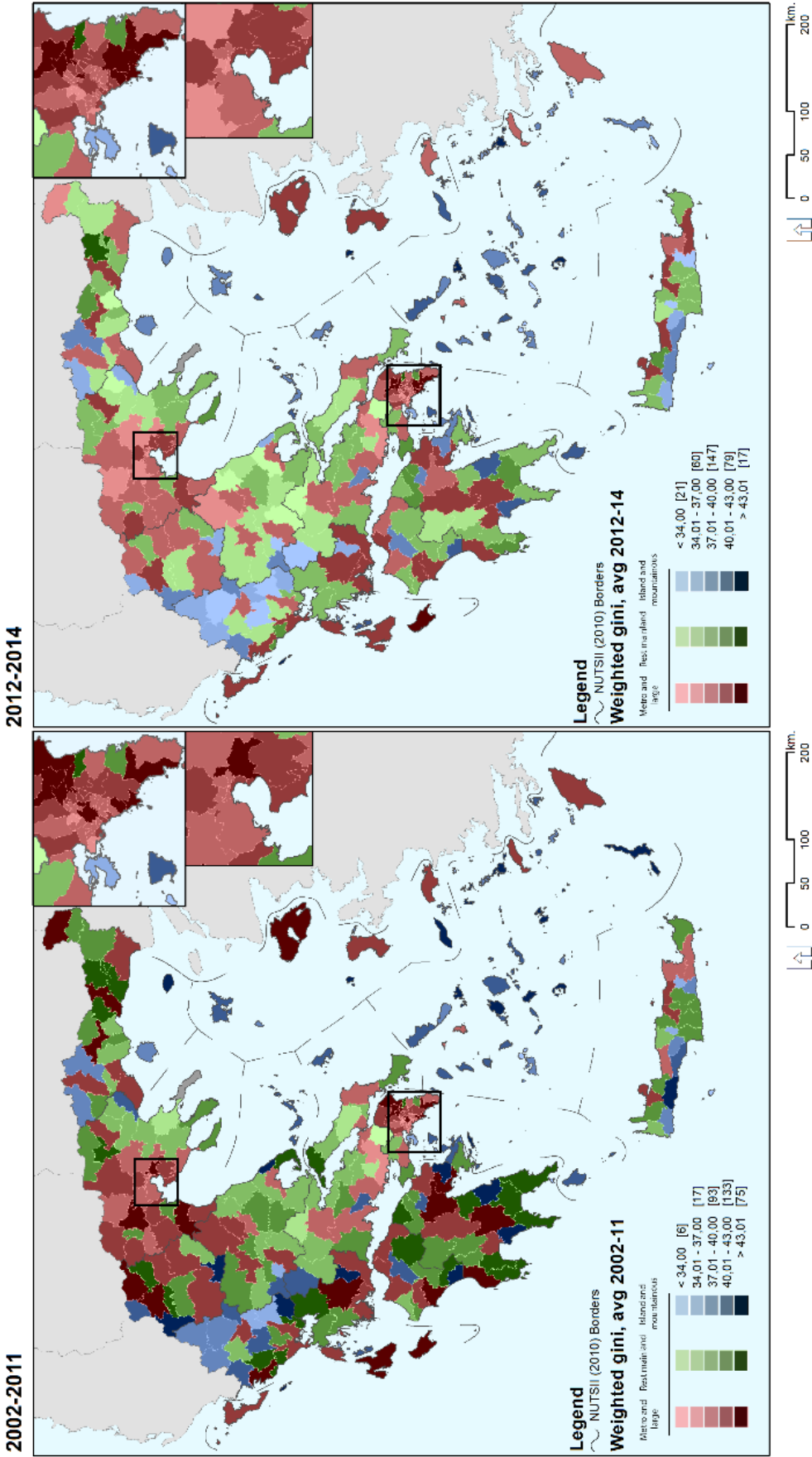


Figure III-2. Average declared Income per capita at municipal level in Greece (2002-2011 & 2012-2014)



Source: Greek Ministry of Finance, authors' elaborations

Figure III-3. Average income inequality of declared income at municipal level in Greece, periods (2002-2011 & 2012-2014)



Source: Greek Ministry of Finance, authors' elaborations

III.3.3 Income per capita and interpersonal income inequality within municipalities: exploratory spatial statistical analysis

In order to identify patterns of income per capita and income inequality, we proceed with the use of exploratory statistical analysis (Rey, 2018). More specifically, at the beginning we test for global autocorrelation for the two variables under consideration, income per capita and income inequality. The estimation of the spatial autocorrelation index is based on a spatial matrix which takes into consideration the nearest three neighboring municipalities. The results have been checked and are robust to matrixes with different numbers of nearest neighboring municipalities.

Exploratory statistical analysis provides strong statistical evidence that income per capita and income inequality show a strong global statistical autocorrelation. **Table III-1** shows the Moran's *I* values for income per capita and income inequality and verifies the high and statistically significant levels of global autocorrelation. Regarding income per capita, the Moran *I* index for global autocorrelation is ranking from 0.77 to 0.83. The values for income inequality are smaller ranging from 0.38 to 0.54, yet still statistically significant. This shows that space is not at all neutral with regard to income per capita and income inequality.

This documents that income and income inequality are polarized. There is a large degree of spatial association of wealth across municipalities. There are hot spots and cold spots of wealth and inequality across space. There are some poles of high income and income inequality and some others with lower incomes and inequality.

Table III-1. Global autocorrelation (Moran's *I*) for declared tax income per capita and income inequality in Greece (2002-2014)

Year	income per capita		income inequality	
	Moran's <i>I</i>	z-score	Moran's <i>I</i>	z-score
2002	0.7787	15.92	0.4819	5.57
2003	0.7907	16.17	0.4779	5.42
2004	0.7961	16.70	0.4745	5.25
2005	0.7980	16.64	0.5173	6.70
2006	0.7965	16.33	0.5455	7.83
2007	0.7940	16.40	0.5054	6.45
2008	0.8161	17.32	0.5143	6.77
2009	0.8087	16.71	0.4867	5.66
2010	0.8139	17.16	0.4987	6.09
2011	0.8110	17.11	0.5345	7.44
2012	0.8362	17.68	0.4799	5.53
2013	0.7922	16.02	0.5463	7.81
2014	0.7875	16.07	0.3860	2.29

Notes: p-value < 0.0002, expected EI = -0.003125, variance(I)= 0.038429

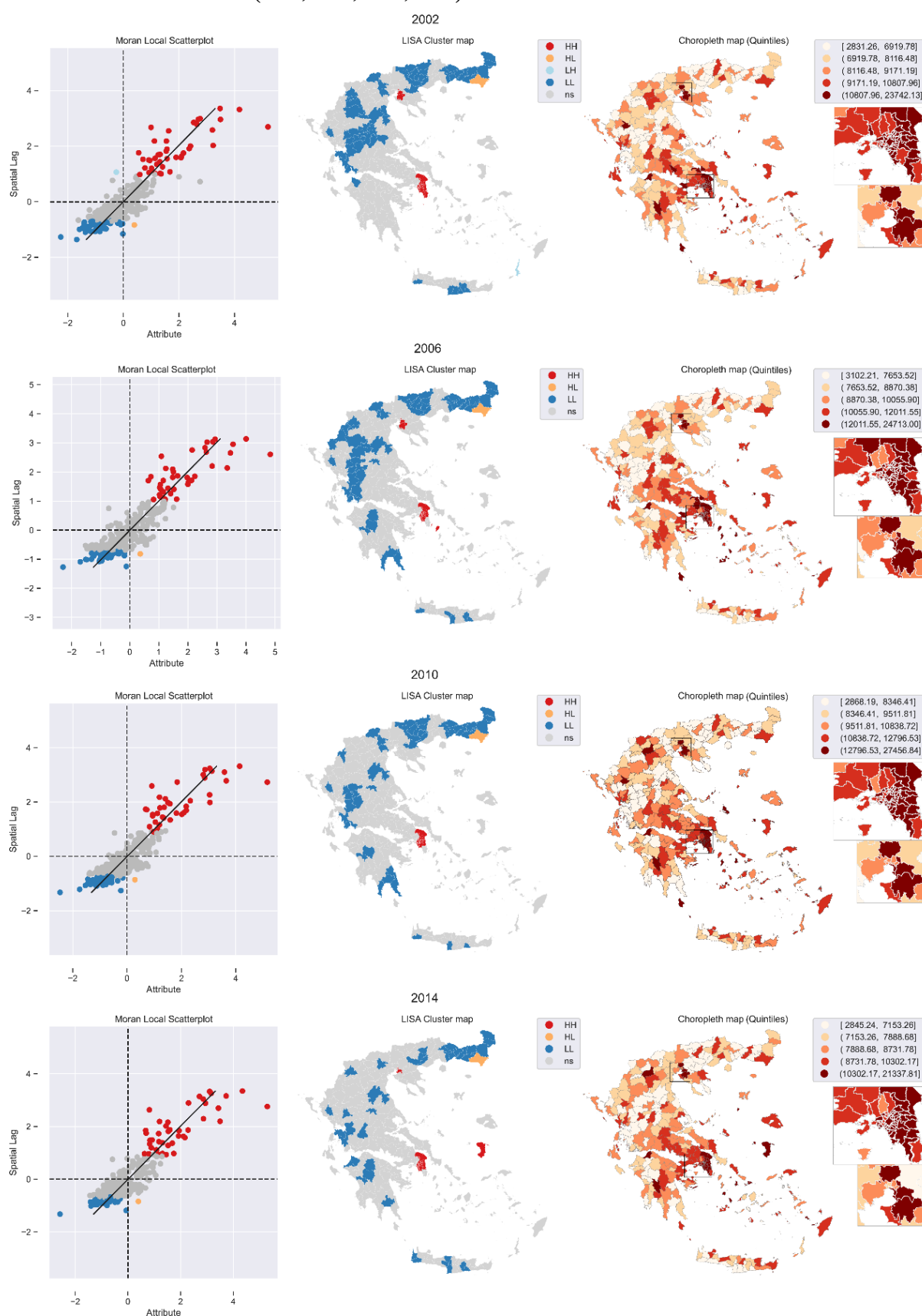
Accordingly, the analysis proceeds with the estimation of local autocorrelation and presents the LISA estimations. More precisely, **Figure III-4** provides a synoptic overview of (1) income level by municipality across the country, (2) the scatterplot of Moran I for spatial autocorrelation and (3) LISA cluster maps with local autocorrelation. These findings have been estimated for the years 2002-2014. Although the analysis has been conducted for the total number of years, **Figure III-4** presents the findings for a selected number of years, the starting year of the analysis 2002, the year 2006, the year 2010, when the first bailout program was signed, and the year 2014 which represents the last year in our analysis.

Income per capita maps show that there is a spatial pattern of income level with high and low values across municipalities. The geographical pattern shows that there is a gradient in income level between the most urbanized areas and the most remote and mountainous areas of the country. Most prosperous municipalities could be identified on the development axes around Athens. One axis crosses Peloponnese and the other crosses continental Greece. There are also some islands which enjoy high levels of income. Conversely, the majority of municipalities in the mountainous areas of the country, in northern Greece and in western Greece, with some very specific exceptions such as Thessaloniki and large cities and areas with industrial activity, show low levels of income per capita.

The scatterplot diagram shows that there is high level of spatial autocorrelation. High levels of spatial autocorrelation can be found in Athens and Thessaloniki and on some Aegean islands. This spatial autocorrelation seems to remain relatively stable. However, there are some changes such as the case of Thessaloniki which gradually fades out as a case of high-high spatial clustering.

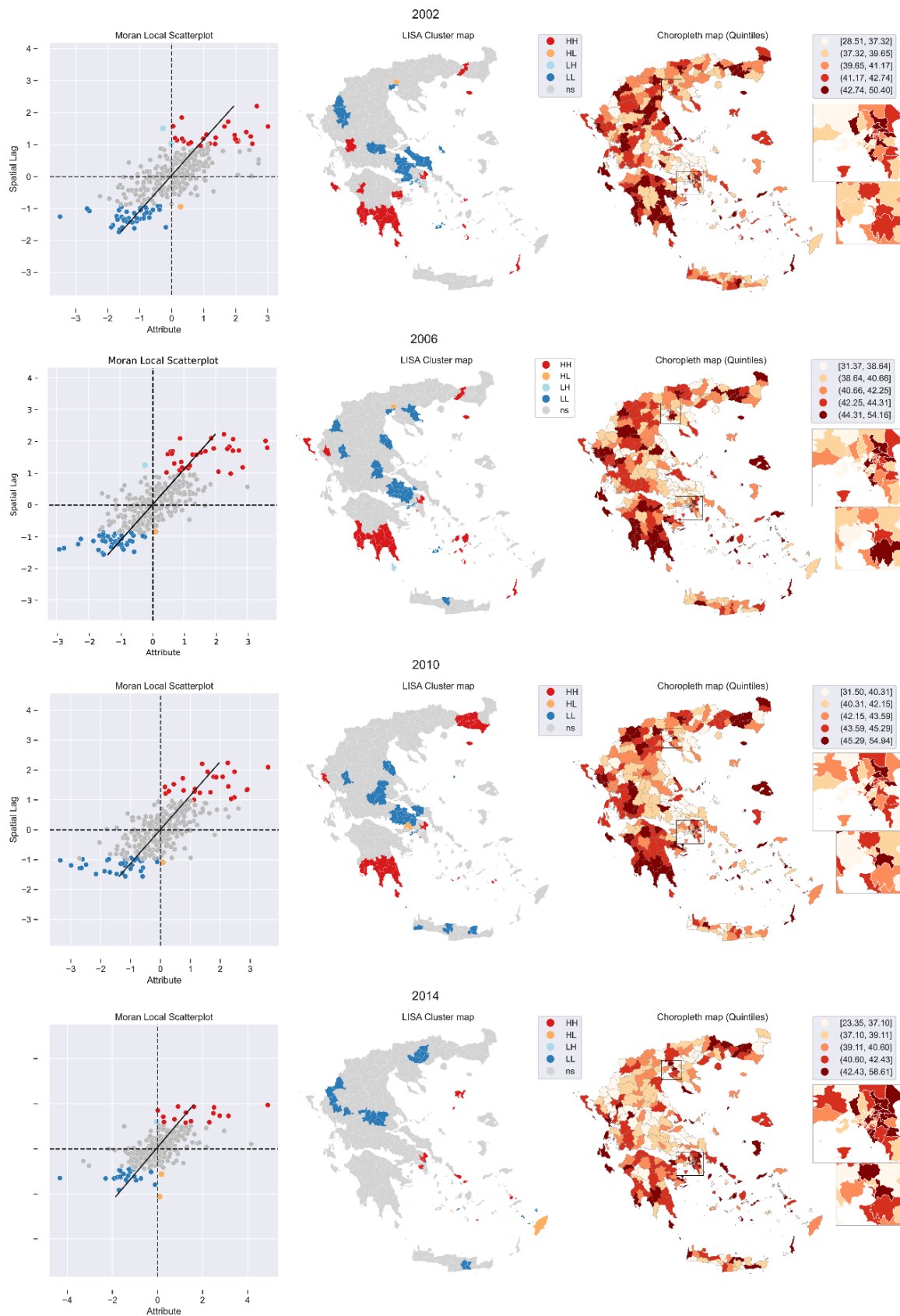
The analysis has also been conducted for income inequality. **Figure III-5** presents the geographical pattern of income inequality, the spatial autocorrelation scatterplot and the LISA cluster map. The pattern of income inequality differs from the pattern of income per capita. High values of income inequality could be met in Southern Greece and in central and north east municipalities of the country as well as on some islands. The LISA maps show that hotspots of inequality could be met in Athens, especially during the years of the economic crisis, as well as in Southern municipalities in Peloponnese and in the North East of the country. These hotspots wane and disappear during the economic crisis. The only ones remaining are some cases around Athens and on some islands. Conversely, cold spots with low income inequality could be met in some specific areas in continental Greece.

Figure III-4. Portraying declared income per capita and local indicators of spatial autocorrelation at municipal level in Greece (2002, 2006, 2010, 2014)



Source: Greek Ministry of Finance. authors' elaborations

Figure III-5. Portraying income inequality of declared income and local indicators of spatial autocorrelation at municipal level in Greece (2002, 2006, 2010, 2014)



Source: Greek Ministry of Finance. authors' elaborations

These findings show that the geographical pattern of inequality is complex. High inequalities exist in metropolitan areas as well as in municipalities in continental Greece and on islands. The multiple expression of inequality extends beyond the urban/rural divide and requires further examination and interpretation.

Finally, **Figure III-6** and **Figure III-7** present the Estimated LISA-Markov chain transition probability matrix for income per capita and income inequality by the state of spatial concentration as defined with the four quadrants in the Moran scatter plot, namely, HH (cluster with high values), LH (pockets with high values), LL (clusters of low values), HL (Pockets of low values) over the period 2002-2014. These document that the probability for a municipality to stay in the same quadrant is higher for income per capita than for income inequality. The probability for a municipality of stay in a cluster with high values (HH) of income per capita is 0.917. Conversely, the probability for a municipality to staying at a cluster with high values (HH) of income inequality is 0.748. It is more probable to change income inequality than to change income per capita. The pattern of inequality either in income per capita and income inequality remains relatively stable. However, when a municipality belongs to cluster with low values is more difficult to change state of spatial concentration.

Figure III-6. Estimated LISA transition probability matrix for declared income per capita (LISA-Markov chain)

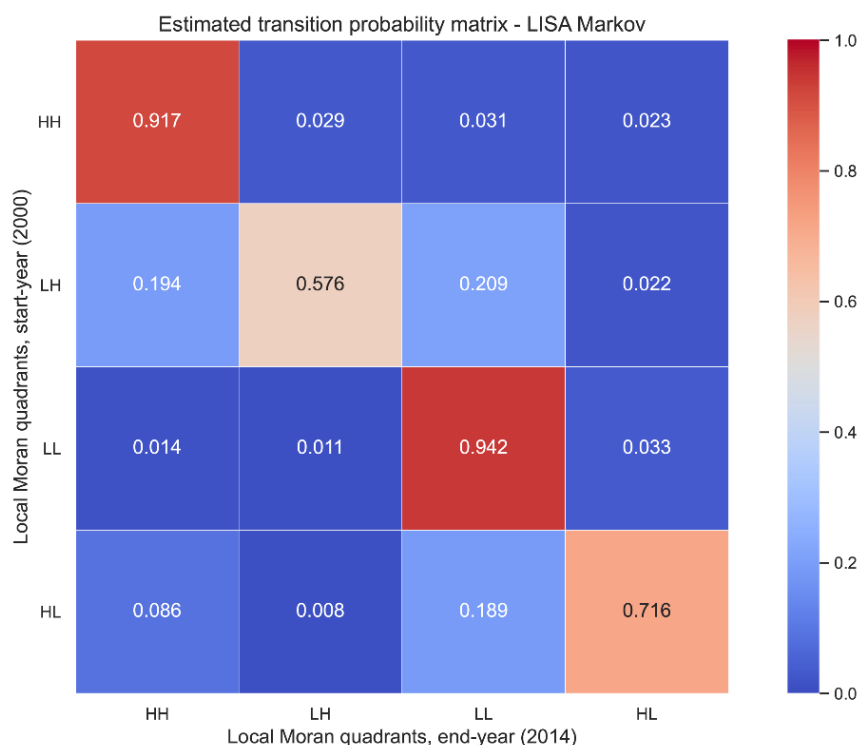
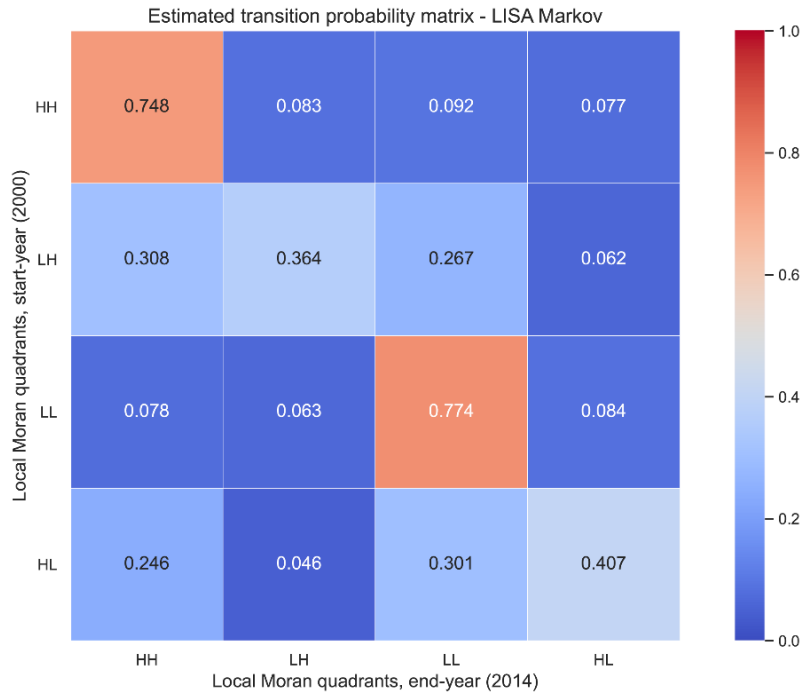


Figure III-7. Estimated LISA transition probability matrix for income inequality of declared income (LISA-Markov chain)



Summing up, the exploratory spatial analysis has provided evidence of strong spatial autocorrelation for income per capita and income inequalities at the municipal level in Greece. Municipalities with higher relative income can be found in large metropolitan areas, on the development axis with a proximity to Athens, on some islands and selectively in different areas of the country with large cities or manufacturing activity. Conversely, low income municipalities are located in agricultural and mountainous and remote areas. Low income inequalities could also be met within metropolitan areas. The geographical pattern of income inequality differs significantly from the geographical pattern of income. These findings will be further examined with the use of an econometric model.

III.4 Econometric specification

This paper examines whether income per capita and income inequality are associated with the geographical characteristics of the municipality and whether this association differs between the period before economic crisis and the period during the crisis, using the following empirical functions.

$$\begin{cases} IncPC_{it} = f(Geo_i, Controls_{it}) \text{ if } 2002 \leq t \leq 2011 \text{ or } 2012 \leq t \leq 2014 \\ IncIneq_{it} = f(Geo_i, Controls_{it}) \text{ if } 2002 \leq t \leq 2011 \text{ or } 2012 \leq t \leq 2014 \end{cases}$$

where,

- $IncPC_{it}$ is declared or taxable income per capita for the population as a whole or employees for municipality i at year t and
- $IncIneq_{it}$ is declared or taxable income inequality for the population as a whole or employees for municipality i at year t .
- Geo_i is time-invariant geographical characteristics of municipality i .

These characteristics are: a) a categorical variable for Klisthenis type, i.e. metro district (base category), large or medium-size island, small island, large mainland, medium-size mainland, and small and mountainous mainland; b) a categorical variable for the degree of urbanisation, i.e. city (base category), city and town and suburbs, rural area, and town and suburbs; c) a variable for the type of surface, i.e. the percentage of plains (base category), semi-mountainous surface and mountainous surface; and d) a variable for the land use (Corine landcover), i.e. the percentage of urban (base category), artificial, agricultural, forest and wetlands. All these geographical characteristics control for spatial autocorrelation of income per capita and income inequality.

- $Controls_{it}$ is a set of control characteristics of municipality i in year t .

We use two sets of control variables: a) variables which are extracted from the annual household declarations and are population density, mean number of children, mean number of cars, the percentage of married people, and the percentage of proprietors (base category), traders, farmers, employees, self-employed and retired; and b) variables which are extracted from EL.STAT. (Greek Statistics) for 2001 (these variables are assumed time-invariant for the period before the crisis) and 2011 (these variables are assumed time-invariant for the period within the crisis), and are mean size of household, unemployment, the percentage of people with no education (base category) and with the highest level of education attained is primary, secondary or tertiary), and the percentage of employment in the primary (base category), secondary and tertiary sector.

Taking into account that both declared and taxable income dropped after 2011 (**Figure III-1**); when $2002 \leq t \leq 2011$, it is considered as a period before the crisis, and when $2012 \leq t \leq 2014$, it is considered as a period within the crisis.

Our database contains information in cross-sectional time-series data. The cross-sectional information is reflected in the changes between municipalities, while the time-series (or within-municipality) information is reflected in the changes within municipality. As this paper focuses on the time-invariant geographical characteristics of municipalities, we use a between effects estimator because it only uses the cross-sectional information and completely discards the time-variation in the data within the period 2002-2011 or the period 2012-2014.

Table III-2. Descriptive statistics

	2002-2011					2012-2014				
	Obs	Mean or %	St dev	Min	Max	Obs	Mean or %	St dev	Min	Max
POPULATION AS A WHOLE										
Declared income per capita	3,088	10.147	3.100	2.192	27.457	924	9.161	2.554	2.845	23.811
Declared income inequality	3,088	41.175	3.703	27.218	55.772	924	38.829	3.498	27.291	55.799
EMPLOYEES										
Declared income per capita	3,087	11.305	2.706	2.540	26.318	923	9.815	2.752	2.808	26.395
Declared income inequality	3,087	36.940	4.477	12.455	59.077	923	37.657	4.908	10.960	55.451
KLISTHENIS TYPE										
Metro district	3,118	0.151	0.358	0.000	1.000	934	0.151	0.358	0.000	1.000
Island: large or medium-size	3,118	0.067	0.251	0.000	1.000	934	0.066	0.249	0.000	1.000
Island: small	3,118	0.067	0.250	0.000	1.000	934	0.066	0.249	0.000	1.000
Mainland: large	3,118	0.295	0.456	0.000	1.000	934	0.296	0.457	0.000	1.000
Mainland: medium-size	3,118	0.308	0.462	0.000	1.000	934	0.308	0.462	0.000	1.000
Mainland: small and mountainous	3,118	0.112	0.315	0.000	1.000	934	0.112	0.316	0.000	1.000
URBANISATION										
Cities	3,118	0.167	0.373	0.000	1.000	934	0.167	0.373	0.000	1.000
Cities, and towns and suburbs	3,118	0.035	0.185	0.000	1.000	934	0.035	0.185	0.000	1.000
Rural areas	3,118	0.445	0.497	0.000	1.000	934	0.444	0.497	0.000	1.000
Towns and suburbs	3,118	0.353	0.478	0.000	1.000	934	0.353	0.478	0.000	1.000
SURFACE (%)										
Plain surface	3,118	43.886	38.628	0.000	100.000	934	43.913	38.676	0.000	100.000
Semi mountainous surface	3,118	28.638	30.413	0.000	100.000	934	28.571	30.439	0.000	100.000
Mountainous surface	3,118	27.477	32.993	0.000	100.000	934	27.516	33.047	0.000	100.000
CORINE LANDCOVER (%)										
Urban	3,118	10.622	23.382	0.000	100.000	934	10.637	23.405	0.000	100.000
Artificial	3,118	3.325	7.528	0.000	49.870	934	3.328	7.536	0.000	49.870
Agricultural	3,118	34.703	23.033	0.000	91.820	934	34.706	23.061	0.000	91.820
Forest	3,118	47.806	25.092	0.000	94.770	934	47.811	25.129	0.000	94.770
Wetlands	3,118	3.544	5.062	0.000	34.570	934	3.518	5.003	0.000	34.570
CONTROLS										
Source: Declarations										
Population density inh/km ²	3,087	73.454	197.594	0.074	1258.181	924	66.163	177.876	0.068	1174.883
Mean number of children	3,088	0.444	0.089	0.129	0.912	924	0.444	0.100	0.118	0.844
Mean number of cars	3,088	0.631	0.182	0.013	1.223	924	0.525	0.276	0.015	1.221
Married people (%)	3,088	53.577	6.243	35.171	85.938	924	51.063	5.326	34.702	82.278
Proprietors (%)	3,087	5.432	2.681	0.000	17.447	924	6.785	3.033	0.000	21.449
Traders (%)	3,087	13.728	4.261	0.000	42.614	924	11.747	5.432	1.266	36.879
Farmers (%)	3,087	14.292	11.166	0.469	79.687	924	12.350	8.556	0.134	54.211
Employees (%)	3,087	31.469	10.554	3.865	64.055	924	29.809	10.021	2.703	61.474
Self-Employed (%)	3,087	4.836	2.882	0.000	21.356	924	4.252	2.713	0.000	19.701
Retired (%)	3,087	30.250	8.125	4.412	65.169	924	35.065	8.633	10.895	68.803
Source: ELSTAT										
Mean size of household	3,118	2.926	0.247	2.000	3.803	934	2.616	0.213	2.040	3.400
Unemployment	3,118	11.194	3.373	2.360	24.160	934	17.714	4.512	7.920	32.970
Education: no (%)	3,118	14.642	6.812	1.890	35.820	934	15.768	4.959	6.140	30.210
Education: primary (%)	3,118	36.089	8.810	7.410	62.040	934	30.410	8.561	7.240	59.370
Education: secondary (%)	3,118	39.507	9.009	8.240	57.870	934	40.460	6.895	11.320	53.670
Education: tertiary (%)	3,118	9.764	6.626	1.120	45.820	934	13.362	7.849	2.340	50.470
Employment: primary (%)	3,118	26.967	20.592	0.320	93.750	934	19.927	16.733	0.240	83.090
Employment: secondary (%)	3,118	22.081	7.934	2.580	44.400	934	18.110	5.818	4.620	43.200
Employment: tertiary (%)	3,118	50.952	16.851	3.670	86.400	934	61.964	15.770	11.380	89.950

Table III-2 presents the descriptive statistics of the database for the two periods. While declared income per capita for the population as a whole is higher in the period before the crisis than within the crisis, income distribution is more equal during / within the crisis. Income distribution for employees is higher and more equal than that for the whole population, i.e. higher income per capita and lower income inequality.

Table III-2 also shows that most Greek municipalities a) are characterised by large mainland (Klisthenis type), b) are rural areas, c) have plain surface, and d) are forest. As for the controls, population density decreased within the crisis, which is likely to be a sign that people moved from urban to rural areas for better occupational chances. It is hardly surprising that the percentage of married people and the mean number of cars decreased, and the unemployment rate increased within the crisis. The percentage of traders, farmers, employees and self-employed within a municipality decreased after the commencement of the economic crisis and, as a result, the percentage of proprietors and retired increased. The percentage of the population with tertiary education, as well as the percentage of people employed in the tertiary sector, increased in the period 2012-2014. Despite the economic crisis, the mean number of children within a municipality had not changed. Finally, an unexpected finding was that the mean size of households was lower in the period 2012-2014 than in the period 2002-2011.

III.5 Regression results

III.5.1 Income distribution for the population as a whole

Table III-3 and **Table III-4** display the regression results of declared income per capita and declared income inequality for the population as a whole, before and within the economic crisis. The postulated models of income distribution fit quite well, explaining 92-95 per cent of the variation in income per capita (**Table III-3**) and 56-67 per cent of the variation in income inequality (**Table III-4**).

Concerning the determinants of income per capita (**Table III-3**), there is evidence that according to land use CORINE data agriculture and forest areas show level of income lower to urban areas both before and during the economic crisis. The same applies to mountainous areas especially before the economic crisis. Cities and towns and suburbs show lower level of income comparing to the large cities. Small islands seem to enjoy comparatively higher levels of income. However, this requires careful interpretation given the small size of small island municipalities comparing with the large heterogeneity of production base for cities. It is also observed that municipalities with a high percentage of wetlands are the wealthiest ones after the crisis.

Table III-3. The determinants of declared income per capita for the population as a whole

	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012- 2014
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KLISTHENIS TYPE								
Metro district	base	base						
Island: large or medium-size	0.9385***	0.2257						
Island: small	2.0825***	1.0257***						
Mainland: large	-0.0002	-0.4070*						
Mainland: medium-size	0.3683	-0.2253						
Mainland: small and mountainous	0.6282*	-0.0479						
URBANISATION								
Cities			base	base				
Cities, and towns and suburbs			-0.7169**	-0.9458***				
Rural areas			0.6805**	-0.0994				
Towns and suburbs			0.2460	-0.2661				
SURFACE (%)								
Plain surface					base	base		
Semi mountainous surface					0.0029	0.0003		
Mountainous surface					-0.0022	-0.0021		
CORINE LANDCOVER (%)								
Urban							base	base
Artificial							-0.0069	-0.0022
Agricultural							-0.0234***	-0.0232***
Forest							-0.0149***	-0.0145***
Wetlands							0.0078	0.0242**
CONTROLS								
Source: Declarations								
Population density	-0.0000	0.0001	-0.0002	0.0000	-0.0003	0.0005	-0.0021***	-0.0015***
Mean number of children	-2.1092*	-2.5421**	-2.4340**	-3.3829***	-3.0562**	-3.7063***	-2.9319**	-2.9783***
Mean number of cars	5.1998***	3.5493***	4.0659***	2.4795***	3.7068***	2.2026***	4.3529***	3.5911***
Married people (%)	-0.0671***	-0.0366**	-0.0679***	-0.0228	-0.0753***	-0.0261*	-0.0672***	-0.0260*
Proprietors (%)	base	base	base	base	base	base	base	base
Traders (%)	0.0323	-0.0188	0.0568*	0.0025	0.0812**	0.0087	0.0878***	0.0036
Farmers (%)	0.0783***	-0.0184	0.0695***	-0.0177	0.0872***	-0.0108	0.0839***	-0.0098
Employees (%)	0.0954***	0.0464**	0.0803***	0.0374*	0.0913***	0.0421*	0.0946***	0.0429**
Self-Employed (%)	0.0553	0.0577	0.0504	0.0551	0.0569	0.0481	0.0548	0.0549
Retired (%)	0.0896***	0.0249	0.0756***	0.0151	0.0868***	0.0182	0.0852***	0.0277
Source: ELSTAT								
Mean size of household	0.2157	-0.0117	0.2174	0.0157	0.1219	0.0572	-0.0442	-0.1527
Unemployment	-0.0848***	-0.0495***	-0.1041***	-0.0629***	-0.0973***	-0.0639***	-0.0856***	-0.0635***
Education: no (%)	base	base	base	base	base	base	base	base
Education: primary (%)	-0.0021	-0.0538**	0.0060	-0.0544**	0.0089	-0.0504**	0.0105	-0.0573***
Education: secondary (%)	-0.0184	-0.0544***	-0.0144	-0.0515***	-0.0192	-0.0524***	-0.0109	-0.0533***
Education: tertiary (%)	0.2976***	0.1882***	0.3084***	0.1934***	0.3153***	0.2020***	0.3010***	0.1773***
Employment: primary (%)	base	base	base	base	base	base	base	base
Employment: secondary (%)	0.0348***	0.0502***	0.0448***	0.0636***	0.0488***	0.0668***	0.0364***	0.0569***
Employment: tertiary (%)	0.0168*	-0.0149*	0.0278***	-0.0059	0.0188**	-0.0084	0.0083	-0.0160**
Time-dummies	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-9.4216	9.7374***	-10.1687	8.4290***	-8.7149	8.1659***	-9.2106	10.8632***
Observations	3,087	924	3,087	924	3,087	924	3,087	924
R-between	0.9468	0.9309	0.9409	0.9270	0.9372	0.9238	0.9418	0.9352

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table III-4. The determinants of declared income inequality for the population as a whole

	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012- 2014
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KLISTHENIS TYPE								
Metro district	base	base						
Island: large or medium-size	1.8439**	2.9125***						
Island: small	2.4719**	2.1765**						
Mainland: large	2.3690***	2.4582***						
Mainland: medium-size	1.9639**	2.0868***						
Mainland: small and mountainous	1.7756**	1.2461						
URBANISATION								
Cities			base	base				
Cities, and towns and suburbs			0.6071	0.9469				
Rural areas			1.2662*	2.0373***				
Towns and suburbs			1.1905*	1.9072***				
SURFACE (%)								
Plain surface					base	base		
Semi mountainous surface					0.0109**	0.0040		
Mountainous surface					0.0141***	-0.0021		
CORINE LANDCOVER (%)								
Urban							base	base
Artificial							0.0202	0.0010
Agricultural							0.0245*	0.0315**
Forest							0.0327**	0.0208
Wetlands							0.0658**	0.0766***
CONTROLS								
Source: Declarations								
Population density	0.0013	-0.0002	-0.0002	-0.0014	-0.0003	-0.0032***	0.0018	-0.0003
Mean number of children	-3.5252	-0.8140	-2.2759	0.7983	-3.9746	1.1582	-2.9964	0.2224
Mean number of cars	-1.8264	-1.0670	-1.5350	-0.2813	-0.3998	-0.0800	-0.0071	-0.2060
Married people (%)	0.0063	-0.0517	0.0158	-0.0520	0.0263	-0.0590	0.0212	-0.0633
Proprietors (%)	base	base	base	base	base	base	base	base
Traders (%)	-0.2797***	-0.2155***	-0.2912***	-0.2684***	-0.2940***	-0.2339***	-0.2874***	-0.2489***
Farmers (%)	-0.4029***	-0.2591***	-0.4187***	-0.3120***	-0.4378***	-0.2823***	-0.4147***	-0.2711***
Employees (%)	-0.4935***	-0.3396***	-0.5098***	-0.3914***	-0.5177***	-0.3777***	-0.5036***	-0.3569***
Self-Employed (%)	-0.5232***	-0.2937**	-0.5170***	-0.3506***	-0.5607***	-0.3357***	-0.5294***	-0.3379***
Retired (%)	-0.5697***	-0.4891***	-0.5804***	-0.5362***	-0.6175***	-0.5095***	-0.5796***	-0.5129***
Source: ELSTAT								
Mean size of household	0.7417	0.1311	0.7364	-0.2018	0.7083	-0.1288	0.8364	-0.1157
Unemployment	0.0390	0.0462	0.0413	0.0486	0.0445	0.0435	0.0446	0.0340
Education: no (%)	base	base	base	base	base	base	base	base
Education: primary (%)	-0.0143	0.0780	-0.0227	0.0529	-0.0283	0.0687	-0.0170	0.0690
Education: secondary (%)	-0.0164	0.0609	-0.0146	0.0532	-0.0189	0.0546	-0.0176	0.0485
Education: tertiary (%)	0.2238***	0.2587***	0.1974***	0.2263***	0.1618***	0.2131***	0.2068***	0.2406***
Employment: primary (%)	base	base	base	base	base	base	base	base
Employment: secondary (%)	-0.0637***	-0.0247	-0.0621**	-0.0231	-0.0749***	-0.0154	-0.0683***	-0.0030
Employment: tertiary (%)	-0.0385	-0.0242	-0.0312	-0.0101	-0.0388*	-0.0119	-0.0448*	-0.0133
Time-dummies	yes	yes	yes	yes	yes	yes	yes	yes
Constant	60.1715***	59.6544***	62.1003***	64.7339***	69.8620***	64.3767***	56.0383***	61.7232***
Observations	3,087	924	3,087	924	3,087	924	3,087	924
R-between	0.5804	0.6673	0.5627	0.6486	0.5727	0.6358	0.5678	0.6525

Notes: *** p<0.01, ** p<0.05, * p<0.1

As to the determinants of income inequality (**Table III-4**, metro district municipalities have the most equal income distribution. While small islands were the wealthiest Greek areas, especially before the crisis (**Table III-3**), they had the highest income inequality. During the crisis, the

income distribution of large or medium-size islands is the most unequal. Moreover, differences in income distribution between metro district municipalities and the remaining ones are greater before the crisis than during the crisis. Taking into account the degree of urbanisation, rural areas and towns and suburbs have the highest income inequality, which increased even more after the crisis. As for the surface type, the income distribution of the (semi-) mountainous surface municipalities is the most unequal, but only before the crisis, as there is no evidence for any difference in inequality by surface type within the crisis. Finally, wetlands are areas with the higher income inequality for the whole period, and it is even higher after the crisis.

III.5.2 Income distribution for employees

Table III-5 and **Table III-6** display the regression results of declared income per capita and declared income inequality for employees. These models have lower R-between than the respective models of income distribution for the population as a whole. The determinants of income distribution for employees explain 83-88 per cent of the variation in income per capita (**Table III-5**) and 34-45 per cent of the variation in income inequality (**Table III-6**). Hence, a significant proportion of cross-sectional variations in income inequality still remain unexplained.

Table III-5 shows that small islands were the most prosperous areas before the economic crisis, while recession hit income level of employees of large mainland areas more than other areas. Cities, and towns and suburbs are the less well-off areas for employees which is more intense after the crisis. Once more, there are no differences in welfare by surface type. Agricultural and, then, forest areas have the less affluent areas which is stronger for employees than for the population as a whole (i.e. for citizens with other income sources) and higher within the crisis period (**Table III-3** versus **Table III-5**).

Taking into account the determinants of income inequality within municipalities (**Table III-6**), the distribution of employees declared income for the metro district areas is the most equal, while that of the small islands before the crisis and of the large or medium islands after the crisis is the most unequal. However, these differences are higher for employees (**Table III-4** versus **Table III-6**). While there are no differences in income inequality by degree of urbanisation before the crisis, there are strong differences within the crisis. More specifically, rural areas and towns and suburbs have the most unequal distribution for employees which, once more, is higher for employees than for citizens with other income sources (**Table III-4** versus **Table III-6**). Semi-mountainous areas have the highest income inequality for the whole period of analysis. Both for income inequality for the population as a whole and for employees

(Table III-4 and Table III-6), wetlands are areas with the highest income inequality for the whole period, and it is even higher not only after the crisis but also for employees.

Table III-5. The determinants of declared income per capita for employees

	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012- 2014
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KLISTHENIS TYPE								
Metro district	base	base						
Island: large or medium-size	0.2025	-0.3009						
Island: small	1.3606***	0.7254						
Mainland: large	-0.4423	-1.0610***						
Mainland: medium-size	0.1437	-0.5881						
Mainland: small and mountainous	0.4903	-0.2262						
URBANISATION								
Cities			base	base				
Cities, and towns and suburbs			-1.3564***	-1.9225***				
Rural areas			0.1901	-0.6368				
Towns and suburbs			-0.1512	-0.7308**				
SURFACE (%)								
Plain surface					base	base		
Semi mountainous surface					0.0033	0.0012		
Mountainous surface					0.0026	0.0001		
CORINE LANDCOVER (%)								
Urban							base	base
Artificial							-0.0117	-0.0044
Agricultural							-0.0325***	-0.0402***
Forest							-0.0182***	-0.0230***
Wetlands							0.0024	0.0160
CONTROLS								
Source: Declarations								
Population density	-0.0003	-0.0002	-0.0004	-0.0001	0.0002	0.0011**	-0.0022***	-0.0024***
Mean number of children	-1.7392	-2.5811	-2.2721	-3.9193**	-3.5724**	-4.4509***	-2.8731**	-3.1750**
Mean number of cars	6.3078***	5.2057***	5.4183***	3.6585***	5.2504***	3.6490***	6.0675***	5.6059***
Married people (%)	-0.0072	-0.0160	-0.0076	-0.0001	-0.0116	-0.0034	-0.0016	-0.0030
Proprietors (%)	base	base	base	base	base	base	base	base
Traders (%)	-0.0977***	-0.1393***	-0.0668*	-0.0949**	-0.0579	-0.0998***	-0.0502	-0.1066***
Farmers (%)	0.0314	-0.0152	0.0395	0.0043	0.0419	-0.0048	0.0419	-0.0032
Employees (%)	-0.0344	-0.0303	-0.0332	-0.0237	-0.0273	-0.0253	-0.0243	-0.0295
Self-Employed (%)	0.0052	0.0781	0.0265	0.1022	0.0079	0.0678	0.0139	0.0882
Retired (%)	0.0582*	0.0080	0.0633**	0.0137	0.0540*	0.0059	0.0627**	0.0208
Source: ELSTAT								
Mean size of household	0.8190**	0.3646	0.8091**	0.4599	0.7541**	0.5405	0.5672	0.2417
Unemployment	-0.1022***	-0.0261	-0.1139***	-0.0416**	-0.1137***	-0.0438**	-0.0911***	-0.0401**
Education: no (%)	base	base	base	base	base	base	base	base
Education: primary (%)	-0.0252	-0.1234***	-0.0194	-0.1170***	-0.0178	-0.1188***	-0.0152	-0.1258***
Education: secondary (%)	-0.0113	-0.0873***	-0.0094	-0.0829***	-0.0135	-0.0880***	-0.0016	-0.0852***
Education: tertiary (%)	0.2205***	0.1371***	0.2321***	0.1524***	0.2386***	0.1602***	0.2226***	0.1202***
Employment: primary (%)	base	base	base	base	base	base	base	base
Employment: secondary (%)	0.0315***	0.0570***	0.0379***	0.0718***	0.0377***	0.0703***	0.0243**	0.0554***
Employment: tertiary (%)	0.0313***	-0.0022	0.0353***	0.0040	0.0265**	-0.0001	0.0120	-0.0104
Time-dummies	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-30.4902***	17.6429***	-31.6948***	14.6936***	-29.5056***	15.3103***	-29.1588***	19.1897***
Observations	3,086	923	3,086	923	3,086	923	3,086	923
R-between	0.8802	0.8498	0.8745	0.8448	0.8660	0.8331	0.8814	0.8612

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table III-6. The determinants of declared income inequality for employees

	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012- 2014
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KLISTHENIS TYPE								
Metro district	base	base						
Island: large and medium-size	3.2831***	3.6252**						
Island: small	3.5382***	2.9073*						
Mainland: large	1.2274	2.1529**						
Mainland: medium-size	1.2484	2.9379**						
Mainland: small and mountainous	0.9541	1.3074						
URBANISATION								
Cities			base	base				
Cities, and towns and suburbs			-1.4437	-0.5498				
Rural areas			1.2514	3.4680***				
Towns and suburbs			0.6427	2.4118**				
SURFACE (%)								
Plain surface					base	base		
Semi mountainous surface					0.0127**	0.0166**		
Mountainous surface					-0.0012	-0.0112		
CORINE LANDCOVER (%)								
Urban							base	base
Artificial							0.0053	-0.0081
Agricultural							-0.0176	0.0084
Forest							0.0057	0.0032
Wetlands							0.1159***	0.1213**
CONTROLS								
Source: Declarations								
Population density	0.0008	-0.0025	-0.0008	-0.0033*	-0.0005	-0.0049***	-0.0011	-0.0045
Mean number of children	2.3503	2.5936	3.3947	5.1247	2.2510	4.5789	2.2289	3.9298
Mean number of cars	-0.1234	-2.6728	-1.4654	-1.0551	-1.3973	-1.8813	1.0769	-0.4810
Married people (%)	-0.1045*	-0.1756**	-0.0998*	-0.1792**	-0.1087*	-0.1918***	-0.0877	-0.2023***
Proprietors (%)	base	base	base	base	base	base	base	base
Traders (%)	0.1200	0.0809	0.1337	0.0055	0.1556	0.0992	0.1581	0.0683
Farmers (%)	-0.1435*	-0.1755*	-0.1859**	-0.2535**	-0.1684**	-0.1679	-0.1653*	-0.1656
Employees (%)	-0.1733*	-0.1389	-0.2269**	-0.2029*	-0.2183**	-0.1520	-0.1957**	-0.1375
Self-Employed (%)	-0.2465*	-0.0812	-0.2892**	-0.1450	-0.3005**	-0.0911	-0.2949**	-0.1354
Retired (%)	-0.0723	-0.1590*	-0.1227	-0.2160**	-0.1153	-0.1413	-0.1031	-0.1609*
Source: ELSTAT								
Mean size of household	0.4691	-0.1104	0.4738	-0.6386	0.3879	-0.1998	0.2499	-0.7479
Unemployment	0.0652	-0.0019	0.0332	0.0108	0.0503	0.0050	0.0650	-0.0213
Education: no (%)	base	base	base	base	base	base	base	base
Education: primary (%)	-0.0127	-0.1096	-0.0047	-0.1407	-0.0025	-0.1067	0.0089	-0.1153
Education: secondary (%)	-0.0246	-0.0431	-0.0161	-0.0614	-0.0272	-0.0617	-0.0089	-0.0730
Education: tertiary (%)	0.3556***	0.2377**	0.3415***	0.2035**	0.3413***	0.2049**	0.3493***	0.2054*
Employment: primary (%)	base	base	base	base	base	base	base	base
Employment: secondary (%)	-0.0350	-0.0310	-0.0201	-0.0369	-0.0163	-0.0166	-0.0426	-0.0081
Employment: tertiary (%)	-0.0584*	-0.0898**	-0.0246	-0.0743**	-0.0414	-0.0890**	-0.0713**	-0.0947***
Time-dummies	yes	yes	yes	yes	yes	yes	yes	yes
Constant	32.9014	70.6852***	33.3500	76.6402***	41.3029	73.1147***	27.3400	76.1644***
Observations	3,086	923	3,086	923	3,086	923	3,086	923
R-between	0.4451	0.3407	0.4331	0.3405	0.4299	0.3368	0.4454	0.3266

Notes: *** p<0.01, ** p<0.05, * p<0.1

III.5.3 What really matters?

Table III-3 - Table III-6) indicate that what is important is not only the declared income level of a municipality, but also how this income is actually distributed within the municipality. Both time and place matter for income distribution, as there are differences in distribution between the two periods as well as between the geographical characteristics of the municipalities. There are strong differences in income per capita and income inequality between the different types of municipalities and between the periods 2002-2011 and 2012-2014. However, all these differences are stronger for employees.

The analysis shows that there are different geographies of wealth and inequality. The main findings are the following. First, income per capita is higher in metropolitan municipalities and on islands. Income per capita is lower in mountainous areas before the crisis and in agricultural and forest areas. Second, income inequality was relatively higher for areas outside the metropolitan municipalities for almost all geographical divisions, especially before the economic crisis. The pattern on wealth is different from the pattern of income inequality.

As for the controls, no matter whether income refers to the population as a whole or to employees, the regression results show the following (**Table III-2 - Table III-6**). First, an increase in income per capita within a municipality is associated with an increase a) in the mean number of cars, b) in the percentage of the population with tertiary education and c) in the percentage of secondary employment, and with a decrease a) in the mean number of children and b) in unemployment. Second, a more unequal income distribution is associated with an increase in the percentage of tertiary education. Hence, distribution of income is highly correlated with distribution of tertiary education.

All these results are also robust to the definition of income, i.e. declared or taxable income (*see Appendix: Table A-III-7 - Table A-III-10*).

III.6 Conclusions

The chapter offers an empirical investigation of income per capita and interpersonal income inequality in Greece based on declared household income statistical data. The length of the time period under investigation allows the examination of spatial and temporal patterns of income inequality for a long period of time, one of the lengthiest ever studied in the literature. The time period allows the comparative analysis of income inequality in Greece before and during the economic crisis and under fiscal consolidation reforms. The analysis has provided some interesting findings.

- First, there is a large degree of autocorrelation for income per capita and income inequality across municipalities. This shows that geography matters for the level of wealth and inequality.
- Second, the geography of income per capita is very complex and extends beyond the north-south and the urban-rural dichotomy. High income municipalities can be found in large metropolitan areas as well as in municipalities on the development axes that cross the Peloponnese and Continental Greece which are regions adjacent to Athens. High income values were seen on some islands, in some cities and areas with expertise in manufacturing.
- Third, the geography of inequality follows a pattern different from the geography of wealth. High interpersonal inequalities were seen within selected metropolitan municipalities and in other areas outside the metropolitan agglomerations. Hot spots of high income inequity can be found in some large mainland municipalities in the southern and north-eastern parts of the country as well as on some islands.
- Fourth, education is the key determinant of income inequality. Interpersonal inequality decreases with family size and increases with the number of cars.
- Fifth, industry mix and specialization in manufacturing provides as an important determinant of increasing income per capita and decreasing income inequality.

These results are sensitive to the variable under consideration and the structure of local labor market. Tax declarations capture primarily wage employees which could be found predominantly in urban labor markets. The labor market outside the cities and metropolitan areas is completely different from urban agglomerations. Due to the structure of local labor market, the relatively smaller number of employees in agricultural and rural areas cannot boost income per capita of those territories and make it comparable to the one in large cities. However, these employees are sufficient to increase income inequality within municipality. This could provide an explanation regarding the different geographies of wealth and inequality across space in Greece. Economic crisis and fiscal consolidation reforms had a substantial impact on wealth and inequalities across the country.

Finally, these results have some policy implications. More geographically targeted and people centered policies are necessary to ameliorate income disparities and to promote more a balanced and equitable social environment across space. Horizontal cuts and austerity should be avoided in the post 2020 cohesion policy and post COVID-19 recovery policies.

This chapter has provides some novel aspects regarding the geography of income inequality in Greece. However, much works remains to be done. The extension of the time span of the analysis and the focus on income inequalities within cities and metropolitan areas constitutes a promising avenue for future work.

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Appendix

Table A-III-7. The determinants of taxable income per capita for the population as a whole

	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012- 2014
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KLISTHENIS TYPE								
Metro district	base	base						
Island: large or medium-size	0.9314***	0.2025						
Island: small	2.0831***	0.9507***						
Mainland: large	0.0027	-0.3668*						
Mainland: medium-size	0.3668	-0.1864						
Mainland: small and mountainous	0.6269**	-0.0290						
URBANISATION								
Cities			base	base				
Cities, and towns and suburbs			-0.7098**	-0.9001***				
Rural areas			0.6847**	-0.0634				
Towns and suburbs			0.2437	-0.2259				
SURFACE (%)								
Plain surface					base	base		
Semi mountainous surface					0.0030*	0.0004		
Mountainous surface					-0.0021	-0.0019		
CORINE LANDCOVER (%)								
Urban							base	base
Artificial							-0.0067	-0.0022
Agricultural							-0.0233***	-0.0219***
Forest							-0.0147***	-0.0140***
Wetlands							0.0089	0.0232**
CONTROLS								
Source: Declarations								
Population density	-0.0001	0.0001	-0.0003	0.0000	-0.0003	0.0004	-0.0021***	-0.0015***
Mean number of children	-2.1370*	-2.8430***	-2.4480**	-3.6050***	-3.0860**	-3.9196***	-2.9522**	-3.2315***
Mean number of cars	5.3304***	3.6544***	4.2086***	2.6899***	3.8461***	2.4406***	4.5052***	3.7183***
Married people (%)	-0.0673***	-0.0286*	-0.0680***	-0.0157	-0.0753***	-0.0189	-0.0672***	-0.0191
Proprietors (%)	base	base	base	base	base	base	base	base
Traders (%)	0.0322	-0.0160	0.0562*	0.0033	0.0808**	0.0095	0.0874***	0.0051
Farmers (%)	0.0738***	-0.0249	0.0646**	-0.0242	0.0825***	-0.0177	0.0794***	-0.0156
Employees (%)	0.0891***	0.0300	0.0738***	0.0220	0.0850***	0.0264	0.0885***	0.0279
Self-Employed (%)	0.0493	0.0508	0.0442	0.0498	0.0510	0.0423	0.0492	0.0495
Retired (%)	0.0830***	0.0056	0.0689***	-0.0030	0.0801***	-0.0002	0.0789***	0.0093
Source: ELSTAT								
Mean size of household	0.2106	0.0587	0.2137	0.0824	0.1188	0.1222	-0.0470	-0.0801
Unemployment	-0.0840***	-0.0456***	-0.1033***	-0.0575***	-0.0965***	-0.0587***	-0.0848***	-0.0582***
Education: no (%)	base	base	base	base	base	base	base	base
Education: primary (%)	-0.0009	-0.0497**	0.0071	-0.0506**	0.0099	-0.0468**	0.0116	-0.0529***
Education: secondary (%)	-0.0177	-0.0474***	-0.0136	-0.0447***	-0.0184	-0.0458***	-0.0101	-0.0465***
Education: tertiary (%)	0.2986***	0.1861***	0.3093***	0.1908***	0.3161***	0.1985***	0.3021***	0.1759***
Employment: primary (%)	base	base	base	base	base	base	base	base
Employment: secondary (%)	0.0339***	0.0444***	0.0439***	0.0564***	0.0478***	0.0594***	0.0354***	0.0506***
Employment: tertiary (%)	0.0151*	-0.0180**	0.0261***	-0.0099	0.0171*	-0.0123*	0.0065	-0.0194***
Time-dummies	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-8.5399	10.4972***	-9.2793	9.2650***	-7.7875	9.0694***	-8.4153	11.5642***
Observations	3,087	924	3,087	924	3,087	924	3,087	924
R-between	0.9474	0.9313	0.9415	0.9281	0.9378	0.9247	0.9424	0.9358

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table A-III-8. The determinants of taxable income inequality for the population as a whole

	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012-2014	2002- 2011	2012- 2014
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KLISTHENIS TYPE								
Metro district	base	base						
Island: large or medium-size	2.0225**	3.5240***						
Island: small	2.7686***	3.5650***						
Mainland: large	2.3757***	2.4787***						
Mainland: medium-size	2.0038***	2.2402***						
Mainland: small and mountainous	1.8786**	1.7783**						
URBANISATION								
Cities			base	base				
Cities, and towns and suburbs			0.5549	0.7265				
Rural areas			1.3397*	2.2820***				
Towns and suburbs			1.2460**	2.0061***				
SURFACE (%)								
Plain surface					base	base		
Semi mountainous surface					0.0104**	0.0051		
Mountainous surface					0.0129***	-0.0042		
CORINE LANDCOVER (%)								
Urban							base	base
Artificial							0.0182	-0.0022
Agricultural							0.0224*	0.0239*
Forest							0.0300**	0.0202
Wetlands							0.0654**	0.0958***
CONTROLS								
Source: Declarations								
Population density	0.0012	-0.0002	-0.0002	-0.0014	-0.0005	-0.0033***	0.0014	-0.0007
Mean number of children	-3.6212	-0.6521	-2.4898	-0.0433	-4.0904	0.1972	-3.1580	-0.5155
Mean number of cars	-2.3912	0.4829	-2.3443	0.1644	-1.2730	0.1404	-0.8667	1.0322
Married people (%)	-0.0048	-0.1344***	0.0040	-0.1228***	0.0126	-0.1316***	0.0079	-0.1343***
Proprietors (%)	base	base	base	base	base	base	base	base
Traders (%)	-0.2707***	-0.1322**	-0.2766***	-0.1654***	-0.2760***	-0.1209**	-0.2699***	-0.1465**
Farmers (%)	-0.3738***	-0.1731***	-0.3899***	-0.2235***	-0.4061***	-0.1826***	-0.3840***	-0.1819***
Employees (%)	-0.4513***	-0.1445**	-0.4693***	-0.2056***	-0.4762***	-0.1857***	-0.4620***	-0.1687***
Self-Employed (%)	-0.4903***	-0.1513	-0.4845***	-0.2140*	-0.5260***	-0.1921*	-0.4957***	-0.1994*
Retired (%)	-0.5300***	-0.2767***	-0.5428***	-0.3343***	-0.5766***	-0.2993***	-0.5402***	-0.3052***
Source: ELSTAT								
Mean size of household	0.7722	0.0332	0.7588	-0.2175	0.7117	-0.1040	0.8243	-0.1554
Unemployment	0.0242	0.0036	0.0237	-0.0090	0.0279	-0.0143	0.0280	-0.0261
Education: no (%)	base	base	base	base	base	base	base	base
Education: primary (%)	-0.0213	0.0020	-0.0283	-0.0231	-0.0330	-0.0025	-0.0222	-0.0099
Education: secondary (%)	-0.0263	0.0036	-0.0239	-0.0018	-0.0287	0.0003	-0.0271	-0.0078
Education: tertiary (%)	0.2327***	0.2801***	0.2088***	0.2518***	0.1746***	0.2429***	0.2167***	0.2546***
Employment: primary (%)	base	base	base	base	base	base	base	base
Employment: secondary (%)	-0.0555**	0.0294	-0.0520**	0.0452*	-0.0638***	0.0562**	-0.0579**	0.0609**
Employment: tertiary (%)	-0.0282	0.0084	-0.0194	0.0319*	-0.0276	0.0285	-0.0338	0.0214
Time-dummies	yes	yes	yes	yes	yes	yes	yes	yes
Constant	54.2847***	44.8060***	56.1197***	48.8084***	63.4884***	47.8740***	50.2619**	46.7841***
Observations	3,087	924	3,087	924	3,087	924	3,087	924
R-between	0.5817	0.8052	0.5634	0.7957	0.5711	0.7874	0.5669	0.7959

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table A-III-9. The determinants of taxable income per capita for employees

	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012- 2014
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KLISTHENIS TYPE								
Metro district	base	base						
Island: large or medium-size	0.1877	-0.3428						
Island: small	1.3696***	0.6403						
Mainland: large	-0.4422	-1.0118***						
Mainland: medium-size	0.1404	-0.5268						
Mainland: small and mountainous	0.4881	-0.1986						
URBANISATION								
Cities			base	base				
Cities, and towns and suburbs			-1.3525***	-1.8776***				
Rural areas			0.1931	-0.5759				
Towns and suburbs			-0.1573	-0.6879**				
SURFACE (%)								
Plain surface					base	base		
Semi mountainous surface					0.0034	0.0014		
Mountainous surface					0.0027	0.0005		
CORINE LANDCOVER (%)								
Urban							base	base
Artificial							-0.0117	-0.0049
Agricultural							-0.0325***	-0.0392***
Forest							-0.0181***	-0.0224***
Wetlands							0.0032	0.0174
CONTROLS								
Source: Declarations								
Population density	-0.0003	-0.0003	-0.0004	-0.0002	0.0002	0.0010*	-0.0022***	-0.0024***
Mean number of children	-1.8082	-2.8570*	-2.3303	-4.0783***	-3.6553**	-4.6316***	-2.9425**	-3.3764**
Mean number of cars	6.4029***	4.9686***	5.5237***	3.5912***	5.3494***	3.5933***	6.1743***	5.4923***
Married people (%)	-0.0073	-0.0142	-0.0076	0.0006	-0.0114	-0.0025	-0.0015	-0.0025
Proprietors (%)	base	base	base	base	base	base	base	base
Traders (%)	-0.0957**	-0.1327***	-0.0651*	-0.0915***	-0.0560	-0.0954***	-0.0482	-0.1020***
Farmers (%)	0.0300	-0.0225	0.0378	-0.0030	0.0404	-0.0121	0.0406	-0.0091
Employees (%)	-0.0376	-0.0424	-0.0365	-0.0346	-0.0304	-0.0361	-0.0273	-0.0392
Self-Employed (%)	0.0032	0.0777	0.0243	0.1042	0.0061	0.0697	0.0124	0.0911
Retired (%)	0.0550*	-0.0034	0.0601**	0.0039	0.0507	-0.0038	0.0598**	0.0116
Source: ELSTAT								
Mean size of household	0.8252**	0.4787	0.8170**	0.5665	0.7626**	0.6495	0.5751	0.3522
Unemployment	-0.1011***	-0.0284	-0.1128***	-0.0415**	-0.1127***	-0.0443**	-0.0899***	-0.0404**
Education: no (%)	base	base	base	base	base	base	base	base
Education: primary (%)	-0.0239	-0.1161***	-0.0181	-0.1103***	-0.0166	-0.1124***	-0.0138	-0.1186***
Education: secondary (%)	-0.0117	-0.0840***	-0.0097	-0.0801***	-0.0139	-0.0856***	-0.0019	-0.0825***
Education: tertiary (%)	0.2200***	0.1346***	0.2316***	0.1489***	0.2381***	0.1556***	0.2223***	0.1175**
Employment: primary (%)	base	base	base	base	base	base	base	base
Employment: secondary (%)	0.0311***	0.0578***	0.0375***	0.0707***	0.0373***	0.0690***	0.0239**	0.0551***
Employment: tertiary (%)	0.0312***	0.0005	0.0351***	0.0055	0.0263**	0.0013	0.0117	-0.0089
Time-dummies	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-29.9744***	18.2580***	-31.1856***	15.4145***	-28.9583***	16.0791***	-28.7056***	19.7882***
Observations	3,086	923	3,086	923	3,086	923	3,086	923
R-between	0.8809	0.8537	0.8751	0.8497	0.8666	0.8377	0.8822	0.8663

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table A-III-10. The determinants of taxable income inequality for employees

	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012- 2014	2002- 2011	2012- 2014
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KLISTHENIS TYPE								
Metro district	base	base						
Island: large and medium-size	3.4464***	3.8814***						
Island: small	3.7156***	3.7140**						
Mainland: large	1.2662	1.7819*						
Mainland: medium-size	1.3287	2.6145**						
Mainland: small and mountainous	1.0526	1.4280						
URBANISATION								
Cities			base	base				
Cities, and towns and suburbs			-1.4545	-0.9957				
Rural areas			1.3084	3.1898***				
Towns and suburbs			0.7258	2.1543**				
SURFACE (%)								
Plain surface					base	base		
Semi mountainous surface					0.0123**	0.0149**		
Mountainous surface					-0.0019	-0.0124*		
CORINE LANDCOVER (%)								
Urban							base	base
Artificial							0.0040	-0.0033
Agricultural							-0.0183	-0.0003
Forest							0.0048	-0.0004
Wetlands							0.1178***	0.1151**
CONTROLS								
Source: Declarations								
Population density	0.0007	-0.0018	-0.0009	-0.0026	-0.0007	-0.0040***	-0.0013	-0.0041
Mean number of children	1.9038	2.6918	2.8319	4.1678	1.8323	3.5815	1.7516	3.2054
Mean number of cars	-0.5942	0.5189	-2.0997	0.8196	-2.0216	-0.1230	0.4990	1.8664
Married people (%)	-0.1054*	-0.1782***	-0.1013*	-0.1720***	-0.1118**	-0.1869***	-0.0901	-0.1949***
Proprietors (%)	base	base	base	base	base	base	base	base
Traders (%)	0.1166	0.0244	0.1346	-0.0234	0.1573	0.0672	0.1587	0.0349
Farmers (%)	-0.1328	-0.1325	-0.1740**	-0.2028**	-0.1558*	-0.1172	-0.1535*	-0.1232
Employees (%)	-0.1488*	-0.0502	-0.2023**	-0.1181	-0.1942**	-0.0677	-0.1713**	-0.0600
Self-Employed (%)	-0.2414*	-0.0879	-0.2829**	-0.1560	-0.2945**	-0.1088	-0.2898**	-0.1543
Retired (%)	-0.0580	-0.0730	-0.1090	-0.1356	-0.0999	-0.0633	-0.0888	-0.0831
Source: ELSTAT								
Mean size of household	0.4217	-0.5105	0.4150	-0.9279	0.3160	-0.5145	0.1759	-1.0664
Unemployment	0.0541	-0.0133	0.0208	-0.0173	0.0389	-0.0224	0.0533	-0.0485
Education: no (%)	base	base	base	base	base	base	base	base
Education: primary (%)	-0.0212	-0.1769*	-0.0127	-0.2028**	-0.0098	-0.1670*	0.0013	-0.1809*
Education: secondary (%)	-0.0241	-0.0759	-0.0155	-0.0895	-0.0270	-0.0892	-0.0086	-0.1027
Education: tertiary (%)	0.3678***	0.2609***	0.3552***	0.2361**	0.3550***	0.2439***	0.3616***	0.2295**
Employment: primary (%)	base	base	base	base	base	base	base	base
Employment: secondary (%)	-0.0322	-0.0292	-0.0164	-0.0210	-0.0121	0.0005	-0.0389	0.0016
Employment: tertiary (%)	-0.0572*	-0.0948***	-0.0229	-0.0713**	-0.0399	-0.0859***	-0.0700**	-0.0938***
Time-dummies	yes	yes	yes	yes	yes	yes	yes	yes
Constant	29.8679	63.7806***	30.2917	68.2599***	37.9978	64.8030***	24.3069	68.9359***
Observations	3,086	923	3,086	923	3,086	923	3,086	923
R-between	0.4599	0.4729	0.4462	0.4758	0.4422	0.4712	0.4585	0.4602

Notes: *** p<0.01, ** p<0.05, * p<0.1

Chapter IV

The geographical incidence of Covid-19 mortality in Greece: Comparative evidence from the six waves of the pandemic

In this chapter we try to investigate the geographical variations in the COVID-19 mortality in Greece using novel statistical information cross-classified by Regional Administrative Units, ten-year age groups, and six waves of the pandemic. The material employed in this analysis covers forty-two weeks over the period 26-10-2020 to 22-3-2022 representing one of the lengthiest time periods ever studied in the spatiotemporal analysis of COVID-19. The estimation of Standardized by ten-year age-group Case-Fatality Ratios (SFR) makes it possible to control for differences in the age distributions of deaths and cases across the regional populations and over the waves of observation. Furthermore, the application of a Spatial Durbin Econometric Model (SDEM) provides an assessment of the validity and statistical significance of the socio-economic, demographic, and geographical variables for the appraisal of the spatiotemporal variations of the mortality rate from COVID-19. The results are relevant to regional health policy and could be utilized for the design of appropriate policies to control the spread and mitigate the impacts from epidemic shocks in the future.

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Disclaimer

This paper, co-authored with Yannis Psycharis (Professor – Department of Economics and Regional Development, Panteion University), Cleon Tsimbos (Emeritus Professor – Department of Statistics and Insurance Science, University of Piraeus) and Leonidas Doukissas (Post PhD researcher – Department of Economic and Regional Development, Panteion University), is currently under review at Journal *Papers in Regional Science*.

IV.1 Introduction

The pandemic ushered modern civilization into a new historical era influencing the ways of thinking and acting of individuals and of collective or institutional actors. The abrupt halt of production activity and the everyday routine of billions of people across the globe, the interruption of travel flows of people and goods, and the changing patterns of interaction and communication have reshaped our thinking and our interpretation of the role of space in scientific investigation and in policy action (Bailey *et al.*, 2020; Dodds *et al.*, 2020; Martin, 2021; Gong *et al.*, 2022; Keil, 2020)). The Pandemic has triggered a voluminous body of research on the role of space as an integral and inherent part of our understanding of and reaction to the incidence/ occurrence and transmission of the disease and the endurance/resistance, vulnerability and resilience of citizens and places (ESPON & European Union, 2022; OECD & European Union, 2022; Böhme *et al.*, 2022).

The literature has provided a voluminous body of empirical research which attempts to capture the multiplicity of expressions of the disease in differentiated spatial contexts, by making use of a variety of statistical data, the implementation of analytical techniques, and the exploitation of theoretical standpoints and interpretations. Empirical analyses cross over continents and individual countries offering multi-scalar analyses ranking from supranational, global, and continental levels to urban, regional, local and neighborhood levels (Gulbrandsen, 2022 for Norway; Ascani *et al.*, 2021 for Italy; Pandey, 2022 for India; Li *et al.*, 2022 for China; Sartorius *et al.*, 2021 for the UK; de Souza *et al.*, 2021 for Brazil; Ramírez-Aldana, 2020 for Iran; Widiawaty, 2022 for Indonesia). The proliferation of the scientific research is still going on (i.e., Special Issue Journal of Regional Science 2022, Coulson *et al.*, 2021; Special Issue Regional Studies, 2021; Brodeur, 2021; Florida *et al.*, 2022; Glaeser, 2022; Batty, *et al.*, 2022).

The aim of this paper is to analyze the geographical incidence and mortality from COVID-19 by providing novel empirical evidence from Greece. The voluminous and still flourishing scientific research provides robust evidence that space and geography are not at all neutral in the incidence of, transmission of, and defense against the disease (Díaz Ramírez *et al.*, 2022; Rodríguez-Pose and Burlina, 2021; Capello and Caragliu, 2021; Konstantinopoulos *et al.*, 2022; Feinhandler *et al.*, 2020; Xie *et al.*, 2021). This research constitutes an attempt to communicate and interact with the rich international debate and to provide an evidence-based empirical analysis from Greece.

The multidimensional expressions of the disease call for a multidisciplinary approach in the study of its incidence and its dynamics of diffusion. This research engages methods, concepts and analytical techniques from different scientific disciplines such as regional and urban

economics, demography, spatial planning and thematic cartography, statistics, and spatial econometrics with an emphasis on epidemiological models. This research explicitly constitutes an interdisciplinary approach with the participation of demographers, economists, spatial analysts, and thematic cartographers.

However, while the approach deployed in this research engages the existing literature, it does not simply constitute a repetition or/and mitigation of existing works. On the contrary, this work contains some novelties that could add to our understanding of the geographical dimension of COVID-19 and offer methodological tools and results that could enrich the international debate and research. As such, this work has some very distinctive merits, not only for the analysis of a specific case study, but also for the enrichment of our thinking and the enhancement of our understanding of one of the most severe and critical issues of our times. The merits of this paper can be seen as follows.

First, the rich and diverse geographical landscape of Greece which includes remote and sparsely populated areas, along with mountainous areas, a mosaic/scattering of islands, lengthy coastlines, as well as metropolitan conurbations and medium-sized cities, make this case study very useful to a broader audience. The unique geomorphological and immensely diversified landscape could be seen as a laboratory for studying the role of space in the incidence, evolution, and variations of COVID-19, as well as the underlying factors that determine the spread of the pandemic and the vulnerability and resistance of people in different geographical contexts.

Second, the analysis is based on a unique dataset which provides precise information regarding the incidence of and deaths from COVID-19 at a geographically disaggregated level. The construction of the database is based on the recently established administrative division of *Regional Units* of the country. Law 3852/2010 legislated Regional Units as part of the reforms towards a new architecture of the administrative system of the country. As a result, the reshuffling of the former fifty-one NUTS 3 regions resulted in the formulation of seventy-two geographical jurisdictions/entities. These more disaggregated statistical units allow a more accurate representation/inspection of regional features of Greece and offer a closer and more targeted investigation for the study of the geographical incidence of COVID-19 in the country⁹.

⁹ According to Eurostat the NUTS 3 geographical level in Greece included fifty-one spatial units (the so-called *nomoi*). This classification, which was widely used in regional analysis, had important shortcomings, one of which was the large differences in population size among spatial units. As an example, Attiki, which included Athens, the capital city of Greece, was considered as one out of fifty-one cases. The ‘Kallikratis’ Program (L. 3852/2010), introduced *Regional Units*, as part of the administrative reforms in the country. The seventy-four *Regional Units* represent a higher degree of geographical disaggregation comparing to NUTS 3 classification. As an example, in the new classification, the former Attiki NUTS 3 region, is divided into eight geographical units (Central Athens, North Athens, West Athens, South Athens, East Attika, West Attika, Piraeus, and

Third, the dataset provides the classification of cases and deaths by ten-year age-groups. This information allows the estimation of the Age-Standardized Fatality Ratio (*SFR*) which constitutes a more articulated age-specific estimation of the mortality relative to the simple indicator, without any age-specific weighting. However, while the literature has underlined the significance of age-adjusted estimations of mortality rates (Bhopal, 2020), there is a scarcity of research based on the *SFR*, not only at the regional level, due to lack of statistical data, but at the national level as well (Gallo *et al.*, 2021). Estimation of the *SFR* constitutes a much closer approximation of reality with regard to the geography of mortality and allows for more reliable comparisons across space and over time. This research approach aims at counterbalancing, in part, the scarcity and gaps in the existing literature. This measure has rarely been utilized in the empirical research and enables the replacement of the single and most widely used mortality expression with a more articulated age-specific indicator on the regional scale.

Fourth, the analysis is based on the waves of the pandemic. Literature has underlined that the pandemic has been deployed in waves. These fluctuations defer in the length and intensity. Waves relate to different expressions of the disease (named with the Greek Alphabet *Alpha*, *Beta*, *Delta*, *Omikron*) and different moments in the preparedness of the health system, and the policy measures taken by countries. Periods without any specific medical treatment have turned to periods with vaccination. However, vaccination rate fluctuates over time and over space. The vaccination rate has an important influence on the protection from the disease. Lockdowns, restrictions in travelling play also an important role in the diffusion of the disease. In this research, the time length of the analysis covers six waves of the pandemic of different duration and intensity. Tracing the evolution of COVID-19 by wave provides a better understanding of the spread of the disease and allows for the implementation of appropriate policies. A concise presentation of waves is provided in the next section.

Fifth, the paper employs a spatial epidemiological model – a Spatial Durbin Econometric Model (SDEM), which is superior to the spatial models since it allows for more accurate methods which are consistent with the relevant literature on spatial analysis of the evolution and the determinants of the disease (LeSage and Pace, 2009; Elhorst, 2014; LeSage, 2014)

Islands). Another major change has to do with Cyclades and South Aegean Islands which are now divided into thirteen *Regional Units*. Given the availability of historical statistical data based on the former classification, most studies at the NUTS 3 geographical level were based on the fifty-one spatial units. To the best of our knowledge, this is the first, or one of the first papers of regional analysis for Greece that explicitly utilizes the new classification, having transformed all the variables that are included in the analysis accordingly. The official names of *Regional Units*, and the border lines, are clearly indicated in the thematic maps throughout the paper.

Sixth, this paper provides empirical evidence from Greece, an economy which is largely based on tourism. The abrupt halt of transport impacted incomes in a variety of socio-economic groups and localities. Tourism not only represents a large part of GDP and is the main source of income in many areas such as on the islands. It is also one of the sectors of the economy most affected by the pandemic and this fact had a major impact on local economic and social conditions.

Finally, to the best of our knowledge, this is the first research that delves into the geographical incidence and mortality of COVID-19 in Greece. The data provide fertile ground for an investigation of the geographical features of the pandemic by adding to our knowledge about the incidence, transmission, and casualties from the disease.

Summing up, the unique and novel dataset, the estimation of a ten-year age adjusted *SFR* and the implementation of econometric models which explicitly account for epidemiological studies constitute the novel aspects of this research attempt. Tracing the evolution of the incidence rate and the fatality rate during one of the longest time periods ever studied in the relevant literature constitutes another important merit of this study. The findings could be utilized for the design and implementation of appropriate policies and could be extended to areas beyond the country-specific case-study and could be useful for epidemiological episodes that could be extended beyond the COVID-19 pandemic.

IV.2 The geography of incidence and mortality from COVID-19: a concise literature review

The geographical aspects regarding the incidence and deaths from the pandemic, as well as the underlying factors that explain this statistical evidence, have been studied widely in the literature.

The literature regarding the geographical dimension of the pandemic has followed many trajectories. The geographical incidence of COVID-19 in cities, metropolitan areas and large urban agglomerations (González-Val and Sanz-Gracia, 2022); the intra-urban disease spread has been studied in relation to living conditions and income inequality (Ehlert, 2021); comparative studies regarding urban *vis-à-vis* rural areas (Pandey, 2022), country-specific case studies, and supranational cases, provide a large spectrum of cases and fieldwork. The spatiotemporal analysis of COVID-19 constitutes another distinct strand of scientific literature (Coura-Vital *et al.*, 2021; Liu *et al.*, 2021b; Maiti *et al.*, 2021)

The geographical perspective of COVID-19 was introduced with the logic of risk analysis (e.g., Sigler *et al.*, 2021; Wang *et al.*, 2020; Liu *et al.*, 2020). Following this approach, several

researchers focused on the correlation of human mobility and the spatial distribution of COVID cases and deaths through checking the effectiveness of lockdowns and other measures intended to limit transmission of the virus (e.g. Iacus *et al.*, 2020; Irini *et al.*, 2021; Francetic and Munford, 2021; Seto *et al.*, 2022).

Another broad group of articles and studies concerns the *geospatial ecological study* approach of mapping spatial concentrations of COVID-19 cases and deaths in predefined spatial units and assessing the impact of ecological factors such as health behaviors, clinical care and burden, socioeconomic and physical features related to the environment during the COVID-19 pandemic. Typically, these studies also aim to identify high-risk areas for targeting public health and economic challenges and to prioritize resource and infrastructure allocation needs. The geographic perspective is usually expressed through the geo-location of cases and the corresponding grouping into spatial units where statistical data are available. In some cases, this perspective includes the introduction of variables – in the USA - regarding social distancing as a measure to limit the transmission of the virus (e.g. Kathe and Wani, 2021; Yang *et al.*, 2021; Ehlert, 2021; Fonseca-Rodriguez *et al.*, 2021; Yu *et al.*, 2022).

One variation of the role of "space" as an interpretive factor is the analysis of accessibility to health services and its correlation with the effects of the pandemic in terms of mortality and the intensity of the occurrence of waves (e.g., Souris and Gonzalez, 2020; Kang *et al.*, 2020; Park and Goldberg, 2022; Qi *et al.*, 2022). An important observation concerns the differential effect of socioeconomic factors on the spread of the virus in a different context and spatial scale of analysis (Alidade and Sharifi, 2022).

Investigating the spatial relationship and existence of spatial autocorrelation between COVID-19 cases, morbidity and deaths through exploratory analysis has been a significant field of study. Global and local measures of spatial autocorrelation were used at the municipal level in Catalonia to identify spatial clusters of COVID-19 cases weekly (Arauzo-Carod, 2021). Bilal *et al.*, (2021) examined spatial clusters of high and low positivity, confirmed cases, and mortality in three U.S. cities and ascertained that were co-located with clusters of low and high social vulnerability. Parvin *et al.*, (2021), attempting to detect the hotspot of the novel coronavirus in India examined total population, population density, foreign tourist arrivals in India, reported confirmed cases of the COVID-19 and found statistically significant autocorrelation.

During the coronavirus pandemic, crude incidence and mortality rates have been widely reported. Most studies employ the crude Case Fatality Rate *CFR* estimation in order to trace the evolution of casualties from the disease and to make comparisons between countries. However, the literature provides robust statistical evidence that the age structure of the cases explains much of differences in the crude *CFR* between countries and adjusting for age

substantially reduces this variation (Hong *et al.*, 2021; Green *et al.*, 2020; Gallo *et al.*, 2021). Therefore, age-standardized fatality rates reduce the distortions, provide a better approximation to reality, and improve comparability between countries. Age-specific and age-adjusted fatality measures should be used for comparisons. This research makes an application of age adjusted mortality ratios and makes the empirical investigation into a lower geographical level.

IV.3 Data, stylised facts and the estimation of Standardized Fatality Ratio (FSR) from COVID-19

IV.3.1 Data and initial stylised facts

The analysis of this study is based on official data on diagnosed deaths from and confirmed cases of COVID-19 registered nationwide in Greece during the period 26-10-2020 to 22-3-2022. The analysis relies on 2,741,487 confirmed cases and 25,598 diagnosed deaths from COVID-19 observed nation-wide during the entire study-period.

The statistical material employed in the analysis has been extracted from the official database of the National Organisation for Public Health (EODY). Cases were recorded according to the date of diagnostic test and deaths according to the date of death. The dataset does not include deaths and cases for which the place of residence was not declared. In the primary dataset, COVID-19 deaths and cases were classified at the municipality level. However, due to the large number of municipalities, such a detailed double classification (age group and district of habitation) resulted in a very large number of zero or negligible frequencies. Hence, for the purpose of the statistical analysis, appropriate area aggregations were performed to attain the data to correspond to the Regional Administrative Units of Greece's formal Administrative Division System. The Municipality of Mount Athos (Agion Oros) was excluded from the analysis due to its special conditions and composition of its population as well as the very small number of events observed. The island of Melos was also excluded from the analysis due to the lack of COVID-19 deaths during the study period. Thus, our analysis focuses on 73 Regional Units with valid observations of COVID-19 deaths and cases. For the period under investigation, EODY distinguishes six waves of the pandemic.

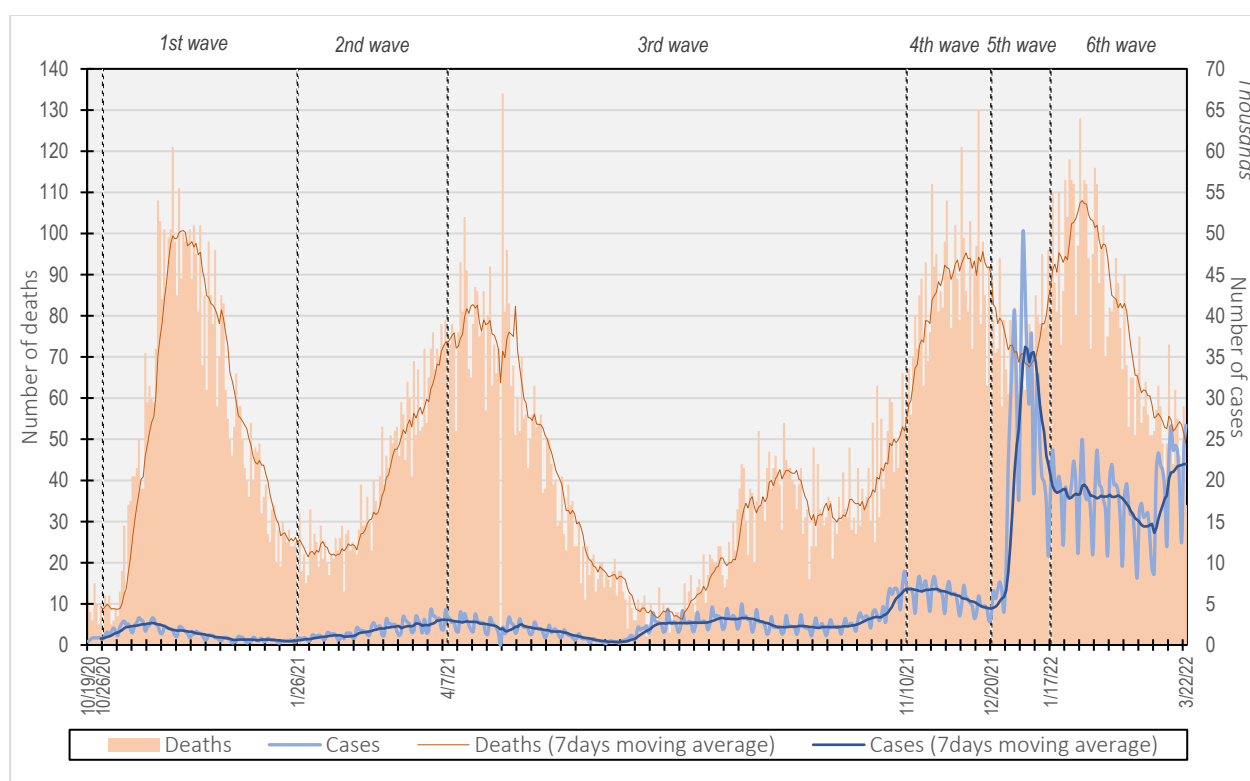
Table IV-1 shows the total number of cases and deaths from COVID-19 in Greece grouped by wave during the time-period under study. **Figure IV-1** builds upon this material and provides a better visualisation of waves, time periods, cases (measured on the left vertical axis), and deaths (measured on the right vertical axis). **Table IV-1** and the **Figure IV-1**, along with **Table IV-2**, and the corresponding **Figure IV-2** provide some interesting findings.

Table IV-1. Total number of cases and deaths from COVID-19 in Greece by wave

Wave	Period	Cases	Deaths
Wave 1	26/10/2020 - 25/1/2021	115,460	4,946
Wave 2	26/1/2021 - 06/04/2021	132,689	2,844
Wave 3	07/04/2021 - 9/11/2021	500,275	7,528
Wave 4	10/11/2021 - 19/12/2021	224,780	3,414
Wave 5	20/12/2021 - 16/01/2022	621,191	2,095
Wave 6	17/01/2022 - 22/03/2022	1,147,092	4,771
All Waves	20/10/2020 - 22/03/2022	2,741,487	25,598

Source: National Organisation for Public Health (EODY) (authors' own elaboration)

Figure IV-1. Number of cases and deaths from COVID-19 in Greece by wave of the disease: October 2020 to March 2022



Source: Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University [CSSEGISandData] (<https://github.com/CSSEGISandData/COVID-19>)

The first observation is that the cumulative number of infected people for all waves amounts to 2,737,735 cases, which represent 27% of total population of the country. The total number of deaths amounts to 25,591. This number of COVID-19 deaths represents 12.5% of the total number of deaths of the country during the period under study (**Table IV-2**)¹⁰. Furthermore,

¹⁰ As a matter of comparison, COVID-19 accounted of 400,000 deaths representing the 8% of all deaths in the EU in 2020 and 520,000 deaths representing the 10% of all deaths in 2021 (OECD/European Union, 2022).

based on the evolution of incidence and deaths, there is a clear difference between the first three and the second three waves. The deaths/infections ratio is higher during the first three waves *vis-à-vis* the later three waves. On the contrary, the deaths/infections ratio is lower during the three last waves in comparison with the first three waves. This demonstrates that during the first three waves, the *relative* number of deaths was higher compared with the three last waves. This could probably be attributed to the absence of a vaccine and the small percentage of vaccination coverage of the population during this period¹¹. This shows that during the first three waves, people had been more exposed to the disease and less protected, and therefore the death/incidence ratio was higher compared with the three last waves.

Table IV-2. COVID-19 deaths as a percentage of total deaths (all causes) in Greece by wave

Wave	Number of deaths		Percentage (%) COVID-19
	COVID-19	All causes	
Wave 1	4,946	36,256	13.6
Wave 2	2,844	25,312	11.2
Wave 3	7,528	84,111	9.0
Wave 4	3,414	17,725	19.3
Wave 5	2,095	11,595	18.1
Wave 6	4,771	29,863	16.0
All waves	25,598	204,862	12.5

Source: National Organisation for Public Health (EODY) (authors' own elaboration)

However, while the *relative* number of deaths was higher during the first three waves of the pandemic compared with the three last waves, the *absolute* number of cases was much higher during the three later waves. A plausible explanation for this is that despite the increasing numbers of cases, the gradual progress of vaccination shielded population from fatal exposure to the disease. In addition, it seems that the intensity of the virus gradually wanes over time. The variants of the disease including *Alpha*, *Beta*, *Delta*, and *Omicron*, seem to have been less harmful compared with the initial strength of the disease, even though the variants of the disease had been more infectious relative to the original virus¹². As a result, although the *relative*

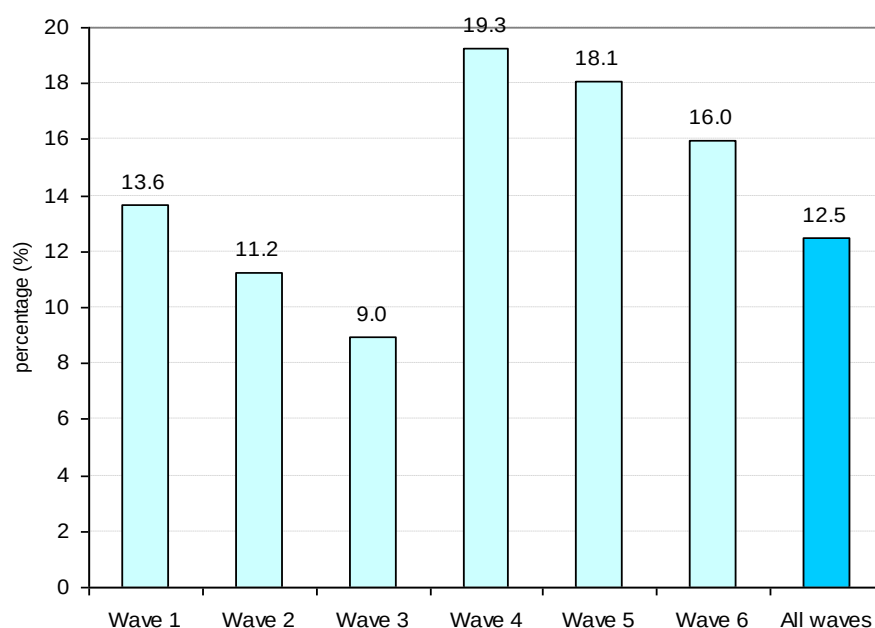
¹¹ The vaccination in Greece started on Sunday 27 December 2020. President, and the Prime Minister of Greece had been among the first who received the vaccine.

¹² The World Health Organization (WHO) names new coronavirus variants using the letters of the Greek alphabet. Since the beginning of the pandemic, we have seen several prominent variants, including *Alpha*, *Beta*, *Delta*, and *Omicron*. *Alpha* variant emerged in Great Britain in November 2020 and infections surged in December of that year. *Alpha* faded away with the rise of the more aggressive *Delta* variant. It is estimated that *Delta* caused more than twice as many infections as previous variants, it was estimated to have been 80 to 90% more transmissible than the *Alpha* variant. In June 2021, after a steady decline in Covid-19 cases and hospitalizations, the arrival of *Delta* coincided with a rapid reversal of that trend. People in England had double the hospitalization risk with *Delta* than they did with *Alpha*, the previously dominant variant in that country. The

number of deaths was higher during the first three waves of the pandemic, the total number of deaths is much higher during the second three waves of the pandemic due to the high increase in the *absolute* number of cases during the three last waves. This explains why the highest percentage of deaths from COVID-19 observed during the fourth wave (19.3%) compared with the total number of deaths during the period under investigation.

Another interesting finding is the gradual decline of the intensity of the disease within the first three and the second three waves of the pandemic. A close inspection of **Figure IV-2** shows that among the three first waves, wave two was less intense, and wave three even less intense from the previous ones. The same applies to the latter three waves. Wave five was less intense than wave four and wave sixth even less intense than fourth and fifth. This trend could be probably attributed to policy measures. Policy measures seem to have had an impact on the transmission of the disease. As an example, the nationwide lockdown that was imposed on March 13, 2020, had an impact on controlling the spread of the disease.

Figure IV-2. COVID-19 deaths in Greece as a percentage of total deaths (all causes) by wave



Source: EODY and Hellenic Statistical Authority (authors' calculations)

On November 3, 2020, the Greek nationwide lockdown limited transmission around the country. In addition, the gradual progress in the vaccination coverage of the population shielded populations from the hazardous impacts of the disease. Wearing masks, introducing more

variant of *Beta* was identified in South Africa at the end of 2020 and spread to other countries. Beta was about 50% more contagious than the original coronavirus strain (Yale Medicine, 2022, <https://www.yalemedicine.org/news/covid-19-variants-of-concern-omicron>)

rigorous hygiene habits, and following strict protocols for social distancing etc. helped to protect the population and therefore the mortality rate was gradually decreasing during the first three waves. Similar arguments could be used for the interpretation of the gradually decreasing fatality in the three last waves of the pandemic. However, the decreasing trend of fatality during the later three waves could also be attributed to the variants of the disease which proved less damaging compared with the initial strength of the virus.

IV.3.2 Standard and Standardised fatality measures: methodological approach

The case fatality rate is an important parameter in epidemiology that illustrates the seriousness and risk of a disease that leads to death. For the purpose of this study, the Case Fatality Rate (*CFR*) is calculated as the number of diagnosed deaths from COVID-19 observed in a population during a specified period, per 100 confirmed COVID-19 cases of the given population. This measurement is calculated by Regional Unit as well as by wave of the disease. Additionally, we compute for each region (*i*) Fatality Location Quotients (*FLQ_i*) using the simple ratio,

$$FLQ_i = \frac{CFR \text{ of region } i}{\text{national } CFR} \times 100 \quad (1)$$

in order to portray the relative excess or deficit of the severity of the disease at the local level compared to the fatality rate of the whole population.

Particularly when they are available at a regional level, case fatality rates can be useful to assess a range of health-related issues such as public-health policy measures, health care and hospital provisions, vaccination outcomes, medical treatments and health campaigns. On the other hand, however, case fatality rates have some shortcomings including, among others: difficulties in evaluating the actual course of the disease; complications in assessing the time elapsed between the onset of the disease and the occurrence of death; and complexities in the diagnosis and reporting of cases and deaths (Luo *et al.*, 2021; Thomas and Marks, 2021).

From the demographic point of view, a further weakness in *CFR* may be attributable to differences in the age distribution of the cases and deaths. As the numerator and denominator of the conventional *CFR* include total numbers (through all ages) of deaths and cases, differences and variations in the age distributions in the aforementioned events across the populations under research may have an influence on the observed value of the indicator.

As noted above, the material used in this study refers to numbers of COVID-19 deaths and cases cross-classified by 10-year age groups, by Regional Units and by waves of the disease. At such a level of statistical detail, in most instances, the observed numbers of deaths are very small or even zero, and thus data does not allow the calculation of age-specific fatality rates to

permit further refined elaboration and appraisal. Hence, in this study we approach the sub-national COVID-19 fatality analysis, statistically, on the basis of the ratio of observed to expected number of COVID-19 deaths making use of the notion of the indirectly age standardization methodology used in the demographic analysis of mortality.

For each administrative unit (i), we calculate a Standardized Fatality Ratio (SFR_i) as follows:

$$SFR_i = \frac{\text{observed number of covid-19 deaths in region } i}{\text{expected number of covid-19 deaths in region } i} \times 100 = \frac{O_i}{E_i} \times 100 \quad (2)$$

or

$$SFR_i = \frac{\sum_x \left(\frac{O_{x,i}}{C_{x,i}} \right) \cdot C_{x,i}}{\sum_x E_{x,i}} \times 100 = \frac{\sum_x f_{x,i} \cdot C_{x,i}}{\sum_x F_x \cdot C_{x,i}} \times 100 \quad (3)$$

and finally:

$$SFR_i = \frac{O_i}{\sum_x F_x \cdot C_{x,i}} \times 100 \quad (4)$$

where:

- $O_{x,i}$ is the number of COVID-19 deaths of persons aged x in region i
- $C_{x,i}$ is the number of COVID-19 cases of persons aged x in region i
- $f_{x,i}$ is the age-specific case fatality rate (per person) of the population in region i , and
- F_x is the age-specific case fatality rate (per person) of a chosen standard (reference) population:

$$F_x = \frac{D_x}{C_x} = \frac{\text{covid-19 deaths aged } x \text{ in the standard population}}{\text{covid-19 cases aged } x \text{ in the standard population}} \quad (5)$$

We calculate regional Standardized Fatality Ratios ($SFRs$) for all waves combined (for the entire period of observation) as well as separately for each wave of the disease using as standard age-specific fatality schedule (F_x) the age distributions of COVID-19 deaths and cases of the national population (country) of each wave.

As expression (3) shows, the value of the regional estimated standardised fatality ratio depends on the differences in the age-specific fatality rates between the study population ($f_{x,i}$) and the reference population (F_x). A value of SFR greater than 100 denotes that the observed deaths are more than the expected ones, indicating a relative excess of COVID-19 fatality in the population under study, compared to the standard (general population); the opposite is revealed when $SFR < 100$.

Following the notion and applications of the well-known Standardized Mortality Ratio (*SMR*), the statistical significance of the ratios of the observed to expected numbers of deaths of each regional unit ($O_i \div E_i$) can be assessed on the basis of a chi-2 test or on the estimation and evaluation of appropriate confidence intervals (Armitage *et al.*, 2002; Breslow and Day, 1987; Liddell, 1984).

The interpretation of the Standardised Fatality Ratios (*SFR*) is similar to the indices of Fatality Location Quotients; however, the use of the *SFR* in the analysis has some advantages; firstly, we control for differences in the age distribution of the events across populations; secondly, we can assess the statistical significance of the measure; and thirdly, we can calculate more *SFR* values employing the alternative reference population. For instance, a possible implementation could be to use the national age-specific fatality rates of the first wave as the standard fatality schedule (F_x) throughout the analysis to examine possible differentials by region and time.

IV.4 The estimation and visualisation of *SFR*

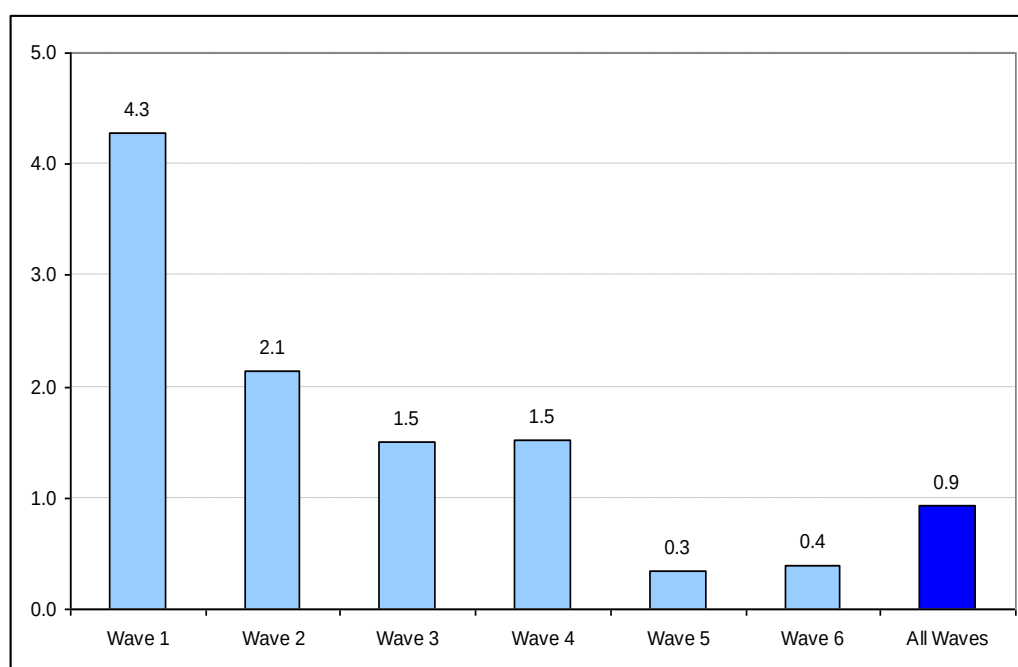
IV.4.1 Portraying the results

According to the methodology proposed in the previous section, the paper proceeds with the estimation and presentation of *SFR* by wave and Regional Unit. In the final part of this section there is an application of LISA maps in order to test for spatial clustering.

Figure IV-3 provides some stylised facts regarding the volume and variation of mortality by wave. It is obvious that there are striking differences between waves. Simple calculations show that the case fatality rates reach a maximum of 4.3 deaths per 100 cases in wave 1 but after that they gradually diminish over time. When considering the total period under study, the fatality rate of the population reaches the level of one death per 100 cases of COVID-19.

Although the highest volume of cases is observed in the wave 6, the highest value of the mortality rate is observed in wave 1. This is probably due to the fact that during the first wave neither medical treatment nor a vaccination had been produced for the protection of the population. On the contrary, during the later stages, although the virus was more contagious, the spread was more rapid, and the contagion rate was much higher, the mortality rate was relatively lower probably due: to progress in the vaccination rate of the population; the lockdowns and restrictions that had been imposed on travelling and contacts; the obligatory use of masks; and in general the habituation of people concerning hygiene practices in their everyday habits.

Figure IV-3. Case fatality rates per 100 by wave of the disease: 26/10/2020 – 22/3/2022



Source: EODY and Hellenic Statistical Authority (authors' calculations)

A comparison between the regional crude and standardized fatality indices confirms that the effect of the proposed age-adjustment methodology is perceptible. Evidently, areas with high values of crude fatality rates tend also to exhibit high values of standardized fatality ratios. However, in most regions, there are palpable deviations between the two measures due to the different age distributions of the cases of COVID-19 observed in different districts. The experiential deviations between the conventional and the age standardized fatality measures are more pronounced in areas with a moderate to high risk of the disease (**Figure IV-4**).

This is in line with (Green *et al.*, 2020) who argue that the crude case-fatality rates (*CFR*) for COVID-19 hide more than they reveal, and therefore it is misleading to use crude COVID-19 *CFRs* comparisons between countries. Rather, age-specific and age-adjusted *CFRs* should be used for comparisons. Sudharsanan *et al.*, (2020) argue that removing age distortions and focusing on differences in age-adjusted case fatality will be essential for accurately comparing countries' performances in caring for patients with COVID-19 and for monitoring the epidemic over time.

Considering the entire period, the standardized fatality ratios (*SFR*) range from 18 to 179; the lowest value corresponds to the island of Karpathos (located in South Aegean Sea) denoting an 82% lower COVID risk compared to the national average; the highest *SFR* value refers to the northern region of Pella (located in Central Macedonia) indicating an elevated disease risk of 79% compared to the national average. Of the 73 regions, 43 (59%) are mainland areas and the remaining 30 (41%) are islands; overall, 75% of the regional units exhibit fatality ratios lower

than national average. **Figure IV-5** presents the mean *SFR* values for the 13 administrative regions of the country. Islands exhibit the lowest COVID risk (47% to 52% lower than the national average) while the highest *SFR*s are observed in the regions of Eastern Macedonia and Thrace; as well as in Central Macedonia (10% and 52% higher than national average, respectively).

Figure IV-4. Scatterplot between crude fatality rates and standardized fatality ratios amongst the 73 regions of the study (all waves)

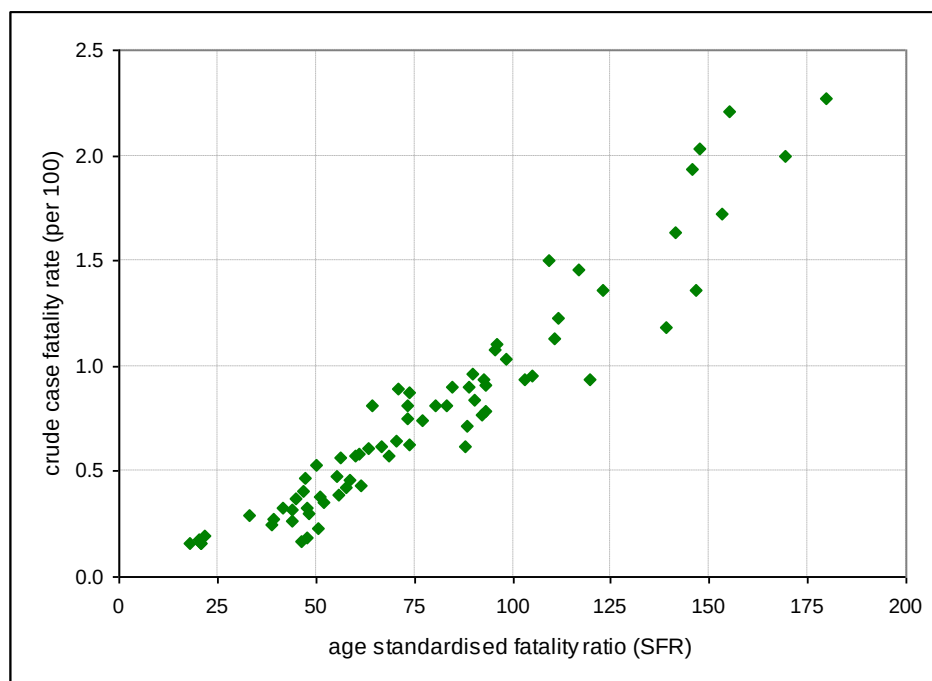
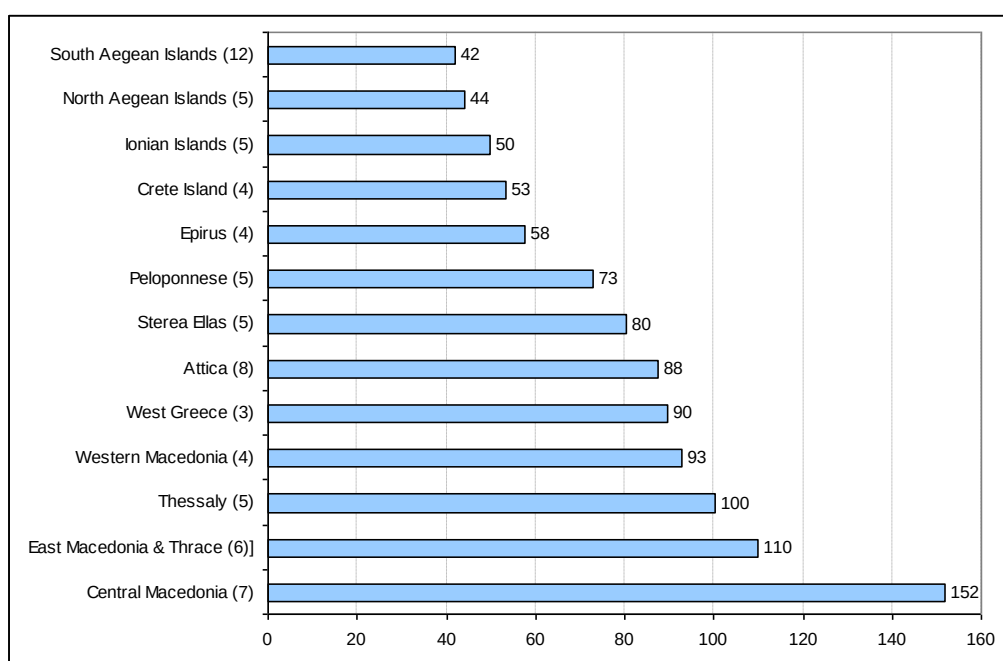


Figure IV-5. Mean *SFR* values for the 13 Regions of the country: all waves (in parenthesis the number of Administrative Units)



IV.4.2 Portraying SFR using thematic cartography

Figure IV-6 (Maps 1-7) shows that during the first wave, the areas that had been more affected by the virus were the Northern and North-Eastern parts of the country. During the first wave, populations had been more exposed to the disease without strong defensive measures such as vaccines. The concentration of high mortality rates in Northern parts of the country, at least during the first stages of the pandemic, is probably due to the high degree of interactions that exist between northern Greece and the neighboring countries in the Balkan Peninsula. This probably explains the low values of mortality in areas such as the Peloponnese in the South of the country, an area with much less intense international flows and interactions. Furthermore, the strong persistence of high rates of mortality in Northern and North-Eastern regions of the country could also be attributed to other reasons such the relatively lower level of economic development and the socio-economic and demographic attributes of the areas and the populations.

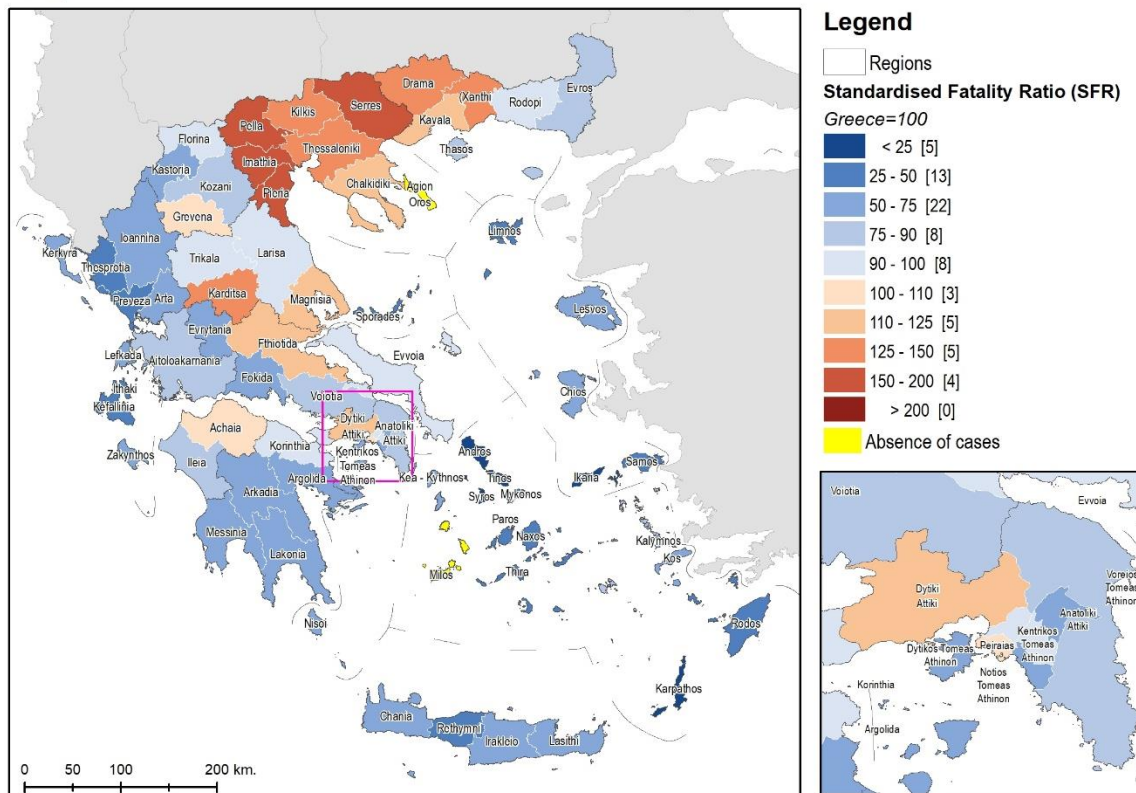
Another striking issue that attracts attention is the concentration of high mortality rates in the metropolitan area of Athens. However, closer inspection of the geographical pattern of the disease shows that the mortality rate is not distributed equally across the entire metropolitan territory. The western part of the region accounts for a disproportionately higher number of casualties' *vis-à-vis* the rest of the region. This fact could be attributed to the lower level of economic development, poorer living conditions, lower level of education and higher concentrations of immigrants and minorities in this part of the region.

In order to test for spatial clustering, the analysis is making use of the most notable application of spatial autocorrelation with the estimation Local Indicators of Spatial Association (LISA) maps (Anselin, 1995). This method constitutes an established point of reference for a wide variety of applications. This method has been used for the estimation of spatial association in the geographical analysis of incidence and deaths from COVID-19 (Bag *et al.*, 2020; Ghosh and Cartone, 2020; Liu *et al.*, 2021a; Mollalo *et al.*, 2020).

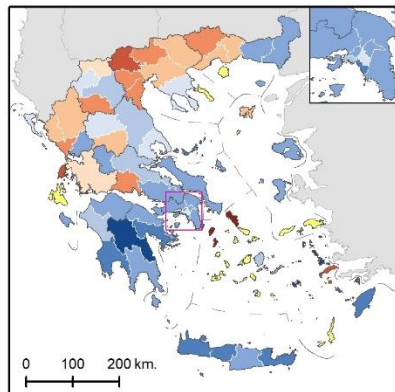
LISA maps have been estimated taking into consideration for each observation the six neighboring Regional Units. The analysis includes the entire period under study as well as the individual waves. Results are presented in **Figure IV-7**.

Figure IV-6. Mapping SFR by wave and Regional Unit in Greece

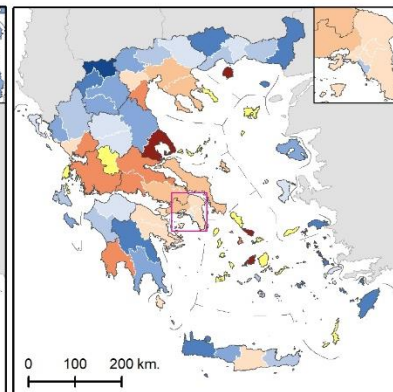
Total period



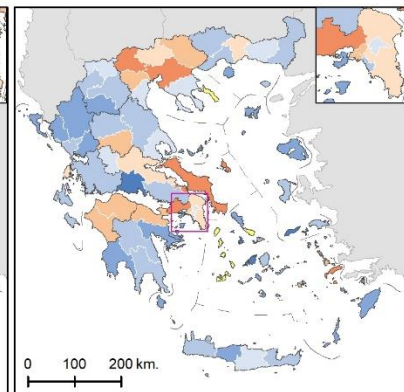
1st wave



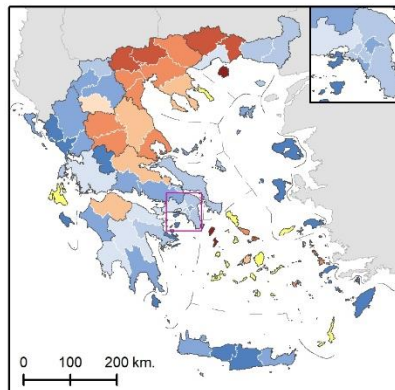
2nd wave



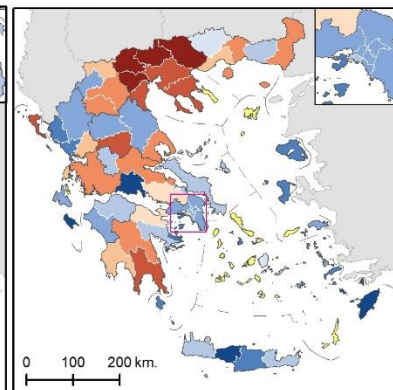
3rd wave



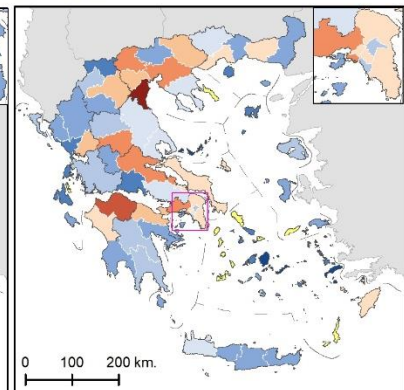
4th wave



5th wave



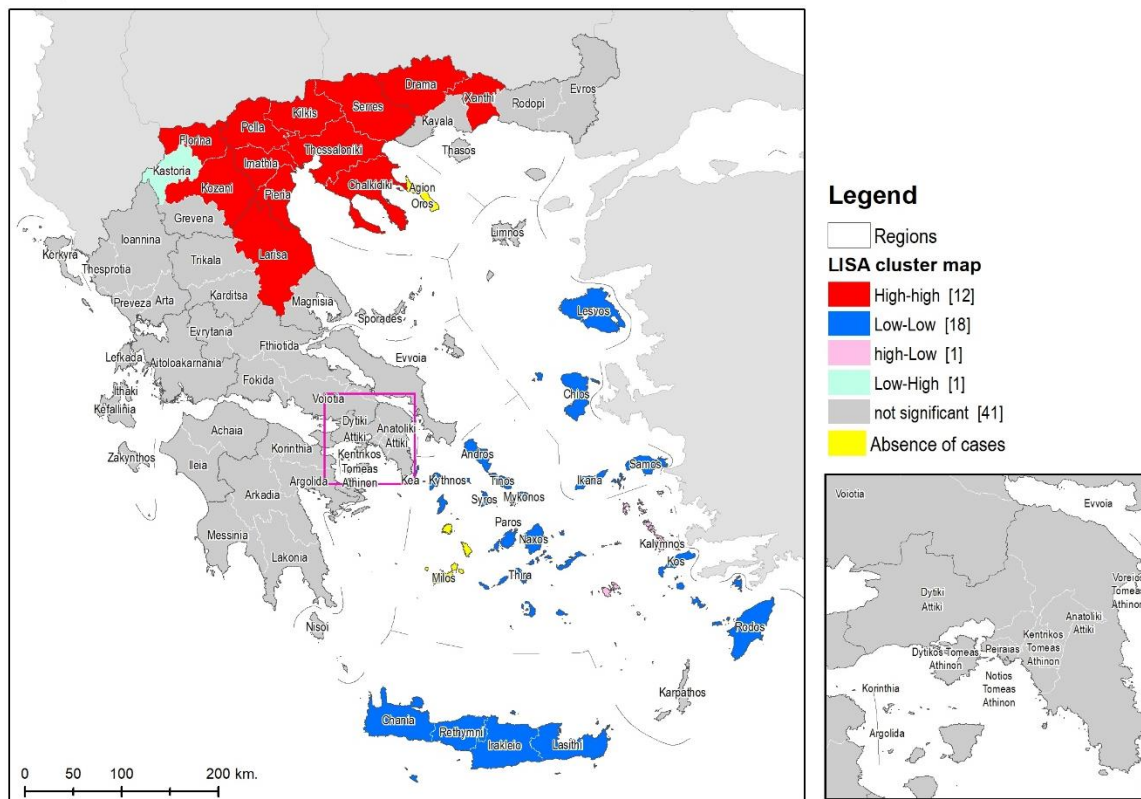
6th wave



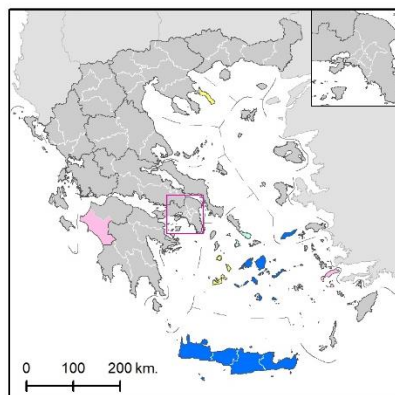
Source: EODY and Hellenic Statistical Authority (authors' calculations)

Figure IV-7. Mapping Spatial Autocorrelation LISA maps by wave and Regional Unit in Greece (6n)

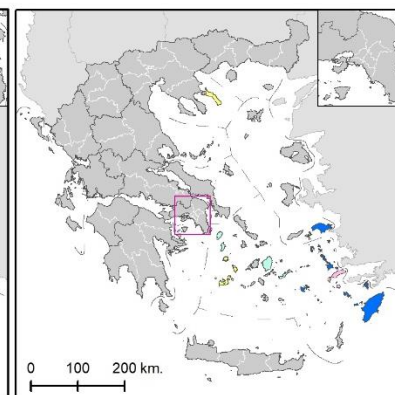
Total period



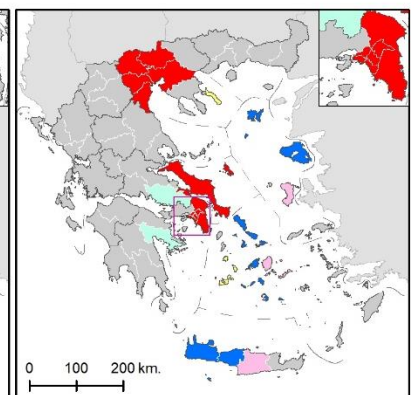
1st wave



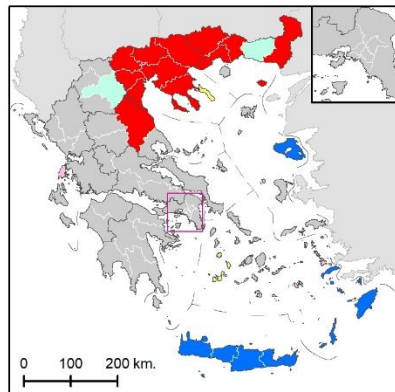
2nd wave



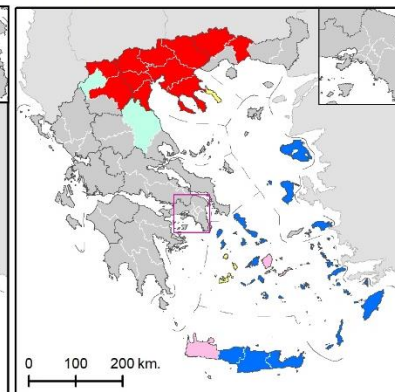
3rd wave



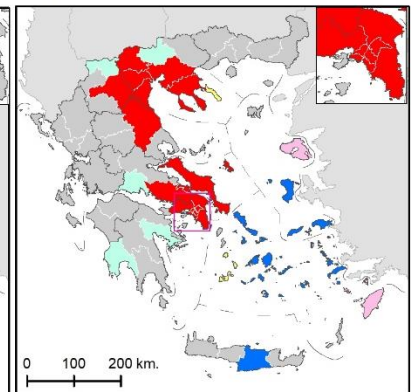
4th wave



5th wave



6th wave



Source: EODY and Hellenic Statistical Authority (authors' calculations)

IV.4.3 Spatial clustering of SFR

The spatial autocorrelation is further intensified by the LISA indices. As **Figure IV-7** illustrates, both for the total period as well as the separate waves of the disease, the value of spatial autocorrelation is high and positive. Hotspots can be identified in the areas of the Northern and the North-Eastern parts of the country, the metropolitan area of Athens and to the lower extent in Achaia/ Patras, and in Volos/Larisa which represent the third and fourth urban agglomerations in ranking respectively. Cold spots can be identified in the Southern and the Western parts of the country and on the islands. The majority of hot spots could be identified along the two main transport corridors of the country; the PATHE that starts from Evzonoi, the small city at the border of Greece and Bulgaria, extends to Thessaloniki and runs across the eastern part of the country, crossing region of Thessaly and passing through the dipole Larisa and Volos, reaching the industrial agglomeration/ zone of Voitia, a region adjacent to Attica, which constitutes an extension of Attica's production system, passes Attika, heading towards Patras, the third city in size of Greece, running across the northern part of Peloponnese. The other important transport axis runs across the Northern part of the country, from the borders with Turkey to the North-Western part of the country in Igoumenista, one of the most important ports which is an important sea gateway that connects Greece with Italy and the rest of Europe. Islands exhibit Low-Low clusters for the entire period and only in the sixth wave Lesbos, one of the biggest Greek islands, and Rhodes, one of the most attractive tourism destinations turn to become High-Low spots. Other similar spots for the islands could be found sporadically across waves, like Kalymnos in the first and second, Chios, Naxos and Irakleio in the third and Naxos and Chania in the fifth waves.

IV.5 Variable selection and model specification

IV.5.1 Selection of variables

In this section we propose a spatial econometric model in order to assess the relationship between the Standardized Fatality Ratio (SFR_t) with a selection of independent explanatory variables. Aiming to examine risk factors which contribute to COVID-19 vulnerability, a set of 14 possible covariates. The variable set is divided into 3 groups (**Table IV-3**). Demographic (ageing), Socioeconomic (education, number of beds, location quotient in the primary, secondary and tertiary sector, foreign and domestic tourists) and Geographic (accessibility, island, border, mobility within settlement of residence, mobility within administrative unit and settlements under 2000 inhabitants). Stepwise regression was performed to select the core set of independent variables that contribute significantly to all the models. The key variables in all

the models were the following: 1) Ageing, 2) Education, 3) Accessibility, 4) Island, 5) Border, 6) Mobility within settlements, and 7) Beds ratio. Subsequently, the remaining independent variables from the set of 14 were then incorporated into different models (**Table IV-3**). Our analysis showed that intra-income inequality (Wgini) and mean declared income equivalent (Wmean) in regional units (see chapter II.3) are not linearly correlated with the SFRt index (see **Appendix Figure A-IV-8** and **Figure A-IV-9**).

Table IV-3. Variable definition and variable name

Variable	Definition
Ageing	Ratio of elderly population (aged 65 years and over) per 100 individuals younger than 14 years old in resident population (2011)
Education	Residents with tertiary education (%) (2011)
Accessibility	The ESPON multimodal accessibility indicator, which describes how easily people in one region can reach people located in other regions, integrates accessibility by road, rail and air, and its calculation is based on the population in NUTS-3 regions and the travel time to reach them.
Island	Administrative units that include only island territories (2021). Categorical variable (1= island, 2 = island with neighboring regional unit, 3 = mainland)
Border	Administrative units that include land borders with other countries. Categorical variable (1 = regional units that include land borders, 0 = regional units do not include land borders).
Mobility_w_Settle	Employees with a place of work within the settlement of residence (%) (2011)
Mobility_w_AU	Employees with a place of work within the administrative unit of permanent residence (%) (2011).
Pop_under2000	Inhabitants in settlements less than 2000 inhabitants (%) (2011)
LQ_e1	Location quotient (LQ) of employed population in the primary sector (2011)
LQ_e2	Location quotient (LQ) of employed population in the secondary sector (2011).
LQ_e3	Location quotient (LQ) of employed population in the tertiary sector (2011)
Beds_ratio	Ratio of beds in units of the national health system per 1000 in patients (2021)
Foreign_Tourist_Arr	Ratio of foreign tourist arrivals per resident population (2021)
Domestic_Tourist_Arr	Ratio of domestic tourist arrivals per resident population (2021)

In order to examine the relationship between the COVID-19 incidence rate and a set of related variables, spatial regression models have been applied (Hu *et al.*, 2020). The use of spatial econometrics incorporating spatial heterogeneity contributes to a better and more efficient interpretation of the spatial relationship between the dependent variable and a set of explanatory variables. Spatial econometric analysis based on with Moran's *I* coefficient in Brazil indicates a positive spatial autocorrelation with high mortality and cases from COVID-19 in the north, northeast and in the largest urban centers between cities in the southeast region (Castro *et al.*, 2021). More specifically, when studying the geographic variation in the COVID-19 incidence rate and mortality in New York City, a relation exists between socio demographic factors, mobility, and environmental factors (Kim *et al.*, 2021). Spatial regression confirmed that the increasing population density of the area increased the virus infection rate (Kulu *et al.*, 2021).

Total population, poverty and income were found to be the key factors in moderating total fatalities when spatial regression models were applied in the European region to selected demographic and socioeconomic variables (Sannigrahi *et al.*, 2020). Spatial and temporal trends in the US in COVID-19 cases revealed geographic disparities and a more severe impact upon urban counties in relation to rural areas (Jackson *et al.*, 2021). Spatial transmission of Covid-cases in Wuhan, China showed obvious global and local spatial aggregations (Liu *et al.*, 2021b). Spatial regression models were applied in Iran with a focus on examining the relationship between socio-demographical factors and cases of COVID-19 and highlighted that literacy is a factor associated with a decrease in the number of cases (Ramirez *et al.*, 2020). Spatial error and spatial lag models were also applied in Bangladesh concluding that there exists a statistically significant relationship between COVID-19 cases and a set of demographic factors such as population density and the number of people aged 60 or higher (Sarkar *et al.*, 2021).

Spatial determinants of COVID-19 cases and deaths in US counties was examined through a set of socioeconomic and demographic variables and it emerged that age, disability, language, race, occupation, and urban status increase vulnerability to COVID-19 (Andersen *et al.*, 2021). Spatial regression modeling was also applied in the study area of Brazil which identified that spatial effects are present and that there is a strong relationship between the GINI index and the mortality rate in the increase of COVID-19 relative risk (Martines *et al.*, 2021). Across England, spatial models examined the COVID-19 mortality rate and spatial inequalities of socioeconomic and environmental factors which demonstrated a significant difference between COVID-19 mortality and non COVID-19 mortality (Sun *et al.*, 2020).

Spatial analysis conducted in Oman demonstrated the spatial dimension of COVID-19 and examined a set of sociodemographic covariates that interpreted the relationship between cases and a set of variables indicating that the elderly population aged 65 and above, population density, hospital beds, and diabetes rates are statistically significant determinants of COVID-19 incidence rates (Mansour *et al.*, 2021). Spatial regression models applied in Bangladesh, in order to explain spatial variability of COVID-19 disease incidence, found that urban residence, monthly consumption, number of health workers and distance from the capital city are significant factors of COVID-19 incidence (Rahman *et al.*, 2021). A significant factor influencing the spread of COVID-19 is high population density found in informal settlements in the city of São Paulo (Urban *et al.*, 2021). Spatial regression models applied in the State of Louisiana concluded that race, poverty, and age have a most constant effect on COVID-19 cases (van Holm *et al.*, 2021). It is worth noting that geographically weighted regression models have also been applied providing insightful results showing the relationship between case fatality and COVID-19 mortality and a set of demographic and socioeconomic independent variables

(Hassaan *et al.*, 2021; Liu *et al.*, 2021a, Raymundo *et al.*, 2021; Zhai *et al.*, 2021; Zhang *et al.*, 2021).

IV.5.2 Model specification and econometric analysis

In the present study, a Spatial Durbin Error Model (SDEM) was selected which constitutes a general local spatial model (LeSage and Pace, 2009; Elhorst, 2014; LeSage, 2014). The existence of spatial autocorrelation in the study variable of Standardized Mortality Ratio (*SFRt*) empowers the use of spatial models to incorporate spatial dependence into a regression model. More precisely, a local spatial model becomes essential since neighboring regional units affect neighboring regional units especially in the case of COVID-19. Receiving information on neighboring areas, Spatial Durbin Error Models provide us exclusively with extra knowledge about the significance of direct and indirect effects for each explanatory variable which comprises a comparative advantage over other spatial models. To our knowledge, this model has not been applied to COVID-19 data and therefore makes its selection particularly useful. Likelihood ratio tests are applied in order to find out if SDEM should be restricted to a simpler, nested model such as the Spatial Error Model (SEM) (LeSage and Pace, 2009; Elhorst, 2014).

The Spatial Durbin Error Model (SDEM) with the addition of spatial lag effects on independent variables and spatial error effects is:

$$FLQ_i = \frac{CFR \text{ of region } i}{\text{national } CFR} \times 100 \mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{WX}\boldsymbol{\theta} + \mathbf{u}, \mathbf{u} = \lambda \mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon} \quad (1.1) \mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{WX}\boldsymbol{\theta} + \mathbf{u}, \mathbf{u} = \lambda \mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon} \quad (6)$$

The Spatial Durbin error model is expressed in equation (6) where:

- θ is the spatial autocorrelation coefficient,
- y is the dependent variable of the data of each regional unit, X
- X is the independent variable of the data,
- W is the standardized spatial weighted row matrix,
- β is coefficient of the independent variables,
- λ is spatial error coefficient,
- u is the spatial error in the regional unit and
- ε is the model error.

IV.6 Results and discussion

The application of the spatial regression model, using 4 *k*-nearest neighbors for spatial weights, provides some interesting results which are presented in **Table IV-4**. These could be summarized as follows: First, somewhat unexpectantly, in all models the coefficient of the variable Ageing is negative, indicating that ageing has an inverse relationship with *SFR_t* and overall, decreases COVID-19 risk. A plausible explanation for this finding is that although older people are more vulnerable, ageing *per se* is not sufficient to exert an influence on a positive correlation with *SFR* since when taking the entire set of explanatory variables into the model, determinants other than ageing supersede the explanatory strength of aging in the positive correlation with *SFR* to such a degree that ageing correlated negatively with *SFR*. Second, in all models, the variable education is negatively associated with *SFR_t* indicating an inverse relationship between education and the COVID-19 mortality risk. Third, accessibility has a positive coefficient suggesting that the higher interactions between regional units the greater COVID-19 mortality ratio. Fourth, when comparing the mainland to the Islands there is a positive and statistically significant relation revealing higher COVID-19 mortality ratio in the mainland compared to islands. As a result, the mainland showed the greatest vulnerability regarding the standardized mortality ratio. Fifth, mobility within settlements of residence has a positive and statistically significant coefficient in most models, indicating the strong relationship that exists between COVID-19 mortality and the mobility of the inhabitants. Sixth, likewise, mobility within an administrative unit has a positive but not significant coefficient in the models. Seventh, the percentage of inhabitants of places with more than 2000 inhabitants has a positive and statistically significant coefficient signifying the strong relationship that exists between COVID-19 mortality ratio and this specific variable. Eighth, location quotients of the population employed in the primary sector has a negative coefficient indicating a negative relation between COVID-19 mortality and the specific variable. On the contrary, secondary sector employment has a positive and not significant relationship with COVID-19 mortality, while results are mixed with respect to location quotients for the tertiary sector and the bed ratios. Ninth, foreign tourists' arrivals do not appear to affect COVID-19 mortality while the coefficient of the explanatory variable Domestic tourists highlights the important relationship between COVID-19 mortality and domestic tourist arrivals, exhibiting an inverse and statistically significant relationship.

Additionally, Spatial Durbin models can significantly contribute to the evaluation of the relationship between the dependent variable, *SFR_t*, and the neighboring values. In other words, these models show to what extent the dependent variable is related to neighboring regional unit values of the independent variable. Therefore, we can derive the following. First, the Ageing

coefficient takes negative values pointing to an inverse relationship between neighboring regional unit values of ageing and SFR_t . Secondly, it is worth noting that neighboring values of the tertiary sector have a negative coefficient and are statistically significant (Model 1), implying an inverse relationship between neighboring values of the location quotient in the tertiary sector and COVID-19 mortality. Thirdly, neighboring values of beds ratio has a negative and statistically significant (Model 3) coefficient, indicating an inverse relation between beds ratio and COVID-19 mortality. Fourthly, the negative and statistically significant coefficient of neighboring foreign tourist arrivals (Model 2) and domestic tourist arrivals (Model 3) signify the importance of the aforementioned variables in COVID-19 mortality.

In all models, a strong statistically significant autocorrelation exists indicating the spatial nature of Standardized Mortality Ratio (SFR_t) of COVID-19. To test for heteroskedasticity we conducted studentized spatial Breusch-Pagan test indicating that heteroscedasticity is not present in any of the models considered. Interpreting the lambda coefficient in Models 3 and 6, a multiplier of the residuals, which equals to 0.45 for Model 3, and 0.59 for Model 6, indicates that a higher unexplained value for Standardized Fatality Ratio in a neighboring regional unit increases the specific regional's unit residuals and therefore the value of SFR_t .

In line with the Akaike Information Criterion (AIC), the best Spatial Durbin Error Model is Model 3 (**Table IV-4**). Results indicate that for Model 3, the statistically significant variables are education, island, mobility within settlement, population under 2,000 inhabitants, domestic tourist arrivals and lags of islands, lagbeds_ratio and lag_domestic tourists.

Conducting Likelihood Ratio tests (LR test) in order to examine the hypothesis for the restricted model ($p_{value}=0.17$) confirms that the model selection should be restricted to a Spatial Error Model (SEM). The best SEM Model is Model 7. Model 6 shows that ageing, education, island (level 3 - mainland), mobility within settlement, and population under 2000 inhabitants are statistically significant variables. Negative coefficients appear in ageing and education. On the other hand, strong positive relationships exist between island (factor 3), mobility within

A great advantage of SDEM is that it allows us to examine the significance of *direct* and *indirect* effects for every explanatory variable in each regional unit. In other words, the SDEM makes it possible to examine how the independent variables affect values of SFR_t and, in addition, how neighboring independent values affect SFR_t (**Table IV-5**).

Table IV-4. Spatial Durbin and Spatial Error Models

Variables	SDEM			SER		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ageing	-2.91 (0.02)**	-1.97 (0.14)	-1.54 (0.13)	-2.67 (0.02)**	-2.34 (0.06)*	-1.65 (0.09)*
Education	-73.81 (0.48)	-85.92 (0.39)	-166.96 (0.07)*	-117.52 (0.26)	-91.39 (0.33)	-192.11 (0.03)**
Accessibility	0.51 (0.10)*	0.49 (0.10)*	0.30 (0.27)	0.60 (0.03)**	0.63 (0.02)**	0.41 (0.12)
factor(Island)2	13.58 (0.33)	19.34 (0.18)	10.59 (0.43)	16.05 (0.25)	20.35 (0.15)	12.26 (0.36)
factor(Island)3	32.27 (0.01)**	32.95 (0.00)**	24.79 (0.02)**	44.07 (0.00)**	49.04 (0.00)**	37.06 (0.00)**
factor(Border)1	-2.22 (0.80)	5.08 (0.57)	-0.41 (0.96)	6.27 (0.47)	7.30 (0.41)	7.85 (0.35)
Mobility_w_Settle	95.97 (0.02)**	62.75 (0.21)	65.42 (0.08)*	83.59 (0.03)**	65.29 (0.15)	61.38 (0.09)*
Mobility_w_AU		26.30 (0.69)			1.83 (0.97)	
Pop_under2000			38.74 (0.01)**			39.50 (0.01)**
LQ_e1	-2.94 (0.65)			-0.75 (0.90)		
LQ_e2		0.30 (0.98)			2.36 (0.85)	
LQ_e3	-13.31 (0.80)			7.61 (0.88)		
Beds_ratio	-0.11 (0.68)	0.13 (0.64)	-0.25 (0.33)	0.04 (0.89)	0.15 (0.59)	-0.01 (0.98)
Foreign_Tour_A		-0.17 (0.81)			0.20 (0.76)	
Domestic_Tour_A	-17.59 (0.00)**		-13.57 (0.01)**	-10.36 (0.05)**		-7.85 (0.12)
lag.Ageing	-4.91 (0.07)*	-3.36 (0.29)	-2.41 (0.34)			
lag.Education	346.24 (0.19)	205.85 (0.49)	56.06 (0.81)			
lag.Accessibility	0.55 (0.37)	0.57 (0.39)	0.42 (0.54)			
lag.factor(Island)2	-29.27 (0.26)	2.08 (0.94)	-39.68 (0.10)*			
lag.factor(Island)3	-7.22 (0.73)	7.34 (0.70)	3.07 (0.87)			
lag.factor(Border)1	6.16 (0.77)	38.88 (0.15)	16.77 (0.39)			
lag.Mobility_w_Settle	150.07 (0.14)	226.83 (0.12)	102.54 (0.33)			
lag.Mobility_w_AU		-123.28 (0.33)				
lag.Pop_less2000			-24.20 (0.54)			
lag.LQ_e1	-14.28 (0.33)					
lag.LQ_e2		5.62 (0.85)				
lag.LQ_e3	-203.64 (0.09)*					
lag.Beds_ratio	-0.64 (0.31)	-0.16 (0.79)	-1.29 (0.02)**			
lag.Foreign_Tour_A		-2.95 (0.08)*				
lag.Domestic_Tour_A	-26.46 (0.02)**		-33.57 (0.00)**			
<i>Lambda:</i>	0.37	0.53	0.45	0.58	0.60	0.59
<i>AIC:</i>	705.09	714.42	697.16	698.85	702.42	691.13
<i>LRtest</i>	15.76 (0.15)	9.99 (0.53)	13.97 (0.17)			
<i>R_square</i>	0.77	0.75	0.78	0.73	0.72	0.75
<i>Moran's I</i>	0.26 (0.00)**	0.29 (0.00)**	0.30 (0.00)**	0.26 (0.00)**	0.26 (0.00)**	0.30 (0.00)**
<i>Breush – Pagan</i>	21.69 (0.48)	24.07 (0.34)	20.41 (0.43)	10.81 (0.45)	12.60 (0.32)	6.86 (0.74)

Note: AIC, Akaike information criterion; LR test, Likelihood ratio test. * $p < 0.1$, ** $p < 0.05$

Table IV-5. Impacts of SDEM model 3

Variables	Direct	Indirect	Total
Ageing	-1.54 (0.13)	-2.41 (0.34)	-3.96 (0.19)
Pop_under2000	38.74 (0.01)**	-24.20 (0.54)	14.54 (0.75)
Education	-166.96 (0.07)*	56.06 (0.81)	-110.90 (0.69)
Accessibility	0.30 (0.27)	0.42 (0.54)	0.72 (0.29)
factor(Island)2	10.59 (0.43)	-39.68 (0.10)*	-29.09 (0.20)
factor(Island)3	24.79 (0.02)**	3.07 (0.87)	27.86 (0.10)*
factor(Border)1	-0.41 (0.96)	16.77 (0.39)	16.36 (0.43)
Mobility_w_Settle	65.42 (0.08)*	102.54 (0.33)	167.96 (0.17)
Domestic_Tour_A	-13.57 (0.01)**	-33.57 (0.00)***	-47.14 (0.00)***
Beds_ratio	-0.25 (0.33)	-1.29 (0.02)**	-1.54 (0.02)**

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Searching for an explanation for the sign of the ageing variable, arguments could be drawn from a Swedish study which demonstrates the effect of contextual factors on COVID-19 mortality (Fonseca-Rodriguez *et al.*, 2021: 295). This finding highlights the importance of public healthcare system as a defensive mechanism against epidemiological shocks. Therefore, there has been a clear message to governments and policy makers regarding the improvement and reinforcement of the healthcare systems as a *sine-qua-non* condition to defense efficiently epidemiological shocks.

IV.7 Conclusions and discussion

This study has focused on the geographical incidence of COVID-19 fatality in Greece. Due to the multidimensional expressions of the disease, it was necessary to set up an interdisciplinary approach since the study of the pandemic due to its complexity crosses many scientific disciplines and requires a variety of analytical tools and methods. Located at the intersection of spatial economics, demographics, planning and geography, this research draws on and builds on a combination of disciplines and methods of empirical analysis. The novel database offered the appropriate background for the estimation of age-adjusted *SFR* and the implementation of statistical analysis and econometric techniques for delving into geographical aspects of the incidence of COVID-19 mortality. Analysis has provided some interesting results that could

facilitate and enrich the dialogue on a serious issue of our times, both for scientific discourse and policy making.

The first outcome of this research is that space matters for the unfolding, the incidence, the transmission, and fatality from the disease. The spatial autocorrelation and spatial dependence have unveiled areas/geographies with relatively higher incidences and fatality from the disease as well as areas that are less affected. The Northern part of Greece, given its high level of interactions with the neighbouring countries in the Balkan Peninsula and Turkey proved more susceptible to infections while Southern Greece and the islands were affected to a lesser extent.

Second, the analysis by wave provides a better understanding of the evolution and transmission of the disease across space and over time. The number of cases was smaller during the first three waves *vis-à-vis* the later three waves. This can be attributed to the fact that the variants of the disease had proven more contagious than the original virus. However, the mortality rate wanes over the course of the explosion of the disease. This documents the fact that despite the greater spread of the disease, the gradual vaccination of the population along with other policy measures such as wearing masks, following strict hygiene habits and keeping social distances diminished the lethality of the disease.

Third, apart from the high incidence of COVID-19 in Northern areas of the country, the other most affected cases could be identified in the less well-off areas within the boundaries of the large urban conurbations such as Athens. High degree of infections could also be identified in areas that rank high in the urban system in Greece, such as Patras in the Northern Peloponnese which belongs to the Regional Unit of Achaia and Larisa and Volos in Thessaly belonging to the Regional Units of Larisa and Magnesia respectively. Thus, large cities and metropolitan areas seem to have been more vulnerable to the disease, especially in the marginal areas in term of economic status and social conditions.

Fourth, our econometric analysis shows that the critical determinants from the pandemic go beyond the age structure of the population. Analysis has shown that age *per se* does not constitute an explanatory factor for a positive correlation with the fatality rate. While older people are more vulnerable to the disease, living conditions, and income level assert significant explanatory power in the study of the evolution and expression of the disease.

Fifth, our results highlight the critical role of healthcare system and educational in defending ourselves against the pandemic. In all econometric models, education, which also proxies the level of economic prosperity, and hospital beds have a negative and statistically significant direct effect on mortality, indicating the crucial role these play on COVID-19 vulnerability.

Sixth, results denote that small settlements of less than 2,000 inhabitants with relatively higher employment in the primary sector and agricultural activities have a negative coefficient with mortality. Conversely, areas with higher levels of employment in the secondary sector show higher rates of mortality.

Finally, incoming international tourism has not proved to aggravate the level of mortality, while statistically significant negative direct, indirect, and total effects appear in domestic tourist arrivals. In all models, islands show lower mortality *vis-à-vis* the mainland.

This work offers the ground for policy proposals. The globalisation and urbanization are at a critical point, since COVID-19 and its epidemiological threat have been added as a critical centrifugal factor in the agglomeration economies. Although it is quite early to predict the future direction of megatrends such as globalisation and urbanization, quite often in history, external and unexpected events act as catalysts for the transformation and the shaping of future dynamics. What will cities be like after the pandemic? Will there be a reverse trend in urbanisation? What will the centrifugal and centripetal forces be after the pandemic? Taking into consideration the environmental crisis, climate change, the food /nutrition crisis, the ageing of population, and the energy crisis, how will these transform space and the interaction between places? The ‘location in space’, as the title of the seminal book by Lloyd and Dicken (1977) denotes, is anticipated to undergo gradual transformations, with the influence of the huge dynamics in action in every historical moment.

These results highlight the role of education, living conditions and the healthcare system in the explanation of the fatality. The role of public policy is of critical importance. The re-emergence of the necessity for policy action brings into question the dominant orthodox economic thinking which paved the way for the expansion of the market as the most appropriate player to settle economic activity and social conditions and shrinking the state. The cascade of crises constitutes state intervention ‘practical necessity’ as Nobel laureate Gunnar Myrdal (1898-1987) (Myrdal, 1939) referring to a similar historical moment. In the case of the pandemic, the national health systems across the globe took on the burden to protect people and help the economy and society to survive. ‘The return of the state’ proved indispensable for the protection of people, societies, and the economy from the disease. State intervention becomes even more critical for reigniting the economy and safeguarding the necessary public goods that improve living conditions, promote cohesion and inclusiveness, and safeguarding the essential public goods for the wellbeing and prosperity of people and territories.

Finally, results provide evidence that the most disadvantaged areas and populations paid the heaviest toll during the pandemic. Health inequalities, inequalities in living conditions and high rates of deprivation, poverty, and unemployment have pushed populations ‘living at the

margins' as well as 'left behind places' (Pike *et al*, 2023) to suffer even further. These places and populations require closer attention and policy action towards enhanced inclusiveness, improved socioeconomic cohesion and adequate provision of affordable living conditions for citizens, and sustainable development for places and territories.

Despite these merits this research has also caveats/limitations. The accuracy of registries, especially at the small geographical levels, could create false impressions and distort comparisons. The analysis could be complemented with information and statistical data about the vaccination spatiotemporal coverage. Finally, the availability of statistical data on population by age and regional unit will make it possible to make estimations of mortality at regional level.

Future extensions of this research could go deeper to examine the relationship between social inequalities with the incidence and mortality rates from the pandemic in different geographical subsets such as in large cities and metropolitan areas, in rural areas and on islands.

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Appendix

Figure A-IV-8. Scatterplot of weighted Gini of declared income equivalent 2019 by SFR total, Regional units

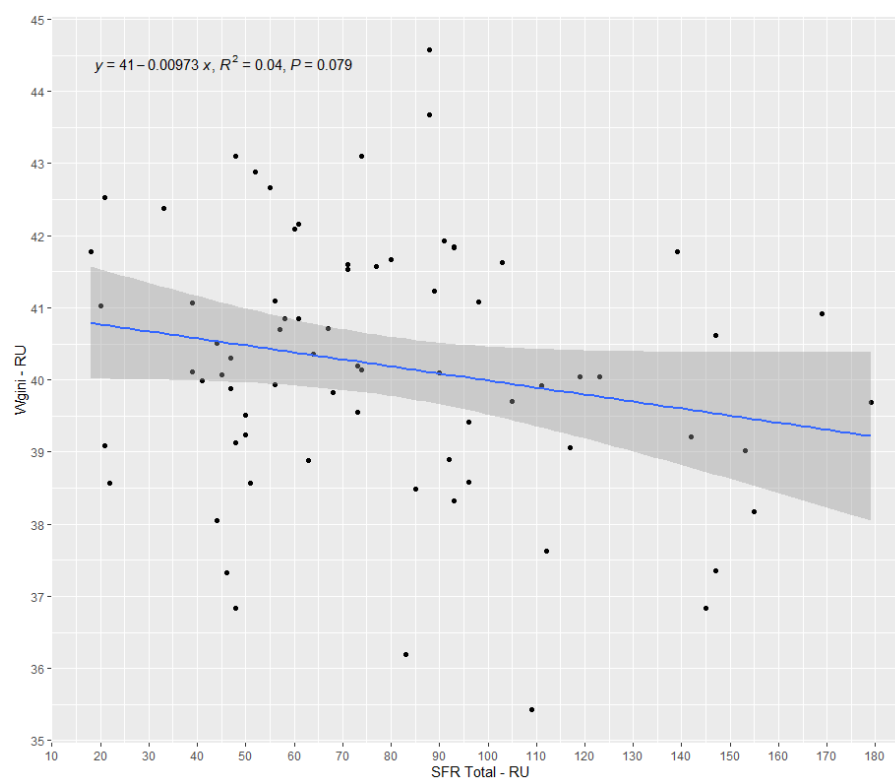
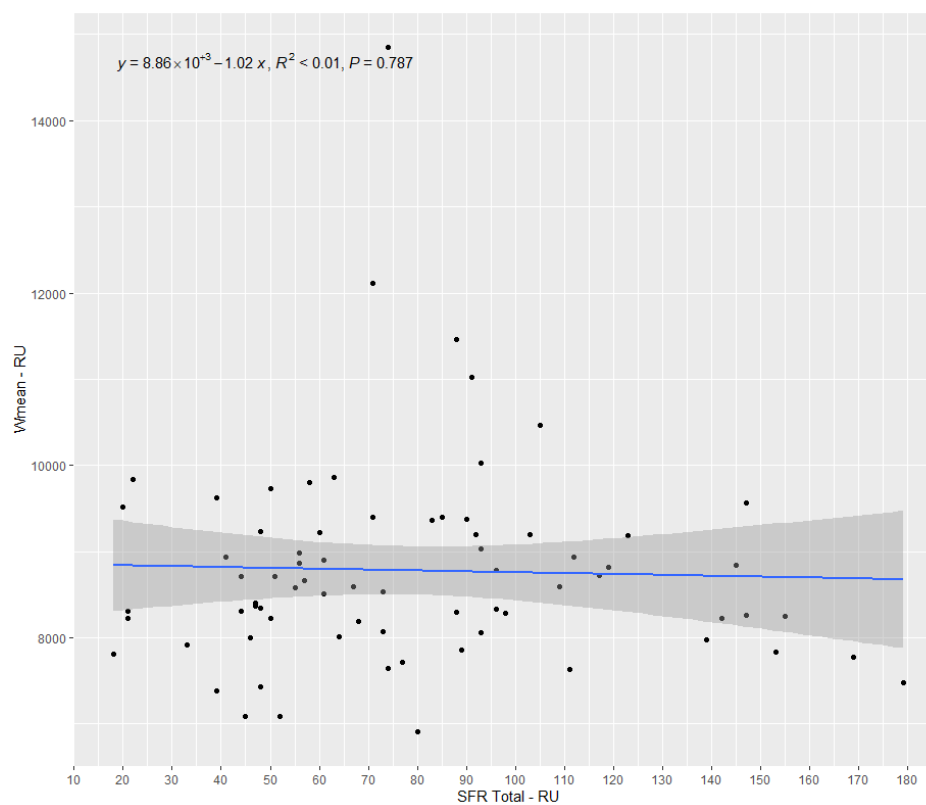


Figure A-IV-9. Scatterplot of weighted mean of declared income equivalent 2019 by SFR total, Regional units



Chapter VI

Conclusions

The geographic dimension of income inequality, a thriving field of research, offers empirical studies from various countries around the world. The paper aims to analyze the geographical dimension of declared income inequality in Greece. The analysis covers a long period of time starting from the time of the adoption of the Euro in Greece in 2002 to 2014, including the years of the financial crisis that began in 2008. The negative consequences of the economic crisis were more evident in Greece than in any other country. Moreover, the implementation of the Economic and Fiscal Adjustment Programmes in 2010 and the fiscal reforms implemented in the country have attracted the interest of a wider scientific audience. The economic crisis and the fiscal reforms carried out have had a huge impact on the income and tax burden of various income classes in Greece. The analysis related to the geographical dimension of income inequality has yielded interesting results that can contribute to the international literature and scientific debate.

Another important issue arising from the analysis is that the implementation of a fiscal adjustment policy has resulted in a reduction in inequality in declared income. This was the result of two combined trends: on the one hand, there is the increased tax burden on the lower income strata, and, on the other, the reduction in the incomes of the highest income strata due to wage and pension cuts, the increase in the tax rate on the highest income strata, and the implementation of the solidarity levy. However, this "reduction" of inequality in a period of economic recession, rising unemployment, deteriorating living conditions, and rising poverty call into question the reforms implemented during the recession and their ability to safeguard the policy goals of justice and inclusion. The fiscal reforms implemented have had a detrimental impact on society and equality. These results confirm the finding that low-income households in some EU member states have seen their living standards deteriorate disproportionately following the implementation of these fiscal reforms, as the European Commission admits in relevant reports.

In addition, another important conclusion of this research is that geography matters for income inequalities. The level of income and the dispersion of income inequality are significantly different between municipalities. In particular, metropolitan municipalities and large mainland municipalities have higher levels of economic wealth and higher inequalities compared to small mainland and small island municipalities. The geographical dimension of income inequality provides an interesting path for further scientific research.

The impact of the crisis and the implementation of fiscal reforms has been asymmetric and calls into question fairness and inclusion of implemented policies. An inclusive policy requires careful geographical targeting to raise the living standards and well-being levels of populations in different regions.

Finally, there are some interesting results on the correlation between income level and income inequalities between different municipalities. More specifically, the correlation between income and income inequality is influenced by the time analysis period (before and during the economic crisis), the type of municipality, and the level of economic wealth. The combination of these factors reveals different geographies of income inequality in the country.

Specifically, the study has focused on the geographical frequency of death from COVID-19 in Greece. Due to the multidimensional manifestations of the disease and its complexity, an interdisciplinary approach was adopted and various analytical tools and methods were applied. The analysis of this phenomenon lies at the intersection of scientific fields, such as spatial economics, demography, programmatic planning and geography, and is therefore based on a combination of disciplines and methods of empirical analysis. The analysis yielded some interesting results that could facilitate and enrich the debate on a serious issue of our time, both in the context of science and policy-making.

The key conclusion of this research is that space matters for progression, incidence, transmission and death from disease. Spatial autocorrelation and spatial dependence analyses have revealed regions/geographies with relatively higher incidence and mortality from the disease, as well as areas less affected. Northern Greece, given its high level of interactions with neighboring Balkan Peninsula countries and Turkey, proved more vulnerable to infections, while Southern Greece and the islands were less affected. Second, wave analysis provides a better understanding of disease progression and transmission in space and time. The number of cases was lower in the first three waves than in the last three waves. This can be attributed to the fact that variants of the disease had proven to be more contagious than the original virus. However, the mortality rate decreases during the outbreak of the disease. This finding may substantiate the fact that despite the greater spread of the disease, gradual vaccination of the population along with other policy measures such as wearing masks, adhering to strict hygiene habits and social distancing reduced the mortality of the disease.

In terms of geographical distribution, apart from the high incidence of COVID-19 in the northern regions of the country, the other worst affected cases are found in less affluent areas within the boundaries of large urban agglomerations, such as Athens. A high degree of infections is also found in areas that hold a high position in the urban system in Greece, such as Patras in Northern Peloponnese, which belongs to the Regional Unit of Achaia, as well as

Larissa and Volos in Thessaly, which belong to the Regional Units of Larissa and Magnesia, respectively. In this way, large cities and metropolitan areas appear to have been more vulnerable to the disease, especially in areas marginal in terms of economic and social conditions. The main determinants of the pandemic go beyond the age structure of the population. The analysis showed that age per se is not an explanatory factor that has a positive correlation with the mortality rate. While older people are more vulnerable to the disease, living conditions and income levels show significant explanatory power in studying disease progression and onset.

Our results highlight the critical role of the healthcare system and education in protecting ourselves against the pandemic. In all econometric models, education, which also reflects the level of economic well-being, and hospital beds have a negative and statistically significant direct effect on mortality, indicating the critical role they play regarding vulnerability to COVID-19. The results suggest that small settlements of less than 2,000 inhabitants with relatively higher employment in the primary sector and agricultural activities show a negative correlation with mortality. In contrast, areas with higher levels of employment in the secondary sector have higher mortality rates. Finally, inbound international tourism has not been shown to exacerbate the level of mortality, while statistically significant negative direct, indirect and overall impacts from domestic tourist arrivals appear. In all models, the islands show lower mortality than the mainland.

Finally, the results provide evidence that the most disadvantaged areas and populations paid the highest price during the pandemic. Health inequalities, inequalities in living conditions, as well as high rates of unemployment, poverty and deprivation have pushed populations "living on the margins" as well as "left behind" (Pike et al., 2023) to suffer even more. These places and populations require greater attention and political action for enhanced integration, improved socio-economic cohesion and adequate provision of affordable living conditions for citizens, and sustainable development for places and regions.

In summary, this paper is a first attempt to analyze the spatial dimension of wealth and inequality in Greece before and during the economic crisis. One of the most important results is that geography matters for the evolution and dispersion of income and income inequality within space. The diversity in geographies of wealth and income inequality calls into question the effectiveness of implementing horizontal fiscal adjustment policies that disproportionately affected lower-income categories of taxpayers across the country. More place-based and people-centred policies are needed for inclusive growth in all regions.

This study provided an initial insight into the geographical dimension of income inequality in Greece. However, more research is needed. A closer look at the income inequalities of cities and metropolitan areas, as well as the geography of wage inequalities in space, is an interesting and promising avenue for future research. Globalisation and urbanisation are at a critical juncture, with COVID-19 and its epidemiological threat added as another critical centrifugal factor in accumulating economies.

Although it is quite early to make predictions about the future course of major trends such as globalization and urbanization, very often in history, external and unexpected events act as catalysts for transformation and shaping future dynamics. What will cities look like after the pandemic? Will there be a reverse trend in urbanization? What will be the centrifugal and centripetal forces after the pandemic? Considering the environmental crisis, climate change, food/nutrition crisis, ageing population and energy crisis, how will these developments transform space and the interaction between places? The "place in space", as the title of Lloyd and Dicken's (1977) seminal book suggests, is undergoing gradual transformations, following the influence of the enormous dynamics that take place at each historical moment. Successive crises make state intervention a "practical necessity," as Nobel laureate Gunnar Myrdal (1898-1987) argued in reference to a similar historical moment. The "return of the state" proved necessary to protect people, societies and the economy from the disease.

The re-emergence of the necessity for policy action calls into question the dominant orthodox economic thought that paved the way for market expansion as the most appropriate player to regulate economic activity and social conditions, leading to the shrinking of the state. State intervention becomes even more crucial to relaunch the economy and ensure the necessary public goods that improve living conditions, promote cohesion and inclusiveness, the well-being of people and territories.