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National Stability, Local Reconfiguration: Demographics, Labour Markets, and Redistribution in Spatial Income Inequality

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National Stability, Local Reconfiguration: Demographics, Labour Markets, and Redistribution in Spatial Income Inequality[1]

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Abstract

This paper examines how stable national disposable income inequality can coexist with substantial local reconfiguration in spatial inequality within a small, open, and highly integrated economy. Focusing on Luxembourg, where strong commuting flows and a nationally uniform tax-benefit system limit sub-national institutional variation, it analyses how demographic change, labour market restructuring, and redistribution shape municipality-level inequality between 2011 and 2021. The paper develops a spatial microsimulation framework that combines EU-SILC microdata, Census aggregates, and the EUROMOD tax-benefit model to recover local distributions of disposable income where representative small-area income data are not directly available. This framework enables the joint analysis of market income generation and redistribution at a fine spatial scale and is transferable to other countries operating within the EU-SILC-EUROMOD architecture. Three findings emerge. First, inequality is driven mainly by disparities within municipalities rather than by differences between them. Second, although disposable income inequality is spatially clustered, this clustering weakens significantly over time, indicating local adjustment rather than strong spillovers across neighbouring municipalities. Third, stable national inequality conceals substantial local heterogeneity: inequality declines in Luxembourg City and its urban belt, but rises in the southern industrial belt, the northern region, and the remaining municipalities. Counterfactual decompositions show that demographic change tended to increase local inequality outside the urban core, while labour market change and the tax-benefit system offset part of that pressure. The results shows that aggregate distributional stability can conceal substantial local change in spatial inequality.

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[1] Results presented here are based on EUROMOD version J0.1+ and the 2012 and 2022 EU-SILC cross-sectional datasets on Luxembourg, adapted to be used with EUROMOD. Originally maintained, developed and managed by the Institute for Social and Economic Research, since 2021 EUROMOD is maintained, developed and managed by the Joint Research Centre of the European Commission, in collaboration with Eurostat and national teams from the EU Member States. **This research is funded by the National Research Fund in Luxembourg (FNR), under the CORE Scheme (PI: D.M. Sologon, grant C22/SC/17411636/SPIN).**

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1 Introduction

Spatial inequality within small and highly integrated economies poses a difficult analytical problem. Common national institutions, extensive commuting and an integrated labour market might be expected to compress territorial differences in living standards. Local inequality, however, may still persist or be reconfigured over time, because municipalities differ in the demographic composition of their resident population, in the distribution of labour market incomes across households, and in the way national redistribution interacts with local income profiles. Even where taxes and transfers are set uniformly at the national level, their distributional effects do not need to be spatially neutral, since they operate on populations that differ across places (Figari et al., 2015; Immervoll and Richardson, 2011). Understanding how these forces combine is central to debates on territorial cohesion, spatial equilibrium, and the relative roles of place-based and people-based policies. However, the evidence remains limited when the object of interest is not average income, productivity, or employment, but the full distribution of disposable income at a granular geographical scale (Perugini and Martino, 2008).

This question is especially relevant in small and highly integrated economies, where strong commuting flows, common national policies, and the limited sub-national institutional variation might be expected to reduce spatial disparities. Such settings enable testing whether substantial local inequality differences can persist or be reconfigured over time, even when the broader institutional environment is shared. Luxembourg provides a particularly informative empirical setting of this type. It is a small, open and highly integrated economy, characterised by substantial commuting across municipalities of residence and work (STATEC, 2021), a nationally unified tax-benefit system (Sologon et al., 2026), and substantial demographic change over the last decade towards a more educated population and an increase in knowledge-intensive occupations. In particular, strong population growth driven largely by international migration has made the resident population increasingly diverse, with substantial heterogeneity in educational attainment and skill profiles (Chauvel et al., 2024). In such a context, spatial differences in disposable income inequality are unlikely to reflect region-specific institutions in the usual sense. They are more likely to reflect residential sorting, differences in demographic composition, how labour market incomes are distributed across resident households, and how redistributive policies transform market incomes into disposable incomes. Luxembourg, therefore, provides a useful setting for examining how differences in local inequality among residents are related to demographic composition, labour market characteristics, and the redistributive effects of a common national tax-benefit system.

A further reason why this setting is informative is that aggregate distributional stability need not imply spatial stability. Previous evidence for Luxembourg points to relatively stable trends in disposable income inequality at the national level, including during periods of major macroeconomic shocks such as the COVID-19 crisis, highlighting the cushioning role of the tax-benefit system (Sologon et al., 2022). In a context of high inter-municipal commuting for work, where place of residence and place of work are increasingly decoupled, stable national trends may nevertheless conceal substantial spatial reconfiguration across municipalities (Sarkar et al., 2024). Offsetting local dynamics may leave aggregate indicators overall unchanged, even as inequality declines in some areas and rises in others. This makes it important to move beyond national trends and examine how inequality evolves across local areas and why.

This paper addresses *three gaps* in the literature. *First*, much of the regional inequality literature focuses on differences in average income, wages, productivity, or employment across places, while much less is known about the geography of disposable income inequality at a fine spatial scale (De Nicolò and Ferrante, 2025; Iammarino et al., 2019; Piketty, 2014). A growing literature has used nighttime light data as an alternative proxy for regional income and spatial inequality, particularly in settings where sub-national income data are incomplete or unavailable. These studies show that luminosity measures can capture general patterns of regional convergence, spatial dependence, and inequality, although they remain indirect proxies rather than full income distributions (Lessmann and Seidel, 2017; Achten and Lessmann, 2020; Pérez-Sindín et al., 2025).

Second, while the small-area estimation and microsimulation literature has made substantial progress in generating local socio-economic profiles, fewer studies have combined this with a full income generation framework capable of recovering detailed municipality-level distributions of disposable income and its components, including market incomes and the effects of the tax-benefit system (Elbers et al., 2003; Ballas et al., 2005a; Tanton and Edwards, 2013; Li and O'Donoghue, 2013). Notable exceptions include spatial microsimulation approaches that estimate local income distributions and poverty rates (Ballas et al., 2005a; Campbell and Ballas, 2013; Panori et al., 2017; Crespo and Hernandez, 2020), as well as more recent work using EUROMOD relying on synthetic local populations to evaluate the geography of child poverty and inequality at the province level in Italy (Figari et al., 2026). Most papers typically rely on static reweighting, probabilistic algorithms, or deterministic imputation rather than a structured income generation model combined with tax-benefit simulations.

Third, although demographic change, labour market change, and tax-benefit redistribution are recognised as important drivers of inequality, their contributions to changes in spatial inequality are rarely assessed within a common empirical framework. Most of the contributions in understanding the drivers of inequality have been done at national level, either looking at cross-national differences in income inequality or the decomposition of changes in national income inequality over time (Sologon et al., 2023; Černiauskas et al., 2022; Li et al., 2021; Doorley et al., 2021; Figari et al., 2015; Immervoll and Richardson, 2011; Matsaganis and Leventi, 2014; Sologon et al., 2021; Fortin et al., 2011; Firpo et al., 2009). Meanwhile, fewer studies have decomposed the drivers of spatial inequality at a fine geographic scale (Mussini, 2017).

To address these gaps, we develop a multi-stage empirical strategy that connects a national income generation model to local demographic and fiscal dynamics through the use of European Survey for Income and Living Conditions (EU-SILC) microdata, Census aggregates, and the EUROMOD tax-benefit simulator to estimate disposable income distributions. The empirical strategy proceeds in three steps. First, we estimate a national income generation model that captures labour market participation, employment structure, wage determination, and multiple sources of market income building on recent developments in decomposition-based approaches to inequality analysis (Bourguignon et al., 2008; Bargain, 2012; Sologon et al., 2021, 2022, 2023). Second, we calibrate the simulated population to municipality-level demographic and labour market totals using a two-step spatial alignment procedure that combines calibration reweighting (Williamson et al., 1998; Lovelace and Dumont, 2016; Tanton and Edwards, 2013; Li and O'Donoghue, 2014; Lovelace and Philips, 2014) with a constrained assignment procedure for labour-related characteristics, in which individuals are ranked according to predicted probabilities and allocated to satisfy aggregate constraints (Lovelace and Ballas, 2013; Tanton and Clarke, 2014). This allows us to generate a synthetic population for municipalities in Luxembourg for 2011 and 2021 that aligns demographic and labour-market characteristics at the municipal level, representing a practical extension of existing methods. Third, we apply the tax-benefit rules using EUROMOD (Sutherland and Figari, 2013; Sologon et al., 2026) to derive municipality-level distributions of disposable income, and use these to analyse the spatial structure of inequality and its evolution over time. We examine municipal inequality dynamics through two complementary lenses: (i) spatial decomposition and convergence analysis, which document patterns, and (ii) counterfactual decomposition, which quantifies mechanisms.

By combining distributional modelling with spatial calibration, this paper makes *three contributions* to the literature on spatial inequality. *First*, it shows that in small, open and highly integrated economies, stable national inequality trends can conceal substantial spatial reconfiguration of inequality across local areas. *Second*, it develops a municipality-level empirical framework that combines income simulation, spatial calibration, and tax-benefit modelling to recover local distributions of disposable income among residents where representative small area income data are not available. This addresses an empirical constraint in small area distributional analysis: survey data contain rich information on incomes and household circumstances but are not representative at the municipal level, while Census and administrative data provide spatial detail but do not observe the full set of income components needed to analyse disposable income inequality. This is particularly valuable in Luxembourg, where administrative sources do not cover all income sources or all population groups. This framework can incorporate self-employed individuals

(10% labour force), international civil servants (3% labour force), and capital, rent or property, and private pension income, while also offering a methodological solution in a context where strict data-protection rules limit access to personal tax records. Because the framework builds on EU-SILC data and the pan-European model EUROMOD, it is also scalable and transferable to other countries operating within the same comparative survey and tax-benefit modelling infrastructure. *Third*, it uses counterfactual decompositions to quantify the contributions of demographic characteristics, labour market characteristics, and tax-benefit policy to changes in local inequality.

Three results stand out. *First*, overall inequality is driven overwhelmingly by disparities within municipalities rather than disparities between them, indicating that spatial inequality is less a story of sharply segmented rich and poor places than of heterogeneous populations within places (Shorrocks, 1980; Mookherjee and Shorrocks, 1982; Cowell and Fiorio, 2011). This distinction matters for policy. If the main source of inequality were disparities between municipalities, natural responses would be territorial instruments such as infrastructure spending and regional investment incentives. Since within-municipality disparities dominate, however, the relevant instruments should be local: policies that reduce residential segregation, expand affordable housing, improve access to childcare, jobs and services, and strengthen the capacity of municipalities to manage socio-economic changes. *Second*, the spatial clustering of inequality weakens over time. This is evidence of spatial convergence, although the pattern is not uniform across the territory. Stable national inequality conceals substantial heterogeneity across municipalities, with local declines in inequality in the urban belt around the capital offset by increases elsewhere. *Third*, the counterfactual decompositions reveal that changes in local inequality are shaped by multiple forces rather than by one dominant mechanism: demographic changes tended to increase local inequality outside the urban core, while labour market changes and the tax-benefit system offset part of that pressure.

2 Methodology

This paper aims to explain not only how inequality differs across municipalities, but also how changes in demographic composition, labour market structure, and tax-benefit policy shape the evolution of local disposable income inequality over time. For this purpose, we need to construct disposable income distributions at the municipal level for periods in which representative small area microdata are not directly available. The methodological challenge is first, to recover municipality-level disposable income distributions from nationally representative microdata, and second, to preserve both the structure of income generation and the institutional consistency of the tax-benefit system.

To address this challenge, the paper develops a spatially calibrated microsimulation framework to generate municipality-level disposable income distributions that combines an income generation model estimated on national survey microdata with municipality-level calibration and alignment procedures based on Census aggregates and the EUROMOD tax-benefit simulator. Market incomes are generated through a hierarchical modelling structure capturing labour market participation, employment characteristics, and returns, while disposable income is derived using a tax-benefit simulator to ensure institutional consistency across periods. Spatial heterogeneity is obtained by aligning demographic and labour market characteristics to observed municipal structures, while the underlying income-generating relationships are assumed to be nationally invariant within an integrated labour market.

This approach extends dynamic income nowcasting methodologies (Bourguignon et al., 2001; Navicke et al., 2014; Leventi et al., 2014; Bronka et al., 2020; Almeida et al., 2021; Sologon et al., 2022; Li et al., 2022; Monteduro et al., 2024) to the spatial dimension by combining regression-based income modelling with small-area reweighting and alignment procedures (Tanton et al., 2011), an income generation model, and a tax-benefit simulation via EUROMOD (Sutherland and Figari, 2013; Sologon et al., 2026). Standard small-area estimation techniques and deterministic reweighting methods mainly calibrate the sampling design weights to a set of new weights based on a distance measure, by using the available data at spatial scale. These methods can reproduce local population totals but do not preserve the structural link between labour market outcomes, income sources, and redistribution. Conversely, national microsimulation models capture institutional mechanisms but lack spatial resolution. By combining these dimensions, the framework developed in this paper generates municipality-level disposable income distributions that are internally consistent, comparable across time, and suitable for inequality decomposition and spatial econometric analysis. For example, it captures the effects of migration-driven sorting by fitting the weights to accommodate population groups for each municipality according to different Census cross-tabulations (e.g. international migrants, education, age groups, labour force by gender). Consequently, changes in inequality capture both compositional shifts in municipal population driven by migration, internal residence mobility, and changes in the age and educational structure, as well as temporal variation in the estimated returns to individual characteristics within the income generation model.

The framework proceeds in three stages. *First*, we estimate a national income generation model (IGM) using the European Union Survey on Income and Living Conditions (EU-SILC) for 2012 and 2022 (income reference year 2011 and 2021). *Second*, we spatially calibrate the microdata and align the IGM to reproduce the demographic and labour market structure of each municipality using 2011 and 2021 Census aggregates. *Third*, we apply the EUROMOD tax-benefit model for 2011 and 2021 to simulate disposable income distributions for each municipality under tax-benefit rules of each period.

Rather than identifying structural causal effects at the municipal level, this framework is designed to construct distribution-consistent synthetic populations. These reproduce observed local demographic and labour market structures while preserving the relationships between observed personal characteristics, and the income components estimated from survey microdata. Using the resulting synthetic municipality-level income distributions, we implement a set of complementary decompositions to analyse the structure and drivers of spatial inequality, including decomposing overall inequality into within- and between-municipality components, spatial convergence analysis and spatial counterfactual decompositions to quantify drivers.

2.1 National income generation model

The core of the spatial framework is a national income generation model for household disposable income (IGM), following Sologon et al. (2021, 2022)[1]. The IGM represents the formation of household disposable income by combining the prevalence and the level of market income components and tax-benefit policy.

Household disposable income (y_h) is defined as:

$$y_h = \underbrace{y_h^L + y_h^K + y_h^O}_{Market} + \underbrace{y_h^B - y_h^T}_{Non-market} \tag{1}$$

- y_h^K represents household capital income (including capital investment and property or rental income),
- y_h^L represents labour income (including employee, self-employed incomes),
- y_h^O represents other household non-benefit pre-tax incomes (including private pension, private transfers, and other incomes),
- y_h^B represents public benefits, and y_h^T direct taxes and social insurance contributions.

Each of them is composed of income subcomponents, which are modelled separately as a function of their prevalence and level, allowing the model to capture household heterogeneity in income components.

Household labour income y_h^L aggregates employment and self-employment income of household members (hi). Its formation follows a process that describes first if the individual is working, based on a binary indicator I_{hi}^{lab}. Second, for those working, we model the probability to be employed or self-employed ($I_{hi}^{employed}$ and $I_{hi}^{selfemp}$). For those employed, we model the level of employment income $y_{hi}^{employed}$ as a

[1] Please refer to the source methodology in Sologon et al. (2021) for a detailed discussion of the income generation model.

function of (wage*hours of work). For the self-employed, we model the level of self-employment income $y_{hi}^{selfemp}$.

$$y_h^L = \sum_{i=1}^{n_h} I_{hi}^{lab} \left(I_{hi}^{employed} y_{hi}^{employed} + I_{hi}^{selfemp} y_{hi}^{selfemp} \right) \tag{2}$$

For modelling capital incomes, we model first the prevalence of investment and property incomes based on the binary indicators I_{hi}^{inv} and I_{hi}^{prop}. For those holding these income sources, we model the level, represented by $y_{hi}^{inv}$and y_{hi}^{prop}. Similarly, we model the prevalence of private pensions and other income sources, and their levels.

$$y_h^K = \sum_{i=1}^{n_h} \left(I_{hi}^{inv} y_{hi}^{inv} + I_{hi}^{prop} y_{hi}^{prop} \right);\ y_h^O = \sum_{i=1}^{n_h} (I_{hi}^{pripen} y_{hi}^{pripen} + I_{hi}^{Other} y_{hi}^{Other}) \tag{3}$$

Household benefits (y_h^B) aggregate pensions, means-tested and non-means tested benefit, whereas direct taxes (y_h^T) aggregate income taxes (tax) and social security contributions (ssc):

$$y_h^B = y_h^{pens} + y_h^{mtb} + y_h^{nmtb};\ y_h^T = y_h^{tax} + \sum_{i=1}^{n_h} y_{hi}^{ssc}. \tag{4}$$

We employ the EUROMOD tax-benefit model for Luxembourg (see Sutherland and Figari (2013), Sologon et al. (2026)) to model income taxes, social insurance contributions, social assistance benefits, social insurance benefits and universal benefits. The EUROMOD tax-benefit model captures Luxembourg's welfare policy changes during the study period (2011-2021), which focused mainly on strengthening the fiscal progressivity on the taxation side and targeted support on the benefit side. The 2017 reform expanded the personal income tax schedule to 23 brackets with a top marginal rate of 42%, and replaced several flat tax allowances with income-dependent refundable tax credits[2]. Meanwhile, Luxembourg's *safety net* system changed in 2019 from *Guaranteed Minimum Income (RMG)* to *Social Inclusion Income (REVIS)* , with the purpose of incentivising employment by disregarding 25% of the gross income of the household when calculating their eligibility. Other benefits were simplified, such as the 2016 child benefit reform with a uniform amount for children born after August 2016; while others were modernised, such as parental leave that moved from an income-based "replacement income" that is more financially attractive (A detailed summary of these policy changes can be found in Table A–3 in the appendix)

Modeling of income components

For each income component, we specify parametric relationships with observed individual and household characteristics, following Sologon et al. (2021).[3] and for each income component, we apply a two-stage procedure. First, we estimate the probability of having the income component, I_{hi} using logistic models (Agresti, 2010). Second, we estimate the level of the income component y_{hi}, conditional on receiving it.

Labour income is modelled through a sequence of conditional steps. *First*, we estimate the probability of working as a function of individual characteristics x_{hi}. This is the participation indicator I_{hi}^{lab} for person i in household h above, which depends on individual characteristics x_{hi}, model estimates Υ^{lab} and random residuals ϵ_{hi}^{lab}, estimated separately for men, single women and women in a couple.

[2] Other major tax policy changes during this decade included raising the standard VAT rate to 17% in 2015, giving married couples the choice of individual taxation starting in 2018 and increasing the unemployment fund surcharge to its current levels of 7% or 9%

[3] See Sologon et al. (2021), Appendix A for a detailed description. The structure and the estimation of the models in the IGM follow closely the original paper,

Second, conditional on being in work, we estimate the probability to be an employee versus a self-employed, determined by individual characteristics x_{hi}, model parameters Υ^{emp} and the random residual ϵ_{hi}^{emp}.

Third, conditional on working, we model the sector (public/private), occupation (8 categories, based on the ISCO-08 classification) and industry (8 categories[4]).

The public sector is estimated using a binary logit model, which is a function of $(x_{hi}, \epsilon_{hi}^{pub}, \Upsilon^{pub})$, and is entered as an explanatory variable in the occupation model. Occupation is itself an explanatory variable in the industry model; both occupation and industry are specified using multinomial logit models, following Sologon et al. (2021) and Bourguignon et al. (2008). They are both determined by a set of explanatory factors x_{hi} and a vector of 8 individual-specific, extreme-value-distributed error terms $\epsilon_{hi}^{k,occ}$ and $\epsilon_{hi}^{k,ind}$ $(k = 1, \ldots, 8)$, conditional on the parameter vector δ^{occ} and δ^{ind}.

Next, the level of income sources is modelled, conditional on their presence. For employees, labour income is modelled as a product between the hourly wage rate and the number of hours of employment s_{hi}, $y_{hi}^{emp} = w_{hi} * s_{hi}$. Given the central role of wages in the formation of household income, we go beyond the conditional mean and model them applying a flexible parametric distributional regression which captures the relationship between individual characteristics and the entire conditional wage distribution (see Biewen and Jenkins (2005) and Van Kerm (2013)). Individual wage is given by $w_{hi} = F_{X=z}^{-1}(\upsilon_{hi}^{emp}) = b(z)[(1-\upsilon_{hi}^{emp})^{-\frac{1}{q(z)}} - 1]^{\frac{1}{a(z)}}$,where υ_{hi}^{emp} is a random term uniformly distributed, $q(z)$ is a shape parameter for the 'upper tail', $a(z)$ is a shape parameter for the 'spread' for both tails of the distribution, and $b(z)$ is a scale parameter. a, b and q parameters have a log-linear function of demographic and labour market characteristics (z) (e.g. age, education, marital status, number of children, citizenship, occupation, industry, sector). Hours are estimated using a linear model. For the self-employed, income is estimated using a log-linear regression model $y_{hi}^{se} = exp(x_{hi}\beta^{se} + \upsilon_{hi}^{se})$.

In a nutshell, household labour income y_h^L depends on the characteristics x_{hi} of the household members (n_h), the model parameters $(\gamma^{lab}, \gamma^{emp}, \delta^{pub}, \delta^{occ}, \delta^{ind}, \beta^{se}, \sigma^{se}, \gamma^{hrs}, \beta^{a,emp}, \beta^{b,emp}, \beta^{q,emp})$ and residual heterogeneity terms $(\epsilon_{hi}^{lab}, \epsilon_{hi}^{emp}, \epsilon_{hi}^{k,occ}, \epsilon_{hi}^{k,ind}, \epsilon_{hi}^{pub}, \epsilon_{hi}^{hrs}, \upsilon_{hi}^{se}, \upsilon_{hi}^{emp})$.

Other non-tax-benefit incomes are modelled at a more aggregated level due to their limited prevalence. The same two-stage approach is applied: we first estimate the probability of receipt, I_{hi}^S, using logistic models, then model income levels, y_{hi}^S, $S \in$\{inv, prop, pripen, other\} using log-linear models. Household capital and other incomes, y_h^K and y_h^O, depend on the characteristics x_{hi} of the n_h household members, residual heterogeneity terms $(\epsilon_{hi}^{inv}, \epsilon_{hi}^{prop} \epsilon_{hi}^{pripen}, \epsilon_{hi}^{other}, \upsilon_{hi}^{inv}, \upsilon_{hi}^{prop}, \upsilon_{hi}^{pripen}, \upsilon_{hi}^{other})$ given the model parameters.

Income taxes, social insurance contributions, social assistance benefits, social insurance benefits, and universal benefits are simulated using the EUROMOD tax-benefit model for Luxembourg (see Sutherland and Figari (2013) and Sologon et al. (2026)). Since the model incorporates both current and past tax-benefit rules, it enables users to "swap" policies across time periods (see, for example, Levy et al. (2007), Bargain and Callan (2010), and Bargain (2012)).[5]

In summary, the national IGM consists of a system of hierarchically structured multiple equations for disaggregated income components, combining (i) a set of individual and household characteristics, X, (ii) parameters describing how employment, the prevalence, and level of income components vary with personal and household characteristics, ξ, (iii) residuals linking model predictions to observed income components, Υ. All estimated relationships should be understood as reduced-form projections that capture

[4]Agriculture = A - Agriculture, Forestry and Fishing; Manufacturing = B - Mining and Quarrying & C - Manufacturing & D - Electricity, gas, steam and air conditioning supply & E - Water supply, sewerage, waste management and remediation activities; Construction = F - Construction; Commerce = G - Wholesale and retail trade; repair of motor vehicles and motorcycles & I - Accommodation and food service activities & J - Information and communication & K - Financial and insurance activities & L - Real estate activities & M - Professional, scientific and technical activities & N - Administrative and support service activities; Transport = I - Transporting and storage; Public Administration = O - Public administration and defence; compulsory social security; Education/Health / Social = P - Education & Q - Human health activities; Other = R - Arts, entertainment and recreation & S - Other services activities & Activities of households as employers; undifferentiated goods - and services - producing activities of households for their own use.

[5]We also estimate the distribution of partially simulated and non-simulated variables in EUROMOD, following Sologon et al. (2021).

empirical links between observed characteristics and income components. These projections are used to construct synthetic distributions at more granular geographic levels using external calibration statistics at the municipal-level. Combined with the EUROMOD tax-benefit simulator, we obtain disposable incomes.

This paper uses the EU-SILC survey for years $s = 2012$ and $t = 2022$ to estimate the parameters of the income generation model from the national surveys. At time s and t, the IGM describing the distributions of disposable income in the two years can be formalized as

$$Y_s = f(X, \Upsilon; l_s(\xi); r_s(\xi); tb_s(\xi)), Y_t = f(X, \Upsilon; l_t(\xi); r_t(\xi); tb_t(\xi)), \tag{5}$$

where Y is disposable income, l is the labour market structure, r is the structure of returns and tb is the tax-benefit system. The income generation model is a statistical representation of the structure of the presence and the level of market incomes (and its components), and the tax-benefit rules. The model assumes that conditional income-generating relationships are spatially invariant within Luxembourg. Spatial heterogeneity arises from differences in population composition and labour market structure, not from municipality-specific returns.

2.2 Simulating spatial income distributions at municipal level

The IGM extended with spatial calibrating techniques is used next to simulate local distributions of income at the municipal level m at time s and time t starting from the estimated IGM based on national SILC survey year s and year t described in equation (5).

Our simulations assume that the conditional income-generating relationships estimated from national microdata are spatially invariant across municipalities. This implies that the parameters governing labour market participation, income generation, and returns to observable characteristics are assumed to be common across space. Spatial heterogeneity in income distributions therefore arises from differences in demographic composition and labour market structure rather than from municipality-specific returns. This assumption is plausible in the Luxembourg context, given the country's small size, strong inter-municipal commuting, a unified institutional framework, and largely national wage-setting mechanisms.

We simulate the distributions of disposable income at municipality level m in two steps. *First*, we estimate spatial calibration weights at municipality level from Census statistics for each year by developing an algorithm based on the STINMOD spatial approach (Tanton et al., 2011) and reweighting-nowcasting methods (Almeida et al., 2021). The spatial weights take into account municipality statistics by age and gender, education and gender, employment and gender, and foreign-citizen and gender. *Second*, we apply the income generation model transformations with the spatial weights aligning our simulations via regression based alignment (Similar to nowcasting techniques as in Sologon et al. (2022)). For each year, we generate $m = 102$ synthetic distributions.

This hybrid approach allows for the correction of unexplained spatial variation and improves the geographical fidelity of the simulation. The spatial reweighting procedure thus serves as a corrective mechanism to reflect better local population structures and enhance the reliability of geographically disaggregated policy simulations (Tanton and Edwards, 2013; Ballas et al., 2005b, 2004), while the regression-based alignment of labour market variables ensures‘ that the simulated output matches exogenous totals to accurately represent the population of the targeted spatial unit (Baekgaard, 2002).

2.2.1 Spatial Reweighting: Estimating spatial weights at municipality level from Census statistics W_m

Spatial reweighting is used to adapt nationally representative survey data to municipality-specific population structure.[6] The objective is to adjust the survey weights of each observation (e.g., individuals,

[6]Spatial reweighting is among the multiple methods used in microsimulation modelling and regional economics for small area estimation. An extensive review can be found in Tanton and Clarke (2014).

households) so that the weighted microdata reproduce the marginal distributions observed in Census data for each municipality. This is especially useful when applying models built on national-level data to sub-national regions or smaller spatial units, so that the weighted sample reflects the population structure of a geographical area different from the one originally sampled (Tanton and Vidyattama, 2010; Li and Vidyattama, 2019).

The reweighting procedure applied here aligns the distribution of characteristics in the survey data with municipality-level Census margins. The calibration variables include 13 age groups by gender, education by gender, employed by gender, and foreign born by gender. These margins are sourced from auxiliary data sources, in this case, the Luxembourg Census for 2011 and 2021, and are used to construct a synthetic population for each municipality that is consistent with observed local demographic structures (STATEC, 2011, 2021). We calibrate the synthetic population derived from the survey microdata with known municipal-level distributions, thus enhancing the representativeness and precision of the simulation outcomes (Birkin and Clarke, 1988).

The procedure to calibrate the survey weights to external totals follows the recursive algorithm from Creedy (2003)[7]. To apply the algorithm, we compute the total municipal population, followed by a re-scale of the initial weights according to the municipality population size. Moreover, we set tolerance levels that are relative to the survey sample and municipality size. We iteratively recalculate individual survey weights so that weighted totals for age, education, foreign share, employment match the external population targets. After each iteration, our procedure checks whether the reweighted population is within $\pm5\%$ of municipal total population recorded in the Census; if not, it lowers the tolerance and re-calculates until convergence. The procedure dynamically lowers the tolerance if convergence is not reached. Once successful, it keeps the final tolerance and bounds and moves on to the next municipality[8].

The output of this step are two spatial weights vectors for m municipalities for periods s and t, denoted W_{m_s} and W_{m_t}.

2.2.2 *Simulating m municipality-level local distributions through regression-based alignment*

Calibration weights alone cannot guarantee that simulated labour market outcomes reproduce municipal employment and income structures. We therefore complement spatial reweighting with a regression-based alignment procedure. Using the estimated IGM for period s and t, together with the municipal-level calibration weights W_{m_s} and W_{m_t}, we simulate m municipality-level local distributions of household disposable income in both periods, while keeping the simulation constrained to the municipal total number of in-work, employees, public employees, and number of workers by industry and occupation retrieved from census tabulations for 2011 and 2021. The aim is to generate local distributions of disposable income by aligning the labour market, income and tax-benefit transformations so as to reflect the local situation in each municipality $m = 1, ..., M$ ($M = 102$ municipalities).

Labour market structure alignment

The first step is the *labour market alignment*. It involves simulating population structures at the local level (municipality) with respect to core labour market characteristics such as employment, sector, occupation, industry, unemployment, retirement. This is done by combining the estimated parameters and the residuals from the national labour market models for period s and period t with municipality-level Census constraints. For binary outcomes, such as being in work or not, we rank individuals according to the latent propensity implied by the model and select them so that the simulated totals match the corresponding Census margins. For multinomial outcomes, such as occupation and industry, we apply the same logic

[7]We employ the "sreweight" Stata command described in Pacifico (2011), which is based on the foundational work of Deville and Sarndal (1992) that provides a general theory for constructing estimators that match known population characteristics.

[8]See Appendix A.1 for details on estimating the spatial weights.

across categories, selecting individuals in a way that reproduces the observed local structure. By doing so, we follow the approach utilised in dynamic microsimulation to address a range of simulation-related problems found in alternative calibration methods (Li and O'Donoghue, 2014). This step simulates employment characteristics that reflect Census labour market statistics.

This procedure produces municipality-level labour market structures that are consistent with the Census statistics on the employment composition by age and gender, the sector composition by age and gender, the occupation and industry structure by gender. The spatial weights W, therefore, enter the IGM as a calibration device that shapes the local demographics and labour market composition of the synthetic population. Formally, the municipality-level income distribution can be written as:

$$\tilde{Y_m} = f_\xi(X, \Upsilon; \tilde{l_m}(\xi; W_m)), m = 1, ..., M \tag{6}$$

where $\tilde{l_m}(\xi; W_m)$ is the local labour-market structure (participation, employment type, sector, occupation, industry, hours), obtained by calibrating local targets using the spatial weights W_m.

This step introduces spatial heterogeneity through labour market composition. The working population updates its labour market characteristics, captured by the new vector $\tilde{l_{m_s}}(\xi; W_{m_s})$ and $\tilde{l_{m_t}}(\xi; W_{m_t})$, consistent with municipality-level structure in each period.

Returns and tax-benefit transformations

Given the aligned labour market structure, in a second step, we perform the *returns transformation*. We simulate the corresponding income sources at municipality level m. Wages, self-employment income, and all other income sources are generated conditional on the updated employment, sector, occupation and industry characteristics. Those who are simulated without a job (e.g. unemployed, retired), have their incomes simulated accordingly.

The *tax-benefit system* is then applied through EUROMOD to generate disposable incomes in each municipality and each period.

$$\tilde{Y_{m_s}} = f(X, \Upsilon; \tilde{l_{m_s}}(\xi; W_{m_s}); \tilde{r_{m_s}}(\xi; W_{m_s}); tb_s(\xi)), \tilde{Y_{m_t}} = f(X, \Upsilon; \tilde{l_{m_t}}(\xi; W_{m_t}); \tilde{r_{m_t}}(\xi; W_{m_t}); tb_t(\xi)), \tag{7}$$

where $\tilde{r_m}(\xi; W_m)$ is municipal-level market income structure and tb is the tax-benefit system.

Since incomes and tax-benefit rules refer to the same year, there is no need to uprate incomes. If however, the tax-benefit parameters and the incomes do not refer to the same year, before applying the tax-benefit parameters we need to update all pre-fiscal monetary variables applying the EUROMOD uprating factors to align them with the policy parameters of the targeted year.

This second step transforms the reweighted microdata into municipal-level disposable income distributions that are both spatially aligned and policy-consistent. Calibration ensures consistency with municipality-level demographic and labour market totals, while the IGM and EUROMOD preserve the structural links with labour market characteristics, income sources and redistribution. The result is a set of synthetic income distributions at the municipal level suitable for spatial analysis and inequality decompositions.

Our methodological contribution is a hybrid spatial approach that integrates calibration reweighting with regression-based income modelling and EUROMOD-based tax-benefit simulation to generate municipal level disposable income distributions consistent with both microeconomic behaviour and local demographic constraints.

2.3 Decomposing spatial inequality and its changes over time

Using the synthetic municipality-level income distributions, $\tilde{Y}_{m_s}$ and $\tilde{Y}_{m_t}$, we implement a set of complementary decomposition strategies to analyse both the structure of spatial inequality and the mechanisms underlying its evolution over time, $G_{\tilde{Y}_m}$. We proceed in three steps. First, we decompose overall inequality into within- and between-municipality components to assess whether national inequality mainly reflects disparities within local areas or between them. Second, we estimate a spatial convergence model to examine whether municipality-level inequality tends to persist, diverge, or converge over time once local characteristics and spatial dependence are taken into account. Third, we construct counterfactual income distributions to quantify the contribution of demographic change, labour market change, and tax-benefit policy to observed changes in local inequality.

2.3.1 *Between and Within-Municipality Decompositions*

We begin by decomposing overall inequality into within- and between-municipality components and by assessing the presence of spatial clustering across municipalities. Understanding whether national inequality primarily reflects disparities within municipalities or between municipalities is important for interpreting the role of local structural factors and for assessing the relevance of place-based policies.

Throughout the analysis we focus on the Gini coefficient, the most widely used measure of income inequality. The Gini index has a clear and intuitive interpretation based on pairwise income comparisons, measuring the average absolute difference in incomes between all pairs of individuals, scaled by the mean.[9] Despite its intuitive interpretation, the Gini inequality index is not directly decomposable by population subgroups using a simple top-down approach. When the population is partitioned into groups (e.g., municipalities), a standard decomposition into within-group and between-group inequality generates an additional overlap term reflecting the extent to which income distributions across groups intersect.[10]

To overcome this limitation, we adopt the bottom-up approach proposed by Ebert (1984, 2010). Rather than decomposing an aggregate index into group components, this approach builds on the pairwise definition of the Gini coefficient and decomposes inequality directly into contributions from pairs of individuals belonging to the same municipality and to different municipalities.

Let $W = \sum_{i=1}^{n} w_i$ denote the total population. The weighted Gini coefficient is given by

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j |y_i - y_j|}{2W \sum_{i=1}^{n} w_i y_i} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j |y_i - y_j|}{2W^2 \bar{y}}, \tag{8}$$

where y_i is income for individual i, w_i the survey weight for individual i, and $\bar{y} = \frac{\sum_{i=1}^{n} w_i y_i}{W}$ the weighted mean income. Total Gini inequality can be written as: $G = G_{\text{within}} + G_{\text{between}}$.

Within-Municipality Component

For each municipality m, let G_m denote the weighted Gini coefficient computed using exact pairwise differences within that municipality, while W_m represents its population size, $W_m = \sum_{i=1}^{n_m} w_i$. The within-municipality component is given by:

$$G_{\text{within}} = \sum_{m} \frac{W_m}{W} G_m, \tag{9}$$

Between-Municipality Component

The between-municipality component captures income differences between individuals living in different municipalities. In standard top-down Gini decompositions, the between component is obtained by replacing all individual incomes within each municipality with mean income and computing inequality

[9] Values range from 0 (perfect equality) to 1 (maximum inequality).

[10] This overlap occurs because individuals in different municipalities may hold similar income positions in the national distribution, preventing a clean separation of inequality into purely within- and between-group components.

across these municipality-level means. Since this approach captures only differences in mean incomes across municipalities, the top-down decomposition generates an additional residual (overlap) term, due to the overlap between the income distributions of different municipalities.

The approach proposed by Ebert (2010, 1984) addresses this limitation by calculating the between-component directly from the pairwise income differences between individuals belonging to different municipalities. By construction, this bottom-up approach eliminates the residual overlap term because every cross-municipality comparison is accounted for. Although conceptually appealing, this becomes computationally costly in large datasets. We, therefore, use a tractable approximation that preserves the logic of the bottom-up decomposition while reducing the computational burden. We approximate the between-municipality component using percentiles of each municipality's income distributions instead of all individual pairwise comparisons. This approach allows us to incorporate information on differences in the shape of the income distributions across municipalities, beyond their means. We show that this percentile-based approximation closely reproduces the between-component obtained using the full Ebert pairwise decomposition, while substantially reducing the computational burden.

The between-group component is approximated using percentile representations of each municipality's income distribution:

$$G_{\text{between}} = \frac{1}{2W^2\bar{y}} \sum_{m_1 \neq m_2} \sum_{p=1}^{P} \sum_{q=1}^{P} \omega_{m_1}(p)\, \omega_{m_2}(q)\, |y_{m_1}(p) - y_{m_2}(q)| \,. \tag{10}$$

This approximation treats each municipality as a discrete distribution with P mass points (e.g., $P = 100$ for percentiles), $p, q \in \{1, \dots, P\}$ denoting percentile bins, where $y_m(p)$ is the income associated with percentile bin p, and $\omega_m(p)$ is the corresponding population share associated with percentile p in municiplaity m.

The between-group component captures inequality due to differences across municipality income distributions, approximated using percentile income profiles rather than all individual pairwise comparisons. This approach preserves the conceptual structure of the Ebert (2010) decomposition while substantially reducing computational time.

2.3.2 Spatial convergence over time

Next, we examine whether municipal-level inequality tends to persist, widen, or converge over time. The question is whether inequality levels are becoming more similar across municipalities (convergence) or whether inequality is rising at a steeper rate in high inequality areas compared to low inequality ones (divergence). For this purpose, we estimate a spatial econometric model, where the logarithm of the Gini income inequality index (G_t) in municipality i at time t is a function of its lag and local demographic characteristics ($\mathbf{X}_{t-1}$).

We test the presence of spatial dependence, meaning that nearby municipalities are more likely to have similar levels of inequality than those further apart. We use two indicators for spatial correlation, Moran's I and Geary's C: a value of 0 for Moran's I and 1 for Geary's C signals the absence of spatial autocorrelation. The departure from these values for the two indicators indicates the presence of spatial autocorrelation. (Anselin, 1988). For Luxembourg, this dependency can occur through commuting, which links labour markets across municipalities. If income levels and their dispersion are associated with demographic characteristics (such as education, occupation sorting, age structure, productivity), then commuting enables workers in neighbouring municipalities to influence local income inequality elsewhere. By allowing residents to work outside their municipality of residence, commuting connects local labour markets and transmits external wage structures into the local income distribution. In particular, the skill composition and demographic profile of neighbouring municipalities shape the types of jobs available, the level of wages, and the returns to individual characteristics in those areas. Because access to these external opportunities is typically easier for high-skilled or mobile workers, commuting can affect different parts of the income distribution. As a result, the demographic characteristics of neighbouring municipalities reflected in the incomes of commuters can affect local inequality.

If such a spatial dependence exists, the coefficient associated with lagged inequality might be biassed due to the known reflection problem in spatial econometrics (Manski, 1993). This means that any observed similarity in inequality across neighbouring municipalities may reflect either endogenous spillovers or correlated effects driven by shared institutions, policies, or environmental conditions. If ignored, these effects are absorbed in the error term, creating an endogeneity problem. To account for these mechanisms, we model this source of dependence through the spatial lag specification (using the matrix $\mathbf{W}$) and its interactions with local demographic characteristics. We also include a spatial error term, which allows for unobserved spatially correlated disturbances (Anselin, 1988; LeSage and Pace, 2009).

Our final specification follows a spatial autoregressive model with spatially correlated errors (SARAR):

$$\mathbf{G}_{it} = \alpha\mathbf{1} + \beta\mathbf{G}_{it-1} + \rho\mathbf{W}\mathbf{G}_t + \gamma\mathbf{X}_{it-1} + \theta\mathbf{W}\mathbf{X}_{it-1} + \boldsymbol{\varepsilon}_t, \qquad \varepsilon_t = \lambda\mathbf{W}\boldsymbol{\varepsilon}_t + \mathbf{u}_t. \tag{11}$$

The reduced form is: $\mathbf{G}_t = (\mathbf{I} - \rho\mathbf{W})^{-1}\left[\alpha\mathbf{1} + \beta\mathbf{G}_{t-1} + \gamma\mathbf{X}_{t-1} + \theta\mathbf{W}\mathbf{X}_{t-1}\right] + (\mathbf{I} - \rho\mathbf{W})^{-1}(\mathbf{I} - \lambda\mathbf{W})^{-1}\mathbf{u}_t$.

Since the final specification includes different interactions and lag terms, the coefficients cannot be interpreted in isolation. We therefore calculate the marginal effect of lagged inequality on current inequality as follows: $\frac{\partial\mathbf{G}_t}{\partial\mathbf{G}'_{t-1}} = (\mathbf{I} - \rho\mathbf{W})^{-1}\beta$. This matrix captures how changes in lagged inequality propagate throughout the spatial network. To summarise the overall magnitude of this effect, we compute the average total marginal effect across all municipalities: $\frac{1}{N}\mathbf{1}'(\mathbf{I} - \rho\mathbf{W})^{-1}\beta\mathbf{1}$.

Following LeSage and Pace (2009), the total marginal effect of initial inequality, can be decomposed into direct (within-municipality) and indirect (spillover) effects transmitted through the spatial interaction structure. A total effect below one signals spatial conditional convergence, meaning that municipalities with higher initial inequality experience lower subsequent inequality once spatial feedback is taken into account. A total effect above one indicates spatial divergence. A total marginal effect between zero and one indicates persistence without divergence: inequality differences decrease over time, but do not disappear immediately.

The SARAR framework further accounts for spatial spillovers, addressing convergence as a system-wide phenomenon driven by both local dynamics and interactions among neighbouring municipalities, rather than an independent process occurring within each municipality. For this reason, the econometric specification includes spatial lags to measure spatial spillovers across municipalities to uncover whether convergence in inequality is driven by local dynamics and the interactions between neighbouring municipalities.

The results of this section only show whether there is evidence of convergence in inequality while partially controlling for other confounding factors. Nonetheless, no causal interpretation should be inferred. The next section (Section 2.3.3) shows a counterfactual decomposition exercise that aims to isolate the contributions of different factors that explain inequality changes such as demographics, labour markets, and redistribution.

2.3.3 *Counterfactual decompositions of the change in spatial inequality*

To quantify the contribution of structural and policy changes to the evolution of spatial inequality over time, we implement a set of counterfactual simulations inspired by the transform-and-transplant approaches proposed in the inequality decomposition literature (i.e., Sologon et al. (2021); Bargain and Callan (2010); DiNardo et al. (1996), adapted in a spatial context. The method assesses how the spatial distribution of disposable income would change if one component of the income generation process were altered while all other components remained unchanged. Following the approach in Biewen (2014); Biewen and Juhasz (2012), we implement a ceteris paribus decomposition of the inequality change, where we change one component at a time, contrasting the counterfactual with the reference distribution.

We proceed in two steps. *First*, we estimate municipality-specific counterfactual decomposition at the municipality level in order to fully exploit the granularity of the spatial microsimulation framework. This allows us to identify, for each municipality m, the contribution of demographic composition, labour market structure, and tax-benefit policy to changes in disposable-income inequality between 2011 and 2021.

We expect the municipality-level decomposition results to be highly heterogeneous, reflecting differences in local demographic structures, labour market characteristics, and policy exposure. The spatial autocorrelation analysis conducted in the previous step allows us to assess whether this heterogeneity is random or spatially structured. Building on this evidence, in a *second* step, we define spatial regimes (clusters of municipalities with similar inequality dynamics) within which decomposition effects can be meaningfully compared and interpreted. We aggregate municipality-level results into population-weighted regime-level summaries, thereby providing a structured synthesis of local decomposition effects while preserving their relative importance in the national distribution.

Municipality-specific counterfactual decomposition

We start from the synthetic distributions of disposable income in each municipality in 2011 and 2021, denoted as $\tilde{Y_{m_s}}$ and $\tilde{Y_{m_t}}$. The total change in disposable income inequality between period $s = 2011$ and $t = 2021$ for each municipality m can be written as

$$\Delta\theta_m = I(\tilde{Y_{m_t}}) - I(\tilde{Y_{m_s}}) \tag{12}$$

where $\theta(\cdot)$, denotes a functional of interest, for example the Gini inequality index I. Counterfactual simulations are then used to isolate the contribution of structural changes, such as demographic and labour market, and tax-benefit policy changes to this overall change.

We implement a Biewen-style ceteris paribus decomposition where we change one factor at a time (composition of demographic characteristics, labour market characteristics, or policy), holding the rest fixed at a chosen baseline (here t = 2021). The remainder is treated as an additional term that includes interactions between the factors and other population changes which are not isolated by the direct counterfactuals.

The change in disposable income inequality over time in each municipality m is decomposed into the contribution of changes in the demographic structure of municipality residents, $\Delta I_m^{Demographics}$, the contribution of changes in their labour market characteristics, ΔI_m^{LM}, the contribution of changes in tax-benefit policies, ΔI_m^{Policy}, and a remainder, ΔI_m^{Other}.

$$\Delta\theta_m = \Delta I_m^{Demo} + \Delta I_m^{LM} + \Delta I_m^{Policy} + \Delta I_m^{Other} \tag{13}$$

The direct contribution of demographics changes, ΔI_m^{Demo}, is obtained by contrasting the reference distribution in 2021, $I(\tilde{Y_{m_t}})$, with a counterfactual that would prevail in $t = 2021$ if the demographic structure (age, education, gender, household composition, foreign citizenship) reflected the population at time $s = 2011$ in each municipality, $I(\tilde{Y_{m_t}}(Demo_s^{reweighted}; LM_t; Policy_t)$. Following DiNardo et al. (1996), we implement this transformation using a semi-parametric reweighting procedure in each municipality m. Within each municipality m, we build weights so that the microdata at $t = 2021$ reweighted matches the $s = 2011$ joint distribution of X demographic characteristics in that municipality, while keeping everything else fixed in $t = 2021$. The contribution of the demographic changes equals:

$$\Delta I_m^{Demo} = I(\tilde{Y_{m_t}}) - I(\tilde{Y_{m_t}}(Demo_s^{reweighted}; LM_t; Policy_t)) \tag{14}$$

This transformation modifies the distribution of characteristics while preserving the conditional income-generating relationships.

To assess the direct contribution of changes in labour market structure, we apply an analogous reweighting procedure to align the distribution of labour market characteristics, LM, in $t = 2021$ with that observed in s=2011, ceteris paribus. This transformation generates a counterfactual distribution representing the income distribution in $t = 2021$ as if the labour market structure had remained as in $s = 2011$, which is contrasted with the reference distribution at time $t = 2021$. The contribution of labour market changes is:

$$\Delta I_m^{LM} = I(\tilde{Y_{m_t}}) - I(\tilde{Y_{m_t}}(Demo_t; LM_s^{reweighted}; Policy_t)) \tag{15}$$

To assess the direct contribution of tax-benefit changes between period $s = 2011$ and $t = 2021$, we construct a counterfactual distribution of disposable income that would prevail in period $t = 2021$ under tax-benefit rules of period $s = 2011$, $I(\tilde{Y_{m_t}}(Demo_t; LM_t; Policy_s))$. Market incomes and household characteristics in $t = 2021$ are kept unchanged, but disposable income is recalculated by applying the $s = 2011$ tax-benefit rules using the EUROMOD simulator. The contribution of the tax-benefit rule changes is:

$$\Delta I_m^{Policy} = I(\tilde{Y_{m_t}}) - I(\tilde{Y_{m_t}}(Demo_t; LM_t; Policy_s)) \tag{16}$$

Each direct transformation is applied independently starting from the same benchmark distribution of disposable income ($t = 2021$). Because the income generation process is non-linear, the sum of direct effects does not equal the total change in inequality. Following the Biewen (2014) decomposition approach, the remainder effect, ΔI_m^{Other}, captures interaction effects between demographic, labour market, and policy changes, as well as changes in the market income process and other unobserved population differences, and is calculated as a difference between the inequality change and the sum of all direct effects.

Aggregation of counterfactual decompositions into population-weighted regimes

To reconcile the micro-level decomposition with macro-spatial patterns, we aggregate municipality-level decompositions into a small number of population-weighted spatial regimes r. These regimes are defined based on observed spatial clustering and substantive economic geography (urban core, industrial south, peripheral north)[11]. This aggregation serves three complementary purposes.

First, it provides a statistically robust synthesis of municipality-level decompositions. Individual municipalities may be affected by idiosyncratic shocks or small-sample variability, whereas regime-level aggregation reveals systematic patterns that are common across geographically and economically similar areas.

Second, it enables a direct link between spatial patterns and underlying mechanisms. While earlier sections establish whether inequality is increasing or decreasing, and how it is distributed across space, the counterfactual decomposition identifies why. Aggregating the decomposed effects by regimes allows us to assess whether increases in inequality in the southern belt are mostly driven by demographic changes, labour market dynamics, or policy effects, and if these drivers differ systematically from those in the urban core or the northern region.

Third, the aggregation by regime allows us to quantify the contribution of different spatial areas to national inequality dynamics. Regime-level mean effects and their contributions to the overall population-weighted average change in inequality are obtained by weighting municipalities using their population shares. This establishes a clear link between local dynamics and overall results, maintaining consistency between the spatial breakdown and nationwide inequality patterns.

Formally, for each regime r, we compute population-weighted averages of municipality-level m decomposition components $k \in \{Demo, LM, Policy, Other\}$:

$$\Delta \bar{I}_r^k = \sum_{m \in r} \omega_{(m|r)_t} \, \Delta I_m^k, \tag{17}$$

[11] We analyse the Local Moran's I, one of the most popular local indicators of spatial association. For the ith municipality, the local Moran's I is defined as: $I_i = \frac{n(Y_i - \bar{Y})}{\sum_j (Y_j - \bar{Y})^2} \sum_j w_{ij}(Y_j - \bar{Y})$. In this context, Y_i is the Gini value associated with i, and $\bar{Y}$ is the average Gini coefficient across all municipalities. n represents the total number of observations, and it acts as a scaling factor in the computation of Moran's I.

where the weights are defined as: $\omega_{m|r} = \frac{N_{m,t}}{\sum_{j \in r} N_{j,t}}$ and $N_{m,t}$ denotes the population of municipality m in $t = 2021$. This ensures that regime-level effects reflect the relative importance of municipalities within each regime, rather than treating all municipalities equally. To assess the contribution of each spatial regime to the overall national average change in inequality, we aggregate regime-level effects using population shares. Let the population share of regime r be defined as

$$\phi_r = \frac{\sum_{m \in r} N_{m,t}}{\sum_j N_{j,t}}. \tag{18}$$

The contribution of regime r to the national change in inequality for component k is given by

$$\text{Contribution}_r^k = \phi_r \, \Delta \bar{I}_r^k. \tag{19}$$

Summing across regimes yields the national decomposition:

$$\Delta I^k = \sum_r \phi_r \, \Delta \bar{I}_r^k. \tag{20}$$

3 Data and summary statistics

The data used for the spatial simulation correspond to the EU-SILC 2012 and 2022 for Luxembourg. Since EU-SILC asks respondents to report the income earned in the previous year, our spatial calibration employs external control totals for the years 2011 and 2021. These years correspond to the data collection years of the latest Census in Luxembourg (STATEC, 2011, 2021). Table 1 displays how, in aggregated terms, the labour market and demographic characteristics of the synthetic populations derived from the spatial simulations are consistent with the Census population in 2011 and 2021. We find small differences between the census and our synthetic datasets for each year and variable, with national aggregates preserved to <1% on average (Table 1). A detailed validation exercise is presented in the Appendix, showing a good fit and accuracy of the simulation for the municipality-level marginals (Fig. A–1) using different validation measures.

Table 1 also shows the characteristics of the population in Luxembourg and its changes over the last decade. Luxembourg's demographic changes are linked to its educational structure and the share of migrants. According to Census data (see Table 1), the share of 25-year-olds whose highest level of education is secondary decreased by nearly 16 percentage points (pp). Meanwhile, the share holding tertiary education increased by nearly 15 pp. This change is accompanied by a decrease in the share of those holding Luxembourgish citizenship by nearly 12 pp. This population encompasses, to a large extent, the native-born population, and a small share of foreign-born that obtained citizenship after staying in the country for longer than five years. The increase in the foreign population contributed to the shift in the educational structure towards higher levels of tertiary education. People born abroad are over-represented at the two extremes of the education distribution, while native-born are concentrated in the middle part (Chauvel et al., 2024; Verheyden et al., 2024). Moreover, the inflow of largely recent migrants of working age helps explain the relative stability of the population's age structure, as reflected in the distribution of the population across age groups, which changed by only 1 pp between 2011 and 2021.

The working population in the country increased by nearly 3 pp, with the majority of them being employees. The economic sectors have diversified shifting slightly from the traditional manufacturing and mining activities which has a smaller participation in the working population (–3 pp). These workers were absorbed by other sectors summarised within the residual category that combines many non-traditional activities (+3.76 pp). Meanwhile, administrative occupations saw a decline in workers' participation, whereas the share of workers in professional activities increased from 22% to 34%. This major group encompasses professional occupations in fields such as science, health, teaching, business, ICT, and legal, social, and cultural services. Overall, the most pronounced changes over the last decade reflect a strong shift towards higher-education and knowledge-intensive occupations.

Using a bivariate choropleth map, Figure 1 illustrates each municipality's relative position (low, medium, or high) in the distribution of each demographic variable in 2011 and 2021. The map highlights how municipalities rank relative to one another over time, and reveals considerable spatial variation with specific municipalities showing notable demographic shifts. Panel 1a presents the ratio of children to individuals aged 16–64, which is higher in the northern and north-eastern regions of the country. Municipalities in the north-west display a marked reduction in this ratio, whereas a few municipalities in the central region show increases. Panel 1b shows the ratio of older adults to the working-age population. As expected, this ratio exhibits less variation over time across most municipalities. Nonetheless, a decline is observed for a cluster of southern municipalities, and small increases in scattered municipalities. Regarding the share of foreign citizenship, panel 1c indicates a slight increase for a group of municipalities in the north, which shift from the middle to the upper range of the distribution. Meanwhile, a small eastern cluster moved from the highest rank in 2011 to the lowest rank in 2021.

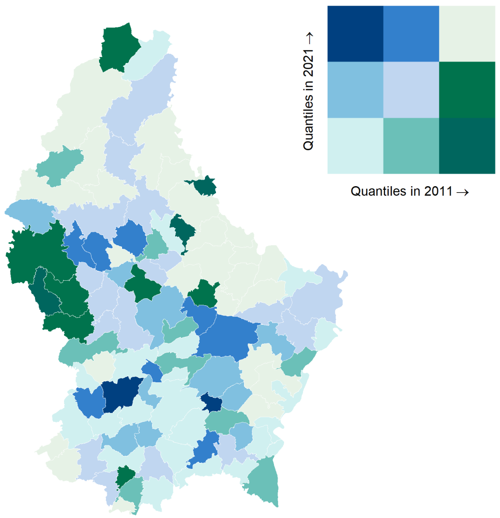
Panel 1d shows a clear clustering pattern in the distribution of tertiary-educated individuals. The central-southern region of the country exhibits the highest concentration of tertiary-educated residents, whereas the northern and north-eastern regions display the lowest concentration. Over the ten-year period, a cluster of municipalities in the centre experienced an increase in the share of the tertiary-educated population, while a cluster in the eastern part showed a slight decline, shifting from the upper to the middle range of the distribution.

Table 1: Demographic characteristics: simulated vs census data 2011 and 2021

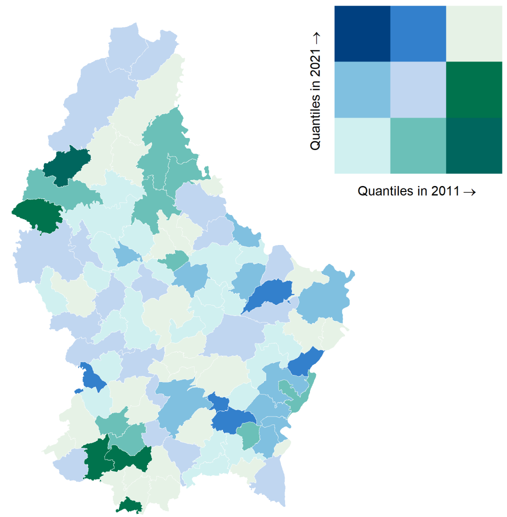
Variable	Simulated data		Census data		Sim-Census	
	2011	2021	2011	2021	2011	2021
Population between 0–15 years (%)	18.80	16.60	17.30	15.93	1.50	0.67
Population between 16–64 years (%)	67.24	68.69	68.70	69.34	-1.46	-0.65
Population 65 years and older (%)	13.96	14.71	14.00	14.73	-0.04	-0.02
Child dependency ratio (%)	27.97	24.17	25.18	22.97	2.79	1.20
Old-age dependency ratio (%)	20.76	21.41	20.38	21.25	0.38	0.16
Male (%)	49.77	49.65	49.76	49.63	0.01	0.02
Primary or no education (% $\geq$ 25 years)	36.45	40.31	36.50	37.41	-0.05	2.90
Secondary education (% $\geq$ 25 years)	42.30	23.64	42.31	26.04	-0.01	-2.40
Tertiary education (% $\geq$ 25 years)	21.24	36.03	21.19	36.55	0.05	-0.52
Citizenship (%)	56.91	45.06	56.96	45.05	-0.05	0.01
In-work (%)	50.24	54.65	50.86	54.28	-0.62	0.37
Employee (%)	91.62	92.61	88.85	91.07	2.77	1.54
Economic Sector:						
- Agriculture (%)	1.58	0.98	1.51	1.03	0.07	-0.05
- Manufacturing, mining, & related (%)	7.59	4.34	7.42	4.39	0.17	-0.05
- Construction (%)	8.65	8.04	8.62	8.11	0.03	-0.07
- Trade, logistics, hospitality, & communications (%)	22.49	22.02	22.32	21.78	0.17	0.24
- Financial & insurance (%)	10.42	9.98	10.71	10.02	-0.29	-0.04
- Real estate activities (%)	0.69	0.89	0.71	1.05	-0.02	-0.16
- Government, education, health, & social services (%)	29.96	31.36	29.39	31.15	0.57	0.21
- Others (%)	18.63	22.39	19.34	22.49	-0.71	-0.10
Occupation:						
- Directors, executives and managers (%)	8.93	8.35	8.87	8.27	0.06	0.08
- Professionalss (%)	22.36	34.11	22.61	33.87	-0.25	0.24
- Intermediate professions (%)	14.47	13.84	14.47	13.85	0.00	-0.01
- Administrative employees (%)	12.92	9.28	12.96	9.26	-0.04	0.02
- Personnel in services, traders & salespeople (%)	12.76	11.79	12.84	11.85	-0.08	-0.06
- Skilled trades in industry & craft (%)	11.04	7.88	10.74	7.99	0.30	-0.11
- Installations & machines Operators, & Assemblers (%)	4.96	3.74	4.84	3.88	0.12	-0.14
- Elementary professions (%)	12.56	11.02	12.70	11.05	-0.14	-0.03

National aggregate validation: Simulated vs. census shares (absolute differences in % points)

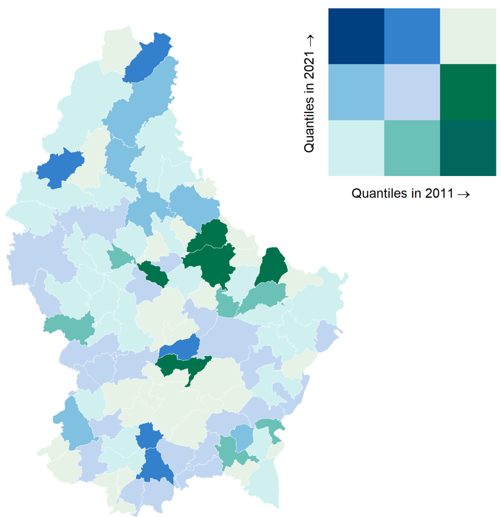
Figure 1: Change in main demographic characteristics over time by municipality



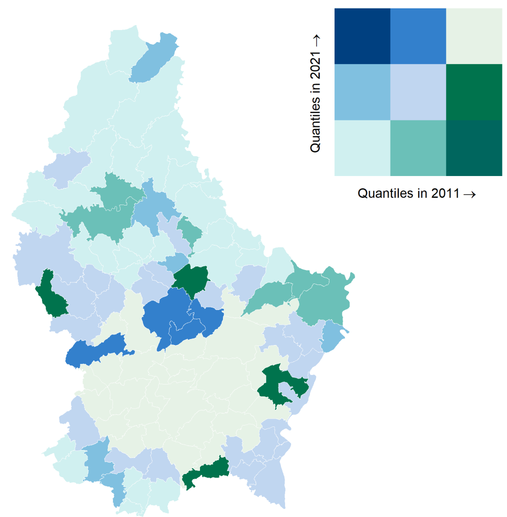
(a) Child dependency ratio



(b) Old-age dependency ratio



(c) Share with foreign citizenship



(d) Share with tertiary education

Source: Authors' calculations using Luxembourg's Census for 2011 and 2021 (STATEC).

4 Results

4.1 Between and Within-Municipality Decomposition

Table 2 shows the average income and Gini values for equivalised household income under four income concepts: gross income before benefits, gross income including benefits, income after benefits and taxes, and disposable income after social contributions. At the national level, gross income before benefits declined by 3 points between 2011 and 2021, while disposable income inequality remained broadly stable over the decade. The tax-benefit system has a strong equalising effect. Considering social benefits reduces inequality by nearly 20 Gini points in 2011, and 16 points in 2021, whereas subtracting taxes further reduces the Gini coefficient by 5.27 points in 2011 and 5.69 in 2021. Once taxes, benefits, and social contributions are taken into account, the overall change in disposable income inequality over the decade is small and insignificant. The stability of the aggregate indicator, however, conceals complex local dynamics.

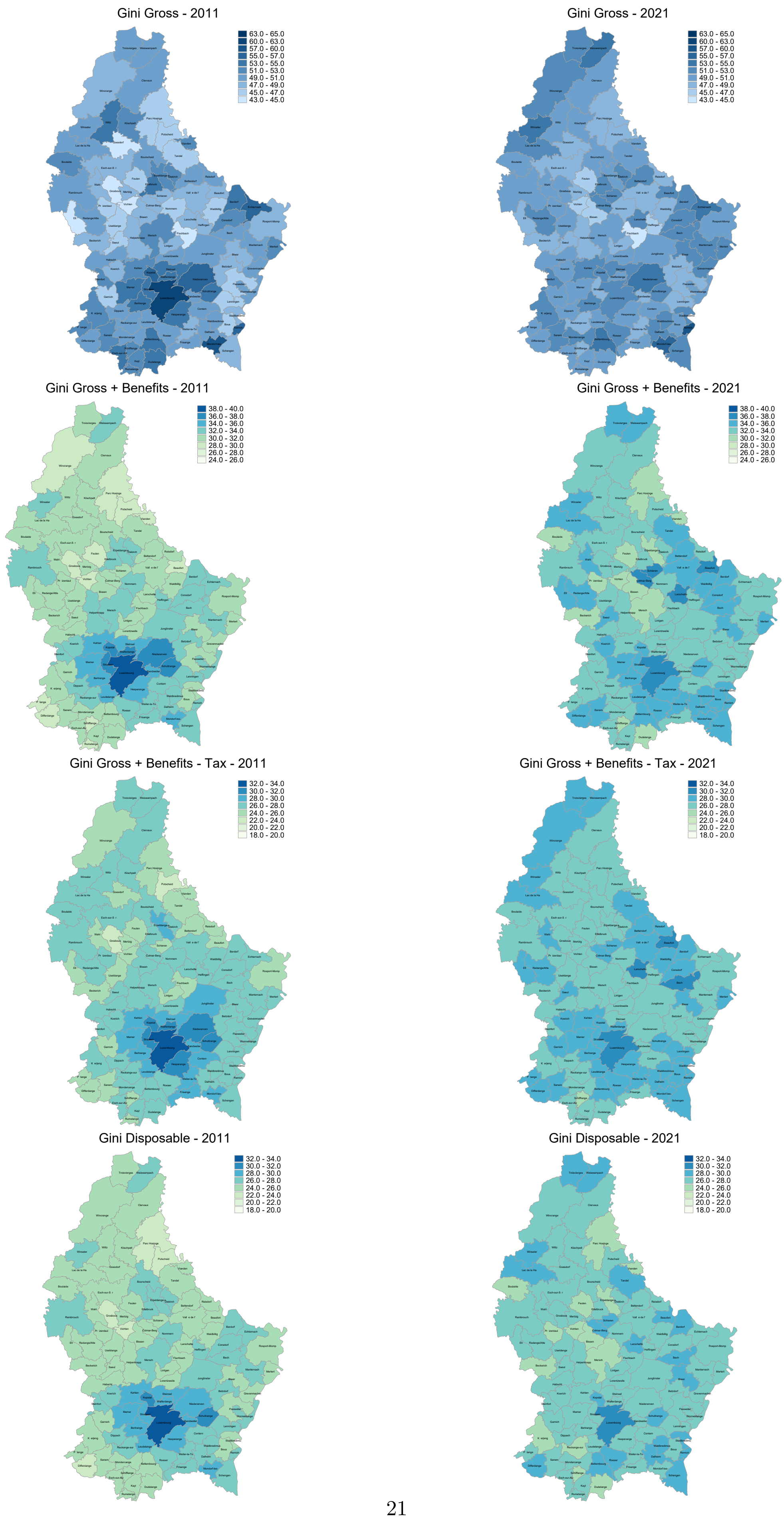
Table 2: Gini decomposition by income component and year

	2011			2021		
Indicator	Value	C.I.	S.E.	Value	C.I.	S.E.
Equiv. gross income						
Mean	2733.58	[2710.96;2756.21]	(11.55)	4053.94	[4008.01;4099.88]	(23.44)
Gini	54.00	[53.68;54.32]	(0.16)	51.01	[50.59;51.44]	(0.22)
Gini_{Ebert}	53.40			50.76		
Within	53.28			50.74		
Between	0.12			0.02		
Equiv. gross income + benefits						
Mean	3885.58	[3864.06;3907.09]	(10.98)	5462.54	[5416.17;5508.92]	(23.66)
Gini	34.13	[33.89;34.37]	(0.12)	34.37	[34.04;34.70]	(0.17)
Gini_{Ebert}	33.43			34.10		
Within	33.36			34.09		
Between	0.08			0.01		
Equiv. gross income + benefits - taxes						
Mean	3388.72	[3372.38;3405.06]	(8.34)	4522.62	[4489.79;4555.44]	(16.75)
Gini	28.86	[28.66;29.06]	(0.10)	28.68	[28.39;28.97]	(0.15)
Gini_{Ebert}	28.35			28.49		
Within	28.28			28.47		
Between	0.06			0.01		
Equiv. disposable income						
Mean	3010.91	[2997.85;3023.98]	(6.66)	4000.38	[3972.08;4028.68]	(14.44)
Gini	27.84	[27.65;28.03]	(0.10)	27.88	[27.56;28.20]	(0.16)
Gini_{Ebert}	27.37			27.69		
Within	27.30			27.68		
Between	0.06			0.01		

Notes: Gini *Ebert* corresponds to the approximation of the weighted Gini decomposition by Ebert (2010) bottom-up approach. The acronyms C.I. and S.E corresponds to the confidence intervals and standard errors based on 100 bootstrap estimates.

Table 2 also presents the decomposition of the weighted Gini coefficient into within- and between municipality components. The within component is computed from individual data, whereas the between component is approximated by the cross-municipality differences in average incomes across percentiles. By replacing millions of pairwise comparisons with a limited number of 100x100 percentile-based comparisons,

Figure 2: Gini Coefficient by year and "equivalized" household income.



Source: Authors' calculations using Luxembourg's Census for 2011 and 2021 (STATEC).

this approach preserves the logic of the Gini decomposition while greatly reducing computational time. Although there are small discrepancies between Ebert's bottom-up approach and the classical Gini, the qualitative pattern is consistent across years and income definitions.

The central finding is that the within-municipality component dominates the between component for all income definitions and in both years. Inequality is, therefore, largely intra-municipality rather than inter-municipality. The differences between municipalities are relatively smaller in absolute terms. Even if higher income households may be somewhat concentrated in certain municipalities, this spatial concentration accounts for only a very small share of total inequality. Similar results were obtained using the Theil index, reported in Table A–2 (Appendix). Theil inequality fell between 2011 and 2021 for every income concept, with the sharpest decline observed for gross income (44.85 to 30.30), while for disposable income it remains much lower and changed only slightly (13.12 to 12.21).

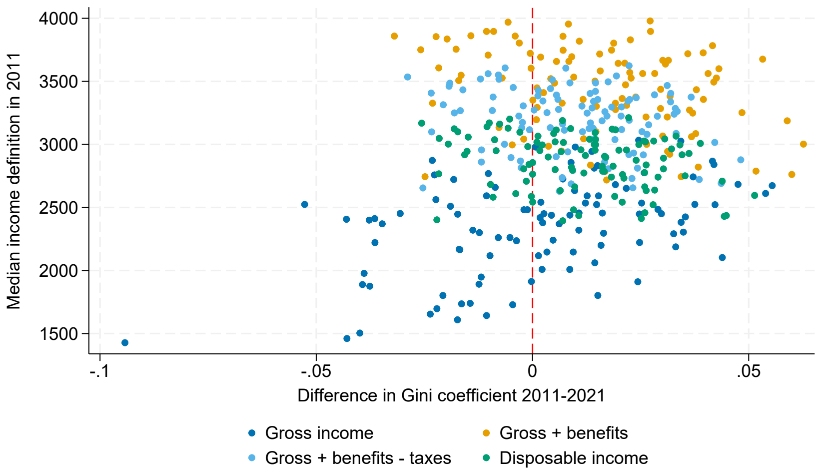
The very small between-municipality component is consistent with the structure of a small and highly integrated economy, where the income distributions of neighbouring municipalities overlap heavily. What the decomposition reveals is that the between component declined more in relative terms than the within component, signalling a convergence in municipal average incomes over the decade (confirmed both by the Gini and Theil decompositions). At the same time, the within-municipality component accounts for the bulk of total inequality in both periods, indicating that the forces generating income dispersion operate primarily within local areas, through demographic composition, labour market structure, and the interaction of gross household incomes with national redistribution. The high levels of inter-municipal commuting in Luxembourg reinforce the interaction between these components. The number of employed residents working outside their municipality of residence increased by around 21% between 2011 and 2021, and many peripheral municipalities now send more than 90% of their employed residents elsewhere for work (STATEC, 2021). As commuting intensifies, municipalities become increasingly composed of residents connected to different employment centres, which helps explain why inequality is driven mainly by within-municipality heterogeneity rather than by large differences between municipalities.

Figure 2 illustrates the spatial distribution of the income Gini index across municipalities in 2011 and 2021 for four income components making the transition from gross to disposable income. Darker shades indicate higher income inequality. Gross income inequality is generally higher and more spatially uneven across municipalities than inequality measured after redistribution. Several municipalities, particularly in the central and southern parts of the country, display relatively high gross income inequality in both years. When social benefits are added, the maps become visibly lighter, indicating the equalising effect of transfers. After both taxes and transfers, inequality is reduced further and becomes more spatially uniform, showing that the tax-benefit system compresses local income distributions across the country.

Spatial disparities, however, do not disappear entirely. We assess next the geographical organisation of these differences, whether they are clustered or randomly distributed. Table 3, which reports the spatial autocorrelation indicators Moran's I and Geary's C, shows statistically significant global spatial autocorrelation in both years for all income concepts. In 2011, spatial clustering is the weakest for gross income and much stronger after benefits and taxes, with the strongest clustering for gross income including benefits. In 2021, both statistics moved closer to their no-autocorrelation benchmarks (0 for Moran's I and 1 for Geary's C), indicating a substantial weakening of spatial clustering over time. The ranking across income concepts also changes: in 2021, clustering is stronger for gross income than for disposable income, whereas the reverse held in 2011. This reversal suggests that, by 2021, gross income inequality became more spatially clustered than disposable income inequality, indicating that the tax-benefit system played a stronger role in reducing the geographic concentration of inequality. This underlines the importance of redistribution in shaping both the level of inequality and its spatial organisation.

The maps also show that this weakening of spatial clustering over time is not spatially neutral. In 2011, Luxembourg City displays the darkest shading in disposable income inequality, indicating the highest level in the country. By 2021, this concentration is less pronounced, and inequality appears more dispersed across municipalities. The pattern therefore shifts from one of strongly concentrated inequality in and

Figure 3: Changes in Gini coefficient and median income in 2011



Source: Author's calculations

around the capital to a more spatially distributed pattern of moderate inequality. This visual result is consistent with the declining between component in the Gini decomposition and points to an increasing degree of spatial homogeneity across municipalities.

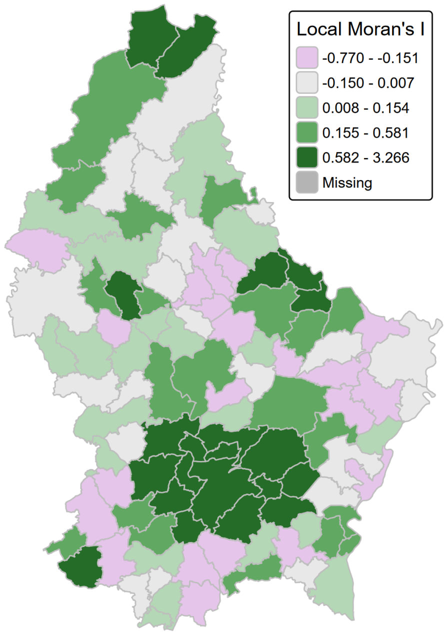
Figure 3 presents a complementary perspective by plotting the change in the municipality-level Gini coefficient between 2011 and 2021 against each municipality's 2011 median income, for each of the four income components. For gross income, municipalities with lower initial median incomes in 2011 experienced negative or weaker changes in inequality. When benefits are added, a larger number of municipalities tend to show positive changes in Gini and the dispersion of changes narrows. Once also taxes are considered, the dispersion narrows further, indicating that the tax-and-transfer system partly compresses the change in Gini across time. For disposable income, the relationship appears flatter, which implies that redistribution cushions differences across municipalities, reducing the correlation between initial income levels and inequality changes over the decade. This suggests that the tax-benefit system moderates both the level and the spatial pattern of inequality change.

Table 3: Spatial autocorrelation for each income component by year

	2011			2021		
Statistic	Value	SD	Z	Value	SD	Z
Equiv. gross income						
Moran's I	0.274	0.049	5.81***	0.144	0.049	3.15***
Geary's C	0.801	0.076	-2.61**	0.880	0.078	-1.54
Equiv. gross income + benefits						
Moran's I	0.636	0.049	13.25***	0.124	0.049	2.73**
Geary's C	0.452	0.082	-6.69***	0.920	0.066	-1.21
Equiv. gross income + benefits - taxes						
Moran's I	0.592	0.049	12.40***	0.139	0.049	3.03**
Geary's C	0.506	0.088	-5.63***	0.916	0.069	-1.23
Equiv. disposable income						
Moran's I	0.607	0.049	12.69***	0.133	0.049	2.90**
Geary's C	0.493	0.087	-5.84***	0.912	0.068	-1.28

Note: The statistics are calculated using a weights matrix based on the distance between municipality centroids. *** p<0.01, ** p<0.05, * p<0.1

Figure 4: Local Moran's I for disposable income inequality in 2011



Source: Authors' calculations

Finally, Figure 4 shows the local Moran's I for disposable income in 2011 and reveals significant local spatial autocorrelation across communes. Positive local Moran's I values indicate clusters of municipalities with similarly high or similarly low inequality levels, while negative values indicate spatial outliers. The map points to clear clustering in central Luxembourg, some southern communes (Southern industrial belt), and some north-western areas. In contrast, a number of communes show significant negative values, suggesting spatial outliers where values differ substantially from neighbouring municipalities.

Based on this evidence and Luxembourg's economic geography, we define four spatial regimes for the decomposition analysis of local drivers of the temporal dynamics across space in Section 4.3: (i) Luxembourg City and its urban belt; (ii) the southern industrial belt (historically manufacturing-oriented communes forming a distinct cluster); (iii) the northern region (lower density, more peripheral); and (iv) a residual group of municipalities that fall outside of a cluster or that appear as spatial outliers mainly located in central-eastern area. We fix the classification to the 2011 Local Moran's I map so that changes in regime-level inequality reflect shifts in the income distribution, not changes in the regime boundaries.

4.2 Spatial convergence over time

In this section, we move beyond visual evidence to explore whether inequality tends to persist, widen or converge over time while controlling for lagged local demographic characteristics and the inequality levels in neighbouring areas through a spatial lag. To do so, we estimate a spatial autoregressive model with spatially correlated errors, using the municipality-level Gini coefficient in 2021 as the dependent variable and its lagged value in 2011 as the main variable of interest. Spatially correlated unobserved shocks are accounted for via spatially correlated error. The Generalized Spatial Two-Stage Least Squares ensures consistent estimation in the presence of simultaneity and endogeneity arising from spatial interactions. The spatially lagged dependent variable is instrumented using the set of control variables and their spatial lags, including first- and second-order spatial lags, following the procedure proposed by Kelejian and Prucha (1998). Each column in Table 4 reports the estimates for the Gini of each income component in 2021. Given the potential presence of spatial dependence, the interpretation of the spatial model is not based on raw coefficients but rather on direct, indirect effects and the sum of the two. Direct effects capture the impact of a variable on the Gini within the same municipality, while indirect effects capture whether a variable in neighbouring municipalities affects inequality in municipality i.

The demographic characteristics of each municipality are used to control for compositional differences across municipalities. These include child and old age dependency ratios, share of tertiary educated (over 25 years), and unemployment rate. To partially account for population mobility, the analysis includes the share of residents with foreign citizenship as a proxy for migration-driven demographic agglomeration. We do not give these coefficients a causal interpretation, as several of these characteristics may themselves be jointly determined with inequality. All variables are included with a one-period lag to reduce simultaneity.

Table 4 shows a convergence for gross income inequality. The direct effect of lagged gross income inequality is negative and statistically significant, and the total effect remains negative and significant once spatial feedbacks are taken into account. This implies that municipalities with higher initial levels of gross income inequality tended to experience lower subsequent inequality, conditional on local characteristics. In other words, gross income inequality exhibits a process of local convergence over the decade.

By contrast, the lagged Gini coefficients for income concepts after benefits and taxes are small and statistically insignificant. Non-significant coefficients for the redistributive income concepts do not prove convergence (or divergence). This suggests that once redistribution is taken into account, dynamic persistence in local inequality becomes weak or disappears. Taxes and benefits appear to neutralise the local adjustment visible in gross income, stabilising disposable income inequality across municipalities over time. Redistribution, therefore, appears to weaken or neutralise the dynamic persistence of local inequality. Whereas gross income inequality converges conditionally, disposable income inequality shows no significant relationship with past levels, consistent with effective automatic stabilisation.

There is no evidence of spatial spillovers across municipalities, meaning that past inequality matters primarily within each municipality, but does not significantly influence neighbouring municipalities over time. Although commuting flows between 2011 and 2021 increased towards few employment centres (STATEC, 2021), the geography of work remained roughly the same with little influence on the neighbour's inequality dynamics. The convergence observed for gross income inequality, therefore, appears to be driven mainly by local adjustment rather than by the spatial diffusion of inequality across space. This interpretation is reinforced by the residual spatial autocorrelation diagnostics reported at the bottom of Table 4, which show that there is no significant remaining Moran's I or Geary's C in the residuals of the model.

The convergence analysis suggests that spatial inequality in Luxembourg evolved mainly through local reconfiguration rather than through inter-municipal spillovers. Gross income inequality shows evidence of conditional convergence, but this dynamic is largely neutralised after redistribution. The role of the tax-benefit system is therefore not only to reduce inequality levels, but also to weaken the persistence of local disparities over time. The convergence model, however, remains a reduced-form exercise. It identifies the presence or absence of persistence and spillovers, but it does not quantify the contribution of particular mechanisms. We turn next to the counterfactual decomposition in order to isolate the roles of demographic change, labour market change, and redistribution in shaping local inequality dynamics.

Table 4:

Spatial AutoRegressive-AutoRegressive: Direct, Indirect, Total Effects

	(1) Gross	(2) Gross + benefits	(3) Gross+benefits-tax	(4) Disposable
Direct Effects				
ln Gini Y(t-1)	-0.368***	-0.068	-0.030	-0.043
	(0.090)	(0.075)	(0.058)	(0.061)
Child dependency ratio (t-1)	1.199	-2.068**	-1.872***	-1.791***
	(0.906)	(0.676)	(0.517)	(0.542)
Old dependency ratio (t-1)	0.131	0.271***	0.213***	0.245***
	(0.090)	(0.073)	(0.057)	(0.059)
Foreign share (t-1)	-0.627***	-0.376	-0.270	-0.333*
	(0.187)	(0.211)	(0.153)	(0.164)
Tertiary education share (t-1)	-0.004**	-0.002*	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment rate (t-1)	0.379***	0.228	0.244*	0.256
	(0.081)	(0.143)	(0.123)	(0.135)
Indirect Effects				
ln Gini Y(t-1)	0.011	0.000	0.000	0.001
	(0.008)	(0.002)	(0.001)	(0.002)
Child dependency ratio (t-1)	-0.036	0.012	0.028	0.028
	(0.038)	(0.057)	(0.048)	(0.049)
Old dependency ratio (t-1)	-0.004	-0.002	-0.003	-0.004
	(0.004)	(0.008)	(0.005)	(0.007)
Foreign share (t-1)	0.019	0.002	0.004	0.005
	(0.012)	(0.010)	(0.006)	(0.008)
Tertiary education share (t-1)	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment rate (t-1)	-0.011	-0.001	-0.004	-0.004
	(0.008)	(0.006)	(0.006)	(0.007)
Total Effects				
ln Gini Y(t-1)	-0.357***	-0.067	-0.030	-0.043
	(0.088)	(0.075)	(0.057)	(0.060)
Child dependency ratio (t-1)	1.164	-2.057**	-1.844***	-1.763**
	(0.879)	(0.677)	(0.513)	(0.537)
Old dependency ratio (t-1)	0.127	0.270***	0.210***	0.241***
	(0.088)	(0.074)	(0.057)	(0.059)
Foreign share (t-1)	-0.608**	-0.374	-0.266	-0.328*
	(0.188)	(0.215)	(0.154)	(0.166)
Tertiary education share (t-1)	-0.004**	-0.002*	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment rate (t-1)	0.368***	0.226	0.241*	0.252
	(0.080)	(0.144)	(0.122)	(0.134)
Spatial Autocorrelation analysis of the Errors				
Moran's I	0.065	0.048	0.051	0.049
p-value Moran	0.064	0.119	0.109	0.117
Geary's C	0.986	1.007	1.007	1.002
p-value Geary	0.416	0.459	0.461	0.489

Standard errors in parentheses. The dependent variable corresponds to the Gini of each income concept.
* < 0.05, ** < 0.01, *** < 0.001

4.3 Determinants of inequality changes: Counterfactual decompositions

The analysis so far has shown that disposable income inequality in Luxembourg remained overall stable at the national level between 2011 and 2021, that most inequality arises within municipalities rather than between them, that spatial clustering of municipality-level inequality weakened over time through local adjustment rather than strong spillovers from nearby municipalities, and that redistribution reduced not only the level and spatial concentration of inequality, but also appears to have weakened its persistence over time. These aggregate patterns, however, do not imply that municipalities evolved in similar ways. On the contrary, they may conceal offsetting local dynamics, with inequality declining in some parts of the country and increasing in others. To identify the mechanisms underlying these changes, we decompose the change in within-municipality disposable income inequality between 2011 and 2021 into four components: demographic composition, labour market structure, tax-benefit policy, and a residual term capturing interaction effects and other changes not isolated by the single-component counterfactual exercises. The decomposition is implemented at municipality level and then aggregated into the four spatial regimes identified in Section 4.1: Luxembourg City and its urban belt, the southern industrial belt, the northern region, and the remaining central-eastern corridor.

The decomposition takes 2021 as the reference period. The contribution of *tax-benefit* changes is obtained by applying the 2011 EUROMOD rules to the 2021 municipal populations, following the standard policy-swapping logic in the redistribution literature. The contribution of changes in the *demographic composition* is estimated through DFL reweighting that adjusts the 2021 population so that, within each municipality, it matches the 2011 joint distribution of age, gender, education, household composition, marital status, and foreign citizenship, ceteris paribus. The contribution of changes in the *labour market component* is obtained through a similar reweighting exercise that aligns the 2021 population with the 2011 joint distribution of employment status, occupation, industry, and sector, again holding all else constant. The residual term is then defined as the difference between the total change in inequality and the sum of the three direct effects, and it captures interaction effects between the components, changes in the market income process and other unobserved population differences not separately identified by the ceteris paribus simulations.

Table 5 reports the counterfactual decomposition in two complementary ways. The upper panel shows, for each *regime*, the population-weighted average change in within-municipality disposable income inequality between 2011 and 2021, together with its decomposition into demographic, labour market, tax-benefit, and residual components. The lower panel expresses these regime-specific effects as *contributions* to the aggregate *national* average change in within-municipality disposable income inequality, weighting each regime by its population share. Read horizontally, each row in the upper panel shows how the total change in inequality in a given regime is built up from the four components. The lower panel shows how much each regime contributes to the aggregate national average change once regime-level effects are weighted by population size, also illustrated in Figure 5.

The results reveal a clear pattern of *offsetting local dynamics*. Inequality declined only in Luxembourg City and its urban belt, where the population-weighted average change in inequality was -1.792 Gini points. In contrast, the three remaining regimes experienced increases in inequality: 1.660 points in the southern industrial belt, 1.890 points in the northern region, and 1.058 points in the rest. The aggregate national average change, at 0.285 Gini points, is therefore not the result of uniform stability across space, but of substantial local declines in the urban core offset by increases elsewhere.

Luxembourg City and its urban belt is the only regime in which all four components contribute to lower inequality. *Demographic changes* reduced inequality by 0.447 Gini points, *labour market changes* by 0.429 points, *tax-benefit policy* by 0.497 points, and the residual component by 0.419 points. The decline in inequality in the urban core therefore appears to be driven by multiple mechanisms rather than one dominant factor. It reflects the joint equalising influence of population recomposition, labour market restructuring, and redistribution.

Outside the capital region, the pattern is reversed: *demographic changes* increase inequality in all three regimes, by 0.721 Gini points in the southern industrial belt, 0.537 in the northern region, and 0.337 in the remaining municipalities. By contrast, *tax-benefit policies* reduce inequality in every regime, with effects ranging from -0.497 Gini points in the capital region to -0.654 in the north. This is consistent with Luxembourg's nationally uniform tax-benefit system, which compresses local income distributions across space. *Labour market* changes are more heterogeneous, but remain equalising in most cases: they reduce inequality in the capital region (-0.429), the south (-0.547), and the rest (-0.306), while slightly increasing it in the northern region (0.201). Taken together, these results suggest that demographic pressures tended to widen local inequality outside the urban core, whereas labour market changes and redistribution worked in the opposite direction.

The demographic pattern is consistent with the spatially uneven population changes documented in Section 3. Luxembourg's population grew by roughly 25% over this period, partially through immigration that raised the foreign-born share from 43% to 55% (see Table 1). The observed spatial inequality trends can be understood through contrasting migration dynamics between Luxembourg City and its surrounding urban belt, on the one hand, and the rest of the country, on the other. The capital attracted a disproportionate share of high-skilled EU workers and appears to have narrowed its skill distribution. Peripheral areas absorbed population with more varied profiles, contributing to wider within-municipality income dispersion, as suggested by Figure 1d. According to recent 2021 Census-based evidence (STATEC, 2023), Luxembourg City and its metropolitan area experienced strong positive international migration inflows, attracting a relatively heterogeneous population in terms of education, skills, and income (Verheyden et al., 2024). At the same time, these urban municipalities recorded negative internal migration balances, as resident households with higher or more stable incomes moved outward towards other municipalities (STATEC, 2023). This outflow may have further reduced inequality in the urban core by shifting higher-income households away from these areas. In contrast, the northern region and the central-eastern corridor attracted fewer international migrants, and were more affected by internal inflows from the urban centre (Docquier et al., 2023). Such inflows may increase local inequality if incoming households differ systematically from existing residents in terms of income, employment status, or skill levels. Combined with weaker offsetting effects from international migration and possibly more segmented labour markets, this helps explain the increase in inequality outside the urban core.

This interpretation is also consistent with recent Census-based evidence on the growing concentration of home-work mobility in Luxembourg (STATEC, 2021). The central conurbation and the southern conurbation account for the most resident jobs, and commuting flows towards these centres intensified between 2011 and 2021 while the main spatial pattern of commuting remained unchanged. This suggests that municipalities are increasingly integrated into a common but spatially uneven residence-employment system. The distributional effects of demographic change therefore depend on who lives in each municipality and how residents are connected to these major employment centres.

Changes in the labour market structure also contribute to the spatial pattern. The labour market reweighting captures changes in the population structure regarding employment status, occupation, industry and sector in each municipality . The most salient of these is occupational upgrading: professional occupations expanded from 22% to 34% of employment nationally (see Table 1), compressing the wage distribution in areas with large service-sector and industrial labour markets (the capital region and the southern industrial belt, the two regimes where the equalising labour market effect is largest in absolute terms). At the national level, the population-weighted labour market effect is concentrated in the south (-0.17) and the capital region (-0.15), the two regimes where occupational upgrading was strongest. By contrast, the small positive labour market effect in the northern region suggests that labour market changes there did not operate in an equalising direction, possibly because the gains from structural upgrading were weaker or more unevenly distributed.

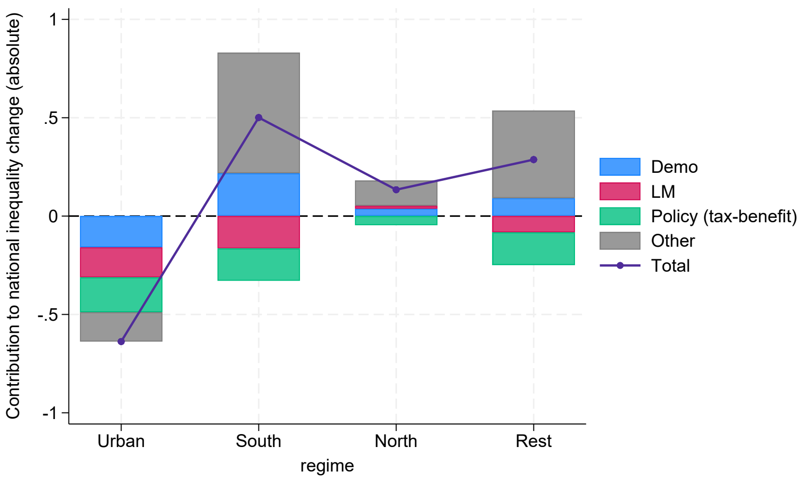
The lower panel of Table 5 and Figure 5 shows how these regime-level effects map into the aggregate national average change. The Luxembourg City and urban belt regime contributes -0.638 Gini points,

Table 5: Decomposition of changes in municipal disposable income inequality by spatial regime (2011–2021)

Regime	**Pop share** ϕ_r	**Total** $\Delta\bar{I}_r^{Tot}$	**Demo** $\Delta\bar{I}_r^{Demo}$	**LM** $\Delta\bar{I}_r^{LM}$	**TB** $\Delta\bar{I}_r^{TB}$	**Other** $\Delta\bar{I}_r^{O}$
Regime-level mean effects						
Lux City & urban belt	0.356	-1.792	-0.447	-0.429	-0.497	-0.419
Southern industrial belt	0.302	1.660	0.721	-0.547	-0.544	2.030
Northern region	0.071	1.890	0.537	0.201	-0.654	1.805
Rest	0.271	1.058	0.337	-0.306	-0.610	1.637
Contribution to national change						
Lux City & urban belt	0.356	-0.638	-0.159	-0.153	-0.177	-0.149
Southern industrial belt	0.302	0.501	0.218	-0.165	-0.164	0.612
Northern region	0.071	0.134	0.038	0.014	-0.046	0.128
Rest	0.271	0.287	0.091	-0.083	-0.166	0.444
National Pop-weighted Average	1.000	0.285	0.188	-0.386	-0.553	1.036

Notes: Changes are in Gini points: a value of -1.792 corresponds to a Gini coefficient decrease of 0.01792. The upper section reports population-weighted regime mean changes in within-municipality disposable income inequality (2011–2021). The lower section reports each regime's contribution to the national change, defined as $\phi_r \times \Delta\bar{I}_r^k$. The Other component is computed as Total $-$ (Demographic + LM + Policy).

Figure 5: Population-weighted contribution to inequality change by regime type (absolute)



partly offset by the positive contributions of the southern industrial belt (0.501), the northern region (0.134) and the rest (0.287). Although the northern region records the largest regime-level increase in inequality, its contribution to the aggregate change remains modest because it contains only 7.1% of the population. By contrast, the southern industrial belt and the remaining municipalities contribute more strongly because they combine rising inequality with substantially larger population shares.

Three further points emerge from the aggregate decomposition. First, the tax-benefit component is the most spatially uniform: at the national level it contributes -0.553 Gini points, with fairly similar contributions across regimes, apart from the North. Second, labour market changes are also equalising on average, contributing -0.386 Gini points nationally, though with greater cross-regional heterogeneity; the strongest equalising contributions come from the southern industrial belt, Luxembourg City and its urban belt. Third, demographic change is inequality increasing on average, contributing 0.188 Gini points to the aggregate national average change, driven mainly by the southern industrial belt. Thus, the main message is that, over this decade, demographic pressures tended to widen within-municipality inequality, while labour-market restructuring and the tax-benefit system offset part of that increase.

The remainder component, by construction, captures factors not captured by the three direct counterfactual transformations and interaction effects between demographic, labour market, tax-benefit changes and these remaining factors, including changes in returns and non-labour incomes (Biewen, 2014; Sologon et al., 2021; Černiauskas et al., 2022). These mechanisms are not separately decomposed here and, therefore, remain part of the residual component. The spatial pattern is consistent with a disequalising effect outside of Luxembourg City and its urban belt. In the south, where the residual is the largest, this interpretation is consistent with substantial redevelopment over the past decade, which may have increased the heterogeneity within the municipality by attracting residents with different levels of education, occupations, and income profiles. Although these changes are partially captured by the demographic and labour market components, the interaction between them remains in the residual term.

Together, the counterfactual decomposition helps clarify the earlier results. The decline in spatial clustering does not reflect a common trajectory across municipalities. Instead, it reflects uneven local adjustment under a common national institutional framework: inequality declined in the capital region, increased elsewhere, and national redistribution moderated these divergent trends without fully eliminating them. Luxembourg's spatial inequality dynamics is therefore better understood as a local reconfiguration than as a diffusion from one municipality to another.

These results carry an important policy implication. In a small and highly integrated economy, stable national inequality can mask very different local trends. National indicators are therefore not sufficient to understand how inequality evolves across space. Since most inequality remains within rather than between municipalities and since the drivers of change differ systematically across regimes, a more distribution-sensitive territorial policy perspective is needed. National tax-benefit policy still plays a central equalising role, but it cannot by itself fully offset the inequality increasing pressures linked to demographic changes and uneven local labour market changes outside the urban core.

5 Conclusions

This paper examined how national stability can coexist with substantial local reconfiguration in spatial income inequality within a small, open, and highly integrated economy. In Luxembourg, common national institutions, strong commuting links, and a unified tax-benefit system might be expected to compress territorial disparities in living standards. These common national factors, however, do not eliminate local differences because municipalities differ in their population structure with respect to demographic and labour market characteristics, and in how national redistribution interacts with local income distributions. Combining survey microdata, Census aggregates, and the EUROMOD tax-benefit model within a spatial microsimulation framework, the paper shows how these forces shape the distribution of disposable income across municipalities.

Three findings stand out. First, inequality in Luxembourg is driven mainly by differences within municipalities, rather than between them. Spatial inequality is not a story of sharply segmented rich and poor places, but of heterogeneous income distributions within local areas. Although inequality shows significant spatial clustering, concentrated in 2011 in Luxembourg City and its surrounding municipalities, this clustering weakens substantially over time. The convergence analysis shows that this reflected local adjustments rather than strong spillovers across neighbouring municipalities. The spatial pattern of inequality is thus better understood as the result of local changes in income distributions under common national institutions, rather than as inequality spreading across space.

Second, the national stability in disposable income inequality conceals substantial local changes. Gross income inequality decreased over the decade, but the tax-benefit system absorbed most of it, leaving disposable income inequality broadly stable at the national level. This aggregate stability, however, conceals divergent local trajectories. Inequality declined in Luxembourg City and its urban belt and increased in the southern industrial belt, the northern region, and the remaining municipalities. The national picture is therefore one of stability, whereas the local picture is one of uneven changes and reordering.

Third, the counterfactual decompositions show that these local dynamics are shaped by multiple mechanisms. Demographic changes increased within-municipality inequality outside the urban core, while labour market and the tax-benefit changes worked in the opposite direction. The capital region is the only regime in which all three channels contributed to lower inequality. Elsewhere, the effects of labour market and tax-benefit changes were not enough to offset demographic pressures. The tax-benefit system is nationally uniform, but its distributional impact is not uniform across space due to the spatial heterogeneity of the population with respect to demographic and labour market profiles.

These findings have clear policy implications. In Luxembourg, spatial inequality does not arise from large gaps in average incomes between municipalities, but from differences *within* municipalities and from the *uneven* local effects of demographic change, labour market restructuring, and national redistribution. National tax-benefit policy remains essential, but it is not sufficient on its own. A more distribution-sensitive territorial policy mix is needed, combining national redistribution with local measures aimed to reduce residential segregation, expand affordable housing, improve access to childcare, jobs and services, and strengthen the capacity of municipalities to deal with socio-economic changes. This is particularly important outside the urban core, where demographic pressures tended to increase local inequality and where redistribution, although equalising, did not fully offset theese pressures.

The paper also makes a methodological contribution. The framework combines a national income generation model with spatial calibration and EUROMOD tax-benefit simulations to recover local disposable income distributions where small-area income data are not directly available. It is useful in settings where administrative data do not capture all income sources or population groups, and where confidentiality rules limit access to detailed tax records. Because the framework is built on EUROMOD and EU-SILC, it is scalable to other countries and regions operating with the same data and policy modelling infrastructures.

Several limitations remain. Most importantly, the decomposition captures demographic, labour market, and tax-benefit channels more directly than mechanisms related to capital income, property income, and returns to non-labour assets. These may be particularly important for understanding why inequality increased in some municipalities despite the equalising role of redistribution. Future research should therefore extend the framework to incorporate a richer treatment of capital and wealth-related incomes, housing costs and imputed rents, and residential mobility. This would allow a more complete account of how spatial sorting, local market structures, and redistribution interact in shaping income dispersion within places.

Overall, this paper shows that in a small and highly integrated economy, national stability can coexist with significant local changes in income inequality. Understanding spatial inequality therefore requires moving beyond aggregate national indicators and looking more closely at how demographics, labour markets, and redistribution interact within areas to reshape disposable income dispersion over time.

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A Appendix

A.1 Spatial Reweighting

This procedure requires external information about the population totals for a set of M relevant variables. Following the calibration framework underlying the reweighting methodology in Deville and Sarndal (1992), let us assume that q_i is the design weight for sample unit i, typically based on the inverse probability of selection. N is the sample size, while $M(< N)$ is the number of calibration variables. $\mathbf{S} = [s_{ik}]$ is the $N \times M$ matrix of calibration variables, and s_{ik} denotes the value of variable k for sample unit i. $\mathbf{T} = [T_k]$ is the vector of known population totals for each calibration variable k.

The objective is to compute a new set of positive weights w_i such that the calibrated weights exactly reproduce the known population totals:

$$\sum_{i=1}^{N} w_i s_{ik} = T_k, \quad \text{for all } k = 1, \dots, M. \tag{21}$$

This system consists of M linear constraints and N unknown weights. The reweighting methodology determines weights that remain as close as possible to the original design weights q_i, using using a quadratic (chi-square) distance function to determine closeness. Specifically, the calibrated weights are obtained by minimizing

$$d(\mathbf{w}, \mathbf{q}) = \frac{1}{2} \sum_{i=1}^{N} \frac{(w_i - q_i)^2}{q_i}, \tag{22}$$

subject to the calibration constraints above.

The following equation shows the associated Lagrangian and Lagrange multipliers $\boldsymbol{\lambda} = (\lambda_1, \dots, \lambda_M)$ as:

$$\mathcal{L}(w_1, \dots, w_N, \boldsymbol{\lambda}) = \frac{1}{2} \sum_{i=1}^{N} \frac{(w_i - q_i)^2}{q_i} - \sum_{k=1}^{M} \lambda_k \left(\sum_{i=1}^{N} w_i s_{ik} - T_k \right). \tag{23}$$

The first-order conditions with respect to w_i are

$$\frac{\partial \mathcal{L}}{\partial w_i} = \frac{w_i - q_i}{q_i} - \sum_{k=1}^{M} \lambda_k s_{ik} = 0. \tag{24}$$

Solving for w_i yields the linear calibration form

$$w_i(\boldsymbol{\lambda}) = q_i \left(1 + \sum_{k=1}^{M} \lambda_k s_{ik} \right). \tag{25}$$

Substituting these weights into the calibration equations leads to a system of M linear equations in the Lagrange multipliers:

$$\sum_{i=1}^{N} q_i \left(1 + \sum_{k=1}^{M} \lambda_k s_{ik} \right) s_{ij} = T_j, \quad \text{for } j = 1, \dots, M. \tag{26}$$

Provided that the matrix $\mathbf{S}^\top \mathbf{Q} \mathbf{S}$, where $\mathbf{Q} = \text{diag}(q_i)$, has full rank, this system admits a unique solution. The resulting calibrated weights exactly match the known population totals while deviating minimally from the original design weights in a least-squares sense.

A.2 Validation for the spatial microsimulation

One of the key element of this paper is the development a microsimulation model that reflects the demographic and socio-economic structure of a population in each small area. This ensures that simulation outcomes, like income distribution, are representative at local or national levels. For this reason, we employed different validation methodologies for the simulated data at the LAU-2 level in Luxembourg (Municipality or Commune), such as the graphical inspection of the simulated data, and the standardized absolute error per area.

$$\textbf{Standardized Absolute Error (SAE):} \quad SAE_z = \frac{|\text{Simulated totals}_z - \text{Census total}_z|}{\text{Census total}_z}$$

A.2.1 Validation: Reweighting demographic variables

To analyze the effectiveness of the reweighting procedure, we calculate the relative difference (Simulated - census total / census total) allowing for inspection for the direction of the difference. The figure A–1 shows a reassuring validation, as most variables are aligned closely with census totals, while the majority remain within the ±5% tolerance band. Figure A–1 reveals a mild positive bias in 2011 reweighting (mean relative difference +0.8%, still <5% tolerance), likely due to survey-census imbalances, while 2022 fit is symmetric. Aggregate national totals are preserved, and sensitivity analysis confirms inequality results are robust.

Table A–1: Average Standardised Absolute Error (SAE) and model fit (R^2) between simulated and census totals

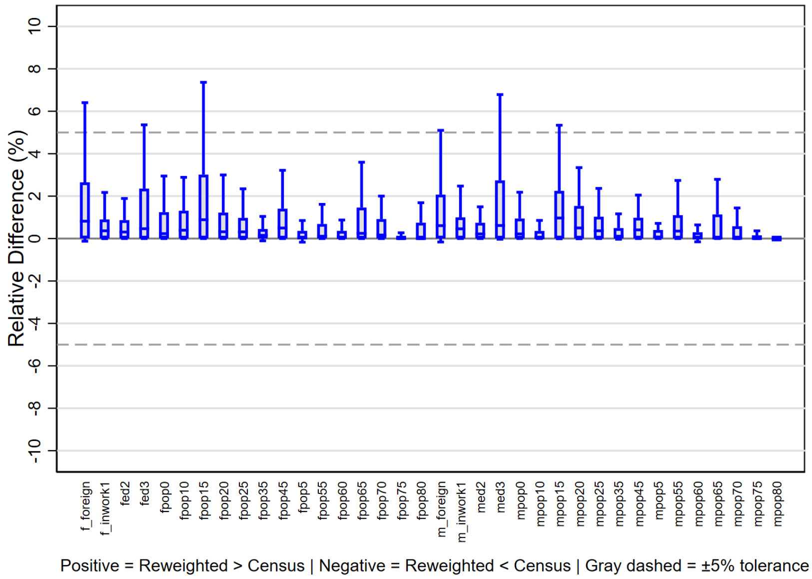
Indicator	**SAE**		R^2	
	2011	**2021**	**2011**	**2021**
In-work	0.007 (0.004)	0.020 (0.005)	0.998	0.983
Employee	0.034 (0.023)	0.010 (0.008)	0.857	0.874
Public	0.034 (0.020)	0.021 (0.014)	0.996	0.995
Occupation 1	0.039 (0.036)	0.017 (0.011)	0.999	0.997
Occupation 2	0.030 (0.027)	0.019 (0.008)	1.000	1.000
Occupation 3	0.028 (0.025)	0.025 (0.009)	0.999	0.996
Occupation 4	0.024 (0.023)	0.039 (0.022)	0.999	0.961
Occupation 5	0.024 (0.021)	0.029 (0.015)	0.998	0.996
Occupation 6	0.045 (0.042)	0.042 (0.026)	0.997	0.994
Occupation 7	0.042 (0.042)	0.045 (0.035)	0.997	0.993
Occupation 8	0.025 (0.022)	0.036 (0.020)	0.999	0.997
Sector 1	0.097 (0.121)	0.049 (0.085)	0.999	0.999
Sector 2	0.076 (0.037)	0.034 (0.034)	0.999	0.990
Sector 3	0.070 (0.036)	0.045 (0.040)	0.999	0.994
Sector 4	0.080 (0.036)	0.013 (0.009)	0.999	0.997
Sector 5	0.079 (0.038)	0.069 (0.123)	1.000	0.994
Sector 6	0.059 (0.060)	0.068 (0.078)	0.989	0.962
Sector 7	0.085 (0.039)	0.010 (0.007)	0.998	0.999
Sector 8	0.078 (0.038)	0.028 (0.023)	0.999	0.997
Retired	0.067 (0.018)	0.032 (0.027)	0.976	0.700

Note: The standard deviations are presented in parenthesis

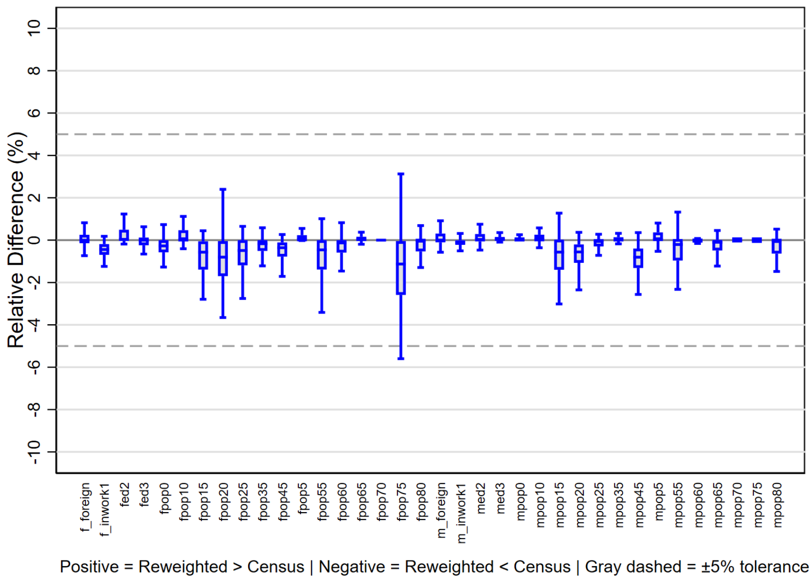
A.2.2 Validation: Calibration labor force structure

The magnitude of the differences between the simulated and census data for the labour force is presented in table A–1. The Table displays the average Standardized Absolute Error (SAE), and the R^2 of a linear regression between the simulated and census totals for each variable. The first measurement calculates the difference between the simulated total number standardized by census totals of people in work, for example, and the value calculated with census information for each municipality. The second measures the degree of variation in the census total explained by the simulated total per municipality. We can conclude that for the majority of the variables the differences between the census and simulated are rather

Figure A–1: Relative difference (%) between simulated versus census totals.



(a) 2011

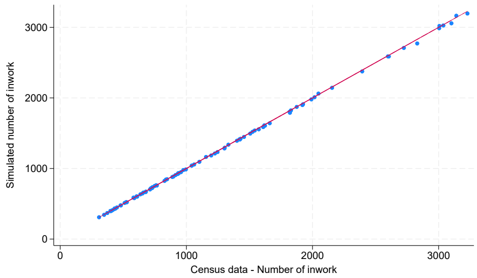


(b) 2021

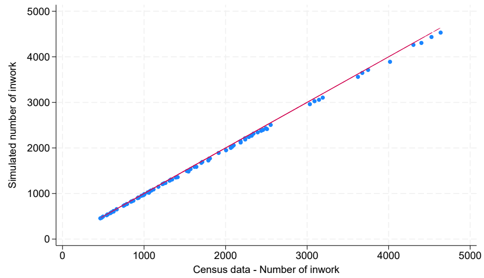
small (less than 5%), with the exception of some particular sectors, for which the difference is above 5% but below 10%.

The figures A–2, A–3, A–4, and A–5 display various scatter plots of the simulated share for each municipality in the y-axis and the actual (census) data shares on the x-axis. The red dotted line represents the 45-degree line. As one can see, the closer the dots are to the 45-degree line, the higher is the correlation between the simulated and real data for each municipality. In terms of the percentage of the population employed, the model slightly underestimates this percentage for most municipalities. In contrast, the share of workers in the first industry category is simulated with good precision. Other categories such as industry 3 and 7 are over-represented, while industry 8 is under-represented. While there are some small differences between the simulated and the industry shares from the census, the spatial distribution in the simulated data resembles the distribution observed using census data.

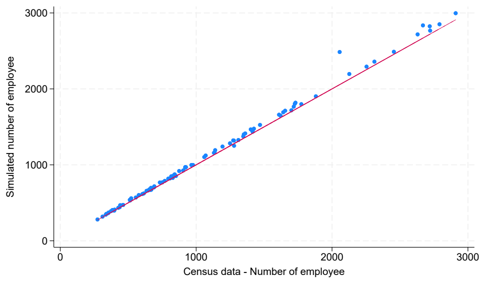
Figure A–2: Simulated versus census totals by variable.



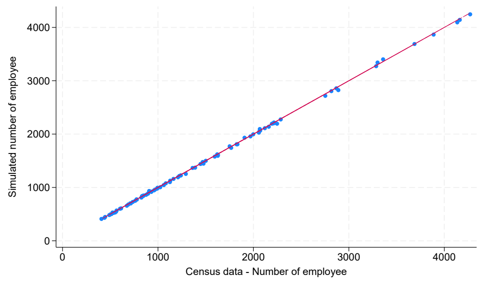
(a) In-work 2011



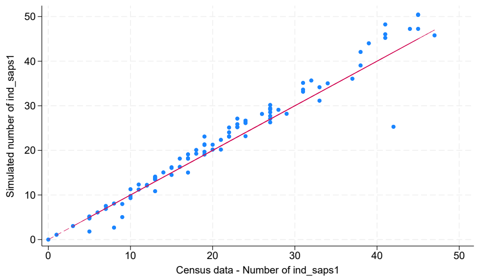
(b) In-work 2021



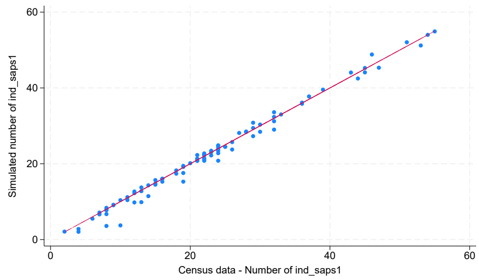
(c) Employee 2011



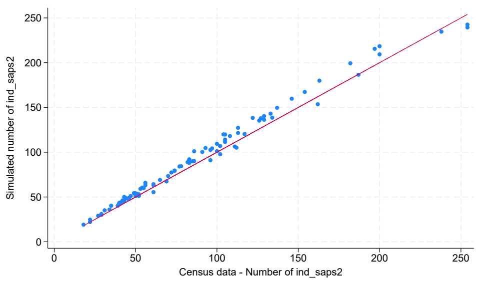
(d) Employee 2021



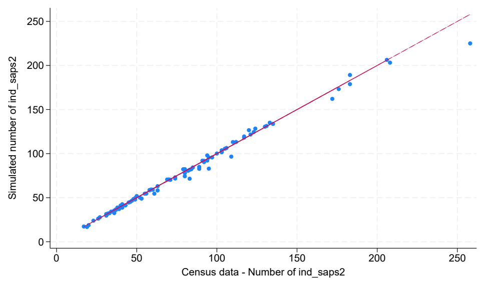
(e) Agriculture, forestry, & fishing 2011



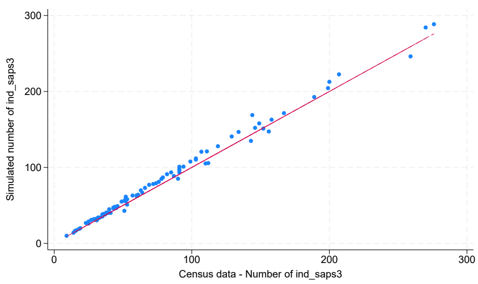
(f) Agriculture, forestry, & fishing 2021



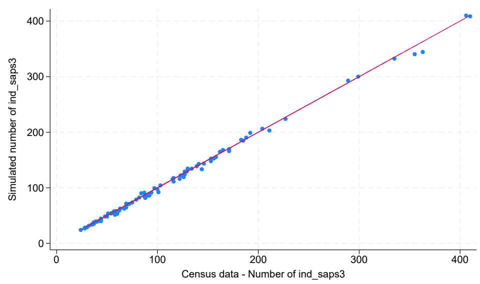
(g) Manufacturing, mining, quarrying, & related 2011



(h) Manufacturing, mining, quarrying, & related 2021

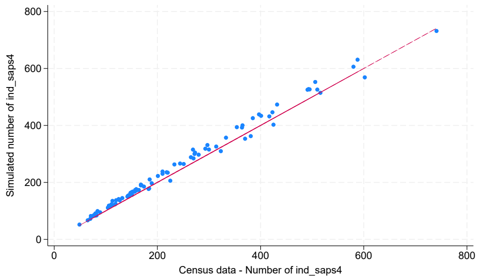


(i) Construction 2011

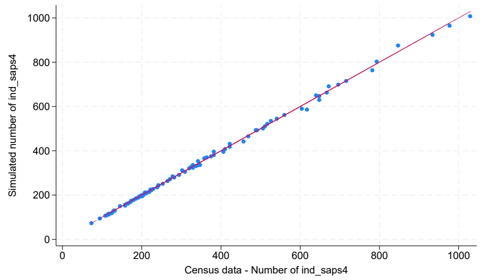


(j) Construction 2021

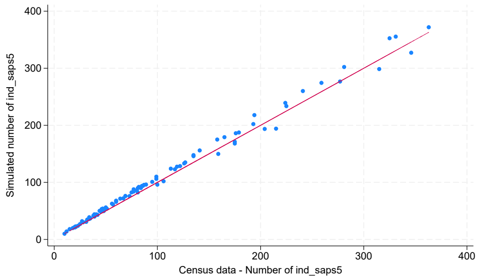
Figure A–3: Simulated shares versus shares from census data.



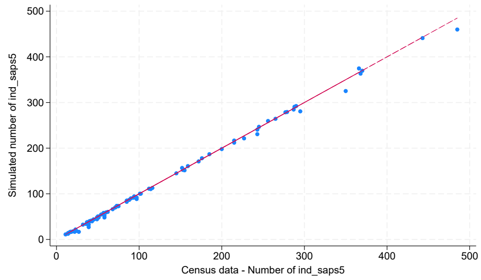
(a) Trade, logistics, hospitality, & communications 2011



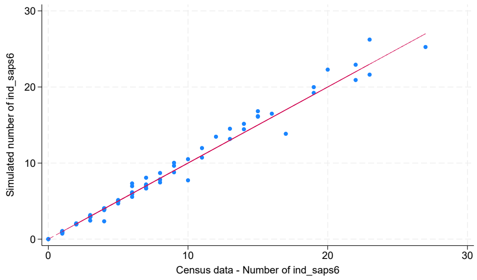
(b) Trade, logistics, hospitality, & communications 2021



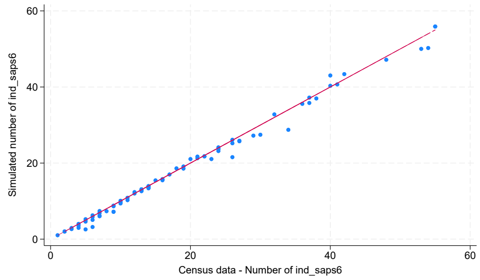
(c) Financial & insurance activities 2011



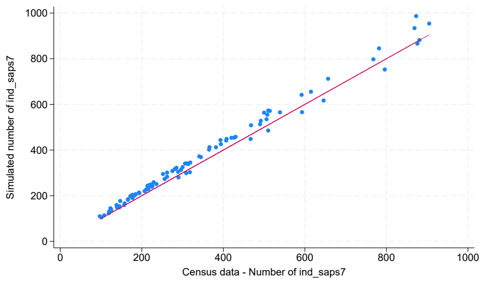
(d) Financial & insurance activities 2021



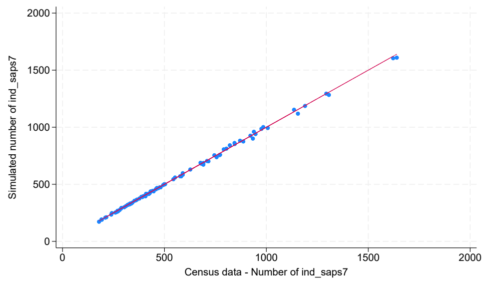
(e) Real estate activities



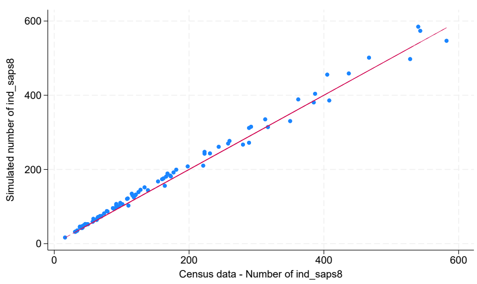
(f) Real estate activities



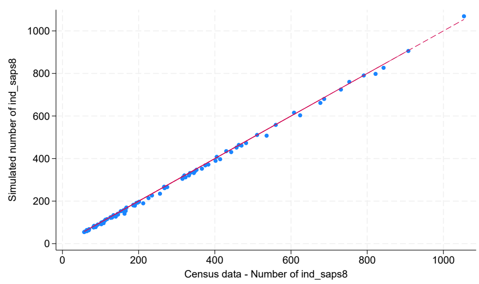
(g) Government, education, health, & social services 2011



(h) Government, education, health, & social services 2021

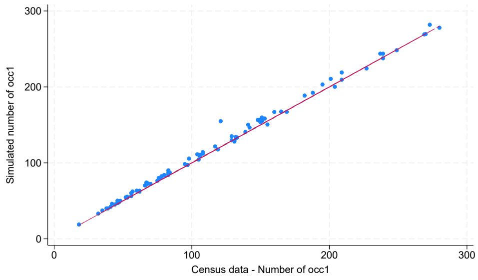


(i) Others 2011

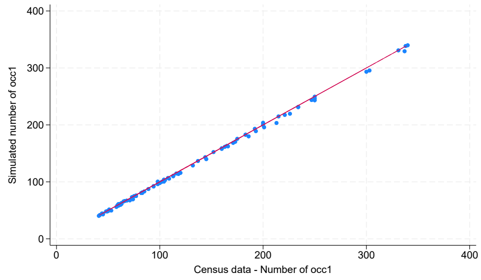


(j) Others 2021

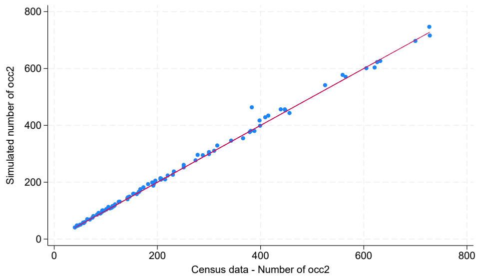
Figure A–4: Simulated shares versus shares from census data for occupations.



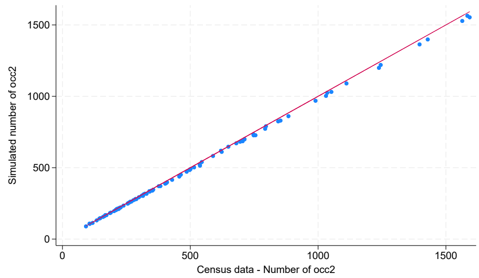
(a) Occ 2011



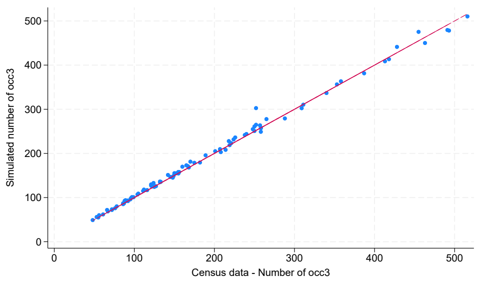
(b) 2022



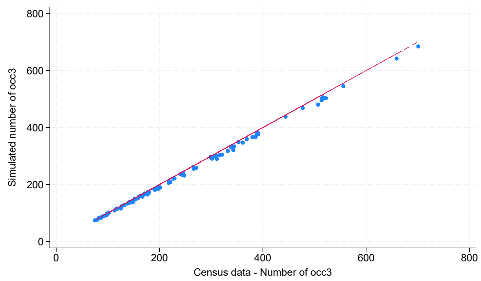
(c) Occ 2011



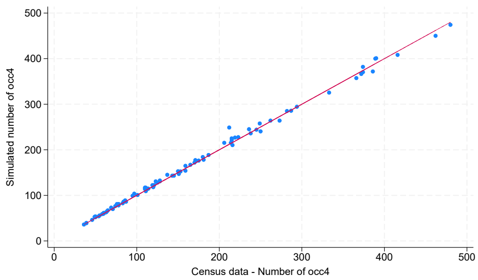
(d) 2021



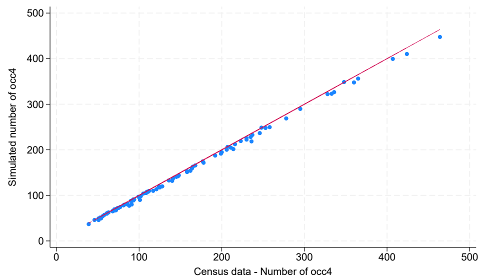
(e) Occ 2011



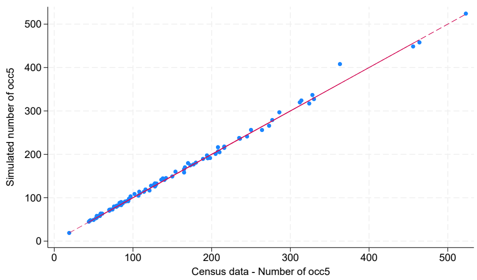
(f) 2021



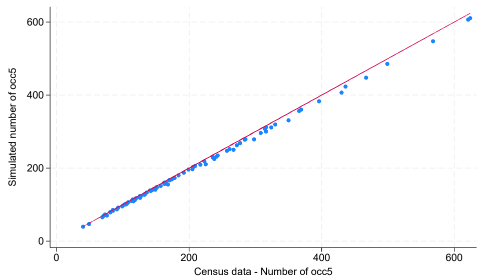
(g) Occ 2011



(h) 2021

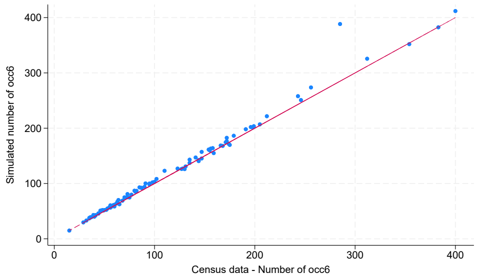


(i) Occ 2011

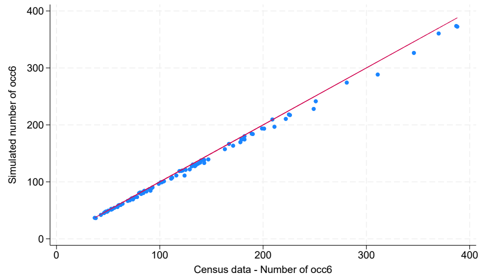


(j) 2021

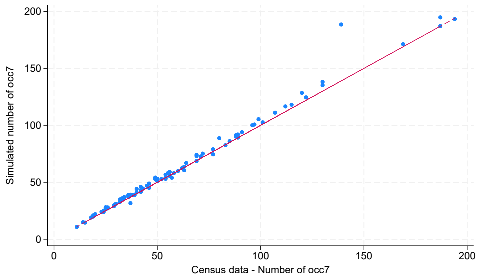
Figure A–5: Simulated shares versus shares from census data for industries.



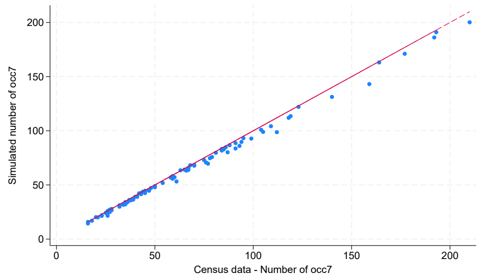
(a) Occ 2011



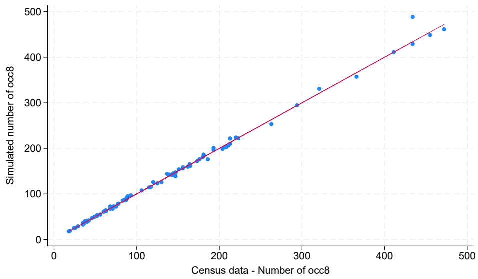
(b) 2021



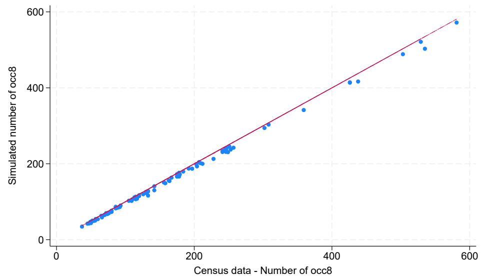
(c) Occ 2011



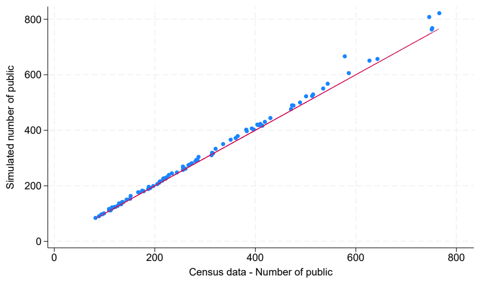
(d) 2021



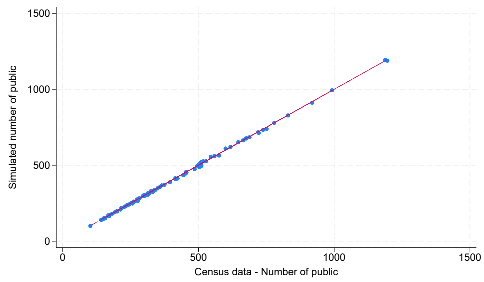
(e) Occupation 8 2011



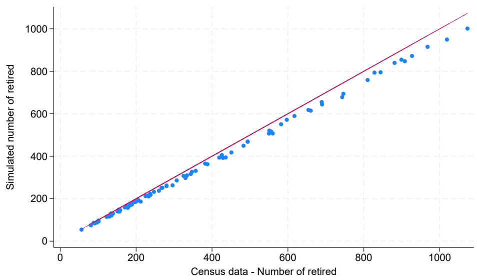
(f) Occupation 8 - 2021



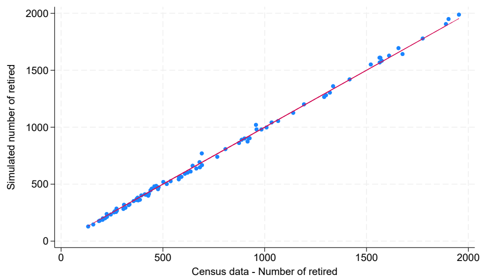
(g) Public employee 2011



(h) Public employee 2021



(i) Retired 2011



(j) Retired 2021

A.3 Robustness: Theil index

Table A–2: Theil index decomposition estimates for 2011 and 2021

	2011			2021		
Indicator	Value	C.I.	S.E.	Value	C.I.	S.E.
Equiv. gross income						
Mean	3005.28	[2977.37;3033.20]	(14.24)	4874.86	[4825.85;4923.88]	(25.01)
Theil	44.85	[44.20;45.50]	(0.33)	30.30	[29.61;30.99]	(0.35)
Within	43.58	[42.93;44.23]	(0.33)	30.01	[29.31;30.70]	(0.36)
Between	1.27	[1.20;1.35]	(0.04)	0.30	[0.25;0.34]	(0.02)
Equiv. gross income + benefits						
Mean	4063.18	[4040.80;4085.56]	(11.42)	5832.56	[5777.64;5887.48]	(28.02)
Theil	20.14	[19.75;20.53]	(0.20)	18.97	[18.51;19.43]	(0.23)
Within	19.46	[19.07;19.85]	(0.20)	18.73	[18.26;19.21]	(0.24)
Between	0.68	[0.64;0.72]	(0.02)	0.24	[0.20;0.28]	(0.02)
Equiv. gross income + benefits - taxes						
Mean	3530.76	[3515.70;3545.81]	(7.68)	4810.82	[4773.88;4847.76]	(18.85)
Theil	13.74	[13.44;14.04]	(0.15)	12.55	[12.29;12.81]	(0.13)
Within	13.31	[13.01;13.61]	(0.15)	12.41	[12.15;12.67]	(0.13)
Between	0.43	[0.41;0.45]	(0.01)	0.14	[0.12;0.16]	(0.01)
Equiv. disposable income						
Mean	3123.79	[3110.87;3136.70]	(6.59)	4212.90	[4187.09;4238.70]	(13.17)
Theil	13.12	[12.83;13.40]	(0.15)	12.21	[11.94;12.48]	(0.14)
Within	12.73	[12.43;13.02]	(0.15)	12.08	[11.81;12.35]	(0.14)
Between	0.39	[0.37;0.42]	(0.01)	0.13	[0.10;0.15]	(0.01)

The calculations in this table excludes household with zero income)

Table A–3: Overview of changes in Luxembourg's tax-benefit system, 2011 vs 2021

Main component	2011 design	Change by 2021
Family cash support	Relied on child benefit, a separate child tax bonus, and a school-start allowance by age & household-size. Children in tertiary education were already excluded from child benefit.	The separate child tax bonus was merged into child benefit, which adopted two regimes depending on whether the child was born or the family arrived before/after 1 Aug 2016. The school-start allowance was simplified to a uniform age-based payment.
Tertiary students support	Already detached from family benefits after excluding children in higher education; the higher-education grant followed the post-2010 framework.	The student-support pillar became mean-tested. The higher-education grant ran under the reformed post-2014 model with later adaptations and indexation (basic amount, mobility allowance, social complement and family supplement).
Minimum-income protection / social assistance	The guaranteed minimum income (RMG) was the main safety net; housing support for low-income renters was partially embedded.	The minimum-income pillar was restructured. The RMG was replaced by the REVIS from 1 Jan 2019. REVIS has a stronger emphasis on social inclusion, activation, supports for households with children and lone parents, and a revised earnings-disregard rule.
Housing support	Embedded within various benefits (rent subsidies, or tax deductions); rental assistance was mainly integrated in the RMG.	Housing support became a distinct policy with a separate rent allowance introduced in 2016. In 2018, the eligibility regarding the types of income that counts become stricter but coverage was broaden. In 2020, income thresholds were raised again.
Family leave / work-family reconciliation	Parental leave was a general childcare leave (gender-neutral), that was more rigid.	From Dec 2016 parental leave became more flexible and earnings-related with full-time, part-time and split options with the aim to encourage fathers' take-up.
Direct taxation	Personal income tax: joint taxation for married couples was compulsory, a progressive schedule topping at 39% (7 brackets), and the unemployment-fund surcharge.	Direct taxation became more progressive at the top and institutionally more flexible. The 2017 reform increased to 23 brackets, and raised the top marginal rate to 42%. In 2018, individual or collective taxation became optional for married taxpayers.
Savings and capital-income taxation	Certain savings income faced a 10% withholding tax.	In 2017, the withholding tax increased to 20% on selected savings income.
Social insurance contributions	Based on contributory for health, pension and long-term care.	Broadly stable with some small changes (e.g., employer accident insurance moved in 2019 to 17 risk classes with a bonus/penalty factor).
Temporary taxes and tax add-ons	The system included the crisis contribution and the unemployment-fund surcharge.	The crisis contribution ended after 2011; a budget-balancing temporary tax was introduced in 2015 and removed in 2017.
Crisis-response	Not a feature.	There is a clearer crisis-buffer, via widened rent-allowance eligibility and state-supported short-time work / partial unemployment measures introduced during COVID.