MAPPING WELL-BEING IN FRANCE

OECD PAPERS ON WELL-BEING AND INEQUALITIES

https://doi.org/10.1787/4ca48f7c-en

WORKING PAPER No.23

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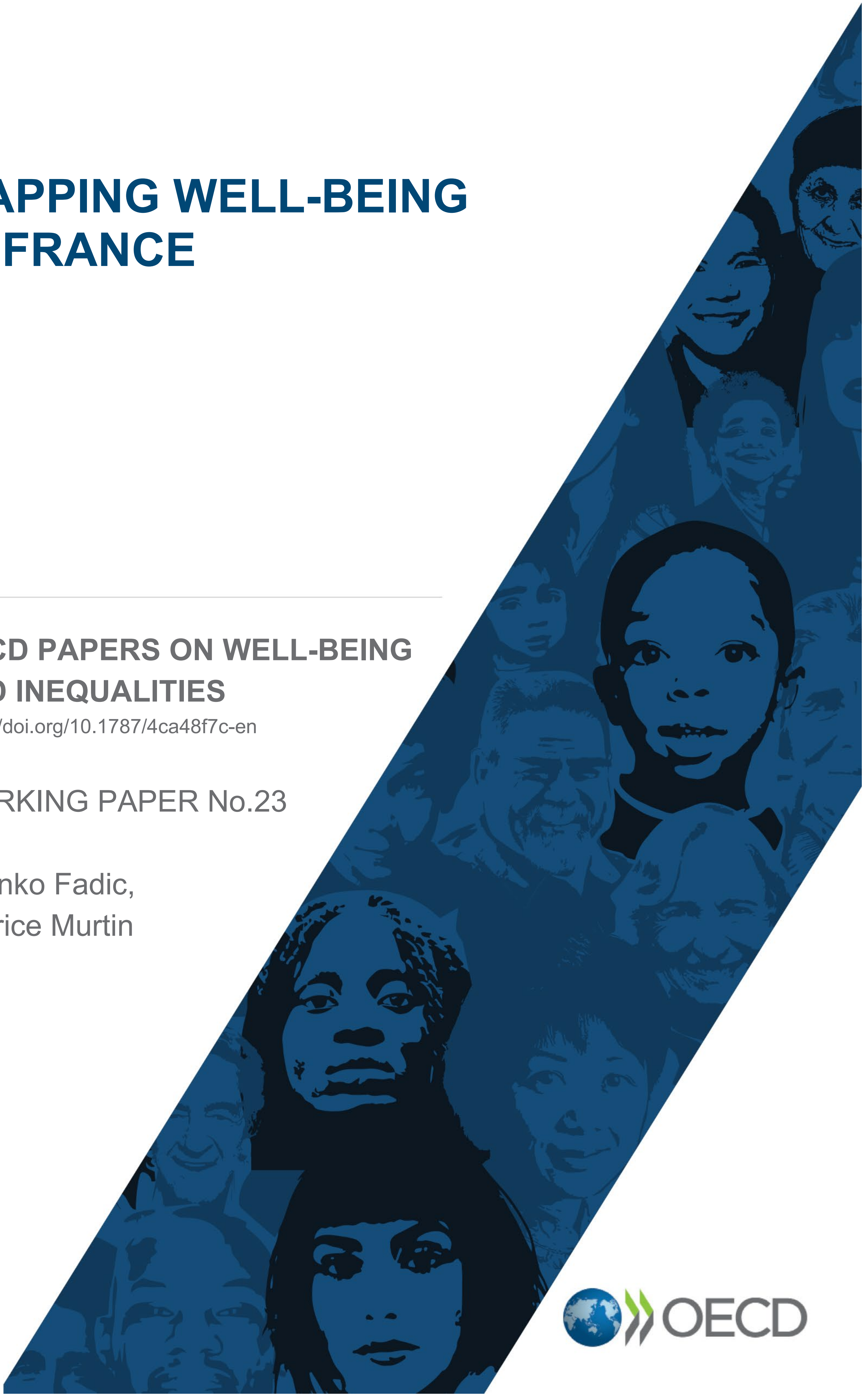

OECD

Organisation for Economic Co-operation and Development

WISE(2024)3

English text only

WELL-BEING, INCLUSION, SUSTAINABILITY AND EQUAL OPPORTUNITY CENTRE

Mapping well-being in France

JEL Classification: I14, I31, I32
Keywords: well-being, poverty, spatial inequality

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The release of this working paper has been authorised by Romina Boarini, Director of the OECD Centre on Well-being, Inclusion, Sustainability and Equal Opportunity (WISE).

Abstract

This paper provides two innovative measures of well-being for French communes, namely a well-being aggregate index and an index of multi-dimensional poverty. These measures provide an unprecedented view of well-being at the local level by using 7 of the 11 key dimensions of the OECD Better Life Initiative (income, unemployment, housing, education, civic engagement, health and environmental quality). The results show that joint deprivation in at least five dimensions of well-being is starkly concentrated among 316 communes, representing as many as 5.2 million inhabitants (7.7% of the French population).

Résumé

Cette étude décrit deux mesures innovantes du bien-être dans les villes françaises, l’une sur le bien-être multi-dimensionnel et l’autre sur la pauvreté multi-dimensionnelle. Ces deux mesures offrent un panorama du bien-être au niveau local basé sur 7 des 11 dimensions-clés de l’Initiative du Bien-Être de l’OCDE (revenu, chômage, logement, éducation, engagement civique, santé et qualité de l’environnement). Les résultats montrent que la déprivation simultanée dans 5 dimensions du bien-être est très concentrée dans 316 communes, qui rassemblent 5.2 millions d’habitants (7.7% de la population française).

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1 Introduction

In the wake of the Stiglitz, Sen and Fitoussi (2009[1]) report, academics and policymakers have increasingly emphasized the need to move beyond national income as the sole measure of economic and social progress. While GDP is a benchmark measure of economic activity and a broad measure of income, it is not informative of many dimensions that are also essential to people's well-being, such as their health and the quality of their environment. Responding to the need to move beyond GDP to measure well-being, the OECD developed the Better Life Initiative (BLI), a measurement framework that quantifies social progress by relying on 11 dimensions of well-being (OECD, 2020[2]). This well-being dashboard – which covers OECD countries since 2013 – has been extended at a regional level as described in *OECD Regions at a Glance* (OECD, 2014[3]). Examining well-being at the sub-national level has allowed for the quantification of spatial inequality in well-being and has shown that, in some areas, disparities *within* countries are greater than those *between* countries (OECD, 2022[4]) . Yet, OECD regions themselves are heterogeneous in various dimensions – including size, demography, and economic structure – and therefore regional measures of well-being do not allow to identify differences that may exist at a local level, such as disparities within metropolitan areas.

This paper is the first effort to extend the well-being methodology at the communal level, the most disaggregated spatial unit typically available in most OECD countries. It does so by providing two distinct and complementary measures of well-being: the multidimensional well-being index (MWB) and the index of multi-dimensional poverty (MDP). The methodology is applied to French communes but can be easily replicated in other countries where information is available.

The MWB indicator provides an unprecedented overview of well-being at the local level by using 7 of the 11 key dimensions of the Better Life Initiative – 3 for material conditions (income, housing and employment), and 4 for quality of life (civic engagement, health, education and environmental quality). The data cover only objective dimensions of well-being, as there is no countrywide survey available to assess subjective well-being at the city level in France. The MWB index is constructed by first normalizing each indicator for every city and using a simple average of all normalised dimensions.

While MWB provides a simple measure of well-being at the local level, the MDP indicator helps identify communes that cumulate relative deprivation. A city is classified as relatively poor in one of the seven dimensions if it is ranked in the bottom 20th percentile of the (population-weighted) national distribution of that dimension. With this measure, a city is defined as multi-dimensionally poor if it scores below the thresholds of relative poverty in *at least* 5 out of 7 dimensions of well-being.

As such, this paper contributes to the literature on spatial inequalities, which have received increasing attention over recent years, thanks to the development of geo-spatial techniques and databases across several dimensions of well-being, such as poverty (Pokhriyala and Jacques, 2017[5]), life expectancy (Congdon, 2014[6]), income (Boulant, Brezzi and Veneri, 2016[7]) or air pollution (van Donkelaar et al., 2016[8]). In particular, Small Area Estimation techniques have been developed to combine several data sources and depict economic conditions at a very granular level (see for instance (Pokhriyala and Jacques, 2017[5]) or (The World Bank, 2018[9])). In that regard, this paper proposes an innovative methodology to calculate life expectancy in small areas.

Moreover, the paper contributes to the literature on multi-dimensional poverty. The index of multi-dimensional poverty has been examined by Bourguignon and Chakravarty (Bourguigon and Chakravarty, 2003[10]) and was illustrated by the United Nations Development Programme indicator (United Nations Development Programme, 2016[11]), which also takes into account poverty depth. The World Bank has conducted similar studies in Nepal (The World Bank and Government of Nepal, 2013[12]) and in Croatia (The World Bank, 2012[13]). We depart from the latter methodologies that rely on the choice of weights for the various dimensions as well as on assumptions for the poverty depth's elasticity, and look at the *intersection* of relative poverty across a significant number of dimensions. This conservative choice has the advantage of simplicity and is made possible by the fact that multi-dimensional poverty is highly concentrated in a reduced number of communes.

By calculating the MWB and MDP indices for the 35 400 French communes, this paper offers three main findings related to well-being and multi-dimensional poverty in France. First, the results highlight stark well-being differences between large communes and rural areas or suburban areas. Specifically, communes located in rural areas including Massif Central, Lower Normandy and Brittany have lower MWB values as their inhabitants tend to have lower incomes, lower educational attainment and higher unemployment rates than in other areas. Other areas that have lower MWB values are Northern France (Nord, Pas-de-Calais, Aisne) and Northern Île-de-France, characterised by low air quality, high unemployment, and lower life expectancy. Conversely, areas like the Western part of Île-de-France and the urban areas of Lyon and Toulouse tend to record very high MWB scores.

Second, the results show that there are 5.2 million inhabitants or 7.7% of French population who are multi-dimensionally poor. The multi-dimensionally poor are concentrated in 316 communes (1% of the number of French communes). These communes are mainly located in the northern area of the functional urban area of (FUA) of Paris, overseas, in former industrial basins of the Northeast of France, and in some Southern communes as well as in several poor arrondissements of Marseille.

The paper is structured as follows. Section 2 presents the data and maps each dimension of well-being. Section 3 introduces the multi-dimensional well-being and the multi-dimensional poverty indexes. Section 4 describes the methodology. Section 5 presents the results and Section 6 concludes.

2 Data

This paper provides a measure of well-being at the commune-level for France by assembling a comprehensive database combining 7 well-being dimensions. The following section describes the sources for this database and provides descriptive statistics on each component of the well-being index.

Sources and definitions

The spatial unit for this study is the 2018 administrative division of French communes (découpage administratif communal français), issued each year by the French government. The administrative division has been publicly available in geographic format (shapefiles) since 2013. The 2018 administrative division consists of 35 355 communes, to which are added 20 municipal districts for Paris, 16 municipal districts for Marseille and 9 for Lyon, for a total of 35 400 communes. The additional administrative units and regional classification used in the text are based on OECD subnational data (see Box 2.1).

Box 2.1. Territorial definitions

The spatial unit for this study is the 2018 administrative division of French communes. All French communes have been mapped to different OECD administrative units and regional classifications. The data in different sub-national geographic levels in France are:

Regions

Regions are classified on two territorial levels reflecting the administrative organisation of countries: large regions (TL2) and small regions (TL3). For France, TL2 and TL3 regions correspond to *Région*s and *Départements*, respectively. TL3 regions are classified according to their access to metropolitan areas (Fadic et al., 2019[14]). Following (OECD et al., 2021[15]), rural areas are cells that do not belong to a city or a town and semi-dense area. Most of these have a density below 300 inhabitants per km^2. Rural regions are regions where the share of population living in rural local units is higher than 50%. Finally, A region is considered to be remote if at least 50% of its population needs to drive 60 minutes or more to reach a populated centre with more than 50 000 inhabitants.

Functional urban areas

Functional urban areas consist of cities – defined as densely populated local units with at least 50 000 inhabitants – and adjacent local units connected to the city (commuting zones) in terms of commuting flows (Dijkstra, Poelman and Veneri, 2019[16]). Metropolitan areas refer to functional urban areas above 250 000 inhabitants

Table 2.1. Well-being dimensions and indicators

Dimension	Indicator	Source	Unit	Year	Website
Civic engagement	Voter turnout	Ministry of Home Affairs	Percentage	2017	https://www.data.gouv.fr/fr/posts/les-donnees-des-elections/
Education	Share of the population holding a secondary education diploma	INSEE – Diplômes et formations	Percentage	2017	https://www.insee.fr/fr/statistiques/fichier/4516086/base-ccx-diplomes-formation-2017.zip
Environment	Air quality – concentration in PM 2.5	OECD ENV/EPI estimate	Micrograms per cubic meter	2017	https://www.oecd-ilibrary.org/environment/population-exposure-to-fine-particles_5jlsqs8g1t9r-en
Health	Life expectancy	INSEE – Naissances, Décès et Mariages	Years	2011-2017	https://www.insee.fr/fr/statistiques/3596218
Housing	Number of rooms per person	INSEE – FiLoSoFi	Ratio	2017	https://www.insee.fr/fr/statistiques/4515532?sommaire=4516107
Income	Median income per unit of consumption	INSEE – FiLoSoFi	€ per unit of consumption and per year	2017	https://www.insee.fr/fr/statistiques/fichier/4291712/indic-struct-distrib-revenu-2017-COMMUNES.zip
Jobs	Unemployment rate	INSEE – Comparateur des territoires	Percentage	2017	https://www.insee.fr/fr/statistiques/fichier/2521169/base-comparateur-2017_CSV.zip
COVID-19	Death records	INSEE-Fichiers des personnes décédées depuis	Deaths	2019-2021	https://www.insee.fr/fr/information/4190491

Note: The table above shows the indicators, sources, units and reference year for each dimension of the well-being index. INSEE refers to the National Institute of Statistics and Economic Studies of France.

Box 2.1 shows the seven well-being dimensions used in this study: civic engagement, education, environment, health, housing, income, and jobs. The other four dimensions identified in (OECD, 2020[2]) are not publicly available at the commune-level due to absence of data or confidentiality constraints. Six out of the seven dimensions are covered by the National Institute of Statistics and Economic Studies of France (INSEE) and easily accessible through data.gouv.fr, the French government portal for open data.

Civic engagement is represented by voter turnout – defined as the number of voters in the first round of the 2017 election divided by the number of registered voters. The data is made available by the French Ministry of Home Affairs. After every election, the voter turnout is collected at each poll station and published at the city-level online on data.gouv.fr (French Minstry of Home Affairs, 2017[17]). Voting in France is not compulsory and usually, voter turnout is higher for the second round of the election. However, since the diversity of the candidates for the first round cover the entire political spectrum in France, votes at the first round are more likely to be votes by adhesion, and to reflect the civic engagement of French citizens.

Education is represented by the share of the population holding at least a secondary education diploma. A secondary education diploma is defined as having an International Standard Classification of Education (ISCED) score of 3 or more. In France, these diplomas are either a baccalaureate, a CAP/BEP (vocational training certificate) or a higher education diploma (UNESCO Statistics Institute, 2007[18]). The database

"Diplômes et Formations en 2017" (INSEE, 2017[19]) contains the distribution of adults who hold a secondary education diploma. The share of the population holding at least a secondary education diploma is thus defined as the sum of the people with a baccalaureate, a CAP/BEP, a higher education diploma, and those aged 18+ still pursuing a degree divided by the total number of people aged 18 or older.

Income is represented by the 2017 annual median income per unit of consumption of the commune. The INSEE definition of a unit of consumption is based on the OECD definition: the first adult in the household accounts for 1 unit, all others aged 14 or more account for 0.5 units and all those aged 13 and less account for 0.3 units. The FiLoSoFi (Fichier Localisé, Social, Fiscal – Fiscal, localised and social file) for the year 2017 (INSEE, 2017[20]) gathers information about income distribution at city level. In order to produce income data, INSEE uses the RDL (Revenus Déclarés Localisés – Declared and Localised Income) database, which uses data from tax returns and data from housing taxes in order to link every taxpayer to a household. Income data is not available for French Guyana and Martinique. Since the coverage for this dimension is imperfect, the departmental value (coming from the same database) is used for communes with missing income data.[1]

Housing is represented by the number of rooms per person (denoted as NBPI). The measure is defined as the average number of rooms in a dwelling divided by the number of persons living in this dwelling. The database "Résidences principales en 2014" (INSEE, 2017[21]) consists in 35 tables comparing the quality of accommodation in France, the access to basic facilities (sanitation, clean water, etc.) for overseas territories, household population and the number of rooms per dwelling at city level. The table PRINC3 contains information about the number of rooms depending on the household type and size, from which it is possible to derive the average number of rooms per person in the city.

Jobs is represented by the unemployment rate. The database "Comparateur des territoires" (INSEE, 2017[22]) provides, at the commune-level, the number of unemployed adults aged 15 to 64 as well as the active population over the same age span for the year 2017. The unemployment rate is obtained by dividing the unemployed adults by those in the labour force.

Health is represented by life expectancy at birth, which provides a summary measure of mortality patterns across age groups (World Health Organization, 2020[23]). Life expectancy is calculated using an abridged life table following Chiang's method (Chiang and World Health Organization, 1979[24]). A key input to the creation of abridged life tables is the mortality rate by age, defined as the total number of deaths per 1 000 inhabitants of a given age, and estimated as the number of deaths divided by the number of people of a given age. This estimation of the mortality rate works well with large communes that record a large number of deaths over which the law of large numbers does apply. In smaller geographic areas (including the ones under study in this paper), however, the quality of the estimation drops due to small sample issues, and statistical aberrations. In order to filter the raw data, mortality rates by age are predicted following the methodology briefly summarised in Annex A. Once mortality rates by age are predicted in every French city, Chiang's abridged life tables and life expectancy are computed at the city-level. The data for the computation of this indicator comes from "Naissances, décès et mariages en 2017" (INSEE, 2017[25]), an INSEE database containing the number of localised deaths in every city from 2011 to 2017.

Environment is represented by air quality defined as the 2017 ground-level air concentration in PM2.5 in µg per cubic meter, the fine particle matter pollution. Data for France is provided by the OECD Environment Directorate (ENV/EPI) based on the methodology outlined in Mackie, Hascic, Cardenas Rodriguez (2016[26]).

1 Except for French Guyana and Martinique, for which we used the value from the 2011 survey "Revenus et pauvreté des ménages" (Household income and poverty). The median income for French Guyana amounts to EUR 19 160 per unit of consumption per year, and for Martinique, EUR 18 960.

Finally, this paper uses the death records (fichier décès) from INSEE to calculate the excess mortality related to COVID-19. These files contain all deaths registered in France with information, in particular, on the date of death and municipality of residency. The measure of death related to COVID-19 are created by looking at the differences in the number of deaths in the commune between April 2020 and March 2021, and April 2019 and March 2020.

Descriptive statistics

Table 2.2 presents descriptive statistics of well-being dimensions in France. French communes are generally very small. The average commune has around 1 800 inhabitants and approximately 85% of communes have less than 2 000 inhabitants. Conversely, each of the 20 communes in the city of Paris (arrondissements) records around 110 000 inhabitants.

Table 2.2. Well-being at commune level in France, 2017

	Observations	Mean	Standard Deviation	Min	Max
Population	35 343	1 828	8 371	1	47 5451
Life expectancy	35 351	82.3	0.84	81.3	85.04
Educational attainment	34 985	0.69	0.07	0.10	1
Voter turnout	35 392	0.83	0.06	0.06	1
Unemployment rate	34 584	0.11	0.05	0.01	0.85
Air quality	32 371	9.73	1.61	2.8	17.91
Rooms per person	34 983	2.02	0.24	0.4	6
Income	31 741	21 108	3 633	7 590	50 280

Note: The table above shows the indicators for each dimension of the well-being index for the year 2017. Life expectancy is calculated using an abridged life table following Chiang's method where commune-level mortality rates are predicted using the methodology developed in the paper. Educational attainment is represented by the share of the population holding at least a secondary education diploma, defined as having an International Standard Classification of Education (ISCED) score of 3 or more (baccalaureate, a CAP/BEP or a higher education diploma Voter turnout refer to the number of voters in the 2017 presidential election divided by the number of registered voters. Unemployment rate is defined as the number of unemployed adults aged 15 to 64 as well as the active population over the same age span for the year 2017. Air quality is defined as the 2017 ground-level air concentration in PM2.5 in µg per cubic meter, the fine particle matter pollution. Rooms per person is defined as the average number of rooms in a dwelling divided by the number of persons living in this dwelling). Income refers to median income per unit of consumption of the commune. The variable population was calculated as the sum of the different age groups in the community and therefore may have slight variations with other indicators. Source: INSEE and OECD Environment Directorate (ENV/EPI).

Figure 2.1 (right panel) shows the 2017 annual median income per unit of consumption of French communes. Overall, communes located in primary rural areas and/or non-metropolitan regions tend to have lower median income than urban areas. Figure 2.1 also highlights stark differences in median income across the country. For example, the northern part of France, which used to be a major industrial region with the leading example of Roubaix (59), a city of 96 000 inhabitants, records an annual median income of only EUR 9 770. Overseas territories generally tend to have a noticeably lower median income: the average income for communes in Guadeloupe and La Réunion is around EUR 13 900 per person, far below the average median income in metropolitan France, which amounts to approximately EUR 21 100 per person and per year.

Paris is on average a rich city, with a median income around EUR 30 000 per person. However, there are large differences between the 20 communes (called arrondissements) that make-up the City of Paris. The 7th, 8th, 16th and 6th arrondissements of Paris rank among the richest communes in France, with an average income over EUR 45 500, whereas the 19th arrondissement remains below the national mean with EUR 20 000. Similar spatial inequalities occur in the City of Marseille, where the 3rd arrondissement has the country's lowest median income observed in the sample with only EUR 7 590 per person per year, while the 7th and 8th districts score above the national mean with around EUR 25 000 per person and per year.[2]

Figure 2.1 (left panel) depicts the share of people holding a secondary education diploma. Educational attainment is higher in primary urban areas, including around Île-de-France, Nantes, Rennes, Lyon, Toulouse, Bordeaux and Aix-Marseille, as well as in Alsace and Moselle. Educational attainment drops in rural areas, in Corsica and in overseas territories, which fall in the bottom third of the ranking. The Seine-Saint-Denis department falls in the bottom third of the educational attainment ranking, with around half of its communes in the bottom 20th percentile of the national and population-weighted distribution, contrasting with its neighbouring areas, all in the top two quantiles.

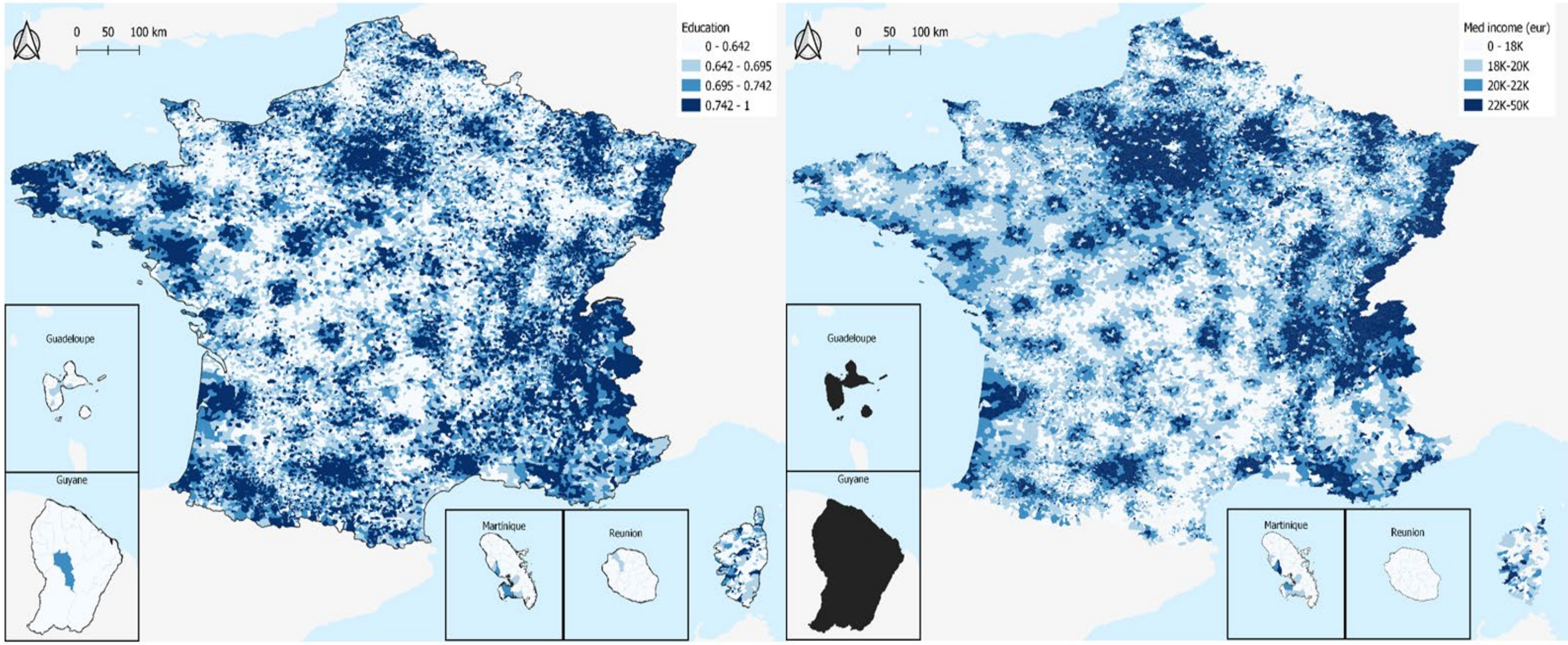
Figure 2.2 (right panel) depicts the exposure to PM2.5 across communes in France. Overall, air pollution is higher inurban areas than in the countryside. The Rhône Valley is the French region with poorest air quality, especially in the Lyon urban area, where the highest average concentrations have been recorded. The neighbouring urban area of Grenoble has also a high concentration of PM2.5 in the air. The topography of the area, narrow valley surrounded by high mountains, and the heavy industrial activity as well as major highways likely contribute to the accumulation of fine particles at ground level. Other noticeable areas with high PM2.5 concentration is the northern part of France, especially around Lens (59), Denain (59) and Lille (59), the Nice (06) urban area, and the Paris urban area. For the Lille-Denain-Lens area, heavy industry also increases the concentration of PM2.5 in the air. Lastly, several zones in Seine-et-Marne (77), Marne (51) and Aube (10) have rather high PM2.5 concentrations, which is explained by the existence of several major highways going to Paris.

Figure 2.2 (left panel) shows predicted life expectancy in French communes. Across all communes, average life expectancy at birth is equal to 82.3 years. Life expectancy tends to be lower in northern France, western Brittany and in overseas departments. Approximately 30 communities in the departments of Somme and Pas-de-Calais record a life expectancy that is almost 3 years lower than the national average. Conversely, life expectancy is greater by almost 1 year (83.4) in communities located in metropolitan areas, including the metropolitan area of Paris, Strasbourg, and Grenoble.

Figure 2.3 (left panel) depicts voter turnout in the first round of the 2017 presidential election. Voter turnout was much lower in overseas territories than in Metropolitan France. The figure also suggests that some regions in Metropolitan France have a higher civic engagement, such as Brittany or Pays de la Loire. In contrast, communes near the French-German and the French-Belgian border or in Central France tend to have lower voter turnout. Moreover, numerous communes around Paris have a noticeably lower voter turnout than the capital itself.

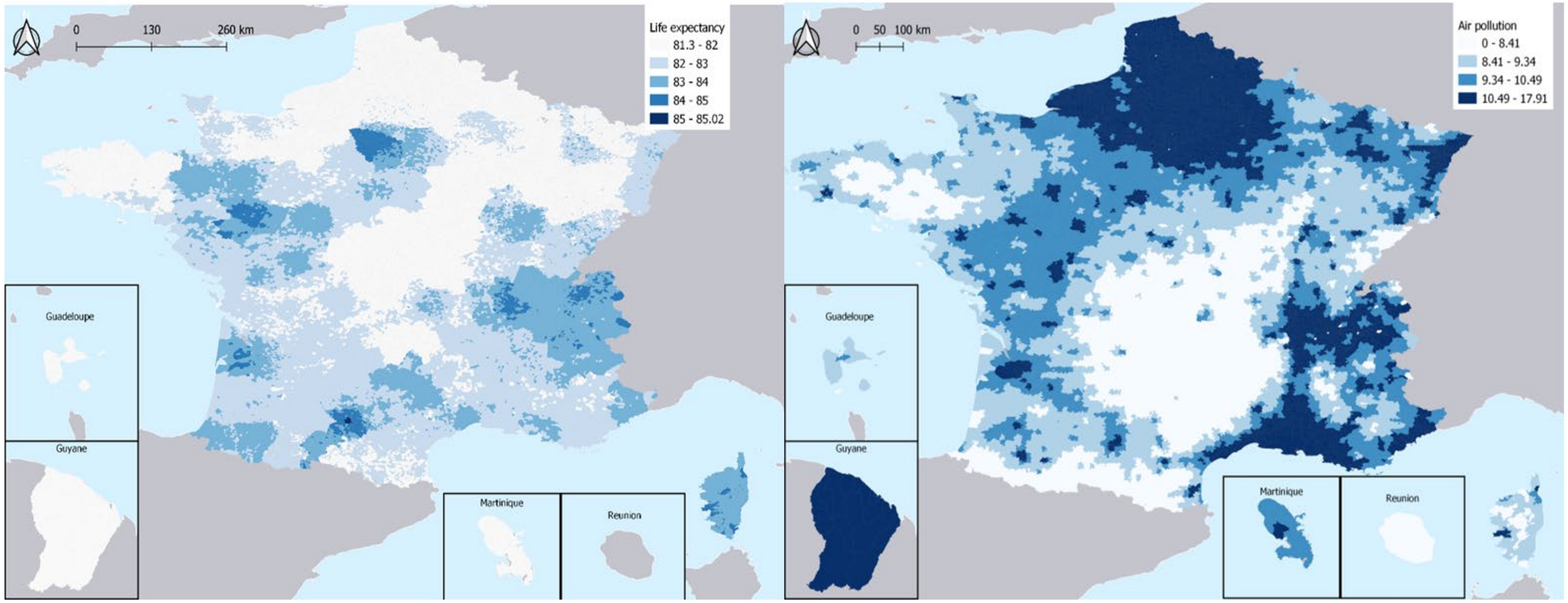
[2] Interestingly, the data show two areas with a particularly high median income. The first area is located in the Yvelines (78) department (around Versailles), where 29 of the 100 richest communes in France are located. The second area is located near the French-Swiss border, in the Ain (01), Haute-Savoie (74) and Bas-Rhin (68). Conversely, areas with particularly low median income are located in Aude department (11) followed by the Nord (59) and the Puy-de-Dôme (63) departments.

Figure 2.1. Commune-level educational attainment and median income in France, 2017



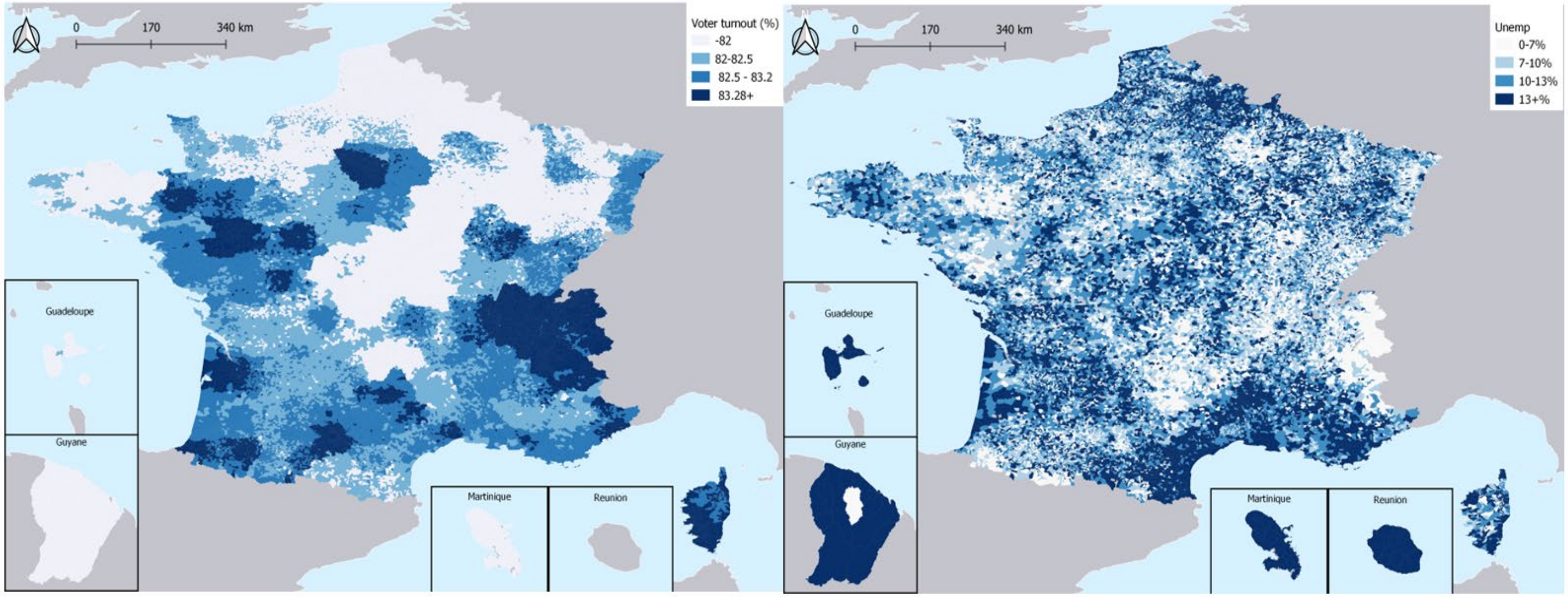
Note: The map on the left presents the commune-level educational attainment in France for the year 2017. Educational attainment is represented by the share of the population holding at least a secondary education diploma, defined as having an International Standard Classification of Education (ISCED) score of 3 or more (baccalaureate, a CAP/BEP or a higher education diploma). The map on the right shows the 2017 annual median income per unit of consumption of the commune. Income data is not available for French Guyana and Martinique. The departmental value (coming is used for communes with missing income data
Source: Diplômes et Formations en 2017 and Fichier Localisé, Social, Fiscal – Fiscal, localised and social file, INSEE, 2017.

Figure 2.2. Commune-level life-expectancy and air pollution in France, 2017



Note: The map on the left presents the commune-level life expectancy in France for the year 2017. Life expectancy is calculated using an abridged life table following Chiang's method where commune-level mortality rates are predicted using the methodology developed in the accompanying paper. The map of the right presents air pollution levels. Air pollution is defined as the 2017 ground-level air concentration in PM2.5 in µg per cubic meter, the fine particle matter pollution.
Source: Naissances, décès et mariages en 2017 (INSEE) and OECD Environment Directorate (ENV/EPI).

Figure 2.3. Commune-level voter turnout and unemployment in France, 2017

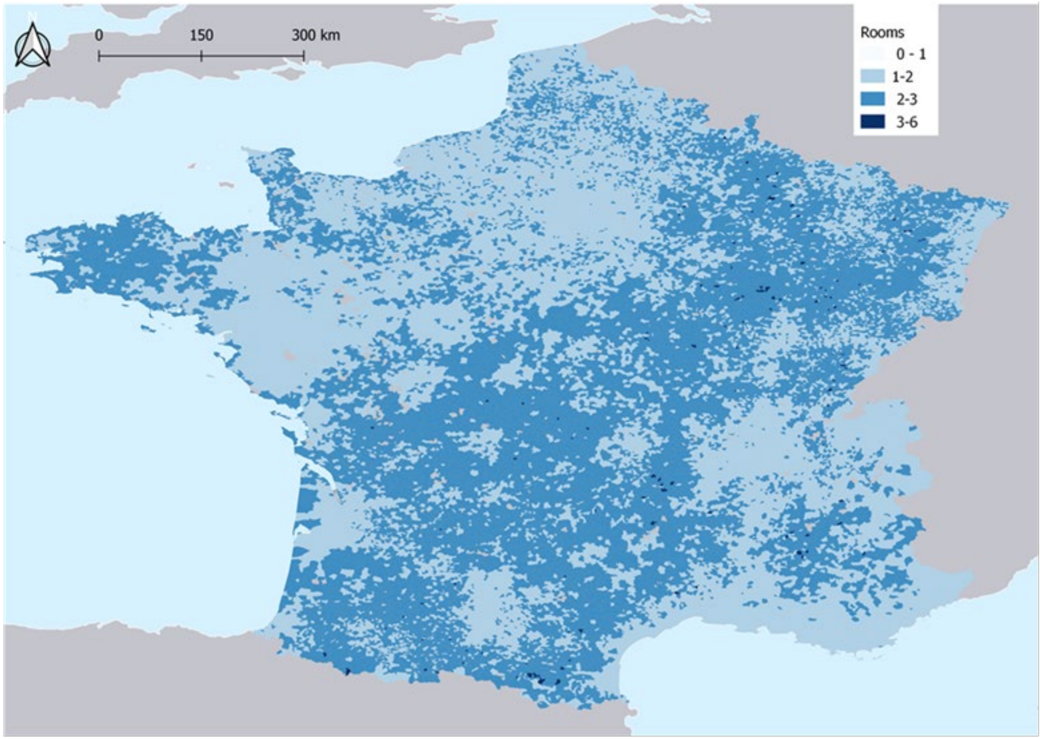


Note: Voter turnout for France in 2017. Voter turnout is defined as the number of voters in the first round of the 2017 election divided by the number of registered voters. The data is made available by the French Ministry of Home Affairs. Unemployment rate is defined as the number of unemployed adults aged 15 to 64 divided by the active population over the same age span for the year 2017.
Source : Comparateur des territoires" INSEE.

Figure 2.3 (right panel) describes the unemployment rate across French communes. High unemployment is recorded in the northern part of the country, the urban areas of Béthune, Lens, Douai, Denain, Valenciennes, and communes near Saint-Quentin where the average unemployment rate rises up to 21.4%. Another zone with very high unemployment rate is Seine-Saint-Denis (93). Focusing on the area going from Argenteuil (95) to Sevran and from Villiers-le-Bel to Montreuil, the average unemployment rate goes up to 20.5%. This area has one of the highest unemployment rates in France, and it is much higher than in Paris or the neighbouring departments such as Hauts-de-Seine (92) and Val d'Oise (95). The south-western France bordering the Mediterranean Sea has a very high unemployment rate: among the top 500 most unemployed communes in France, 45 are in Aude (11). Finally, overseas territories have a very high unemployment rate compared to metropolitan France, averaging at 32%. For instance, the share of communes that belong to the French 500 most unemployed communes in France is 53% in Martinique, 78% in Guadeloupe, 81% in French Guyana and 96% in La Réunion.

Finally, Figure 2.4 depicts the number of rooms per person in the dwelling. Not surprisingly, more densely populated areas record an average number of 2 rooms per person or less, in contrast to more rural areas such as Brittany, Centre and South-West of France.

Figure 2.4. Commune-level rooms per person in France, 2017



Note: The map above presents the commune-level number of rooms per person. The measure is defined as the average number of rooms in a dwelling divided by the number of persons living in this dwelling.
Source: INSEE (2017[27]), "Résidences principales en 2017" (database).

3 Methodology

This section presents the methodology used to create two measures capturing well-being at the local level: the multidimensional well-being index (MWB) and the multidimensional poverty index (MDI). The MWB and MDI are based on the 7 indicators (unemployment, housing, education, income, air quality, life expectancy, and voting) described in the previous section.

Multidimensional well-being

The MWB index is a multidimensional well-being index that relies on 7 key indicators. The index is constructed by first normalizing each indicator for every city. Formally, the normalisation of indicator *I* for city *c* takes the form:[3]

$$I_{x_c} = \frac{x_c - \min x}{\max x - \min x} \in [0,1]$$

where x_c denotes the value for indicator I in city *c* and $\min x$ and $\max x$ denote the minimum and maximum values across all geographical units for indicator I, respectively. As a result, all well-being dimensions use the same 0-1 scale.

Following the normalization of each indicator, the aggregate multi-dimensional well-being index MWB is computed as the average of all normalised dimensions:

$$MWB_c = \frac{1}{7}\left(I_{air} + I_{inc} + I_{housing} + I_{voter} + I_{edu} + I_{unemp} + I_{LE}\right)$$

This methodology is comparable to the one used for calculating the Human Development Index[4] and is standard in the literature (see (Foster, 2005[28]) for an extension to distributional aspects). It presents some well-known limitations related to the absence of proper aggregation weights that would ideally reflect the actual preferences of people for the various well-being outcomes (e.g. air pollution, housing quality, unemployment and health…). As a consequence, the use of ad hoc weights implies puzzling changes of the aggregate index over time as well as implausible implicit valuations of well-being outcomes, as shown for instance by (Ravallion, 2012[29])in the case of life in the Human Development Index. The derivation of proper weights or 'shadow prices' is undertaken by various studies in the literature (e.g. (Viscusi, 2003[30]) on the Value of a Statistical Life and longevity; (Murtin, 2017[31]) and (Boarini, 2021[32]) for the shadow price of (un)employment and longevity) but this valuation methodology is difficult to apply when the number of well-being dimensions becomes too large as is the case in this paper. Moreover, the MWB index is provided as a static descriptive statistics for only one year and for illustrative purposes only.

[3] Negative outcomes such as unemployment or air pollution are expressed in reverse form, i.e. low unemployment being a good I_unemp score.
[4] The HDI index considers the geometric mean rather than the arithmetic mean.

In practice, the MWB index is only mildly correlated with any of its sub-components: the maximum correlation is obtained with longevity (0.78) and education (0.64), voting and income to a lesser extent (around 0.56). Conversely, unemployment and air pollution are negatively correlated with the MWB. This suggests that the MWB adds valuable information by going beyond any individual measure.

Table 3.1. Correlations between the MWB and its sub-dimensions

	Unemployment	Air pollution	Life expectancy	Education	Voting	Housing	Income
Unemployment	1						
Air pollution	-0.01	1					
Life expectancy	-0.25*	-0.02*	1				
Education	-0.36*	0.15	0.44	1			
Voting	-0.35*	-0.01	0.09*	0.32*	1		
Housing	-0.03*	-0.42*	-0.30*	-0.16*	0.05*	1	
Income	-0.45*	0.35*	0.35*	0.60*	0.25*	-0.19*	1*
Well being index	-0.50*	-0.27*	0.78*	0.64*	0.39*	0.04*	0.56*

Note: Correlations between the MWB and its sub-dimensions. A start denotes a p-value of less than .1 (P<0.1).

Multidimensional poverty

Although the multidimensional well-being index provides a simple measure of well-being, it is not sufficient to map the poorest territories in France. The multidimensional poverty index complements the MWB index by providing a headcount of communes that cumulate relative deprivation.

Formally, a city is defined as poor in one of the seven dimensions if it is ranked in the bottom 20th percentile of the national and population-weighted distribution of that dimension. The calculation of poverty thresholds takes into population weights, which is relevant as 90% of French communes have less than 2 000 inhabitants. As a consequence, a city of 115 inhabitants like Cassagnas (48) and a city of 30 000 inhabitants like Clichy-sous-Bois (93) that have the same MWB score (0.4237) do not have the same influence over the various poverty thresholds. Formally, the number of dimensions in which a given city is classified as relatively poor yields a poverty score:

$$POV\_SCORE_c = \sum_X \mathbf{1}(I_C^X \leq P_{20}^X)$$

where $\boldsymbol{P_{20}^X}$ is the population-weighted bottom 20th percentile of indicator $\boldsymbol{X}$ and $\boldsymbol{I_C^X}$ is the value of indicator $\boldsymbol{X}$ in city $\boldsymbol{C}$. Finally, a city is defined as multi-dimensional poor if it is relatively poor in at least 5 out of the 7 dimensions of well-being considered in this paper. The Multi-dimensional Poverty indicator is thus a dummy variable defined as:

$$MDP_c = \mathbf{1}(POV\_SCORE_c \geq 5)$$

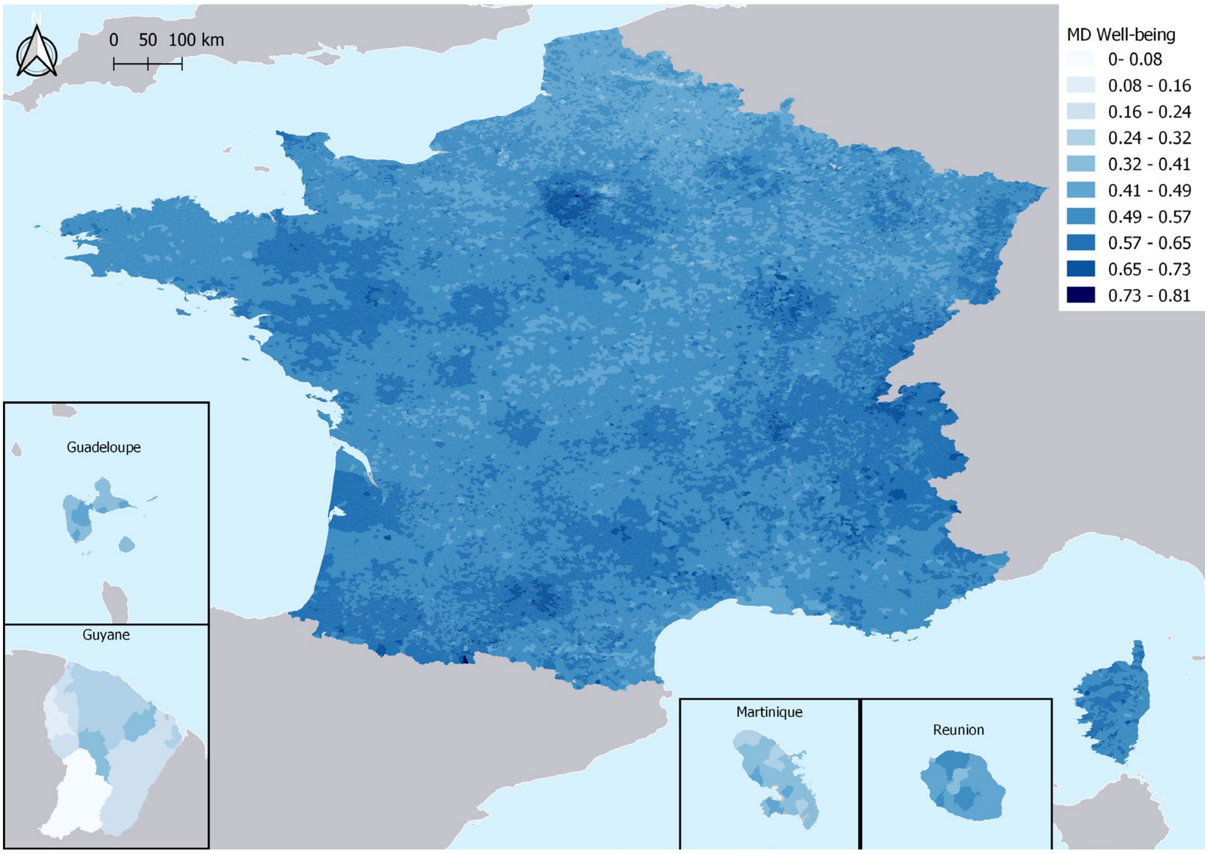
This methodology is analogous to the one used to calculate the Multidimensional Poverty Index in the United Nations Development Programme (see (Alkire, 2018[33]) and (United Nations Development Programme, 2016[11]), which sums deprivation scores across various outcomes to obtain an aggregate score that indicates multi-dimensional poverty. This approach is less elaborated than multi-dimensional poverty as defined by (Bourguigon and Chakravarty, 2003[10]), who rely on the choice of weights for the various dimensions of poverty as well as on some assumptions for the poverty depth's elasticity. As explained above, this paper addresses too many dimensions of well-being and poverty to incorporate sophisticated information on people preferences into aggregation weights.

4 Mapping well-being in France: where are the multi-dimensionally poor?

This section maps multidimensional well-being (MWB index) and multi-dimensional poverty (MDP index) in France. The results show that joint deprivation in at least 5 dimensions of well-being is starkly concentrated among 316 communes, where around 5.2 million inhabitants (7.7% of the French population) live.

Figure 4.1 depicts the multi-dimensional well-being index for France. The figure helps identify two categories of communes with low MWB. First, there are communes located in rural and remote areas (Box 2.1), like Massif Central, Lower Normandy, Brittany and near the French-Spanish border. These communes score poorly because their inhabitants tend to have low income, lower educational attainment and a higher unemployment rate, which are key factors to the MWB. Second, there are communes located in Northern France (Nord, Pas-de-Calais, Aisne), as well as northern Île-de-France and some suburban areas. In these communes, educational attainment is not necessarily much lower there than the national average, but air quality is very poor, unemployment is extremely high and life expectancy tends to be lower. Conversely, communes with a high MWB score are located near the western part of Île-de-France and the urban areas of Lyon and Toulouse. These regions tend to have high income, low unemployment rate and high educational attainment.

Figure 4.1. Multi-dimensional well-being index in French communes

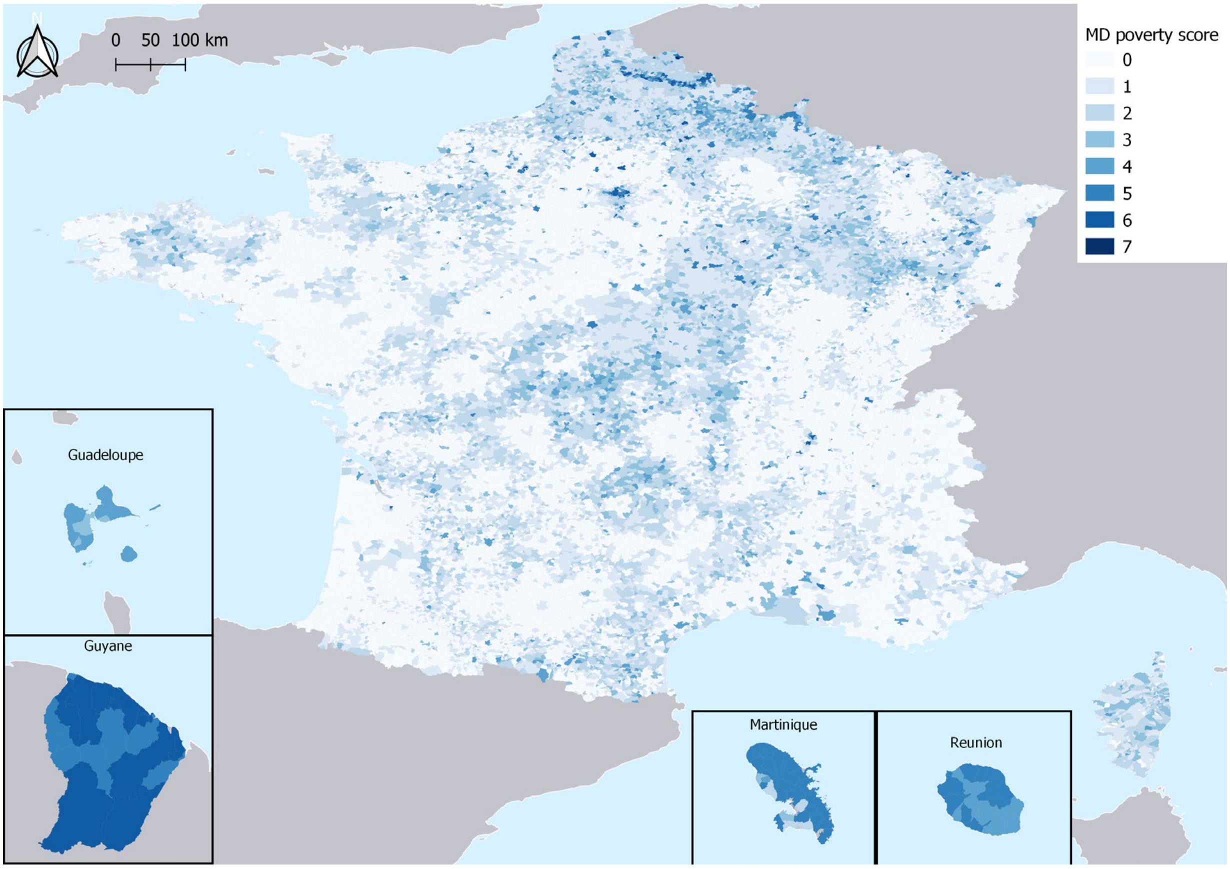


Note: The figure above shows the multidimensional well-being index (MD Well-being) for France. The range of the MWB is 0-1, with a higher value indicating a higher level of well-being. The MWB is based on the 7 indicators (unemployment, housing, education, income, air quality, life expectancy, and voting).

Figure 4.2 highlights French communes that are multi-dimensionally poor. Although this map looks very sparse, MD-poor communes represent in total 5.2 million people, or 7.7% of the French population. Nearly 75% of the population living in MD-poor areas is located in medium-size communes of 5 000 to 50 000 inhabitants, which corresponds to suburban areas or small industrial communes in France. The share of population living in MD-poor small communes is rather small (about 15%), which strengthens the conjecture that multidimensional poverty is concentrated in suburban areas. Finally, approximately 10% of the MD-poor population lives in functional urban areas, agglomerations of communes with a population of at least 50 000 inhabitants. These communes correspond for the most part to the Paris suburbs in Seine-Saint-Denis and to La Réunion.

Interestingly, the index of multi-dimensional poverty depicts a different picture than one-dimensional poverty, such as income relative poverty. While 96% of multi-dimensionally poor communes are also relatively income-poor (i.e. below the 20% percentile of income), only 36% of income-poor communes are also multi-dimensionally poor. When defining the income poverty threshold at the 8th percentile so that income and multi-dimensional poverty both affect about 8% of national population, 76% of MD-poor are income-poor, while 71% of income poor are MD-poor. Hence, *deep* income poverty and multi-dimensional poverty are strongly related, but they are no redundant indicators.

Figure 4.2. Multi-dimensional poverty in France

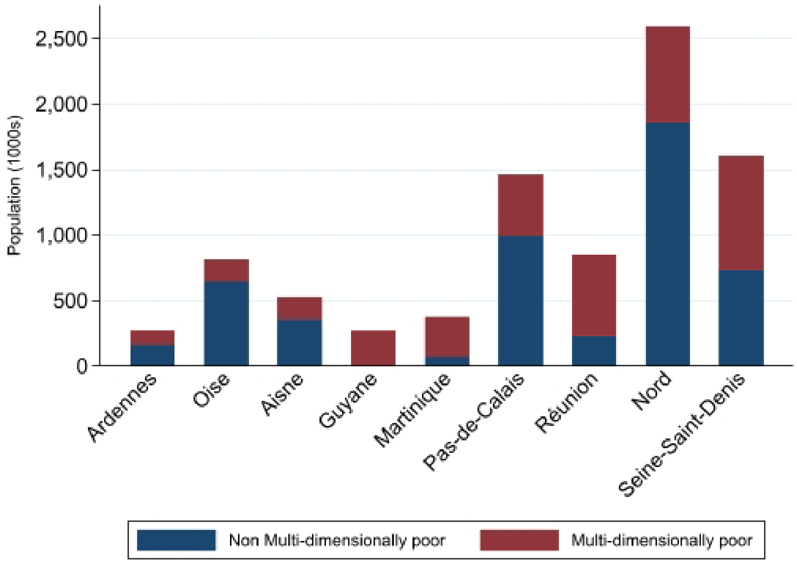


Note: The figure above shows the multi-dimensionally poverty score for communes in France.

Overall, these results are in line with previous studies. Statistical reports by INSEE point at an increase in poverty in territories already vulnerable to poverty, namely northern parts of Île de France (INSEE, 2017[34]), Nord-Pas-de-Calais (INSEE, 2016[35]) and overseas territories (INSEE, 2010[36]). On top of the statistical reports produced by INSEE, parliamentary commissions have been mandated to study the inequalities in some of these territories. Seine-Saint-Denis, for instance, has long been a territory concentrating poverty and a recent parliamentary report points at the ineffectiveness of public policies in reducing the poverty in this territory (Assemblée Nationale, 2018[37]). Another policy report points at the economic and social inequalities of overseas territories compared to metropolitan France, deploring the lack of consistent public plans to reduce these inequalities (Assemblée Nationale, 2016[38]).

Figure 4.3 identifies the departments with the largest share of multi-dimensionally poor people. Seine-Saint-Denis ranks first, with almost a million inhabitants living in MD-poor areas, followed by Département du Nord, La Réunion, and Pas-de-Calais.

Figure 4.3. Departments with the largest number of multi-dimensionally poor people

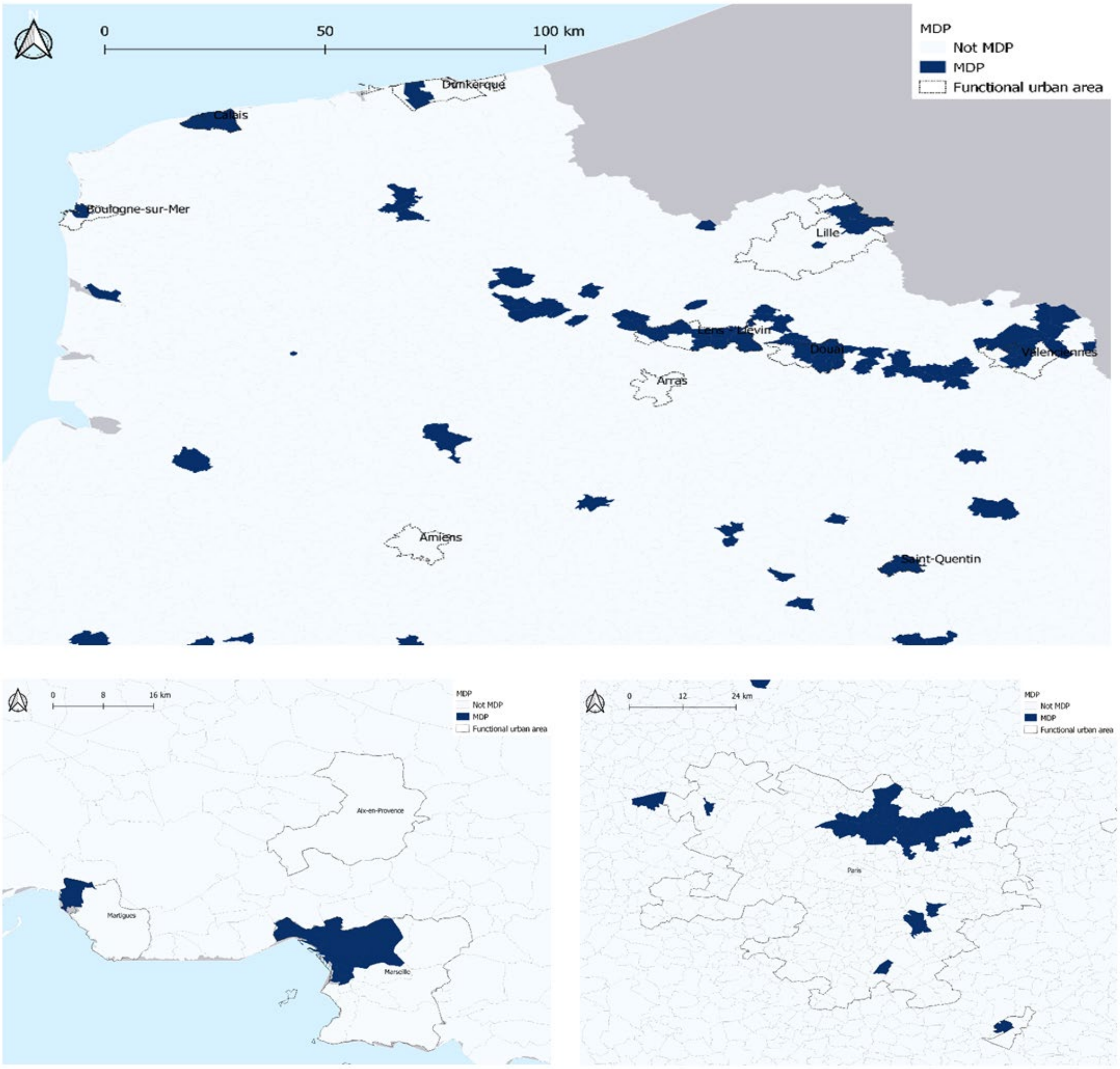


Note: Departments with the largest number of multi-dimensionally poor people, sorted by number of people living in multi-dimensionally poor areas.

Figure 4.4 zooms on the MDP indicator in Northern France, Île-de-France, and Marseille, and it identifies a large number of multi-dimensionally poor communes. The northern region of France used to be a major industrial area, with a lot of coal and steel mines and a well-developed metallurgic industry. With the coal and steel crisis at the beginning of the 1980s, most of the mines and factories were shut down, leading to a rise in unemployment and poverty in Northern France, Belgium and in the Lowlands in Great Britain. Policy measures have been undertaken to attract investors and preserve the industrial power of the region, but it only worked to some extent: unemployment in Nord (59), Aisne (01) and Pas-de-Calais (62) remains high, and the average income per unit of consumption is well below the national average. In addition, the heavy industries of the region lead to poor air quality, which contributes to the concentration of MD-poor communes in the area.

Regarding Île-de-France, the northern part beyond the boundaries of the city of Paris has long been a cosmopolitan area, where workers lived because of the proximity to factories and where immigrants settled. In this area, real estate prices are relatively low (compared to the city centre of Paris), and the department of Seine-Saint-Denis (93) witnessed a massive arrival of immigrants from Portugal first, and then from Maghreb between 1968 and 2005, making it the department in France with the highest proportion of immigrants (29% of the population in 2013). This led to the creation of segregated areas, like the city of Clichy-sous-Bois, where 77% of children aged of 18 or less have at least one parent of foreign ascent.

Figure 4.4. Multidimensional poverty in selected French regions



Note: The figure above shows the multi-dimensionally poor communes in selected regions in France. Top panel shows the regions in Northern France. Bottom left and right panels show the functional urban areas of Marseille and Paris respectively.

5 Conclusion

Several reports have already tried to assess multidimensional deprivation in France, but only by taking one dimension at the time: housing (ONPES, 2017[39]), income and revenues (Sénat, 2008[40]), and some attempts of combining different indicators of social inequalities have been made (INSEE, 2017[34]), but no study has examined inequalities in living conditions at the commune level in France.

The main contribution of this paper is the measurement of well-being at the city-level in France, while focusing on 7 of the 11 key dimensions of the Better Life Initiative (income, unemployment, housing, education, civic engagement, health and environmental quality). A geospatial database is built for about 35 000 communes and municipal districts, while drawing from several sources. An aggregated “Better Life Index” is calculated for each city, as well as an index of multi-dimensional poverty.

The results show joint deprivation across at least 5 dimensions of well-being is starkly concentrated among 316 communes, where around 5.2 million inhabitants live (7.7% of the French population). All communes that concentrate multi-dimensional poverty are listed and constitute a priority for policy intervention.

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Annex A. Computing life expectancy at commune-level

On a first step, the total mortality rates by age are estimated for every French commune. To obtain life expectancy, we build an abridged life table following Chiang's method (Chiang and World Health Organization, 1979[24]). The choice of this method relies on discussions over different methods for estimating life expectancy (Eayres and Williams, 2004[41]).

The mortality rate is the total number of deaths per 1 000 inhabitants. The database "Naissances, décès et mariages en 2017" (INSEE, 2017[42]) contains the number of localised deaths in every city from 2011 to 2017, with data coming from the civil registries. The number of deaths is a Poisson random process whose underlying parameter is the mortality rate:

$$D_c \sim \mathcal{P}(m_c \times P_c)$$

where D_c, m_c and P_c denote respectively the number of deaths, the mortality rate and the population in city c. A first-hand estimator of the total mortality rate is given by:

$$m_c = \frac{D_c}{P_c}$$

This estimator works well at Department level or with communes of large population that record a large number of deaths, over which the law of large numbers applies. In smaller communes, the quality of the estimator drops due to small sample issues, and statistical aberrations are encountered. The following treatments are applied to the data in order to calculate life expectancy at the commune level, including in small communes.

First, the raw data is filtered as total mortality rates are predicted from a regression on all other variables observed at the commune-level, which has the following form:

$$\log \mathbf{m} = X\beta + \rho W . \log \mathbf{m} + \epsilon \qquad \text{(A1)}$$

where **m** is the column vector of total mortality rates, X is the set of city-level observed characteristics, and W is a matrix accounting for the spatial correlations between the mortality rates of neighbouring communes. This is done by using the maximum likelihood estimation of the spatial lag model using the spreg.ML_Lag function of the Python Spatial Analysis Library, using as a weighting matrix (queen contiguity-based weights) the adjacency matrix of the communes in France. The following Table reports the results and shows a significant positive association with unemployment, a negative association with education and civil engagement, a modest spatial autocorrelation equal to 0.08, and a good predictive power of the model with an R^2 of 0.419.

Table A A.1. Mortality rates predicted from commune-level variables

	OLS model	Spatial Model
Unemployment	0.93*** (-0.04)	0.92*** (0.04)
Education	-1.3*** (-0.023)	-1.29*** (0.023)
Income	0.01*** (-0.001)	0.01*** (0.001)
Voting	-0.59*** (-0.038)	-0.61*** (0.038)
Housing	0.41*** (-0.008)	0.4*** (0.008)
Air pollution	-0.1*** (-0.011)	-0.08*** (0.011)
Mortality	-	0.08*** (0.007)
Age share % (0-4)	0.94*** (-0.084)	0.93*** (0.084)
Age share % (5-9)	1.1*** (-0.08)	1.08*** (0.079)
Age share % (10-14)	1.09*** (-0.078)	1.08*** (0.077)
Age share % (15-19)	1.13*** (-0.08)	1.11*** (0.08)
Age share % (20-24)	1.76*** (-0.083)	1.75*** (0.083)
Age share % (25-29)	2.06*** (-0.076)	2.04*** (0.076)
Age share % (30-34)	1.96*** (-0.076)	1.93*** (0.076)
Age share % (35-39)	1.76*** (-0.076)	1.74*** (0.076)
Age share % (40-44)	1.84*** (-0.073)	1.81*** (0.073)
Age share % (45-49)	1.86*** (-0.069)	1.83*** (0.069)
Age share % (50-54)	1.94*** (-0.066)	1.91*** (0.066)
Age share % (55-59)	2.03*** (-0.065)	1.99*** (0.065)
Age share % (60-64)	2.15*** (-0.065)	2.11*** (0.065)
Age share % (65-69)	2.33*** (-0.065)	2.29*** (0.065)
Age share % (70-74)	2.35*** (-0.071)	2.31*** (0.071)
Age share % (75-79)	2.67*** (-0.076)	2.63*** (0.076)
Age share % (80-84)	3.22*** (-0.08)	3.17*** (0.08)
Age share % (85-89)	3.99*** (-0.09)	3.95*** (0.09)
Age share % (90-94)	6.49*** (-0.135)	6.43*** (0.135)

Observations	35 392	35 392
R2 (pseudo)	0.416	0.419

Note: Estimation results of mortality rates predicted from commune-level variables where the dependant variable is the log of mortality per 1 000 people in commune *i*. Column 1 presents the results using OLS while columns 2 shows the results of a spatial lag model estimated by maximum likelihood. The variable voter turnout is defined as the number of voters in the first round of the French 2017 election divided by the number of registered voters. Education is represented by the share of the population holding at least a secondary education diploma. Income is represented by the 2017 annual median income (log) per unit of consumption of the commune. Housing is represented by the number of rooms per person. The unemployment rate is defined as the number of unemployed adults aged 15 to 64 divided by the active population over the same age span for the year 2017. Health is represented by life expectancy at birth. Air pollution is represented as the 2017 ground-level air concentration in PM2.5 in µg per cubic meter. The r-square reported for model in column 2 is the pseudo-R2. Control variables include the share of each age group (1-19). Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Second, mortality rates by age are derived at the commune level with the help of department- level data. The mortality rate in the k-th age interval at department level, denoted by m_d^k, is obtained by dividing the number of deaths in this age interval by the population of the same interval, also available in the civil registries. Because the population of French departments is at least 120 000 inhabitants, this estimator is considered to be accurate. We also compute the total mortality rate for each department, denoted as m_d.

Mortality rates by age at the commune-level are derived from mortality rates by age observed at the department level with the help of an auxiliary model. A classical way of representing the age profile of mortality rate is to use an exponential law: for the k-th age interval (except the first one, which represents infant mortality), the mortality rate has the form $m^k = \exp\,(a + b \times \text{age}_k)$ where age_k is the middle age of the interval and a and b are constants; *a* represents baseline effects for mortality. One assumes that a and b are both specific to the department or to the city, but that at the maximum age $T = 100$ years, all mortality rates are equal within each department. This assumption refers to the convergence of mortality rates at old age, which is observed across both gender and education groups (Murtin, 2021[43]).

For the k-th age interval in city *c* and in department *d,* one has respectively:

$$m_c^k = \exp(a_c + b_c \times \text{age}_k)$$

$$m_d^k = \exp(a_d + b_d \times \text{age}_k)$$

The constraint of equal mortality rates at age T yields:

$$b_c = b_d + (a_d - a_c)/T$$

It follows that:

$$m_c^k = \exp\left(a_c + b_d \times \text{age}_k + (a_d - a_c) \times \frac{\text{age}_k}{T}\right)$$

$$m_c^k = \exp\left(a_d + b_d \times \text{age}_k + (a_c - a_d) \times \left(1 - \frac{\text{age}_k}{T}\right)\right)$$

$$m_c^k = m_d^k . \lambda_{c,d}{}^{1-\frac{\text{age}_k}{T}} \quad \text{with } \lambda_{c,d} = \exp(a_c - a_d) \quad \text{(A2)}$$

Then, one uses the empirical model described above by equation (A1) to predict the counterfactual total mortality rate $\widetilde{m_c}$ in commune *c*, while assuming the age structure of the department *d* (rather than that of the city). This predicted mortality rate is the one that would be observed in city c if it had the same age structure as the department. Formally, it is given by

$$\log \widetilde{m_c} = \widetilde{X_c}\hat{\beta} + \hat{\rho} W_c \,.\log \mathbf{m_c}$$

where $(\widehat{\beta}, \hat{\rho})$ are estimated from equation (A1), $\widetilde{X_c}$ is the set of commune *c* explanatory factors including the counter-factual department-level demographic variables, $(W_c, \mathbf{m_c})$ are the spatial matrix and neighbouring mortality rates of commune *c*.

Interestingly, this predicted total mortality rate can be decomposed as the weighted sum of city-level mortality rates weighted by department-level age structure. Applying equation (A2) then yields:

$$\widetilde{m_c} = \sum_k m_c^k . \frac{P_d^k}{P_d} = \sum_k m_d^k . \frac{P_d^k}{P_d} . \lambda_{c,d}{}^{1-\frac{\text{age}_k}{T}}$$

where P_d^k denotes population of age *k* in department *d* and P_d total population in department *d*. The quantity $\lambda_{c,d}$ is close to 1 so a first-order approximation is

$$\lambda_{c,d}{}^{1-\frac{\text{age}_k}{T}} = \exp\left(\left(1 - \frac{\text{age}_k}{T}\right).\ln(\lambda_{c,d})\right) \approx 1 + \left(1 - \frac{\text{age}_k}{T}\right).\ln(\lambda_{c,d})$$

The commune-level mortality equation then becomes:

$$\widetilde{m_c} = \sum_k m_d^k . \frac{P_d^k}{P_d} + \ln(\lambda_{c,d}) . \sum_k m_d^k . \frac{P_d^k}{P_d} . \left(1 - \frac{\text{age}_k}{T}\right)$$

$$\widetilde{m_c} = m_d + \ln(\lambda_{c,d}) . (m_d - \widetilde{m}_d) \text{ with } \widetilde{m}_d = \sum_k m_d^k . \frac{P_d^k}{P_d} . \frac{\text{age}_k}{T}$$

$\lambda_{c,d} = \exp\left(\frac{\widetilde{m_c} - m_d}{m_d - \widetilde{m}_d}\right)$ (A3)

Equation (A3) provides an estimate of the correction factor $\lambda_{c,d}$, and therefore of mortality by age m_c^k in commune *c* from equation (A3). Estimates of these mortality rates by age arise from two operations: i) a regularization of total mortality at city level with the help of an empirical model with spatial effects; ii) the age standardization of the city mortality rate with the help of the departmental age distribution and the empirical model. The distribution of estimated $\lambda_{c,d}$ is censored at percentiles 5% and 95% to eliminate extreme values.

On a second stage, abridged life tables are constructed at the city level. The first step is to calculate the probability that an individual will die in the *k*-th age interval:

$q_k = \frac{n_k m_c^k}{1 + (1 - a_k) n_k m_c^k}$ (A4)

where a_k is the average fraction of the interval which people died have lived and n_k is the width of the age interval. For a_k is equal to 0.1 for the first age interval (following WHO guidelines, infant mortality in France being lower than 20‰), 0.4 for the next four (for ages 1 to 4, 5 to 9, 10 to 14 and 15 to 19) and 0.5 for the following intervals. We fix the probability of dying in the last age interval, q_{20}, to 1. The values for n_k are 1 for the first interval, 4 for the second and 5 for all the following intervals.

Based on the probability of dying specified in equation (A4), a cohort of 100 000 persons is simulated and one computes how many of them will die in each age interval. The number of living individuals at the beginning of the k-th age interval l_k is given by:

$$l_0 = 100\ 000$$
$$l_{k+1} = l_k(1 - q_k) = l_k - d_k$$

where d_k is the number of deaths in the same age interval. Using this number, one computes the total number of years lived by individuals in this age interval:

$$L_k = n_k(l_k - d_k) + a_k n_k d_k$$

For the last age interval, one imposes $q_{20} = 1$. Finally, we can compute the total number of years lived by individuals from the artificial cohort attaining the starting age of the *k*-th age interval, T_k and the observed life expectancy the age starting the *k*-th age interval, e_k as follows:

$$T_k = \sum_{k}^{20} L_k$$
$$e_k = \frac{T_k}{l_k}$$

A third and final data treatment is operated: in each department, department-level life expectancy at birth is calculated based on: i) observed department-level mortality rates by age m_d^k, which are deemed to yield an accurate life expectancy measure LE_d^0 ; ii) estimated commune-level mortality-rates by age m_c^k derived from equations (A2) and (A3), which are re-aggregated across communes and yield a noisy life expectancy measure LE_d^*. To eliminate the discrepancy between LE_d^0 and LE_d^*, the adjustment factors $\lambda_{c,d}$ are corrected by a department-level factor θ_d estimated via a minimum distance estimator, where the minimized distance criterion yields for each department $\theta_d^* = \underset{\theta_d}{\operatorname{argmin}}\left|LE_d^*(\lambda_{c,d}.\theta_d) - LE_d^0\right|$. At least two reasons suggest that the adjustment factors $\lambda_{c,d}$ may be noisy: i), they rely on noisy estimates of total mortality rates at commune-level $\widetilde{m_c}$, despite their regularization operated by the spatial econometric model; ii) they are derived from a first-order approximation that implies a residual factor.

Nevertheless, at the end of all data treatments, the obtained commune-level life expectancy measures are consistent with data aggregation at the department level and reflect some local variations in mortality as captured by the $\widetilde{m_c}$ quantity. Of course, some caveats apply to this methodology. First, the set of predictors in the empirical model (A1) was chosen based on studies investigating the key drivers of life expectancy at county level in the USA as in (Dwyer-Lindgren et al., 2017[44]) and (Chetty et al., 2016[45]). Unfortunately, some of the factors highlighted in the studies, such as the share of population under the poverty line, ethnic statistics, obesity rate or smoking prevalence are not available at the commune level in France. Second, following the discussion of (Eayres and Williams, 2004[41]), uncertainty surrounding commune-level life expectancy estimates is high given the small size of communes in France. A size of 5 000 population-years at risk is considered to be reasonable, but most communes in France are smaller than 500 population-years at risk. Finally, the life expectancy indicator itself can be challenged when calculated at the commune-level. This indicator can be useful at the country level, or even at regional level, because these are spatial units that are large enough for people to spend their entire life without leaving it. An issue with the commune spatial unit is that it is a very small administrative division, and often people don not spend most of their time in the city there are living in, but in a neighbouring city where they work for instance.

Annex B. Multi-dimensionally poor communes

Table A B.1. List of multi-dimensionally poor communes

City code	Department	Department name	City name	Population
1283	12	Ain	Oyonnax	22 529
2059	20	Aisne	Beautor	2 689
2095	20	Aisne	Bohain-En-Vermandois	5 619
2168	21	Aisne	Château-Thierry	14 856
2173	21	Aisne	Chauny	11 959
2275	22	Aisne	Effry	318
2304	23	Aisne	Fère	2 829
2381	23	Aisne	Hirson	8 955
2408	24	Aisne	Laon	25 173
2684	26	Aisne	Saint-Michel	3 457
2691	26	Aisne	Saint-Quentin	54 337
2722	27	Aisne	Soissons	28 427
2738	27	Aisne	Tergnier	13 525
3125	31	Allier	Guillermie	120
8067	80	Ardennes	Blagny	1 225
8081	80	Ardennes	Bogny-Sur-Meuse	5 126
8090	80	Ardennes	Carignan	2 887
8105	81	Ardennes	Charleville-Mézières	46 637
8172	81	Ardennes	Fligny	165
8185	81	Ardennes	Fumay	3 462
8190	81	Ardennes	Givet	6 734
8195	81	Ardennes	Gomont	320
8242	82	Ardennes	Laifour	438
8323	83	Ardennes	Neuville-Lès-Wasigny	175
8328	83	Ardennes	Nouzonville	5 883
8362	83	Ardennes	Rethel	7 676
8363	83	Ardennes	Revin	6 424
8367	83	Ardennes	Rocroi	2 337
8409	84	Ardennes	Sedan	16 840
8486	84	Ardennes	Vireux-Molhain	1 518
9160	91	Ariège	Lavelanet	6 225
10033	100	Aube	Bar-Sur-Aube	4 913
10034	100	Aube	Bar-Sur-Seine	3 025
10081	100	Aube	Chapelle-Saint-Luc	12 775
10265	102	Aube	Noës-Près-Troyes	3 220
10323	103	Aube	Romilly-Sur-Seine	14 437
13077	130	Bouches-du-Rhône	Port-De-Bouc	16 651
14167	141	Calvados	Colombelles	6 775
14478	144	Calvados	Orbec	2 082
16128	161	Charente	Épenède	181
18106	181	Cher	Grossouvre	275

18279	182	Cher	Vierzon	26 356
23008	230	Creuse	Aubusson	3 385
23105	231	Creuse	Lavaveix-Les-Mines	686
25057	250	Doubs	Bethoncourt	5 681
27116	271	Eure	Brionne	4 324
27275	272	Eure	Gaillon	7 004
27375	273	Eure	Louviers	18 509
27467	274	Eure	Pont-Audemer	10 392
27701	277	Eure	Val-De-Reuil	13 258
28134	281	Eure-et-Loir	Dreux	30 942
28404	284	Eure-et-Loir	Vernouillet	12 473
33249	332	Gironde	Lormont	23 207
38151	381	Isère	Échirolles	35 839
42183	421	Loire	Ricamarie	7 915
51423	514	Marne	Pargny-Sur-Saulx	1 887
52250	522	Haute-Marne	Joinville	3 147
52448	524	Haute-Marne	Saint-Dizier	24 915
52512	525	Haute-Marne	Vecqueville	555
54028	540	Meurthe-et-Moselle	Auboué	2 433
54129	541	Meurthe-et-Moselle	Cirey-Sur-Vezouze	1 640
54323	543	Meurthe-et-Moselle	Longwy	14 688
54382	543	Meurthe-et-Moselle	Mont-Saint-Martin	8 593
54425	544	Meurthe-et-Moselle	Piennes	2 475
54540	545	Meurthe-et-Moselle	Val-Et-Châtillon	597
55292	552	Meuse	Liny-Devant-Dun	175
57058	570	Moselle	Behren-Lès-Forbach	6 629
57160	571	Moselle	Creutzwald	13 168
57207	572	Moselle	Farébersviller	5 505
57224	572	Moselle	Folschviller	4 010
57227	572	Moselle	Forbach	21 601
57240	572	Moselle	Freyming-Merlebach	12 984
57332	573	Moselle	Hombourg-Haut	6 588
57483	574	Moselle	Morhange	3 472
57491	574	Moselle	Moyeuvre-Grande	7 751
57660	576	Moselle	Stiring-Wendel	11 967
57683	576	Moselle	Uckange	6 780
57751	577	Moselle	Woippy	14 096
58079	580	Nièvre	Clamecy	3 816
58117	581	Nièvre	Fourchambault	4 215
58170	581	Nièvre	Monceaux-Le-Comte	110
59002	590	Nord	Abscon	4 425
59008	590	Nord	Aniche	10 282
59012	590	Nord	Anor	3 216
59014	590	Nord	Anzin	13 408
59017	590	Nord	Armentières	24 988
59028	590	Nord	Auby	7 268
59036	590	Nord	Avesnes-Sur-Helpe	4 619
59079	590	Nord	Beuvrages	6 634
59112	591	Nord	Bruay-Sur-L'escaut	11 616
59139	591	Nord	Caudry	14 464
59153	591	Nord	Condé-Sur-L'escaut	9 706
59170	591	Nord	Dechy	5 323
59172	591	Nord	Denain	19 695

59178	591	Nord	Douai	39 617
59179	591	Nord	Douchy-Les-Mines	10 698
59185	591	Nord	Écaillon	1 945
59205	592	Nord	Escaudain	9 596
59207	592	Nord	Escautpont	4 173
59234	592	Nord	Flers-En-Escrebieux	5 821
59249	592	Nord	Fourmies	12 111
59253	592	Nord	Fresnes-Sur-Escaut	7 582
59271	592	Nord	Grande-Synthe	23 268
59276	592	Nord	Guesnain	4 624
59291	592	Nord	Hautmont	14 519
59292	592	Nord	Haveluy	3 145
59324	593	Nord	Jeumont	10 135
59327	593	Nord	Lallaing	6 170
59361	593	Nord	Lourches	3 925
59365	593	Nord	Louvroil	6 518
59385	593	Nord	Marpent	2 737
59390	593	Nord	Masny	4 082
59392	593	Nord	Maubeuge	29 654
59410	594	Nord	Mons-En-Baroeul	20 829
59418	594	Nord	Mortagne-Du-Nord	1 622
59447	594	Nord	Onnaing	8 832
59452	594	Nord	Ostricourt	5 385
59456	594	Nord	Pecquencourt	5 974
59484	594	Nord	Quiévrechain	6 375
59491	594	Nord	Raismes	12 613
59495	594	Nord	Recquignies	2 354
59504	595	Nord	Roeulx	3 830
59512	595	Nord	Roubaix	96 379
59569	595	Nord	Sin-Le-Noble	15 427
59574	595	Nord	Somain	12 465
59599	595	Nord	Tourcoing	97 449
59601	596	Nord	Trélon	2 899
59606	596	Nord	Valenciennes	43 674
59616	596	Nord	Vieux-Condé	10 372
59650	596	Nord	Wattrelos	41 316
59651	596	Nord	Wavrechain-Sous-Denain	1 616
59654	596	Nord	Waziers	7 497
60057	600	Oise	Beauvais	56 004
60104	601	Oise	Breteuil	4 433
60175	601	Oise	Creil	35 713
60221	602	Oise	Esquennoy	715
60233	602	Oise	Feuquières	1 427
60286	602	Oise	Grandvilliers	2 956
60395	603	Oise	Méru	14 620
60414	604	Oise	Montataire	13 335
60463	604	Oise	Nogent-Sur-Oise	19 565
60471	604	Oise	Noyon	13 608
60684	606	Oise	Villers-Saint-Paul	6 366
61169	611	Orne	Flers	14 738
61333	613	Orne	Pontchardon	203
61508	615	Orne	Vimoutiers	3 393
62048	620	Pas-de-Calais	Auchel	10 422

62083	620	Pas-de-Calais	Barlin	7 724
62119	621	Pas-de-Calais	Béthune	25 166
62133	621	Pas-de-Calais	Billy-Montigny	8 145
62139	621	Pas-de-Calais	Blendecques	4 999
62160	621	Pas-de-Calais	Boulogne-Sur-Mer	41 650
62178	621	Pas-de-Calais	Bruay-La-Buissière	22 209
62186	621	Pas-de-Calais	Bully-Les-Mines	12 271
62193	621	Pas-de-Calais	Calais	74 965
62194	621	Pas-de-Calais	Calonne-Ricouart	5 505
62270	622	Pas-de-Calais	Divion	6 903
62318	623	Pas-de-Calais	Étaples	11 001
62321	623	Pas-de-Calais	Évin-Malmaison	4 582
62351	623	Pas-de-Calais	Fouquières-Lès-Lens	6 330
62386	623	Pas-de-Calais	Grenay	6 888
62400	624	Pas-de-Calais	Haillicourt	4 895
62427	624	Pas-de-Calais	Hénin-Beaumont	25 891
62447	624	Pas-de-Calais	Hesdin	2 200
62498	624	Pas-de-Calais	Lens	30 667
62510	625	Pas-de-Calais	Liévin	30 900
62516	625	Pas-de-Calais	Lillers	9 893
62525	625	Pas-de-Calais	Longuenesse	11 002
62555	625	Pas-de-Calais	Marles-Les-Mines	5 568
62563	625	Pas-de-Calais	Mazingarbe	8 041
62570	625	Pas-de-Calais	Méricourt	11 670
62587	625	Pas-de-Calais	Montigny-En-Gohelle	10 163
62617	626	Pas-de-Calais	Noeux-Les-Mines	11 988
62628	626	Pas-de-Calais	Noyelles-Sous-Lens	6 683
62637	626	Pas-de-Calais	Oignies	9 688
62724	627	Pas-de-Calais	Rouvroy	8 687
62765	627	Pas-de-Calais	Saint-Omer	14 426
62771	627	Pas-de-Calais	Sallaumines	9 791
62895	628	Pas-de-Calais	Wingles	8 755
62907	629	Pas-de-Calais	Libercourt	8 345
66137	661	Pyrénées-Orientales	Perthus	588
67447	674	Bas-Rhin	Schiltigheim	31 820
68224	682	Haut-Rhin	Mulhouse	108 945
69091	690	Rhône	Givors	19 288
69199	691	Rhône	Saint-Fons	18 542
69256	692	Rhône	Vaulx-En-Velin	48 468
69259	692	Rhône	Vénissieux	65 371
70279	702	Haute-Saône	Gray	5 463
70308	703	Haute-Saône	Longine	225
70467	704	Haute-Saône	Saint-Loup-Sur-Semouse	3 235
70550	705	Haute-Saône	Vesoul	14 926
72180	721	Sarthe	Mamers	5 299
76231	762	Seine-Maritime	Elbeuf	16 486
76295	762	Seine-Maritime	Gaillefontaine	1 250
76312	763	Seine-Maritime	Gournay-En-Bray	6 152
76384	763	Seine-Maritime	Lillebonne	8 957
76711	767	Seine-Maritime	Tréport	4 905
77257	772	Seine-et-Marne	Lizy-Sur-Ourcq	3 584
77285	772	Seine-et-Marne	Mée-Sur-Seine	20 731
77305	773	Seine-et-Marne	Montereau-Fault-Yonne	19 340

78138	781	Yvelines	Chanteloup-Les-Vignes	10 369
78361	783	Yvelines	Mantes-La-Jolie	43 976
78440	784	Yvelines	Mureaux	32 559
80001	800	Somme	Abbeville	23 195
80016	800	Somme	Albert	9 927
80253	802	Somme	Doullens	6 247
80410	804	Somme	Ham	4 620
80620	806	Somme	Péronne	7 610
80658	806	Somme	Quivières	124
80748	807	Somme	Templeux-Le-Guérard	164
84035	840	Vaucluse	Cavaillon	26 450
88304	883	Vosges	Mirecourt	5 245
88327	883	Vosges	Nomexy	2 110
88367	883	Vosges	Rambervillers	5 295
88372	883	Vosges	Raon-L'étape	6 395
88413	884	Vosges	Saint-Dié-Des-Vosges	19 729
88468	884	Vosges	Thillot	3 465
89005	890	Yonne	Ancy-Le-Franc	889
89025	890	Yonne	Avallon	6 773
89055	890	Yonne	Brienon-Sur-Armançon	3 151
89206	892	Yonne	Joigny	9 832
89257	892	Yonne	Migennes	7 136
89345	893	Yonne	Saint-Florentin	4 430
89387	893	Yonne	Sens	25 917
89418	894	Yonne	Tonnerre	4 717
89461	894	Yonne	Villeneuve-L'archevêque	1 120
89481	894	Yonne	Vireaux	145
91286	912	Essonne	Grigny	28 940
92036	920	Hauts-de-Seine	Gennevilliers	46 615
92078	920	Hauts-de-Seine	Villeneuve-La-Garenne	24 221
93001	930	Seine-Saint-Denis	Aubervilliers	86 032
93005	930	Seine-Saint-Denis	Aulnay-Sous-Bois	84 637
93007	930	Seine-Saint-Denis	Blanc-Mesnil	55 969
93008	930	Seine-Saint-Denis	Bobigny	52 321
93010	930	Seine-Saint-Denis	Bondy	53 173
93013	930	Seine-Saint-Denis	Bourget	16 451
93014	930	Seine-Saint-Denis	Clichy-Sous-Bois	29 820
93027	930	Seine-Saint-Denis	Courneuve	42 459
93029	930	Seine-Saint-Denis	Drancy	70 250
93030	930	Seine-Saint-Denis	Dugny	10 632
93031	930	Seine-Saint-Denis	Épinay-Sur-Seine	55 572
93039	930	Seine-Saint-Denis	Île-Saint-Denis	7 760
93059	930	Seine-Saint-Denis	Pierrefitte-Sur-Seine	29 583
93063	930	Seine-Saint-Denis	Romainville	26 489
93066	930	Seine-Saint-Denis	Saint-Denis	111 307
93071	930	Seine-Saint-Denis	Sevran	50 627
93072	930	Seine-Saint-Denis	Stains	39 596
93078	930	Seine-Saint-Denis	Villepinte	36 640
93079	930	Seine-Saint-Denis	Villetaneuse	13 114
94011	940	Val-de-Marne	Bonneuil-Sur-Marne	17 421
94074	940	Val-de-Marne	Valenton	14 839
94078	940	Val-de-Marne	Villeneuve-Saint-Georges	32 936
95268	952	Val-d'Oise	Garges-Lès-Gonesse	42 573

95585	955	Val-d'Oise	Sarcelles	57 757
95680	956	Val-d'Oise	Villiers-Le-Bel	27 228
97201	972	Martinique	Ajoupa-Bouillon	1 892
97202	972	Martinique	Anses-D'arlet	3 630
97203	972	Martinique	Basse-Pointe	3 188
97208	972	Martinique	Fonds-Saint-Denis	761
97209	972	Martinique	Fort-De-France	80 990
97210	972	Martinique	François	17 174
97211	972	Martinique	Grand'rivière	686
97212	972	Martinique	Gros-Morne	9 871
97213	972	Martinique	Lamentin	40 157
97214	972	Martinique	Lorrain	6 884
97215	972	Martinique	Macouba	1 075
97216	972	Martinique	Marigot	3 258
97217	972	Martinique	Marin	8 810
97218	972	Martinique	Morne-Rouge	5 105
97219	972	Martinique	Prêcheur	1 345
97220	972	Martinique	Rivière-Pilote	12 133
97221	972	Martinique	Rivière-Salée	12 070
97222	972	Martinique	Robert	23 241
97223	972	Martinique	Saint-Esprit	9 420
97224	972	Martinique	Saint-Joseph	16 327
97225	972	Martinique	Saint-Pierre	4 088
97226	972	Martinique	Sainte-Anne	4 165
97228	972	Martinique	Sainte-Marie	16 158
97230	972	Martinique	Trinité	12 488
97232	972	Martinique	Vauclin	9 027
97234	972	Martinique	Bellefontaine	1 623
97301	973	Guyane	Régina	901
97302	973	Guyane	Cayenne	60 531
97303	973	Guyane	Iracoubo	1 835
97304	973	Guyane	Kourou	26 506
97305	973	Guyane	Macouria	12 727
97306	973	Guyane	Mana	10 520
97307	973	Guyane	Matoury	32 436
97308	973	Guyane	Saint-Georges	4 067
97309	973	Guyane	Remire-Montjoly	25 700
97310	973	Guyane	Roura	3 701
97311	973	Guyane	Saint-Laurent-Du-Maroni	43 769
97312	973	Guyane	Sinnamary	2 975
97313	973	Guyane	Montsinéry-Tonnegrande	2 544
97314	973	Guyane	Ouanary	196
97352	973	Guyane	Saül	153
97353	973	Guyane	Maripasoula	12 759
97356	973	Guyane	Camopi	1 735
97357	973	Guyane	Grand-Santi	7 497
97358	973	Guyane	Saint-Élie	125
97360	973	Guyane	Apatou	8 750
97361	973	Guyane	Awala-Yalimapo	1 370
97362	973	Guyane	Papaichton	8 017
97402	974	Réunion	Bras-Panon	12 706
97406	974	Réunion	Plaine-Des-Palmistes	6 315
97407	974	Réunion	Port	34 794

97409	974	Réunion	Saint-André	55 610
97410	974	Réunion	Saint-Benoît	38 140
97411	974	Réunion	Saint-Denis	147 909
97413	974	Réunion	Saint-Leu	33 667
97414	974	Réunion	Saint-Louis	53 183
97415	974	Réunion	Saint-Paul	105 456
97416	974	Réunion	Saint-Pierre	84 168
97418	974	Réunion	Sainte-Marie	33 124
97420	974	Réunion	Sainte-Suzanne	23 188
97423	974	Réunion	Trois-Bassins	7 089