Regional Variation in the Association Between the Changes of the Old-Age and Low-Income Shares in Finland during 2000–2020

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Abstract

Regional differences in ageing lead to differences in the societal challenges caused by ageing population. However, also the development of the socioeconomic composition matters. We investigated how the change of share of the 65+ years old predicted the development of the low-income share in the working-age population in Finnish regions between 2000 and 2020 and how this depended on other regional characteristics. We used full-population register-based data and growth-curve analysis. We found regional and temporal variation in the association between the changes. Other regional characteristics such as urbanicity and GDP per capita helped in explaining the regional variation, although mostly in the 2010s. The trajectories of both shares were associated with regional 'vitality', and in the case of the old-age share, this association seems to be partly mediated by migration. Our findings suggest that straightforward assumptions of income development based on changes in the age composition should be avoided.

Keywords: population ageing, regional development, socioeconomic population composition, Finland urbanicity, migration

Introduction

The population of Europe and of other regions of the world except Africa has been ageing at an accelerating rate (Lutz, Sanderson, and Scherbov 2008; Leeson 2018). This poses challenges to financing of welfare states and to the public provision of social and health services (Harper 2014). In Europe, the old-age dependency ratio has increased in many countries, primarily due to declining fertility and increasing life expectancy (Eurostat 2020). However, population ageing is spatially differentiated: older people are over-represented particularly in rural regions. Regional differences in the age structure have also been increasing in the European Union (Kashnitsky, De Beer, and Van Wissen 2021).

Regional differences in ageing lead to differences in the challenges caused by ageing population. Therefore, forecasts of the challenges, such as increasing costs of social and health services, will require accounting for the predicted development of the age composition at the regional level. This is done for example in Finland in the model used by the government to predict these costs (Honkatukia and Pihlava 2024). However, also the development of the socioeconomic composition of the population matters. It shapes the regional needs for social and health services and their costs (Häkkinen et al. 2020), and it also affects the level and distribution of human capital and well-being in the region (e.g. Prenzel and Iammarino 2021).

Socioeconomic change may exacerbate or counteract the consequences of demographic change, depending on its direction. If changes in the age and socioeconomic distribution of the population are highly correlated, i.e. if the development of the population composition is unidimensional, forecasts of the age composition could be used to predict the development of the socioeconomic composition. However, if the development is multidimensional, with weaker correlations between the developments in different dimensions, predictions of the age composition are less useful for predicting the effects of the socioeconomic development for example on service costs. Awareness of the potentially diverging trajectories of these two aspects of the population composition is needed in regional policy.

The association between the developments of the regional age and socioeconomic compositions has not been studied much. Studies related to this issue have often focused on the age composition within the working-age population, and the outcome has been economic growth or productivity instead of socioeconomic composition of the population (see Zhang, Zhang, and Zhang 2015). Prenzel and Iammarino (2021) similarly focused on the employed labour force, but they used human capital as the outcome, and they demonstrated slower growth of human capital in regions where the employed labour force aged faster. It is difficult to find studies focusing on the similarity of the developments of the age and socioeconomic compositions, particularly if the interest in the age composition focuses on the share of the elderly.

Different aspects of the population composition may have common background factors. Regional characteristics such as economic performance may affect the development of both the age composition and the socioeconomic composition of the population, particularly via migration (Heikkilä and Pikkarainen 2010; Gregory and Patuelli 2015; Prenzel 2021). Additionally, the association between the development of age and socioeconomic compositions could depend on other regional factors. However, it is not yet well understood how regional characteristics may modify this association.

In this study, our focus is on two measures of the age and socioeconomic compositions of regional populations. We investigate how changes of the old-age share of the population (% aged 65 and over) predict changes of the low-income share in the working-age population (% with household income below 60% of national median income) in Finland, where the old-age dependency ratio has risen to a particularly high level (Eurostat 2020). We use full-population register-based data and growth curve analysis. Our study contributes to the understanding of the multi-dimensionality of regional population development.

Our main research questions are:

1. How do regional changes in the old-age share predict changes in the low-income share?
2. Does the association between these two shares depend on other regional characteristics?

Additionally, we ask whether a simultaneous analysis of the trajectories of the old-age and low-income shares with multivariate growth curve analysis adds new insights, and whether net internal and international migration mediate the associations between regional characteristics and the trajectories.

Background and study context

Ageing of regional populations

Regional differentiation in population ageing is connected with another megatrend, urbanisation: population structure differs regionally especially by urbanicity (Kashnitsky and Schöley 2018; Backman and Karlsson 2024). In many European countries, including Finland, the share of population aged 65 years and over is highest in rural or intermediate areas (Eurostat 2020). In a long-term perspective, both rural-to-urban migration and the demographic transition that has led to population ageing – increasing life expectancy and declining fertility – have contributed to urbanisation (Dyson 2011; Bocquier and Costa 2015). Today, migration is an important mechanism contributing to regionally diverging age compositions, as the migration of young adults is directed to growing urban centres (Kashnitsky and Schöley 2018; Kashnitsky et al. 2021; Ghio et al. 2023). Immigration reinforces this pattern (Backman and Karlsson 2024). Therefore, population ageing occurs faster in rural areas, although it also happens in urban areas, due to changes in fertility and life expectancy (Backman and Karlsson 2024; Van Der Gaag and de Beer 2015).

In addition to urbanisation, ageing is associated with the uneven economic development of regions. The economic performance of the region may influence the development of the age composition particularly through migration, as economically strong regions attract young migrants (Gregory and Patuelli 2015; Backman and Karlsson 2024). Ageing, in turn, can influence the economic performance at the regional and national level by reducing the potential for future growth (Brunow and Hirte 2006; Kotschky and Sunde 2018; Cruz and Ahmed 2018; Van Der Gaag and De Beer 2015; Malmberg, Malmberg, and Maskell 2023). Ageing and economic outcomes may be seen as changing jointly, both factors affecting each other (Gregory and Patuelli 2015). The ageing population, selective migration, and the weakening of the economic performance in regions can form a self-reinforcing cycle of development (Prenzel 2021; Backman and Karlsson 2024). Therefore, to understand regional differences in ageing, it is important to consider urbanisation, regional economic performance, and migration in the analysis.

Socioeconomic composition of regional populations and connections with ageing

The socioeconomic composition of the regional population is also associated with the regional economic development and its determinants such as urbanicity. Human-capital-intensive jobs are concentrated in (urban) economic hub regions (Gregory and Patuelli 2015), and skilled professionals with high incomes are an important part of the labour force in these regions. However, also lower incomes may be common, as greater regional economic growth is associated with greater educational and income inequality (Rodríguez-Pose and Tselios 2010). Metropolitan areas often have both higher average incomes and greater income inequality than the rest of the country (Boulant, Brezzi, and Veneri 2016). In rural peripheries, regional disadvantage may be caused by poor access to economic hubs, poor connectedness to central socioeconomic trends, and lack of economic and political power (Bernard and Keim-Klärner 2023). Such factors can contribute to higher low-income shares among the residents of rural areas by restricting their opportunity structures. Therefore, urbanisation and regional economic development matter also for the development of the socioeconomic composition, in potentially complex ways.

Migration can also affect the socioeconomic composition of the regional populations. In internal migration, young and educated workers are attracted to urban areas, while rural areas may suffer from "brain drain" caused by out-migration (Gregory and Patuelli 2015). On the other hand, also immigrants are typically concentrated in larger cities that have more employment opportunities, and many of them work in low-skilled jobs (Backman and Karlsson 2024). Therefore, migrants can contribute both to low- and high-income parts of the regional labour force in economically strong urban regions.

The age and socioeconomic compositions appear to have similar determinants, so they might reflect the same general dimension of regional development. Particularly the economic performance of the region could be a common background factor. This can be expected to be related to urbanicity of the region, as economically strong performing regions are often highly urbanised. Historically, economic development, demographic transition, and urbanisation have contributed to each other (Bocquier and Costa 2015). The aforementioned "self-reinforcing cycle of development" could create a connection between age and socioeconomic compositions: population ageing could affect the economic performance of the region, which could have an impact on migration among young adults, and this, in turn, could further affect both ageing and the economic performance. Socioeconomic composition of the working-age population could be affected in this process both by migration and the economic development.

The age and socioeconomic compositions could also affect each other more directly. If the association between them is assessed in the same population, i.e. both measured in the working-age population or in the total population, the association may be caused directly by the low incomes of the older residents (e.g. Lin, Lahiri, and Hsu 2015). A more open question is how the development of the share of the elderly and the socioeconomic composition of the working-age population could affect each other.

Study context

In Finland, there has been rapid increase of the population aged 65 and over. In 2024, the share of this age group was 24 percent of the Finnish population (Statistics Finland 2025). The old-age dependency ratio is one of the highest in Europe, next to Italy and Greece (Eurostat 2020). Since the turn of the century, the population development has been driven by ageing of the population, a reduced birth rate, an increase in life expectancy, urbanisation, and an increase in immigration (Rotkirch 2021). Since the 2010s, particularly the ageing of the baby boomers has increased the share of the population over 64 (Kuivalainen et al. 2022). The total population of Finland has increased from 5.2 million to 5.6 million between 2000 and 2024, and the growth has been based only on immigration since 2016 (Statistics Finland 2025).

Both population and economic activities have concentrated in the largest centres (Tuomaala 2016). Continuing urbanisation has concentrated population in a few regions due to selective migration (Aro 2020; Lehtonen and Tykkyläinen 2010). Differences in age composition are observed both between regions and between urban and rural areas within regions, and the differences have been increasing (Nevanto, Ilmarinen, and Kauppinen 2024). Particularly young highly educated people tend to concentrate in the capital city region (Heikkilä and Pikkarainen 2010). There are also differences between eastern and western parts of Finland. In eastern Finland the young-age dependency ratio is lower whereas old-age dependency ratio is higher and increasing (ESPON 2021). Population is considerably older in eastern Finland compared to other areas in the country, which may challenge the maintenance of social and health services.

Considering economic development, in the 1990s, after a deep recession, developments in labour productivity and the locations of jobs increased regional differences (Tuomaala 2016). Slower economic and productivity growth in the 21st century has evened regional differences in wages, as there has been decline in the regionally concentrated high productivity industries. In the 2000s, regional differences in the growth of GDP per capita were large, but after the financial crisis of 2008, the differences were reduced, with declining GDP per capita in most regions (Mäki-Fränti 2016). In international comparison, regional differences in GDP per capita are not large (Tervo 2023), and they have decreased more between 2012 and 2022 than in most other EU countries (Eurostat 2024).

Regional differences in income levels have decreased in the 21st century, as income levels have grown faster in lower-income regions than in higher-income regions (Tuomaala 2016; Mäki-Fränti 2016). This has been considered to have been due to migration, which concentrates the population in large regions and reduces regional income differences (Tuomaala 2016). Since the economic recession of the 1990s, especially labour migration has been directed away from areas characterised by low incomes, overrepresentation of primary production, a low level of education and a large proportion of elderly residents (Lehtonen and Tykkyläinen 2010). Even though migration has decreased income differences between regions, it weakens the vitality of areas that already had a weaker position and strengthens areas that benefit from migration, as especially the young and the educated move to cities (Aro 2020; Tuomaala, 2016).

Research design

Data

The dataset was based on individual-level register-based data covering the whole population of Finland annually between 2000 and 2020. Individual-level data were aggregated to 66 mainland sub-regions (*seutukunta*), excluding the Åland islands due to their exceptionality as an archipelago region. The sub-regional level corresponds to European Union's Local Administrative Unit (LAU) level 1. We call these units regions here. They had on average 78,109 residents in 2000, but variation was large, from 6,385 of the Joutsa region to the Helsinki region's 1,3 million. The average increased to 81,016 in 2010 and to 83,385 in 2020, when the range was from 4,996 to 1,6 million. However, the median decreased from 36,802 in 2000 to 35,225 in 2010 and to 33,010 in 2020, due to population decrease outside the largest urban regions (45 regions experienced population decrease between 2000 and 2010 and 51 regions between 2010 and 2020). During the study period, health and social services were organised by municipalities, which are smaller than the sub-regions, and since 2023 by wellbeing services counties, which are larger regions than the sub-regions. The sub-regions can be considered as approximations of labour market regions, and therefore we saw them as particularly relevant units for analysing regional development in population composition.

Our measure of age composition was the share of residents aged 65 and over. We refer to this share as the old-age share. We used low-income share as the socioeconomic indicator, and it was measured as the share of the 'core' working-age (25–59 years old) population with household income less than 60% of the median income in the total population of Finland. Excluding the older people from this indicator means that changes in the old-age share will not automatically cause changes in the low-income share, so the indicators are not dependent by construction (although some members of the households can be over 64 years old and older people are included when calculating the median national income). Household income was measured as the disposable money income per consumption unit. We used the OECD's adjusted consumption unit scale, where the first adult of the household receives the weight 1, other over 13-year-olds receive the weight 0.5, and those below the age of 13 receive the weight 0.3. Both population composition variables were measured annually between 2000 and 2020.

We measured several regional characteristics that could be relevant for the association between the old-age and low-income shares: the urbanicity of the region, the regional GDP per capita (in thousands of euros, deflated to 2010 values), the share of immigrants (foreign-born) in the population, and a classification dividing Finland to northeastern and southwestern parts. These were measured in 2000 and in 2010, which are the baseline years of the follow-ups in the two periods under analysis. The urbanicity variable was based on the urban-rural classification of the Finnish Environment Institute (Helminen, Nurmio, and Vesanen 2020) that categorises each 250 m × 250 m grid cell of Finland into one of seven categories of urbanicity (three urban categories, four rural categories), and it measures the percentage of the population living in the urban categories. The share of immigrants is included, as it can affect both the old-age and low-income shares (e.g. Backman and Karlsson 2024) and the association between them. It can also reflect the position of the region in international networks. The southwestern Finland variable was based on a historical division dividing Finland into a more disadvantaged northeastern part and a more prosperous southwestern part that can still be seen in indicators of well-being (Karvonen and Kauppinen 2009).

We also constructed a factor score variable based on the first principal component from a principal components analysis of urbanicity, GDP, and the share of immigrants. The share of immigrants and the GDP, which had skewed distributions, were normalised with a square-root transformation before the principal components analysis. We call this variable the 'vitality' of the region, as its high values indicate central position in the regional structure, strong economic performance, and internationality.

Finally, we used the low-income share among the 25–59-years-old population in the beginning of each period in the analysis to see whether the baseline level of the low-income share helps to predict the association between the developments of the old-age and low-income shares.

In addition to the baseline characteristics, we measured cumulative net migration annually during the follow-up, separately for internal (between-region) and international migration. These indicators were measured as the cumulative net number of migrants (of all ages) per 1,000 baseline residents.

Table 1 shows the descriptives for the variables used in the analysis. They are shown separately for two periods (2000–2010 and 2010–2020), as preliminary analyses showed differences between the 2000s and 2010s in the results and we decided to do the analyses separately for these periods. For annually measured predictor variables, also descriptives for the within-region centered versions and the within-region means are shown, as these variables are used in the statistical modelling instead of the original untransformed versions. For the baseline characteristics, also descriptives for the grand-mean centered versions are shown, for the same reason. As can be seen in the table, the variation in the changes of the old-age share increased significantly between the periods. This affects the interpretations concerning differences between the periods, and we return to this point in the results section.

Table 1.
Descriptive statistics for the variables.

	2000–2010				2010–2020			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Annually measured variables (N=726)								
Low-income share, %-points	11.96	2.75	5.49	20.10	11.89	2.19	6.81	19.64
Old-age share, %-points	19.20	3.41	10.48	29.83	24.91	5.12	12.01	39.64
Cumulative net internal migration per 1000 baseline residents	-18.48	31.06	-128.14	70.67	-19.90	25.99	-111.30	62.28
Cumulative net international migration per 1000 baseline residents	6.99	6.80	-3.67	39.40	11.22	9.29	0.00	70.75
Annually measured variables, within-region centered (N=726)								
Old-age share, %-points	0.00	1.20	-4.58	3.85	0.00	2.51	-6.18	6.56
Cumulative net internal migration per 1000 baseline residents	0.00	18.33	-54.99	74.34	0.00	18.01	-52.43	59.35
Cumulative net international migration per 1000 baseline residents	0.00	5.85	-16.63	23.70	0.00	7.66	-31.61	39.14
Within-region means (N=66)								
Old-age share, %-points	19.20	3.20	11.11	26.88	24.91	4.46	14.22	35.13
Cumulative net internal migration per 1000 baseline residents	-18.48	25.08	-74.34	37.00	-19.90	18.73	-59.35	27.84
Cumulative net international migration per 1000 baseline residents	6.99	3.46	-1.58	16.63	11.22	5.25	3.42	31.61
Baseline regional characteristics (N=66)								
Share living in urban areas, %	33.31	35.24	0.00	95.71	34.05	35.84	0.00	95.63
GDP per capita, 1000s euros (deflated to 2010 values)	24.051	7.417	14.131	51.933	27.796	6.527	17.675	48.888
Share of immigrants, %	0.95	0.62	0.24	3.64	1.95	1.21	0.64	6.82
Low-income share, %	10.91	2.62	5.84	18.56	12.64	2.56	7.76	19.25
Southwestern Finland	0.61	0.49	0	1	0.61	0.49	0	1
Baseline characteristics, grand-mean centered (N=66)								
Share living in urban areas, %	0.00	35.24	-33.31	62.41	0.00	35.84	-34.05	61.58
GDP per capita, 1000s euros (deflated to 2010 values)	0.000	7.417	-9.920	27.882	0.000	6.527	-10.122	21.091
Share of immigrants, %	0.00	0.62	-0.71	2.69	0.00	1.21	-1.31	4.87
Vitality score, z-scale	0.00	1.02	-1.83	2.64	0.00	1.01	-1.56	3.07
Low-income share, %	0.00	2.62	-5.07	7.65	0.00	2.56	-4.89	6.61
Southwestern Finland	0	0.49	-0.61	0.39	0	0.49	-0.61	0.39

Methods

We applied growth curve analysis as the primary analysis method (e.g. Curran et al. 2012). We used linear regression instead of binomial (e.g. logistic) regression to keep the results easier to understand and to be able to compare variance components between models. We also replicated the analyses using a logit-transformed outcome variable that avoids the potential problem of predictions outside the possible range (0-100%), although there were no out-of-range predictions in our analyses. This yielded similar results, except for two cases that we mention in our reporting of results.

Multilevel linear regression models were fitted separately for the two periods (2000–2010 and 2010–2020), with years as the lower level and the regions as the higher level. The year variable was measured as a difference from the baseline year (2000 or 2010). The old-age share variable was centered within regions by subtracting the mean value of the region during the follow-up from the original values, and its regional mean was also added as an explanatory variable. This follows the practice recommended by Hoffman and Walters (2022), enabling a clear separation of within-region and between-region effects. Random slopes were allowed for the year and old-age-share variables, so the trajectory of the low-income share and the association between the age old-age and low-income shares could vary between the regions.

The initial model (Model 0) can be presented as

$$lowinc_{ti} = \beta_0 + \beta_1\, year_{ti} + r_{0i} + \mathrm{r}_{1i}\, year_{ti} + e_{ti}$$

where $lowinc_{ti}$ is the low-income share in region i in year t, β_0 is the fixed intercept, β_1 is the fixed slope of the year variable, r_{0i} is the random intercept for region i, r_{1i} is the random slope of the year variable for region i, $year_{ti}$ is the number of years since the baseline year in year t for region i, and e_{ti} is the year- and region-specific residual. We specified an unstructured covariance matrix for the random effects, so all variances and covariances are estimated uniquely. We estimated the model with restricted maximum likelihood estimation using the *mixed* command in Stata 18.

In the next phase (Model 1), we added the old-age share variable, resulting in this model:

$$lowinc_{ti} = \beta_0 + \beta_1\, year_{ti} + \beta_2\, age_{ti} + \beta_3 mean\_age_i + r_{0i} + r_{1i} year_{ti} + r_{2i} age_{ti} + e_{ti}$$

Here age_{ti} is the (within-region-centered) share of those aged 65 and over in the population of region i in year t, β_2 is its fixed slope, and r_{2i} is its random slope. Additionally, $mean\_age_i$ is the mean value of the old-age share for region i, and β_3 is its fixed slope.

Combinations of the estimated fixed regression coefficient for the age variable and the regional prediction (best linear unbiased prediction, BLUP) for the random slope coefficient were used to illustrate regional variation in the association between changes in the old-age and low-income shares.

The next step was to add interactions between the old-age share and several characteristics of the regions measured at the baseline of the follow-up, one interaction at a time. For a single interaction variable, the model is as follows:

$$lowinc_{ti} = \beta_0 + \beta_1\, year_{ti} + \beta_2\, age_{ti} + \beta_3 mean\_age_i + \beta_4 intv_i + \beta_5 (age_{ti} \times intv_i) + r_{0i} + r_{1i} year_{ti} + r_{2i} age_{ti} + e_{ti}$$

where $intv_i$ is the value of interaction variable for region i, β_4 is the (fixed) slope of its main effect and β_5 is the slope of the interaction between the old-age share and the interaction variable. The regional characteristics were grand-mean centered by subtracting the mean value of the variable across regions from each region's value. This way the estimate for the main effect of the old-age share is for the situation when the regional characteristic is at its mean.

We also tested for nonlinear interactions, i.e. whether squared terms for the regional characteristics have statistically significant interactions with the old-age share. The squared term of urbanicity had a significant interaction in the first period, so we included it in the model (and interaction) in the first period.

We assessed how much the variance of the random slopes of the year and old-age share variables (r_{1i} and r_{2i}) was reduced by introduction of each interaction to the model. However, these reductions of the variance estimates should be seen only as approximate shares of explained variance (Hoffman and Walters 2022), as for example with predictors with small effects the random slope variance can *increase*.

We also calculated standardised regression coefficients for the old-age share. This can be complicated in multi-level analysis (Wang et al. 2019). We applied the basic method of multiplying the estimates (either the fixed coefficient or its combination with the predicted random slope coefficient for the region) with the standard deviation of the within-region-centered old-age share variable (1.199 in the first period, 2.510 in the second) and dividing by the standard deviation of within-region-centered low-income share (0.851 in the first period, 0.693 in the second). After this standardisation, the coefficients tell by how many standard deviations the average region's low-income share is predicted to change when its old-age share increases by one standard deviation, and these standard deviations refer to the standard deviations of the within-region-centered variables in the whole data (instead of standard deviations estimated separately for each region).

Our final analysis was an application of *multivariate* growth curve analysis: a simultaneous estimation of change in old-age and low-income shares (Curran et al. 2012). This method can be considered a better method than univariate growth curve analysis when both the 'predictor' and the 'outcome' vary systematically as a function of time, i.e. it is suitable for analysing the associations between the *trajectories* of two variables. Details of the data restructuring needed for this method can be found in Curran et al. (2012) and in the supplement of Baldwin et al. (2014).

We used the multivariate model to determine the unadjusted association between the trajectories of the age composition and low-income share variables, and with the vitality score of the region added as a predictor of both trajectories. The latter model can be represented like this:

$$dv_{dti} = \delta_y \left(\beta_0^{(y)} + \beta_1^{(y)} year_{ti}^{(y)} + \beta_2^{(y)} vitality_i^{(y)} + r_{0i}^{(y)} + r_{1i}^{(y)} year_{ti}^{(y)} + e_{ti}^{(y)}\right) + \delta_z \left(\beta_0^{(z)} + \beta_1^{(z)} year_{ti}^{(z)} + \beta_2^{(z)} vitality_i^{(z)} + r_{0i}^{(z)} + r_{1i}^{(z)} year_{ti}^{(z)} + e_{ti}^{(z)}\right)$$

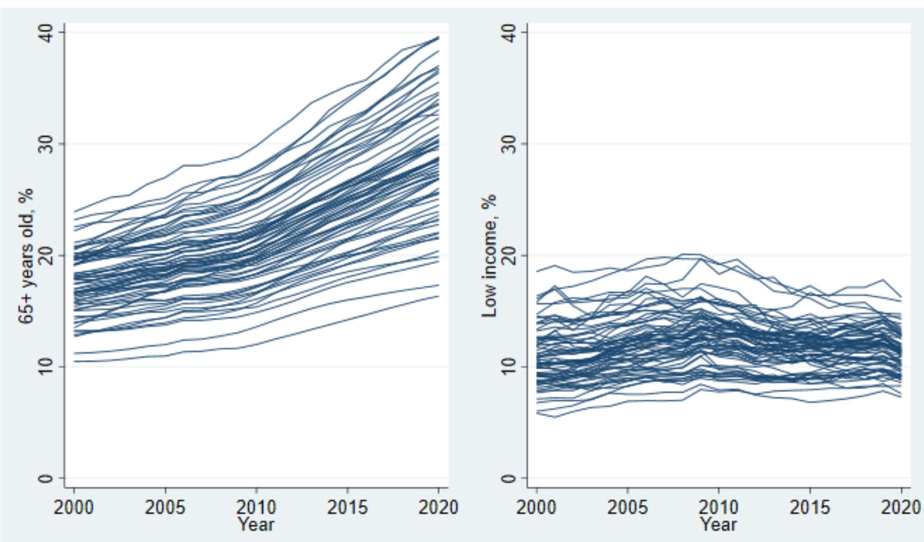
where dv_{dti} is the synthetic outcome representing the outcome variable *d* (the old-age or low-income share) for region *i* in year *t*, δ_y is a dummy variable with value 0 for the old-age share variable and 1 for the low-income share, δ_z is a dummy variable with value 1 for the old-age share variable and 0 for the low-income share, and the superscripts indicate to which of the outcomes each term belongs. This specification allows for separate estimates for the intercept and slopes for each outcome (see the supplement of Baldwin et al. (2014) for codes for model estimation).

As a final step of the multivariate growth analysis, we added variables measuring annually the cumulative net internal and international migration rates of the region (per 1,000 baseline residents) since the baseline year, to see whether migration mediates the associations between the vitality score and the outcomes. These variables were centered within region and also their regional means were added to the models as explanatory variables.

Results

Figure 1 shows the regional development in the old-age share and in the low-income share among the 25–59-years-old population between 2000 and 2020. There was general increase in the share of the population aged 65 years and over but also variation in the development. This variation led to *divergence* between the regions: both standard deviation and the coefficient of variation (CV) increased in both periods (CV from 0.161 to 0.175 between 2000–2010 and to 0.189 by 2020). The low-income share generally increased during the first period and decreased during the second period, following the national development. However, there were regional differences in the development. In this case, there was *convergence* between the regions: the coefficient of variation decreased from 0.240 to 0.202 during the first period, and to 0.167 during the second period. The development of the old-age share is rather linear when assessed by period (2000–2010 and 2010–2020), and there do not seem to be clear within-period nonlinearities in the development of the low-income share, either (a general decrease in the last year in both periods, however). The following analyses have been done separately for the two periods.

Figure 1.
Regional development of the share of the 65+ years old and the low-income share among the 25–59-years-old population, 2000–2020

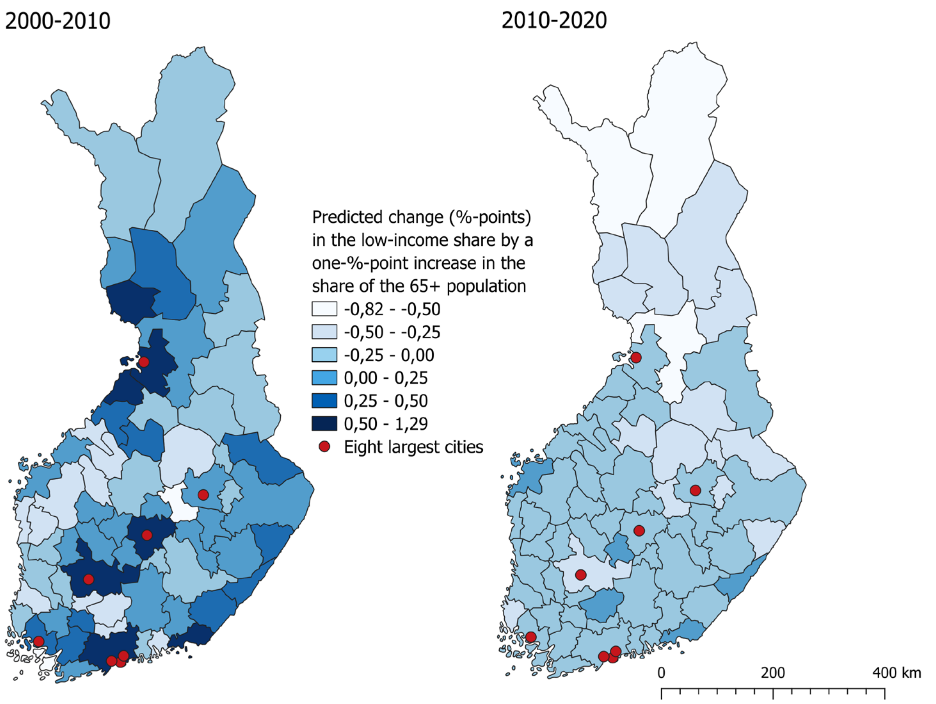


How did changes in the old-age share predict changes in the low-income share?

Controlling for the changes of the old-age share did not help in explaining regional variation in the changes of the low-income share. Before controlling for the changes of the old-age share, the standard deviation of the random slopes of the year variable – describing regional variation in the annual change of the low-income share – was 0.10 percentage-points in the first period and 0.14 percentage-points in the second period. This variation *increased* when controlling for the change of old-age share (and allowing for random slopes for the age variable), to 0.19 percentage-points in the first period and 0.16 percentage-points in the second period. This implies that the regional differences in the development of the low-income share were larger than could be expected by the differences in the development of the old-age share.

Figure 2 shows that there was regional variation in how the changes of old-age share predicted the low-income share particularly in the 2000s. The maps show the predicted change in low-income share among the working-age population by a one-percentage-point increase in the share of the 65+ years old population. These predictions are combinations of the estimate for the fixed slope of the old-age share and the region-specific random slope (empirical-Bayes prediction of the regional deviation from the fixed slope). Due to strong correlation between the random slopes of the year and old-age variables particularly in the first period, we use predictions from models without random slopes for the year variable.

Figure 2.
Regional estimates of the predicted change in low-income share among the working-age population by a one-percentage-point increase in the share of the population aged 65 and over.



The associations between the two changes differ by period. In the first period, the average regional estimate was slightly positive, suggesting that an increased share of the 65+ years old population was associated mostly with a higher low-income share, although there was wide variation in the association (mean slope: .07, standard deviation: .34, positive slope estimate in 56% of regions). In the second period, the associations were mostly negative, i.e. larger increases of the old-age share predicted decreases of the low-income share (mean slope: -.18, standard deviation: .17, 8% positive). The change to negative predictions was driven by the continuing ageing of the populations combined with a changed (decreasing) national trajectory of the low-income rate. The variation between the regions was smaller than in the first period. In the first period, the association between the two changes was mostly positive in the regions of the largest cities and less positive or negative in other regions. This reflects the slower increase of old-age share but faster increase of low-income share in the major urban regions, leading to larger expected increases in the low-income share by one-unit increase of the old-age share. However, in the second period, similar pattern was not observed, and the differences between regions were small.

These findings suggest that the main changes were the change from mostly positive to mostly negative associations and the decreased regional variation. However, as the variation in the changes of the old-age share increased between the periods, the relative significance of a one-percentage-point increase in the old-age share diminished, and that might explain the decreased variation in the association. When the predicted slopes are standardised, the mean slopes are 0.10 in the first period and -0.66 in the second period and the standard deviations are 0.48 and 0.62. This suggests that the main change was the change from positive to negative associations.

The short answer to the first research question is that the general direction of the association between the old-age and low-income shares and its regional variation depend on the period. Prevailing national trends in these shares appear to drive the general association.

How does the association between the changes in the old-age share and the low-income share depend on other regional characteristics?

We explored whether interactions between regional characteristics measured at the baseline of the follow-up and the changes of the old-age share explain the regional variation in the association between the changes of the old-age and low-income shares. To do this, we assessed changes in the random slope variance of the old-age share variable. Table 2 shows these variances as well as the random slope variances for the year variable. In models 2a–2f, both the main effect of the interaction variable and the interaction term between it and the old-age share are added to the model. All other interactions were statistically significant except the interactions of the old-age share with the southwestern Finland dummy and the baseline low-income share in the first period. All random slope variance estimates were statistically significant at the $p<.05$ level, except that information on statistical significance was not provided by Stata for models 2d and 2f in the second period.

The results differ by period. In the first period, interactions between the baseline characteristics and the old-age share mostly did not explain much. The baseline value of the low-income share seemed to explain much of the random slopes variance of the old-age share, although this interaction was not statistically significant. More was explained in the second period, when, however, the variation to be explained was smaller. The largest reduction of random slopes variance of the old-age share, 85 percent, was observed by the interaction with the GDP per capita, and the vitality score interaction achieved a similar share.

Table 2.
Variances of the random slopes of the variables measuring the year and the change of the old-age share, by period and model.

2000–2010	**Random slopes variance**		**Change from Model 1, %**	
	Year	**Old-age share**	**Year**	**Old-age share**
Model 0: Only year	0.011			
Model 1: Year and old-age share	0.036	0.120		
Model 2a: 1 + Urbanicity	0.028	0.104	-24.4	-12.9
Model 2b: 1 + GDP per capita	0.033	0.136	-10.3	13.9
Model 2c: 1 + Share of immigrants	0.033	0.113	-8.1	-5.2
Model 2d: 1 + Vitality score	0.033	0.126	-9.0	4.9
Model 2e: 1 + Southwestern Finland	0.036	0.117	-1.8	-2.0
Model 2f: 1 + Baseline low-income share	0.026	0.041	-29.7	-65.7
2010–2020	**Random slopes variance**		**Change from Model 1, %**	
	Year	**Old-age share**	**Year**	**Old-age share**
Model 0: Only year	0.021			
Model 1: Year and old-age share	0.027	0.022		
Model 2a: 1 + Urbanicity	0.015	0.016	-44.1	-26.0
Model 2b: 1 + GDP per capita	0.012	0.003	-54.1	-85.4
Model 2c: 1 + Share of immigrants	0.013	0.012	-52.7	-45.4
Model 2d: 1 + Vitality score	0.007	0.004	-73.6	-82.4
Model 2e: 1 + Southwestern Finland	0.010	0.011	-61.8	-51.7
Model 2f: 1 + Baseline low-income share	0.017	0.014	-35.1	-35.4

Table 2 shows also that the findings regarding the random slopes variances of the year variable, i.e. the development of the low-income share, are rather similar to the findings for the old-age share variable. In the first period, this variance was reduced very little except for the urbanicity and the baseline low-income share models, which means that the interactions did not explain much of the regional variance in the trajectories of the low-income share. In the second period, more of the variance was explained in all models, the most (74%) in the vitality score model.

Table 3 provides the fixed regression coefficients of the old-age share and interaction variables and the interaction terms in the interaction models. The main effect of the old-age share shows the predicted change in the low-income share by one-unit increase of the old-age share when the interaction variable is at its grand mean, and the interaction term tells how much this association changes by one-unit increase in the interaction variable.

In the first period, an added complexity is that urbanicity had a nonlinear interaction with the old-age share. When plotted (not shown here), it is seen that increases in the old-age share predict increases in the low-income share at above-average urbanicity values so that the fixed coefficient for the old-age share changes from -0.018 (95% c.i.: -0.078, 0.217) when the share living in urban areas is at its mean 33.3 percent to 0.716 (95% c.i.: 0.325, 1.107) when the share living in urban areas is at its maximum of 95.7 percent. At below-average urbanicity values, almost all regions are at the zero percent urbanicity level, and the differences in the old-age share coefficient are within confidence intervals (that all include the zero value for the coefficient).

Otherwise, in the first period, a more positive association between changes in the old-age and low-income shares was predicted by higher GDP per capita, higher share of immigrants, and higher vitality score. This means for example that in regions with a high GDP per capita, increasing old-age share was associated with increasing low-income share, while in low-GDP regions changes in old-age share were not associated with changes in the low-income share. Also living in northeastern Finland predicted a more positive association, as did a low baseline low-income share, but these interactions were not statistically significant. However, the interaction with the baseline low-income share was statistically significant and similar to the interaction in the second period when using a logit-transformed outcome variable.

In the second period, all interactions except the interaction with living in southwestern Finland had the same direction as in the first period. Southwestern Finland now predicted a more positive association between the changes in the old-age and low-income shares. Also urbanicity now had a linear interaction, with higher urbanicity predicting a more positive association between changes in the old-age and low-income shares. All interactions except those with southwestern Finland and the baseline low-income share appear to be weaker in the second period.

Figure 3 illustrates the interaction between the old-age share and the vitality of the region. In regions with a higher vitality score, increase in the old-age share either predicted a larger increase of low-income share (first period) or was not clearly associated with changes in the low-income share (second period). Correspondingly, in the regions with the lowest vitality scores, ageing either was not associated with the changes in the low-income share (first period) or predicted a *decreasing* low-income share (second period). These results indicate a balancing development in the low-income share by regional vitality.

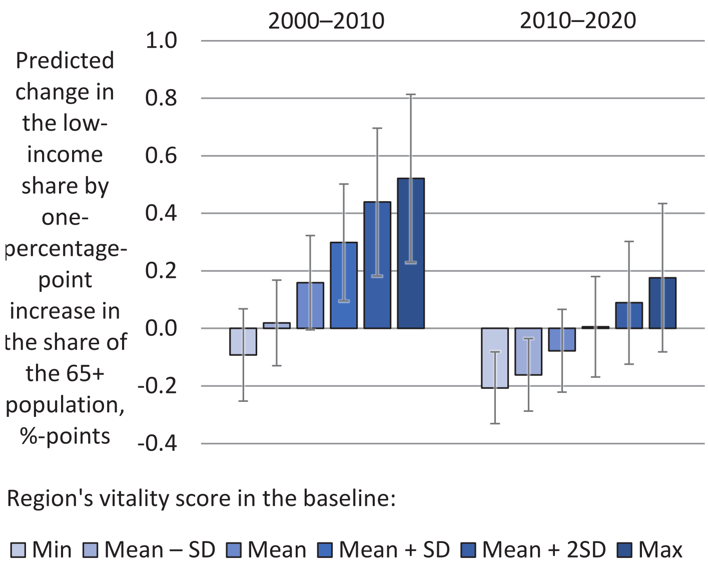
As seen from figure 3, and from table 3 for all the interaction variables, the interactions were otherwise mostly similar in both periods but weaker in the second period. However, with *standardised* regression coefficients for the old-age share (not shown here), several interactions were *stronger* in the second period (those with urbanicity, GDP, vitality score, southwestern Finland, and the baseline low-income share). For example, the predicted increase in the regression coefficient of the old-age share by one-standard-deviation increase in the vitality score was 0.19 standard deviations in the first period and 0.30 standard deviations in the second. Therefore, the interaction between vitality score and old-age share was weaker than before in terms of how *many percentage-points' change in the low-income share was predicted by a one-percentage-point change in the old-age share*, but this was caused by increased variation in the old-age share.

Table 3.
Regression coefficients from interaction models: main effects and interaction terms of the variables measuring the old-age share and baseline regional
characteristics, with 95% confidence intervals (C.I.) and statistical significances (p).

	2000–2010			2010–2020		
	b	95% C.I.	p	b	95% C.I.	p
Model 1: No interaction						
Old-age share, %	0.070	(-0.085, 0.224)	0.379	-0.188	(-0.326, -0.049)	0.008
Model 2a: Urbanicity						
Old-age share (OAS), %	-0.018	(-0.249, 0.213)	0.881	-0.096	(-0.240, 0.048)	0.192
Urbanicity (% in urban areas)	-0.019	(-0.040, 0.001)	0.059	0.012	(-0.004, 0.027)	0.126
Urbanicity squared	0.00049	(-0.00036, 0.00134)	0.258			
Urbanicity * OAS	0.002	(0.000, 0.004)	0.024	0.002	(0.001, 0.003)	0.006
Urbanicity squared * OAS	0.00015	(0.00002, 0.00028)	0.026			
Model 2b: GDP per capita						
Old-age share (OAS), %	0.094	(-0.068, 0.256)	0.255	-0.118	(-0.262, 0.026)	0.108
GDP per capita, 1000s of euros	-0.157	(-0.230, -0.084)	<.001	-0.099	(-0.175, -0.022)	0.012
GDP per capita * OAS	0.016	(0.006, 0.024)	0.001	0.009	(0.002, 0.017)	0.014
Model 2c: Share of immigrants						
Old-age share (OAS), %	0.118	(-0.041, 0.278)	0.147	-0.135	(-0.274, 0.004)	0.057
Share of immigrants, %	-1.242	(-2.190, -0.294)	0.010	-0.079	(-0.043, 0.121)	0.686
Share of immigrants * OAS	0.157	(0.024, 0.290)	0.020	0.050	(0.007, 0.093)	0.023
Model 2d: Vitality score						
Old-age share (OAS), %	0.159	(-.005, 0.323)	0.057	-0.078	(-0.221, 0.066)	0.881
Vitality score, z-scale	-1.183	(-1.795, -0.571)	<.001	-0.145	(-0.677, 0.387)	0.593
Vitality score * OAS	0.137	(0.068, 0.207)	<.001	0.083	(0.033, 0.133)	<.001
Model 2e: Southwestern Finland						
Old-age share (OAS), %	0.063	(-0.099, 0.225)	0.445	-0.131	(-0.249, -0.012)	0.030
Southwestern Finland	-3.072	(-3.878, -2.266)	0.495	-1.501	(-2.284, -0.717)	<.001
Southwestern Finland * OAS	-0.031	(-0.160, 0.097)	0.633	0.226	(0.155, 0.298)	<.001
Model 2f: Baseline low-income share						
Old-age share (OAS), %	-0.023	(-0.138, 0.093)	0.700	-0.080	(-0.183, 0.023)	0.129
Low-income share, %	1.008	(0.963, 1.053)	<.001	0.827	(0.766, 0.888)	<.001
Low-income share * OAS	-0.007	(-0.027, 0.013)	0.484	-0.045	(-0.059, -0.031)	<.001

A short answer to the second research question is that the association between the changes of the old-age and low-income shares depends on other regional characteristics, with higher urbanicity, higher GDP per capita, higher share of immigrants, and higher vitality score consistently predicting a more positive association, and other characteristics having less consistent interactions.

Figure 3.
Predicted change in the low-income share in the region by one-percentage-point increase in the share of the over 64 years old population, by the baseline vitality score.



Multivariate analysis: joint development of the old-age and low-income shares

It may be better to approach the old-age and low-income shares as correlated outcomes potentially affected by a common third factor instead of trying to explain one with the other. We did this by applying multivariate growth analysis, which allows us to assess the correlation between the trajectories and the association of both trajectories with a common predictor.

In the first period, the correlation between the trajectories of the old-age and low-income shares was very weak (.09) and statistically non-significant, based on the covariance between the random slopes of the year variable (Table 4, "Covariance between (2) and (4)" line). In the second period, this correlation was stronger (-.41) and statistically significant (Table 5). This means that in the second period, the deviations of the regions from the average trajectories were opposite in these two outcomes.

Table 4.
Results from the multivariate growth models for the low-income and old-age shares in 2000–2010, fixed and random effects.

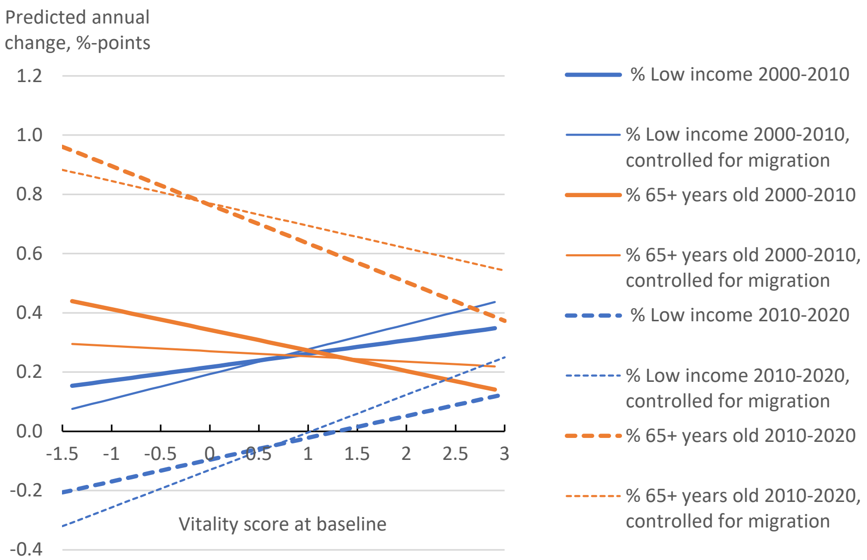
	Without vitality score	95% C.I.	With vitality score	95% C.I.	Also migration variables	95% C.I.
Fixed effects						
Low-income share						
Intercept	10.842	(10.915, 11.489)	10.842	(10.363, 11.321)	9.708	(8.461, 10.956)
Year	0.217	(0.190, 0.243)	0.217	(0.193, 0.241)	0.193	(0.147, 0.239)
Vitality score			-1.806	(-2.285, -1.327)	-1.974	(-2.670, -1.277)
Vitality score * year			0.045	(0.021, 0.070)	0.084	(0.055, 0.113)
Net cumulative internal migration					-0.012	(-0.017, -0.007)
Net cumulative international migration					-0.009	(-0.031, 0.013)
Regional average of internal migration					-0.019	(-0.042, 0.003)
Regional average of international migration					0.128	(-0.029, 0.285)
Old-age share						
Intercept	17.483	(16.801, 18.166)	17.483	(16.919, 18.048)	16.122	(14.500, 17.743)
Year	0.342	(0.305, 0.380)	0.342	(0.309, 0.376)	0.271	(0.237, 0.304)
Vitality score			-1.592	(-2.157, -1.027)	-2.260	(-3.130, -1.390)
Vitality score * year			-0.069	(-0.103, -0.036)	-0.018	(-0.047, 0.011)
Net cumulative internal migration					-0.019	(-0.022, -0.016)
Net cumulative international migration					0.006	(-0.004, 0.016)
Regional average of internal migration					-0.007	(-0.036, 0.022)
Regional average of international migration					0.228	(0.022, 0.435)
Random effects						
(1) Intercept variance (low-income share)	7.148	(5.069, 10.079)	3.890	(2.753, 5.496)	3.797	(2.673, 5.393)
(2) Year slope variance (low-income share)	0.011	(0.007, 0.016)	0.009	(0.006, 0.013)	0.007	(0.005, 0.011)
(3) Intercept variance (old-age share)	7.998	(5.684, 11.254)	5.465	(3.884, 7.692)	5.281	(3.746, 7.445)
(4) Year slope variance (old-age share)	0.024	(0.017, 0.034)	0.019	(0.013, 0.027)	0.012	(0.008, 0.017)
Covariance between (1) and (2)	-0.058	(-0.131, 0.015)	0.024	(-0.025, 0.072)	0.016	(-0.028, 0.061)
Covariance between (3) and (4)	0.160	(0.048, 0.273)	0.050	(-0.029, 0.129)	0.067	(0.001, 0.132)
Covariance between (1) and (3)	3.706	(1.667, 5.744)	0.833	(-0.305, 1.972)	0.808	(-0.311, 1.926)
Covariance between (2) and (4)	0.0015	(-0.0026, 0.0056)	0.0046	(0.0011, 0.0082)	0.0013	(-0.0012, 0.0039)
Covariance between (1) and (4)	0.257	(0.139, 0.375)	0.132	(0.058, 0.206)	0.116	(0.056, 0.177)
Covariance between (2) and (3)	-0.097	(-0.175, -0.018)	-0.025	(-0.082, 0.032)	-0.017	(-0.069, 0.035)

Table 5.
Results from the multivariate growth models for the low-income and old-age shares in 2010–2020, fixed and random effects.

	Without vitality score	95% C.I.	With vitality score	95% C.I.	Also migration variables	95% C.I.
Fixed effects						
Low-income share						
Intercept	12.366	(11.771, 12.961)	12.366	(11.853, 12.879)	13.059	(11.601, 14.517)
Year	-0.096	(-0.132, -0.060)	-0.096	(-0.128, -0.064)	-0.130	(-0.208, -0.053)
Vitality score			-1.256	(-1.769, -0.743)	-1.642	(-2.435, -0.851)
Vitality score * year			0.074	(0.042, 0.105)	0.127	(0.086, 0.167)
Net cumulative internal migration					-0.018	(-0.025, -0.010)
Net cumulative international migration					-0.018	(-0.046, 0.009)
Regional average of internal migration					0.017	(-0.011, 0,044)
Regional average of international migration					-0.017	(-0.128, 0.094)
Old-age share						
Intercept	21.083	(20.210, 21.957)	21.083	(20.382, 21.784)	19.051	(17.306, 20.795)
Year	0.765	(0.716, 0.814)	0.765	(0.727, 0.803)	0.770	(0.719, 0.821)
Vitality score			-2.159	(-2.861, -1.458)	-2.889	(-3.871, -1.908)
Vitality score * year			-0.131	(-0.168, -0.093)	-0.076	(-0.111, -0.040)
Net cumulative internal migration					-0.014	(-0.019, -0.010)
Net cumulative international migration					-0.031	(-0.044, -0.017)
Regional average of internal migration					-0.012	(-0.049, 0.025)
Regional average of international migration					0.158	(0.015, 0.300)
Random effects						
(1) Intercept variance (low-income share)	6.029	(4.271, 8.510)	4.452	(3.150, 6.293)	4.699	(3.280, 6.731)
(2) Year slope variance (low-income share)	0.021	(0.014, 0.030)	0.015	(0.011, 0.023)	0.015	(0.010, 0.023)
(3) Intercept variance (old-age share)	13.099	(9.310, 18.430)	8.440	(5.998, 11.876)	8.227	(5.786, 11.699)
(4) Year slope variance (old-age share)	0.041	(0.029, 0.058)	0.024	(0.017, 0.034)	0.019	(0.013, 0.027)
Covariance between (1) and (2)	-0.227	(-0.333, -0.121)	-0.134	(-0.210, -0.059)	-0.148	(-0.229, -0.067)
Covariance between (3) and (4)	0.572	(0.347, 0.797)	0.290	(0.160, 0.420)	0.277	(0.157, 0.397)
Covariance between (1) and (3)	4.700	(2.264, 7.136)	1.990	(0.424, 3.555)	2.301	(0.634, 3.968)
Covariance between (2) and (4)	-0.0120	(-0.0199, -0.0040)	-0.0024	(-0.0073, 0.0026)	-0.0058	(-0.0105, -0.0011)
Covariance between (1) and (4)	0.306	(0.164, 0.448)	0.142	(0.054, 0.229)	0.162	(0.076, 0.248)
Covariance between (2) and (3)	-0.133	(-0.268, 0.003)	0.027	(-0.066, 0.119)	0.009	(-0.083, 0.102)

The vitality score had opposite associations with the trajectories (Tables 4–5 and Figure 4): higher vitality score predicted *lesser* growth of the old-age share and *larger* growth (or lesser decline) of the low-income share in both periods. In the second period, when low-income shares were generally decreasing, increases in both shares were predicted only in regions with very high vitality scores, while lower vitality scores were associated with a decreasing low-income share in combination with an increasing old-age share (Figure 4).

Figure 4.
Predicted annual change in the low-income share in the working-age population and in the share of population aged 65 and over, by the vitality score of the region at the baseline.



Interaction with the vitality score explained 18 percent of the random slope variance of the year variable in the case of the low-income share and 20 percent in the old-age share in the first period. In the second period, the explained shares were 29 percent and 42 percent, correspondingly. These differences suggest that the trajectories were better explained by the vitality scores in the second period, particularly the old-age trajectory (this difference between the two outcomes was even clearer when using logit-transformed outcome variables). The interaction with the vitality score explained most (80%) of the negative covariance between the two trajectories in the second period, so the association between these two trajectories was predicted quite well with the vitality score.

The multivariate analysis showed that the trajectories of the old-age and low-income shares can both be predicted by a common background factor, here the vitality of the region, which can also explain most of the association between the two trajectories. However, these associations can vary between periods.

Migration as the mechanism

One potential mechanism for how the regional vitality could matter is migration. If migration moves younger people from regions with lower vitality to regions with higher vitality scores, that could explain the negative association between vitality and the growth of the old-age share. Similarly, if low-income people tend to move towards regions with higher vitality scores, this could explain the observed positive interaction between vitality and the growth of the low-income share.

Our migration analysis brought support for the migration mechanism regarding the old-age share but not regarding the low-income share (Tables 4–5 and Figure 4). When we added annually measured indicators of cumulative net internal and international migration rates during the follow-up (and their regional means) as predictors to the multivariate growth model, the interaction between the vitality score and the growth of the old-age share became weaker. Positive net internal migration of one person per 1,000 baseline residents predicted 0.019 percentage-points lesser annual growth of old-age share in the first period (Table 4) and 0.014 percentage-points lesser growth in the second period (Table 5). For international migration, similar rate of migration predicted a 0.006 percentage-points *larger* annual growth of the old-age share in the first period (not statistically significantly) and 0.031 percentage-points *lesser* growth in the second period.

The interaction between the vitality score and the development of the *low-income* share was not explained by adding the migration indicators. Rather, the interaction term increased in both periods (Tables 4–5). Figure 4 illustrates this: after controlling for migration, the associations between the vitality score and the trajectory of the low-income share steepened. Positive net internal migration of one person per 1,000 baseline residents predicted 0.012 percentage-points lesser annual growth of low-income share in the first period and 0.018 percentage-points lesser growth in the second period. International migration was not associated with the growth of the low-income share statistically significantly, although the point estimates suggest negative associations. Similar findings were observed regarding the random slope variances of the year variable, i.e. the regional variation in the trajectories of the old-age and low-income shares (Tables 4–5): larger reduction in the regional variance of the old-age share trajectory.

These results suggest that the migration mechanism is more straightforward in the case of the old-age share than in the case of the low-income share. Potential migration-related explanations for the low-income share trajectories may need more detailed analysis.

Discussion and Conclusion

This study explored the question of whether the development of regional population compositions is unidimensional or multidimensional. We asked, how the development of the old-age share of the regional population predicts the development of the low-income share in the working-age population, and whether this association depends on other regional characteristics. We studied this question in Finland, where population ageing has been particularly fast.

Information on the development of the old-age share was not enough in predicting the development of the low-income share. We found regional variation in the association between the two changes, and differences in the associations by period, with slightly positive general association but large regional variation in the 2000s, and less variation and mostly negative associations in the 2010s.

Other regional characteristics helped in explaining the regional variation, although mostly in the 2010s. The findings indicate opposite associations for example when comparing urban to rural regions or high-GDP to low-GDP regions: a stronger positive association (or less negative association) in more urbanised and economically strong regions and a negative (or less positive) association in rural and economically weak regions. Particularly in the 2010s, also the initial values of the low-income share helped in predicting the association, and this shows the balancing nature of the variation in the association: in regions with a high initial low-income share, population ageing predicted *decreasing* low-income share, while in regions with low initial low-income share, ageing was associated with *increasing* low-income share.

Our findings concerning urbanicity appear to be in contrast to Kashnitsky et al. (2021), who did *not* find urbanisation to be behind the increasing differences between European regions in the share of working-age population, but this could be because the development of the share of working-age population may be less connected with urbanicity than the share of the elderly: the number of children declines more in the rural regions and therefore balances the increasing share of the elderly (Van Der Gaag and de Beer 2015).

When we assessed the development of the old-age and low-income shares simultaneously as parallel outcomes, we found that the trajectories of both indicators were associated with the 'vitality' of the region (high level of urbanicity, GDP per capita, and share of immigrants) but in opposite ways: higher baseline vitality score predicted *lesser* growth of the old-age share and *larger* growth of the low-income share. The vitality score explained regional variation in the trajectories better in the second period, particularly in the case of the old-age share. This suggests that something had changed in the development of the old-age share and it had become more strongly connected with the regional vitality. This might be related to the retirement of the baby-boom generation, but it could also reflect the increasing importance of immigration in slowing population ageing in major urban regions (cf. Backman and Karlsson 2024).

Differences in migration helped to explain variation in the ageing trajectory but not in the low-income trajectory. Positive internal migration – in the 2010s also positive international migration – was associated with lesser growth of the old-age share, and this helped to explain the association between regional vitality and the ageing trajectory. This could be expected based on findings of Ghio et al. (2023) of young migrants around 20 years of age being particularly attracted by high levels of urbanicity and GDP. Regarding international migration, our findings are similar to Backman and Karlsson (2024), who found immigration to slow the population ageing in Swedish municipalities. Potential migration-related explanations for the low-income trajectories may need more detailed analysis.

Our findings of opposite relationships with regional vitality might be specific to the prevailing directions of change in regional variation in old-age and low-income shares. We observed regional convergence in the low-income share. Convergence in regional economic development during our study period (Tuomaala 2016; Mäki-Fränti 2016) most likely contributed to it. In the old-age share, we observed regional *divergence*. The findings could be different in times with different trends. Recent European studies have found variation between regional and temporal contexts in this respect. In ageing, Europe-wide analyses (Kashnitsky, De Beer, and Van Wissen et al. 2020, 2021) found divergence in the share of the working-age population, most clearly in Eastern Europe. Backman and Karlsson (2024) found long-term convergence but recent divergence in ageing across Swedish municipalities. In economic development, Kashnitsky et al. (2020) found convergence across European regions, but with different timing: in Eastern and Western Europe after the 2008 financial crisis but in Southern Europe before the crisis. They also found that the association between regional development in ageing and GDP varies over time and between different parts of Europe.

Observations of convergence or divergence may be dependent on the spatial scale of the analysis. In our study or in the studies by Kashnitsky et al. (2020, 2021), the potentially different developments in the central and peripheral parts of the large regions are not observed, while the smaller spatial scale applied by Backman and Karlsson (2024) could better include also this level of differentiation. That might explain why Backman and Karlsson found indications of different developments by urbanicity, but Kashnitsky et al. (2021) did not. The scale in our study is between these studies. The scale problem is relevant also when searching for explanations for the developments, as the explanations may originate from surrounding areas (Lin et al. 2015; Gregory and Patuelli 2015). Our choice of analysing larger regions instead of municipalities aims to take this into account to some extent.

Regarding the unidimensionality or multidimensionality of the development of population composition, our results could be interpreted to indicate that old-age and low-income shares are part of the same dimension of *regional development*, but that they do not constitute a single dimension of *population* development. Both indicators of population composition are associated with the 'vitality' of the region, but the association between the developments of the two indicators varies.

In addition to being one of the few studies conducted so far related to the associations between the trajectories of the age and socioeconomic compositions of regional populations, the main strength of this study was the reliable administrative dataset covering the complete populations of the regions annually. Perhaps the main limitation is that we only used one indicator for the age composition and one indicator for the socioeconomic composition. The results could be sensitive for these choices. Therefore, it is safer to interpret the results strictly from the viewpoint of the share of population aged 65 and over and the share of the working-age population having household income below 60 percent of the median national income. Additionally, our results related to explained variance and standardised regression coefficients have to be considered approximate, as these topics are complicated in multilevel analysis.

Altogether, our findings suggest that straightforward assumptions of income development based on the changes in the age composition should be avoided. Association between the developments of age and income compositions may change when there are major changes in either dimension.

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