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Determinants of life-expectancy and disability-adjusted life years (DALYs) in European and Organisation for Economic Co-operation and Development (OECD) countries: A longitudinal analysis (1990–2019)

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1. Introduction

Population health has long been the focus of multidisciplinary research. In economics, for example, health is considered an integral part of human capital (Bloom, Canning, & Sevilla, 2004; R. Sharma, 2018), which, in turn, is thought instrumental for economic development, even though clear causality has not been established (Acemoglu & Johnson, 2007; Lopez-Casasnovas & Soley-Bori, 2014; R. Sharma, 2018). Over the last few decades, cross-country studies have investigated potential determinants of population health starting with national income and healthcare system resources, to gradually include other macro-level socio-economic factors as well. It is generally believed that these factors and the causal mechanisms at play may differ according to level of development and wealth, and it has, thus, been customary to focus research on a particular category of development (Boehmer & Williamson, 1996; Mackenbach & Looman, 2013).

Life-expectancy at birth (LEB), or the average number of years someone born today is expected to live provided current mortality conditions persist, is the most widely used indicator to capture population health. Higher LEB is widely considered to represent overall better health status and lower mortality (Murray & Lopez, 1997). Despite exogenous shocks caused by war and pandemics, resource-rich countries recorded more rapid growth in LEB in the last century and a half than in all of the rest of human history (Currow & Soyiri, 2019). In recent years, however, this improvement has been slowing down globally, including in high-income countries (HIC), such as Organisation for Economic Co-operation and Development (OEDC) and European countries (Currow & Soyiri, 2019; OECD, 2019). This, and the observed LEB variations within the same (high-) income class (Amiri & Solankallio-Vahteri, 2019; Zare, Gaskin, & Anderson, 2015), underpins the need for more research to better understand the importance of potential drivers behind these health production differences between countries over time. LEB as a measure has been very useful, especially in cross-national research (Riley, 2001; Sen, 2000), but there have been calls for the wider use of a "new generation" of health indicators (Kindig, 1998) that look beyond just mortality and reflect health-related quality of life as well. The disability-adjusted life years (DALYs) is such a measure. Developed by The World Bank (TWB) and World Health Organization (WHO) in 1993 for the Global Burden of Disease study (GBD) (Evaluation, 2023), it is meant to capture the gap between population health and its hypothetical ideal (Gold, Stevenson, & Fryback, 2002). It is calculated as a weighted average of LEB, the value of life at different ages, the value of future time, and the value of avoiding disability (Fox-Rushby, 2002). In essence (and unlike LEB), it is a measure of loss and its minimization is, therefore, desired. The DALY is considered an important comprehensive index of population health (Dragos, Mare, Dragos, Muresan, & Purcel, 2022) as it combines both longevity and the impact of disease, injury, and disability on human quality of life. It has been and continues to be used extensively to make comparisons between countries and regions.

Multi-country quantitative research of determinants of population health in HIC is usually limited by focusing on a very small number of jointly considered determinants (Gracia-de-Rentería, Ferrer-Pérez, Sanjuán, & Philippidis, 2022; Varbanova & Beutels, 2019), and applies a relatively basic repertoire of analytical techniques (Varbanova & Beutels, 2019) while leaving the increasing abundance of currently available data largely unexplored. Nonetheless, the determinants that have been investigated as if only few other determinants influence LEB are diverse in nature – including demographic, healthcare, life-style, political, psychological, socio-economic, and cultural factors (Varbanova & Beutels, 2019). With the present study we aimed to address the forementioned shortcomings of previous research, by investigating the effects of a large number of national-level determinants simultaneously, via rigorous statistical methodology, in order to identify the most important determinants influencing population health differences

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between relatively wealthy countries over time.

2. Material and methods

Our selection of countries included all 61 European and OECD member states. We show country rankings according to gross national income (GNI) for 2019 (the last year we considered) in Appendix A. As per TWB's classification by income level (Serajuddin & Hamadeh, 2020) from the 1st of July 2020 (to be applied to 2019 GNI), all but one country fall either in the "high-income" or the "upper-middle income" brackets. This selection enables us to collate a rich dataset from existing databases for both the outcomes and potential determinants, allowing for a thorough analytical approach. In a secondary analysis, we took a subset of strictly HIC (38 in total), in order to investigate possible differences in health production between the broader selection and this particular group of countries.

2.1. Outcome variables

We used LEB, as reported by the World Development Indicators database[1] of TWB (Bank, 2021), and DALYs (per 100 000 population), as provided by the Institute of Health Metrics and Evaluation[2] (Network, 2020), as outcome variables for this study. Annual entries for both were obtained for the 30-year period between 1990 and 2019. We decided not to include more recent data in order to avoid a possible confounding effect of the COVID-19 pandemic. Appendix B provides an interactive visualization of the longitudinal LEB and DALY profiles of the countries included in this study.

2.2. Covariates

We obtained data on a total of 68 national-level covariates. These variables reflected healthcare resources, economic, demographic, labor, education, politics, nutrition, life-style, social values, and cultural factors, and were sourced from public databases, such as WHO, OECD and TWB. A full list of this initial set of covariates is presented in Table 1.

2.3. Statistical analysis

Our initial dataset consisted of 2 outcome variables and 68 covariates, for 61 countries, over a 30-year time-span (1990–2019). The dataset had a 2-level structure, as the 6 Hofstede cultural indices are considered time-invariant and thus have just one value per country, instead of annual entries like the other variables. The effects of the 68 covariates were investigated separately for LEB and DALYs in the main branch of the analysis including all 61 European and OECD countries, and again in the secondary branch including only the 38 HIC.

The statistical analysis was completed in three stages, executed in turn for each outcome in each branch. In the first stage, we employed the random forests (RF) (Breiman, 2001) procedure as a variable-selection technique. Fine-tuning model parameters, we ran the procedure a total of 12 times (refer to Appendix C for full details on the statistical methods employed). In order to determine the most important covariates, we looked at the variable importance indicator and ranked covariates according to the number of times each appeared among the "top 25" variable importance scores. Only covariates that showed in the "top 25" in more than half of the procedure runs (7 or more out of 12 possible) were retained for further investigation. We refer to this criterion in the Results section as the "retention threshold".

In the second stage of the analysis, we performed multilevel multiple imputation (MI) in order to address the issue of missing data. At this point, we had 4 reduced datasets based on the outcome (LEB or DALYs)

[1] https://databank.worldbank.org/source/world-development-indicators.
[2] https://vizhub.healthdata.org/gbd-results/.

Table 1
Initial list of covariates.

	Variable	Possible values	Sources	Last accessed
1.	Birth rate, crude (per 1000 people)	numeric	TWB[a]	10.09.2021
2.	Community health workers* (per 1000 people)	numeric	TWB[a]	10.09.2021
3.	Current health expenditure (% of GDP)	numeric	TWB[a]	10.09.2021
4.	GDP per capita, PPP (current international $)	numeric	TWB[a]	10.09.2021
5.	Hospital beds (per 1000 people)	numeric	TWB[a]	10.09.2021
6.	Immunization, DPT* (% of children ages 12–23 months)	numeric (0–100)	TWB[a]	10.09.2021
7.	Labor force, female (% total labor force)	numeric (0–100)	TWB[a]	10.09.2021
8.	Nurses and midwives* (per 1000 people)	numeric	TWB[a]	10.09.2021
9.	Out-of-pocket healthcare expenditure* (proportion of population spending more than 25% of household consumption or income)	numeric (0–100)	TWB[a]	10.09.2021
10.	Physicians (per 1000 people)	numeric	TWB[a]	10.09.2021
11.	Population ages 15–64 (% of total)	numeric (0–100)	TWB[a]	10.09.2021
12.	Population ages 65 and above (% of total)	numeric (0–100)	TWB[a]	10.09.2021
13.	Population density (people per sq. km of land area)	numeric (0–100)	TWB[a]	10.09.2021
14.	Population growth (annual %)	numeric (0–100)	TWB[a]	10.09.2021
15.	Population, female (% of total population)	numeric (0–100)	TWB[a]	10.09.2021
16.	Population, total	numeric	TWB[a]	10.09.2021
17.	Poverty headcount ratio at national poverty lines* (% of population)	numeric (0–100)	TWB[a]	10.09.2021
18.	Research and development (R&D) (% of GDP; capital and current expenditures in the four main sectors: business enterprise, government, higher education, and private non-profit)	numeric (0–100)	TWB[a]	10.09.2021
19.	Surface area* (sq. km)	numeric	TWB[a]	10.09.2021
20.	Unemployment, total* (% of total labor force) (modeled ILO estimate)	numeric (0–100)	TWB[a]	10.09.2021
21.	Urban population (% of total)	numeric (0–100)	TWB[a]	10.09.2021
22.	Political stability and absence of violence/ terrorism	numeric (−2.5 to 2.5)	TWB[b]	06.12.2021
23.	Democracy (Polity2 index: revised combined Polity score = Institutionalized Democracy score - Institutionalized Autocracy score)	numeric (−10 to 10)	Center for Systemic Peace[c]	19.08.2021
24.	Economic freedom (the degree to which the policies and institutions of countries are supportive of economic freedom; ranking based on five areas: size of government, legal structure and	numeric (0–10)	Fraser Institute[d]	25.08.2021

(continued on next page)

Table 1 (*continued*)

	Variable	Possible values	Sources	Last accessed
	property rights, access to sound money, freedom to trade internationally, regulation of credit, labor and business)			
25.	Gini index of income inequality*	numeric (0–100)	UNU-WIDER[e]	25.08.2021
26.	Education* (average number of completed years of education, age 25+, excluding years spent repeating individual grades)	numeric	UNESCO[f]	24.11.2021
27.	Corruption perception index (CPI) (covers the following manifestations of public sector corruption: bribery; diversion of public funds; officials using their public office for private gain without facing consequences; ability of governments to contain corruption in the public sector; excessive red tape in the public sector which may increase opportunities for corruption; nepotistic appointments in the civil service; laws ensuring that public officials must disclose their finances and potential conflicts of interest; legal protection for people who report cases of bribery and corruption; state capture by narrow vested interests; access to information on public affairs/government activities)	numeric (0–100)	Transparency International[g]	16.06.2022
28.	Social expenditure (% of GDP; total for the main social policy areas: old age, survivors, incapacity-related benefits, health, family, active labor market programs, unemployment, housing, and other social policy areas)	numeric (0–100)	OECD[h]	31.08.2021
29.	Vegetables supply* (kilos per capita per year)	numeric	OECD[h]	08.09.2021
30.	Fruit supply* (kilos per capita per year)	numeric	OECD[h]	08.09.2021
31.	Total health care coverage; Government/ social health insurance (% of population)	numeric (0–100)	OECD[h]	15.06.2022
32.	Total health and social employment density (number of persons working in healthcare and social work, per 1000 population)	numeric	OECD[h]	24.09.2021
33.	Psychiatrists density (per 1000 population)	numeric	OECD[h]	24.09.2021
34.	Surgical group of specialists density (per 1000 population)	numeric	OECD[h]	24.09.2021
35.	Practising midwives density (per 1000 population)	numeric	OECD[h]	24.09.2021
36.	Practising physiotherapists density* (per 1000 population)	numeric	OECD[h]	24.09.2021
37.	Total hospital employment density (per 1000 population)	numeric	OECD[h]	24.09.2021
38.	Hospitals (per million population)	numeric	OECD[h]	24.09.2021
39.	Publicly owned hospitals (per million population)	numeric	OECD[h]	24.09.2021
40.	Beds in publicly owned hospitals (per 1000 population)	numeric	OECD[h]	24.09.2021
41.	Computed Tomography scanners (CAT) (total, per million population)	numeric	OECD[h]	24.09.2021
42.	Magnetic Resonance Imaging units (MRI) (total, per million population)	numeric	OECD[h]	24.09.2021
43.	Positron Emission Tomography scanners (PET) (total, per million population)	numeric	OECD[h]	24.09.2021
44.	Gamma cameras (total, per million population)	numeric	OECD[h]	24.09.2021
45.	Dentists* (per 10 000 population)	numeric	WHO[i]	15.09.2021
46.	Pharmacists* (per 10 000 population)	numeric	WHO[i]	15.09.2021
47.	Calories availability* (kcal per person per day)	numeric	WHO[#, j] OECD[h]	03.09.2021 08.09.2021
48.	Fat availability (grams per person per day)	numeric	WHO[#,j] OECD[h]	03.09.2021 08.09.2021
49.	Regular daily smokers* (% of the population, age 15+)	numeric (0–100)	WHO[#,j] OECD[h]	25.08.2021 08.09.2021
50.	Alcohol consumption* (in liters of pure alcohol; total per capita, age 15+)	numeric	WHO[#,i] TWB[l]	19.08.2021 10.09.2021
51.	Emancipative values index* (national culture's emphasis on freedoms in the domains of reproductive choice, gender equality, people's voice, and personal autonomy)	numeric (0–1)	WVS[k]	24.11.2021
52.	Secular values index* (national culture's secular distance to "sacred" sources of authority – religious, patrimonial, normative, and order institutions)	numeric (0–1)	WVS[k]	24.11.2021
53.	Social movement activities* (the extent to which the peaceful social movement activities of petitions, demonstrations, and boycotts are part of a national culture's action repertoire)	numeric (0–1)	WVS[k]	24.11.2021
54.	Informational connectedness* (the diversity of information sources used by the average individual in a nation)	numeric (0–1)	WVS[k]	24.11.2021
55.	Liberal understanding of democracy* (the extent to which people's	numeric (0–1)	WVS[k]	24.11.2021

(*continued on next page*)

Table 1 (*continued*)

	Variable	Possible values	Sources	Last accessed
	understanding of democracy is liberal in the sense that they define it "correctly" by its liberal, including free elections, civil liberties and equal rights)			
56.	Perceived democraticness of own country*	numeric (0–1)	WVS[k]	24.11.2021
57.	Perceived fairness of other people*	numeric (0–1)	WVS[k]	24.11.2021
58.	Standard trust towards unspecified other people*	numeric (0–1)	WVS[k]	24.11.2021
59.	Associational activity* (in recreational/ humanitarian/ environmental, church/ religious, political parties/labour unions/ professional associations)	numeric (0–1)	WVS[k]	24.11.2021
60.	Perceived health*	numeric (0–1)	WVS[k]	24.11.2021
61.	Perceived choice in shaping one's life*	numeric (0–1)	WVS[k]	24.11.2021
62.	Life satisfaction*	numeric (0–1)	WVS[k]	24.11.2021
63.	Power distance ("the degree to which the less powerful members of a society accept and expect that power is distributed unequally")	numeric (0–100)	Hofstede 6-D model of national culture[l]	26.11.2021
64.	Individualism (v Collectivism; "a preference for a loosely-knit social framework in which individuals are expected to take care of only themselves and their immediate families")	numeric (0–100)	Hofstede 6-D model of national culture[l]	26.11.2021
65.	Masculinity (v Femininity; "a preference in society for achievement, heroism, assertiveness, and material rewards for success")	numeric (0–100)	Hofstede 6-D model of national culture[l]	26.11.2021
66.	Uncertainty avoidance ("the degree to which the members of a society feel uncomfortable with uncertainty and ambiguity")	numeric (0–100)	Hofstede 6-D model of national culture[l]	26.11.2021
67.	Long-term orientation (v Short-term Orientation; the degree to which society holds the notion that the world "is in flux, and preparing for the future is always needed" as opposed to the view that "the world is essentially as it was created, so that the past provides a moral compass")	numeric (0–100)	Hofstede 6-D model of national culture[l]	26.11.2021
68.	Indulgence (v Restraint; the extent to which society "allows relatively free gratification of basic and natural human drives related to enjoying life and having fun")	numeric (0–100)	Hofstede 6-D model of national culture[l]	26.11.2021

Abbreviations: OECD = Organisation for Economic Co-operation and Development; TWB = The World Bank; UN = United Nations; UNESCO = United Nations Educational, Scientific and Cultural Organization; WHO = World Health Organization; WVS = World Values Survey.

[*] Variable not retained after the first, random forests, stage of the analysis.

[#] Primary source.

[a] https://databank.worldbank.org/source/world-development-indicators.

[b] http://info.worldbank.org/governance/wgi/.

[c] http://www.systemicpeace.org/inscrdata.html.

[d] https://www.fraserinstitute.org/economic-freedom/dataset?geozone=world&page=dataset&min-year=1970&max-year=2018&filter=1&date-type=range.

[e] https://www.wider.unu.edu/database/world-income-inequality-database-wiid.

[f] http://data.uis.unesco.org/#

[g] https://www.transparency.org/en/cpi/2020/index/nzl.

[h] https://stats.oecd.org/#

[i] https://www.who.int/data/gho.

[j] https://gateway.euro.who.int/en/datasets/european-health-for-all-database/.

[k] https://www.worldvaluessurvey.org/WVSNewsShow.jsp?ID=367&ID=367.

[l] https://geerthofstede.com/research-and-vsm/dimension-data-matrix/.

and branch of analysis (all 61 countries or 38 HIC). The number of covariates was reduced by over 60%, depending on the outcome and branch (see also Results section) and overall missingness now ranged from 23% to 32%. Before we could implement the multilevel multiple imputation, we had to standardize all variables to have a mean of 0 and a standard deviation of 1. Using multivariate imputation by chained equations (MICE) (van Buuren, 2011) predictive mean matching (PMM), we obtained 25 imputed datasets for each of the 4 reduced (incomplete) datasets. Each of these 25 imputed datasets for each of the 4 reduced datasets were then analyzed individually via generalized estimating equations (GEE) (Liang & Zeger, 1986), in the third stage of the analysis. The combination of MI and GEE, or MI-GEE, has been well-established in the statistical literature (Beunckens, Sotto, & Molenberghs, 2008; Birhanu, Molenberghs, Sotto, & Kenward, 2011). Finally, results from the 25 individual GEE models were pooled together for each outcome in each branch of the analysis in order to get an estimate for each covariate's effect (See Fig. 1 for a diagram of the multi-step analysis.).

3. Results

Table 2 shows the covariates retained in the main branch of the analysis, after completing the first, RF variable-selection, stage. Out of the original 68 covariates, 24 were retained with LEB and 25 with the DALYs as outcome. The two selections shared 15 covariates in common, many of which were identified among the "top 25" most important covariates in all or almost all of the RF procedure runs (female labor force, female population, urban population, gross domestic product (GDP), hospital beds, beds in publicly owned hospitals, population density, and indulgence, for example). Democracy, economic freedom, political stability and absence of violence/terrorism were present in the "top 25" in all RF models for LEB, but did not pass the retention threshold, as defined above, for the DALYs. Reversely, long-term orientation, masculinity, and uncertainty avoidance appeared very important for the DALYs (with scores of 12 out of 12), but were not retained for LEB.

In the secondary branch of the analysis including only the 38 HIC, we retained 23 covariates for LEB and 25 for DALYs. Table 3 shows large overlap between covariates retained in the primary and secondary branches of the analysis. However, birth rate, CAT scanners, democracy, economic freedom, MRI units, physicians, and population size no longer met the retention threshold for either outcome, while Gamma cameras, population ages 15–64, practicing midwives, research and development (R&D) expenditure, and total hospital employment, in contrast to the primary application branch now, each met the retention threshold for one of the outcomes. Highest scoring covariates for both LEB and the

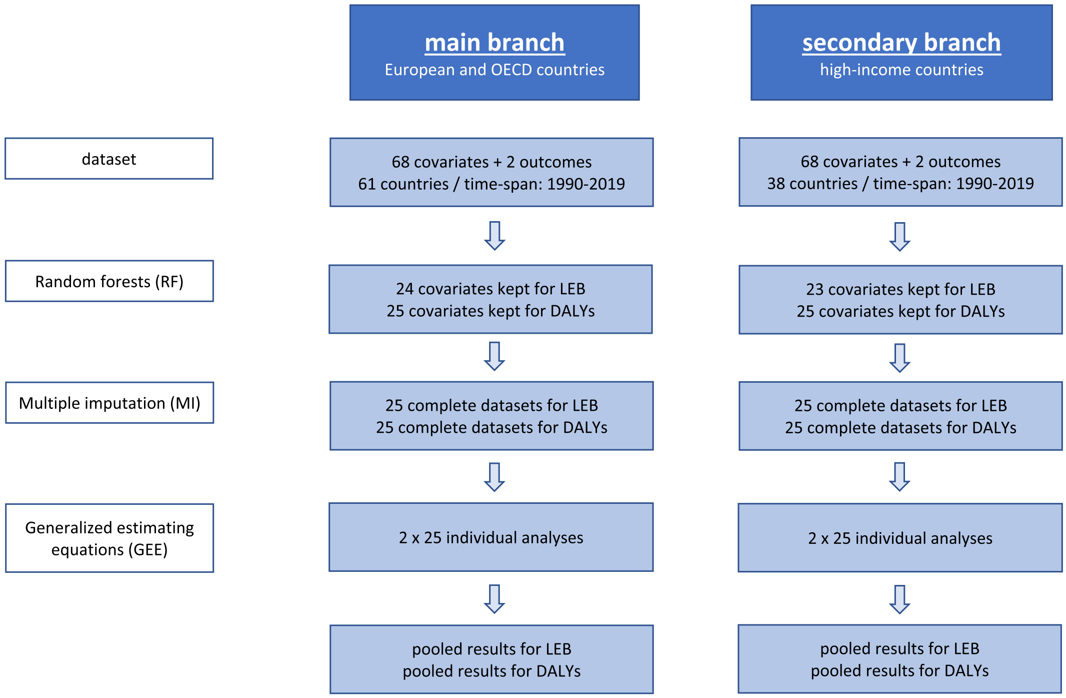

Fig. 1. Flow chart of analytical steps.

Table 2
Covariates retained in the analysis with all countries included based on variable importance scores in the random forests (RF) procedure (if a covariate was retained for a given outcome, its score here shows in how many of the 12 runs of the RF procedure it was among the "top 25"*; covariates listed alphabetically).

covariate	LEB	DALYs
Beds in publicly owned hospitals	11	12
Birth rate	8	n/a
CAT scanners	n/a	9
Corruption perception	12	7
Current health expenditure	12	10
Democracy	12	n/a
Economic freedom	12	n/a
Fat	10	n/a
Female labor force	12	12
Female population	12	12
GDP per capita	12	12
Hospital beds	12	12
Hospitals	n/a	9
Individualism	n/a	11
Indulgence	12	12
Long-term orientation	n/a	12
Masculinity	n/a	12
MRI units	n/a	8
PET scanners	10	n/a
Physicians	n/a	11
Political stability and absence of violence/terrorism	12	n/a
Population ages 65 and above	11	11
Population density	11	12
Population growth	n/a	10
Population size	n/a	10
Power distance	9	10
Psychiatrists	7	n/a
Publicly owned hospitals	9	8
Social expenditure	10	12
Surgeons	7	n/a
Total health and social employment	12	10
Total health care coverage	11	n/a
Uncertainty avoidance	n/a	12
Urban population	12	12

* See detailed explanation in section 2.3. Statistical analysis.

Table 3
Covariates retained in the analysis with only high-income countries based on variable importance scores in the random forests (RF) procedure (if a covariate was retained for a given outcome, its score here shows in how many of the 12 runs of the RF procedure it was among the "top 25"*; covariates listed alphabetically).

covariate	LEB	DALYs
Beds in publicly owned hospitals	12	11
Corruption perception	12	7
Current health expenditure	12	11
Fat	7	n/a
Female labor force	8	n/a
Female population	12	12
Gamma cameras	n/a	8
GDP per capita	12	12
Hospital beds	11	8
Hospitals	8	11
Individualism	n/a	11
Indulgence	12	12
Long-term orientation	n/a	12
Masculinity	n/a	11
PET scanners	12	8
Political stability and absence of violence/terrorism	10	n/a
Population ages 15-64	8	n/a
Population ages 65 and above	11	11
Population density	n/a	11
Population growth	11	10
Power distance	12	12
Practising midwives	n/a	9
Psychiatrists	8	n/a
Publicly owned hospitals	8	9
R&D expenditure	10	n/a
Social expenditure	n/a	11
Surgeons	9	n/a
Total health and social employment	9	11
Total health care coverage	10	9
Total hospital employment	n/a	9
Uncertainty avoidance	n/a	11
Urban population	12	12

* See detailed explanation in section 2.3. Statistical analysis.

DALYs in this secondary branch were beds in publicly owned hospitals, current health expenditure, GDP, indulgence, power distance, female population, population ages 65 and above, and urban population. There were no drastic differences in the lists of retained covariates between the main and the secondary branches when looking at each outcome individually. Still, for LEB, we see that population density, birth rate, democracy, economic freedom, and social expenditure from the main branch were "replaced" by hospitals, population ages 15–64, population growth, and R&D expenditure in the secondary branch now. For the DALYs, female labor force, population size, MRI units, CAT scanners, and physicians no longer passed the threshold, while total health care coverage, total hospital employment, practicing midwives, Gamma cameras, and PET scanners now did.

Tables 4 and 5 show our final results for the main and secondary branches of the analysis, respectively, after pooling the GEE effect estimates over the multiple imputed and separately analyzed datasets. Starting with LEB in the main analysis (Table 4), we observe the strongest statistically significant (at the conventional 0.05-level) associations with female population (−0.339) and GDP (0.331), followed by population ages 65 and above (0.287), and total health and social employment (−0.247). Indulgence and economic freedom also show significant, albeit much smaller, effects of 0.164 and 0.108, respectively. With regards to the DALYs, it is female population again that exhibits the strongest relation with an estimate of 0.374. The other covariates showing statistically significant effects here are population ages 65 and above (0.232), total health and social employment (0.228), GDP (−0.217), corruption (−0.190),[3] social expenditure (−0.142), beds in public hospitals (0.131), and CAT scanners (−0.118).

Examining the pooled estimates from the secondary analysis with only HIC (Table 5), we see a larger number of statistically significant effects, most of which belong to the same covariates between the two outcomes. Results are consistent with those of the main branch, to a degree. The 5 covariates with strongest effects on LEB here are the same ones we saw in the main branch, namely, GDP (coefficient of 0.386), population ages 65 and above (0.338), indulgence (0.270), female population (−0.246), and total health and social employment (−0.242). In addition, hospitals show a positive effect of comparable size (0.226), while R&D expenditure, current health expenditure, total health care coverage, urban population, and population growth show smaller positive, and PET scanners – smaller negative, effects. With the DALYs as an outcome, the 4 covariates with strongest effects in the main analysis have some of the strongest statistically significant effects in the secondary branch as well, though, of course, estimates are not identical. Female population showed as the most important covariate with a coefficient of 0.343, followed by GDP (−0.268), total health and social employment (0.234), individualism (0.222), urban population (−0.219), hospitals (−0.214), and further – population ages 65 and above (0.177), current health expenditure (−0.147), Gamma cameras (0.117), PET scanners (0.109), total health care coverage (−0.100), and population growth (−0.045).

Table 4
Pooled generalized estimating equations (GEE) results of the analysis including all countries (statistically significant effects at the 0.05-level are shown in bold).

covariate	LEB effect (std error; p-value)	DALYs effect (std error; p-value)
Beds in publicly owned hospitals	−0.062 (0.072; 0.397)	**0.131 (0.062;0.043)**
Birth rate	−0.055 (0.062; 0.385)	n/a
CAT scanners	n/a	**−0.118 (0.049; 0.023)**
Corruption perception*	0.067 (0.083; 0.427)	**−0.190 (0.074; 0.015)**
Current health expenditure	0.088 (0.045; 0.059)	−0.010 (0.057; 0.857)
Democracy	−0.054 (0.042; 0.208)	n/a
Economic freedom	**0.108 (0.032; 0.002)**	n/a
Fat	0.029 (0.048; 0.545)	n/a
Female labor force	0.034 (0.050; 0.508)	0.057 (0.046; 0.229)
Female population	**−0.339 (0.052; < .0001)**	**0.374; 0.065; < .0001)**
GDP per capita	**0.331 (0.046; < .0001)**	**−0.217 (0.049; < .0001)**
Hospital beds	−0.024 (0.032; 0.454)	0.098 (0.058; 0.099)
Hospitals	n/a	−0.033 (0.034; 0.337)
Individualism	n/a	0.073 (0.123; 0.560)
Indulgence	**0.164 (0.073; 0.033)**	−0.144 (0.072; 0.055)
Long-term orientation	n/a	−0.040 (0.045; 0.381)
Masculinity	n/a	0.007 (0.064; 0.914)
MRI units	n/a	0.010 (0.074; 0.898)
PET scanners	−0.055 (0.037; 0.146)	n/a
Physicians	n/a	0.003 (0.032; 0.919)
Political stability and absence of violence/terrorism	0.019 (0.039; 0.635)	n/a
Population ages 65 and above	**0.287 (0.081; 0.002)**	**0.232 (0.067; 0.002)**
Population density	−0.081 (0.244; 0.741)	0.203 (0.158; 0.209)
Population growth	n/a	−0.024 (0.015; 0.100)
Population size	n/a	0.078 (0.042; 0.071)
Power distance	−0.046 (0.059; 0.444)	0.129 (0.082; 0.129)
Psychiatrists	0.005 (0.019; 0.791)	n/a
Publicly owned hospitals	−0.031 (0.048; 0.525)	0.023 (0.059; 0.701)
Social expenditure	0.000 (0.048; 0.993)	**−0.142 (0.066; 0.042)**
Surgeons	0.023 (0.029; 0.426)	n/a
Total health and social employment	**−0.247 (0.081; 0.005)**	**0.228 (0.105; 0.039)**
Total health care coverage	0.042 (0.028; 0.149)	n/a
Uncertainty avoidance	n/a	−0.072 (0.101; 0.484)
Urban population	0.061 (0.056; 0.283)	−0.088 (0.066; 0.192)

* The CPI scale runs from 0 = "highly corrupt" to 100 = "very clean".

4. Discussion

In order to investigate underlying determinants of population health on the national level, we performed a longitudinal analysis on data from 61 relatively wealthy countries in the span of 30 years. More specifically, we employed a 3-stage sophisticated statistical methodology that allowed for subsequent variable-selection, missing data imputation, and effect estimation. Following a data-driven approach, we considered a very large number of macro-level determinants – to an extent that, to our knowledge, has not been attempted before. Our results are generally in line with expectations based on intuition and logic. Significant effects have opposite signs (as they should) and are of similar magnitude for LEB and DALYs, with the best examples being 3 of the 4 most important factors overall – GDP, female population, and health and social employment (for the 4th factor see discussion below). Results are also consistent in terms of strongest effects between the two branches of the analysis – the main one including all 61 countries and the secondary, comprising strictly HIC. Examining the list of influential determinants, we notice that they fall within 5 distinct (though not perfectly delineated and still interconnected) categories, according to their nature.

The first group to discuss is that of *macro-economic and political climate factors*. It has been argued before that national income growth

[3] scale runs from 0 = "highly corrupt" to 100 = "very clean".

Table 5
Pooled generalized estimating equations (GEE) results of the analysis with only high-income countries (statistically significant effects at the 0.05-level are shown in bold).

covariate	LEB effect (std error; p-value)	DALYs effect (std error; p-value)
Beds in publicly owned hospitals	−0.122 (0.112; 0.289)	0.179 (0.099; 0.080)
Corruption perception*	−0.011 (0.073; 0.885)	0.003 (0.052; 0.950)
Current health expenditure	**0.137 (0.059; 0.027)**	**−0.147 (0.064; 0.030)**
Fat	−0.030 (0.028; 0.300)	n/a
Female labor force	0.014 (0.049; 0.779)	n/a
Female population	**−0.246 (0.063; 0.000)**	**0.343 (0.068; < .0001)**
Gamma cameras	n/a	**0.117 (0.027; < .0001)**
GDP per capita	**0.386 (0.032; < .0001)**	**−0.268 (0.032; < .0001)**
Hospital beds	−0.117 (0.069; 0.100)	0.031 (0.068; 0.650)
Hospitals	**0.226 (0.071; 0.003)**	**−0.214 (0.076; 0.009)**
Individualism	n/a	**0.222 (0.045; < .0001)**
Indulgence	**0.270 (0.078; 0.002)**	−0.159 (0.089; 0.083)
Long-term orientation	n/a	0.088 (0.066; 0.189)
Masculinity	n/a	−0.044 (0.041; 0.290)
PET scanners	**−0.177 (0.042; 0.000)**	**0.109 (0.042; 0.015)**
Political stability and absence of violence/terrorism	−0.053 (0.040; 0.195)	n/a
Population ages 15-64	0.017 (0.038; 0.660)	n/a
Population ages 65 and above	**0.338 (0.052; < .0001)**	**0.177 (0.040; < .0001)**
Population density	n/a	−0.091 (0.074; 0.229)
Population growth	**0.042 (0.014; 0.004)**	**−0.045 (0.015; 0.002)**
Power distance	0.017 (0.053; 0.752)	0.117 (0.058; 0.053)
Practising midwives	n/a	−0.019 (0.015; 0.213)
Psychiatrists	0.008 (0.016; 0.634)	n/a
Publicly owned hospitals	−0.132 (0.074; 0.085)	0.172 (0.085; 0.053)
R&D expenditure	**0.177 (0.038; < .0001)**	n/a
Social expenditure	n/a	−0.081 (0.046; 0.089)
Surgeons	0.058 (0.039; 0.146)	n/a
Total health and social employment	**−0.242 (0.049; < .0001)**	**0.234 (0.095; 0.019)**
Total health care coverage	**0.136 (0.048; 0.009)**	**−0.100 (0.045; 0.032)**
Total hospital employment	n/a	−0.040 (0.045; 0.376)
Uncertainty avoidance	n/a	0.018 (0.078; 0.819)
Urban population	**0.090 (0.035; 0.013)**	**−0.219 (0.048; < .0001)**

* The CPI scale runs from 0 = “highly corrupt” to 100 = “very clean”.

accounts for about 10–25% of the increase in LEB (Mackenbach & Looman, 2013). In our analysis, GDP was identified as one of the most important determinants. It was consistently placed among the top-scoring variables in all RF models in our variable-selection phase, and it exhibited some of the strongest coefficients in the subsequent GEE analysis. It showed a positive association with LEB and a negative one with the DALYs, thus confirming previous research findings of an overall strong beneficial effect on health (Achim, Văidean, & Borlea, 2020; Barthold, Nandi, Rodriguez, & Heymann, 2014; Bradley, Elkins, Herrin, & Elbel, 2011; Gracia-de-Rentería et al., 2022; Joumard, André, Nicq, & Chatal, 2008b; Khouri, Cehlar, Horansky, & Sandorova, 2017; Lenhart, 2017; Mackenbach, 2013; Mackenbach & Looman, 2013; Onofrei, Vatamanu, Vintilă, & Cigu, 2021; Park & Nam, 2019; Senol, Gokkaya, & Cirakli, 2021; A. Sharma, Sharma, & Tokas, 2022; Socoliuc, Sirghi, Jemna, & David, 2022; Torre & Myrskyla, 2014; Zare et al., 2015). This remains true even for strictly HIC. Interestingly, in this secondary branch of the analysis, we observed a larger number of statistically significant effects compared to the main branch with all 61 countries. Based on this, it can be speculated that when countries achieve a high and stable level of wealth, its effects become less “absorbing” so that those of other factors become visible, too. The Fraser Institute’s economic freedom index we included in our analysis measures national policies and institutions support for economic freedom in 5 broad areas (see Table 1), and is often used as a proxy for institutional quality (Nyström, 2008; Ovaska & Takashima, 2006). On a worldwide level, it has exhibited favorable links with indicators such as GDP, poverty rates, infant mortality, school enrollment, and the UN World happiness index, besides LEB (Gwartney, Lawson, Hall, & Murphy, 2021). In European countries in particular, previous research utilizing this or similar indicators has reported a positive relation between economic freedom and LEB (Dragos et al., 2022; Gracia-de-Rentería et al., 2022; A. Sharma et al., 2022). In agreement, we found a statistically significant, albeit relatively small, positive effect of economic freedom on LEB in the main branch of the analysis with all 61 relatively wealthy countries. Based on all countries in the world for which there was data, another study has uncovered an interaction effect between economic freedom and democracy, where economic freedom continued to positively influence LEB even in the most democratic countries, while the marginal effect of more democracy diminished in countries characterized by high levels of economic freedom (Stroup, 2007). We could not have directly tested such an interaction due to the high complexity of our model, but we do believe our results confirm this, at least to an extent. Political factors have been recognized to influence healthcare system organization for a long time (Elola, Daponte, & Navarro, 1995) and democracy has been the one aspect of national politics most frequently studied in this sub-section of population health research. There exists substantial evidence that higher levels of democracy contribute towards better health (Muntaner et al., 2011). However, we (and others recently (Veas, Crispi, & Cuadrado, 2021)) failed to corroborate this nexus. Just like economic freedom, the Polity2 index we used to measure democracy survived variable-selection only for LEB and only in the full sample of countries, still, subsequently showing non-significant effect. The reason for that could very well be that democracy and economic freedom of the countries in our study are already so advanced that they lose (some of) their relative importance at this level. (In HIC in particular, the average Polity2 index was 9.4 on a scale from −10 to 10, and the average economic freedom index was 7.65 on a scale from 0 to 10.) We could, perhaps, argue along the same vein, why the variable of political stability and absence of violence/terrorism did not show statistically significant effects and was retained after the variable-selection stage of the analysis only for LEB, and why the Gini index of income inequality was not retained at all. The Gini coefficient is the most widely used measure of income inequality; its scale goes from 0, if income was distributed fully equally among members of society, to 100, if only 1 person had all income. Wilkinson’s income inequality hypothesis (Wilkinson, 1996) postulating that unequal distribution of wealth within a society exerts detrimental effect on health has received significant scientific attention in the past few decades. However, methodological critique on research supporting it (Beckfield, 2004; Hu, van Lenthe, & Mackenbach, 2015) led to a still ongoing debate around whether income inequality holds any importance for health production. The “threshold effect” hypothesis (Kondo et al., 2009; Subramanian & Kawachi, 2004) has been put forward as a possible reason for the heterogeneity in empirical findings. Indeed, our results of the relative unimportance of income inequality, similar to those of other recent studies (Gracia-de-Rentería et al., 2022; Senol et al., 2021; A. Sharma et al., 2022; Veas et al., 2021), may be explained by the Gini values in our sample not reaching the levels above which harmful income inequality effects on health become discernible. Last in this group, we draw attention to corruption. Healthcare is one sector considered particularly susceptible (Petkov & Cohen, 2016). Corruption can undermine effectiveness and efficiency of national healthcare systems (Gaitonde, Oxman, Okebukola, & Rada, 2016) by infiltrating a large number of its operational and infrastructural aspects, such as research and innovation, governance and regulation, provision of services by and education of medical personnel, equipment, supplies, and medicine purchase and distribution, marketing relations, construction of health facilities (Petkov & Cohen, 2016; Sommersguter-Reichmann, Wild, Stepan, Reichmann, & Fried, 2018; Vian, 2008). Corruption in general has been shown to have detrimental effects on population health on a global level (Li, An, Xu, & Baliamoune-Lutz, 2018; Lio & Lee, 2016). In the present study, we used the Transparency International's Corruption perception index (CPI) – a principal corruption indicator covering corruption manifestations such as bribery, nepotism, and diversion of public funds, for example (International, 2021). Previous research utilizing CPI in the context of wealthy countries reports that higher levels of corruption are associated with lower LEB (Achim et al., 2020; Socoliuc et al., 2022). In our analysis, CPI survived variable-selection in both branches of the analysis, for both health outcomes. However, it showed a statistically significant relation only with the DALYs and only in the main branch with all 61 countries. Given the CPI scale where 0 stands for "highly corrupt" and 100 – for "very clean", the negative GEE coefficient in our results indicates that lower levels of the corruption variable correspond to lower DALYs. Using an alternative indicator for corruption (the "control of corruption"), another study obtained the same finding (Dragos et al., 2022). A point to keep in mind here is that more corrupt countries would be more likely to manipulate their statistics as well, which may impact the determinants and health outcomes in our dataset to different extents.

The second detectible group is that of *demographics-related determinants*. For the most part in previous research, variables of this kind have primarily served as controls. Our results, however, compel us to pay closer attention. Female proportion of the population (or "female population" for short) turned out to be the most influential determinant in our analysis (with the strongest effect in 3 out of the 4 cases; see Tables 4 and 5), even surpassing GDP per capita. The negative effect of female population on LEB could be explained by the implied higher male mortality, which would exert a downward pull on total LEB. On the other hand, the well-known male-female health-survival paradox (Oksuzyan et al., 2009), or the fact that women live longer lives, and men live shorter ones with fewer long-duration disabilities, may explain the positive effect we observe of female population on DALYs (the effect is quite large, in relation to others, in the HIC branch of the analysis, in particular). Among the 68 covariates we initially included, 6 directly expressed life-style. Although this type of determinant is consistently identified as important to population health in the literature (Dragos et al., 2022; Gracia-de-Rentería et al., 2022; Joumard et al., 2008b; Roffia, Bucciol, & Hashlamoun; van den Heuvel & Olaroiu, 2017; Zare et al., 2015), none but one of these covariates (fat availability) survived our variable-selection procedure, and had non-significant effect at the end. We hypothesize, that life-style influence on health was absorbed by other factors. For instance, higher GDP likely creates more favorable context for healthier behavior, and generally allows for higher expenditures on healthcare and education. Quite striking, in contrast to many previous studies (Dragos et al., 2022; Gracia-de-Rentería et al., 2022; Joumard et al., 2008b; A. Sharma et al., 2022; Socoliuc et al., 2022; Zare et al., 2015), overall education level was not recognized as an important determinant in our analysis. This may be partly due to it being absorbed by other determinants and showing little independent variation among the countries under analysis. Moreover, broad socio-cultural characteristics (see also below) may, too, have an absorbing effect on more specific determinants, including life-style choices. Note also that the female population determinant indirectly absorbs behavioral determinants, because women are known to engage in healthier choices with regards to diet, smoking, and alcohol consumption, although this is also evolving over time, particularly in relation to smoking habits. Additionally, female labor force participation was retained after variable-selection in 3 of the 4 cases, with very impressive variable importance scores (in the RF procedure; see Tables 2 and 3) for the full selection of countries in the main branch of the analysis (even if it did not show statistically significant effect in the end). For comparison, our other labor-related covariate – unemployment rate – was not once placed among the "top 25" most important variables during any of the RF runs. Unemployment has received much attention in research related to population health, but has yielded very mixed results, rendering the effect on the macro-level uncertain (Iversen, 1989). Proportion of the population ages 65 and above was among the 4 most important determinants according to our results (the other 3 were mentioned at the opening of the discussion). It is a special demographic factor that exhibits positive (and quite strong) effects for both outcomes, in both branches of the analysis. Logically, having relatively more elderly people in the population raises LEB; but, on the other hand, the elderly contribute more to the DALYs as well. It is, indeed, a very important covariate to take into account, as recognized by others, too (Dragos et al., 2022; Lenhart, 2017; Reynolds, 2018; Socoliuc et al., 2022). Due to the huge implications for healthcare and welfare systems, population ageing in HIC constitutes a whole research field on its own. Population growth, density, and size were also retained for the final part of our analysis, and growth appeared to be significantly beneficial in terms of both outcomes in the HIC setting. Population growth is the combined result of the births/deaths and the immigration/emigration differences. Countries with healthier populations are characterized by lower death rates and relatively similar fertility rates per income level. Higher net immigration contributes to better health at the national level by stimulating population growth directly and indirectly, by their offspring. Note also that this is modulated by the so-called "healthier immigrant effect", where migrants have been found to be healthier than native-born people who do not migrate (Kennedy, Kidd, McDonald, & Biddle, 2015). Finally, we place proportion of urban population in this grouping as well. It has been hypothesized that there are different health risk factors operating in rural versus urban settings (Bremberg, 2020). Urbanization's relationship to population health, in fact, has been the focus of much research in recent decades, and it is considered to be the result of an intricate interplay between factors constituting the so-called "urban health advantage" and others representing what is known as the "urban health penalty" (Moon & Kearns, 2014; Vlahov, Galea, & Freudenberg, 2005). On the one hand, urban living provides for easier access to public services (including healthcare), better education and employment opportunities, and more healthy life-style options (such as less car-reliance or richer food choices). On the other hand though, cities are plagued by higher levels of pollution, congestion, and stress. In our analysis, urbanization was placed among the "top 25" covariates 100% of the time during the variable-selection phase. Subsequently, it showed beneficial influence on population health contributing to higher LEB and lower DALYs, with stronger and statistically significant effects in the HIC branch. Similar results were found by previous studies, too (Gracia-de-Rentería et al., 2022; A. Sharma et al., 2022; Socoliuc et al., 2022), though, again, a ubiquitous relationship cannot be ascertained just yet.

The third group of determinants is that of *healthcare system resources*. The dominant role of healthcare in the health production process has been seriously questioned already (Asiskovitch, 2010; Braveman, Egerter, & Williams, 2011; Elola et al., 1995; McKeown, 1979; J. B. McKinlay & McKinlay, 1977; John B. McKinlay, McKinlay, & Beaglehole, 1989). We wanted to take advantage of the abundance of available indicators in TWB and OECD databases in order to try to disentangle the effects of healthcare's different aspects. Of the 20 determinants that we initially considered regarding medical personnel, material base, technology, and including total healthcare coverage here as well (refer to Table 1), 12 were kept after variable-selection in each of our two branches, with some differences in between. First and foremost, total health and social employment density – i.e., the number of individuals employed in the healthcare or social work sectors in a country – turned out to be one of the most important factors for both health outcomes in both branches of the analysis (unlike in some previous research (Park & Nam, 2019)). In the presence of this "umbrella" variable, none of the other specific-medical-personnel covariates showed statistically significant effects. PET scanners and Gamma cameras availability came out important in HIC. Hospital density as well, with density of publicly owned hospitals only marginally statistically non-significant in this secondary branch of the analysis. Given a tendency for hospitals in HIC to merge into fewer, larger ones, we reasoned that hospital beds, instead, may be a more important factor to look at. The obtained GEE coefficients for both hospital beds and beds in publicly owned hospitals though were of smaller magnitude and weaker statistical significance overall. All of these healthcare system indicators exhibited a negative association with LEB and a positive one with the DALYs, based on which we can conclude that, indeed, a more resource-rich setting does not directly translate into more health for the population. Lastly, with regards to total health care coverage, we found a significant beneficial effect for HIC. We suspect that the USA, an extreme outlier, may have been responsible for these results, since the majority of other HIC have had universal healthcare coverage in the time period under study here. However, this remains uncertain, as performing sensitivity analyses excluding countries one by one to formally investigate single country influences on overall results was beyond the scope of the present study.

Next, four *expenditure indicators* were taken into account in the present study – current health expenditure, social, general R&D, and out-of-pocket healthcare spending. The first three were included in the final GEE models and showed interesting effects. Income per capita has been considered the best predictor of health expenditure (Newhouse, 1977). Still, in recent decades, health expenditure growth has outpaced GDP growth in advanced economies, occasionally contributing towards fiscal deficits (Barthold et al., 2014; Linden & Ray, 2017). The reasons for this increase in health spending has been attributed to rising costs linked to new technologies (Budhdeo et al., 2015; Willemé & Dumont, 2015), ageing populations, and chronic illnesses (Budhdeo et al., 2015). While it is generally accepted that countries with higher health expenditures have better health outcomes (Dragos et al., 2022), there is evidence of diminishing returns to investment in wealthy countries in particular (Nixon & Ulmann, 2006; Self & Grabowski, 2003). Furthermore, as value-per-money varies across countries even within the same income bracket, the topics of effectiveness of spending (Dragos et al., 2022) and efficiency of healthcare systems (Joumard et al., 2008b) have garnered much interest. Currently, there is no consensus on whether health spending is, indeed, a major driver of population health, and some have argued that social expenditure, in fact, is the more influential determinant of the two (Cervantes, Lopez, & Rambaud, 2020a, 2020b; Reynolds & Avendano, 2018; van den Heuvel & Olaroiu, 2017). Our results do not allow us to take a stand on this matter. We found that in HIC higher health expenditure is advantageous for both LEB and the DALYs, while in the full sample with 61 countries social expenditure has a beneficial influence on the DALYs of very similar magnitude. Social expenditure covers financing old age, disability, family, and unemployment benefits, for example, as well as incentivization programs towards labor market activation and improved housing conditions. Plenty of previous research land supporting evidence that both health (Amiri & Solankallio-Vahteri, 2019; Barthold et al., 2014; Bradley et al., 2011; Onofrei et al., 2021; Park & Nam, 2019; Roffia et al.) and social expenditure (Barthold et al., 2014; Bradley et al., 2011; Reynolds & Avendano, 2018; Roffia et al.; Senol et al., 2021; van den Heuvel & Olaroiu, 2017; Zare et al., 2015) hold significance to health production. What is more, in HIC and with regards to LEB, R&D expenditure exhibited a highly significant positive influence, even stronger than those of health and social expenditures. The indicator we used reflects general R&D investment in basic and applied research, as well as experimental development, in the four main sectors: business enterprise, government, higher education, and private non-profit. This broad, but potentially very important, indicator has been generally neglected in the research on population health so far, and we can only speculate it may, for instance, reflect a country's propensity to adopt medical innovation earlier. However, this finding needs to be confirmed and the underlying mechanism seems a relevant subject for future research.

Finally, *cultural factors*, also highly understudied in previous research, show relevance to population health in our analysis as well. All 6 of the Hofstede indices were retained after the variable-selection phase for the DALYs, and only indulgence and power distance for LEB. Individualism (versus collectivism) was significantly positively associated with DALYs only in the HIC sub-sample, while power distance for HIC and indulgence (versus restraint) in both branches of the analysis had nearly-significant positive and negative, respectively, effects. In the case of LEB, in accord with previous findings (Mackenbach, 2014), indulgence showed a positive statistically significant effect in both branches of the analysis. This cultural index was derived from 3 variables from the World Values Survey (WVS): happiness, perception of life control, and importance of leisure (Minkov, 2007). And while, at first glance, these may allude to hedonism and short-term gratification seeking, the indulgence index (as well as the individualism index) shows negative correlation with health-related behaviors such as smoking and alcohol consumption (Mackenbach, 2014). Given that the main mortality causes, at least in OECD countries, are traffic accidents at younger age and circulatory system diseases and cancers at middle and older ages (OECD, 2019) – all known to be strongly influenced by life-style factors – we can speculate that it is possibly via this channel that the indulgence and individualism aspects of national culture contribute towards higher LEB and lower DALYs.

A few possible limitations to this study need mentioning. First, as population health is a very complex and multidimensional construct, no existing measure trying to capture it is without flaws. There has been criticism that mortality-based indicators (LEB being one of them) are only very crude and superficially useful (Gold et al., 2002; Kindig, 1998) as they completely ignore the qualitative part of human life related to disease, injury, and disability. However, while more sophisticated indicators are, indeed, much desired, the shift towards their wider application has been slow (Minagawa, 2013) and data on them is generally scarce, especially when it comes to a larger number of countries and longer periods of time. We opted to use LEB because data is readily available, and because it is a well-accepted indicator worldwide (Joumard, André, Nicq, & Chatal, 2008a; Or, 2001), showing strong correlations with most other population health measures (Joumard et al., 2008b; R. Sharma, 2018). Next to LEB, we employed the DALYs as well – one of those indicators that do account for both mortality and morbidity in the population. Well-known and used in health economics, the DALY has been criticized, in turn, that since it utilizes experts' ratings on the impact of different disability states on quality of life, it does not represent a universal view on health, as experience of illness and disability is culturally dependent (Fox-Rushby, 2002). While it may be true that the experts' view reflected in the DALYs is that of primarily well-educated, well-off, white persons from North America and Europe, we hope any negative effect resulting from this is limited in our study, since most of the countries in our selection are Western nation as well (though not all, of course). Second, our analysis, as any other, is susceptible to the so-called "omitted variable" bias. While we tried to include as many determinants as possible based on previous scientific literature, there is always the chance that we missed relevant variables due to genuine oversight or data availability issues (e.g., illicit drug use, which we would have liked to have had included). It should also be noted that despite our best efforts to only include indicators suitable for between-country comparisons, there may still be subtle differences in how different countries define and record some of the variables (particularly those reflecting healthcare resources). In addition, we had to make choices when multiple similar variables could be used, in order to eliminate extremely high correlations between covariates in the dataset. As can be expected, there is a great degree of interconnectedness among the factors under study here, but due to the longitudinal nature of the data, we could not apply dimension-reduction techniques, such as principal components, for example. Indeed, multicollinearity as well as lack of degrees of freedom have been recognized as principal difficulties in macro-level research (Bloom et al., 2004). Related to the latter, the third point of potential weakness that we need to mention stems from missing data. While we are confident that we have approached this issue in the (presently) most adequate way, namely, via conducting MI, we were only able to do so after performing variable-selection first. With 70 variables in total (68 covariates and 2 outcomes) and, de facto, only 61 observations (i.e., countries), multilevel MI was technically impossible to do at the start. Thus, there is some chance that our variable-selection procedure (the RF part of the analysis) failed to detect the importance of particular covariates with extreme levels of missingness (for example, WVS covariates for which only less than 10% of the data was available). Additionally, we operated under the "default" missing-at-random (MAR) assumption. If this assumption was not met in reality (something practically impossible for us to check), our inference would be rendered invalid. Finally, in order for the statistical procedures to run, we needed to transform the data, which prevented us from giving a more direct interpretation of effect sizes. Having all data on the same scale, however, allowed for direct comparisons of the strength of the associations among the determinants, as we have readily demonstrated in our discussion.

In conclusion, our findings contribute to understanding what makes for a healthier population. Our study provides strong evidence that health production at the national level in relatively wealthy countries is determined in the first place by income level (as reflected by GDP per capita) and the gender and age-specific composition of the population, followed by available healthcare resources and investments in health and social services. We find that differences in income inequality do not help explain inter-country differences in population health. Above all, our data-driven, rather than hypothesis-driven, analyses show that there is a large number of covariates that influence population health, providing a contextual richness that was routinely ignored in previous analyses on this subject, but should not be ignored in future ones.

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Ethical statement

Ethics approval was not required as the paper did not involve any data collected from human subjects.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Data availability

Data will be made available on request.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2023.101484.

Appendix A. Classification of countries included in the study according to income

Table

Ranking of selected countries according to gross national income (GNI) per capita (in current USD) for 2019 (data not available for Andorra, Liechtenstein, Monaco, San Marino). The World Bank's classification by income level from the 1st of July 2020 shown is based on GNI per capita for 2019*.

Ranking	Country	GNI
high-income (>$12,535)		
1	Switzerland	$84,260
2	Norway	$81,640
3	Luxembourg	$77,040
4	Iceland	$72,900
5	USA	$65,970
6	Denmark	$63,460
7	Ireland	$63,230
8	Sweden	$56,410
9	Australia	$54,910
10	Netherlands	$53,180
11	Austria	$50,960
12	Finland	$49,940
13	Germany	$49,140
14	Belgium	$48,010
15	Canada	$46,550
16	Israel	$43,540
17	UK	$43,460
18	New Zealand	$42,870
19	France	$42,510
20	Japan	$42,330

(*continued on next page*)

Table (*continued*)

Ranking	Country	GNI
21	Italy	$34,870
22	South Korea	$33,860
23	Spain	$30,350
24	Cyprus	$28,600
25	Malta	$28,340
26	Slovenia	$25,950
27	Estonia	$23,250
28	Portugal	$23,170
29	Czech Republic	$22,110
30	Greece	$19,650
31	Slovakia	$19,230
32	Lithuania	$19,050
33	Latvia	$17,790
34	Hungary	$16,520
35	Poland	$15,360
36	Croatia	$15,320
37	Chile	$14,990
38	Romania	$12,620
upper-middle income ($4046 - $12,535)		
39	Costa Rica	$12,090
40	Russia	$11,250
41	Turkey	$9690
42	Bulgaria	$9500
43	Mexico	$9470
44	Montenegro	$9130
45	Kazakhstan	$8820
46	Serbia	$7040
47	Colombia	$6570
48	Belarus	$6370
49	Bosnia and Herzegovina	$6180
50	North Macedonia	$5890
51	Albania	$5230
52	Georgia	$4690
53	Armenia	$4660
54	Kosovo	$4640
55	Moldova	$4580
56	Azerbaijan	$4510
	lower-middle income ($1036 - $4045)	
57	Ukraine	$3310

[*] https://blogs.worldbank.org/opendata/new-world-bank-country-classifications-income-level-2020-2021.

Appendix C. Statistical analysis

- *Data preparation*

Based on data availability for different countries and time periods over the selection of data sources, in the main branch of the analysis we considered data for 61 European or Organisation for Economic Co-operation and Development (OECD) member countries for the years between 1990 and 2019. In a secondary branch, we also ran the whole procedure with a subset of 38 countries that were ranked as “high-income” according to the World Bank’s classification by income level (Serajuddin & Hamadeh, 2020) from the 1st of July 2020, applied to gross national income (GNI) data for 2019 (see Online Resource 1).

Except for the 6 Hofstede cultural indices that are considered time-invariant and thus consist of just one value per country (or region), all other data came in the form of annual entries, which gave our dataset a 2-level structure. We considered only national values for the cultural indices and ignored any sub-country divisions. In the case of Germany, the World Values Survey (WVS) reported separate values for East and West Germany for all waves of the survey. In order to obtain a single national value, we used a weighted average based on the year-specific population size (Bundesamt, 2017). For this set of 12 WVS covariates, we disregarded the original wave-based structure of the obtained data and instead considered the year in which data for a particular country was collected, for the purposes of data integration across the different databases we utilized. This, in addition to the fact that some of the countries of interest had only participated in 1 or 2 waves of the survey, or never at all, resulted in pronounced data sparsity for the WVS indicators, which was treated as other missing data (see more below).

- *Random forests (RF)*

As a first step in both branches of the analysis – with all countries included and only with high-income countries, we employed the random forests statistical procedure as a variable-selection technique, using SAS. Random forests (L. Breiman & A, 2003) is a well-known and widely used supervised machine-learning technique primarily used for predictive modeling. It builds an ensemble of decision trees introducing randomness at two different points in the process of developing each individual tree. On one hand, tree training is done using only a fraction of the original data (in-bag fraction) selected via bootstrap sampling (without replacement, in our case), while the rest of the data is set aside for model validation. On the other hand, the split-variable for each split on each tree is selected from a random sample of the original covariates, thus reducing correlations between the trees. The procedure has great efficiency and is very robust. It is also well suited to handle missing data. In addition to all 68 covariates, we also included a country indicator to account for the clustering in the data. We ran multiple models for both outcomes in both branches of the analysis varying 3 parameters in the model – the number of trees to grow (100 or 200), the number of variables to choose from for splitting (7 values at approximately equal intervals between 2 and the total number of covariates), and the in-bag fraction (0.4, 0.6, or 0.8). In order to determine the most important covariates for life-expectancy at birth (LEB) and disability-adjusted life years (DALYs, per 100 000 population), we looked at the variable importance indicator calculated based on the loss reduction (L. C. Breiman, A., 2003), and took a count of the number of times each covariate appeared among the "top 25" variable importance scores. Covariates that appeared in the "top 25" in 7 or more of the 12 executed procedure runs were then retained for the next phase of the analysis.

- ***Multiple imputation (MI)***

Our initial dataset spanning from 1990 to 2019 and including 61 countries and 70 variables in total (68 covariates and 2 outcomes) showed 47% overall missingness. After variable-selection, we ended up with 4 distinct reduced datasets, where missingness was alleviated to between 23% and 32%. In order to address the remaining missingness, we performed multilevel multiple imputation (in R).

Multiple imputation (Rubin, 1987) is the current "state-of-the-art" approach to dealing with missing data, as it accounts for the inherent uncertainty when imputing, that gets ignored by single imputation techniques. Under the missing-at-random (MAR) assumption, we implemented the multivariate imputation by chained equations (MICE) algorithm (S. G.-O. van Buuren, K., 2011), also known as fully conditional specification (FCS). MICE does not assume a multivariate distribution for the data, but instead uses a set of conditional densities. Imputation is done on a variable-by-variable basis, iterating over a conditionally specified imputation model for each incomplete variable. We used the predictive mean matching (PMM) method, which entails first calculating predictions for each entry of the target variable, whether observed or missing. For each missing entry then, a small number of "candidate donors" among the observed cases is selected, based on proximity between the predictions. At the end, one donor from the group is randomly selected and its observed value is imputed for the missing entry. Some of the advantages of this method are: it ensures that the imputed value is always within the plausible range as it is based on observed data; it has the ability to handle all types of variables (though our dataset contained only continuous ones); and it is robust to transformations. As our variables were on largely differing scales, it was necessary that we standardize all to have a mean of 0 and standard deviation of 1. With each of the 4 reduced datasets (for LEB and the DALYs in the main and secondary branches of the analysis), we implemented the simplest proper imputation model, where for the imputation of a target variable we used all other variables within that dataset. In each case, we obtained 25 imputed datasets – a number considered sufficient given the number of variables needing imputation (S. van Buuren, 2018).

- ***Generalized estimating equations (GEE)***

In the final stage of the analysis, we applied (again in SAS) the generalized estimating equations technique (Liang & Zeger, 1986) to each imputed dataset obtained in the previous step individually, considering the covariates that were previously selected as most important via the random forests procedure (see above). GEE is a well-known semi-parametric approach to analyzing longitudinal data. It belongs to the marginal models family, which treats the within-subject (in our case, within-country) covariance structure as nuisance and focuses on the mean, or population-averaged, response. The procedure has the advantages of being relatively simple computationally and avoiding distributional assumptions. It iteratively calculates re-weighted least squares using a pre-specified working correlation matrix for the weights. In the presence of time-dependent covariates, our only valid choice for this working correlation matrix was that of independence among the responses (Pepe & Anderson, 1994). The normal distribution with the identity link function was used for our two standardized outcomes and all inference was based on the robust, "sandwich estimator", standard errors. The combination of MI and GEE, or MI-GEE, has been well-established in the statistical literature (Beunckens et al., 2008; Birhanu et al., 2011). Lastly, for each of the four scenarios separately – LEB and DALYs in the main branch with all 61 countries, and LEB and DALYs in the branch with only the 38 high-income countries, results from the 25 individual GEE models were pooled together according to Rubin's rules (Rubin, 1987) in order to obtain our final effect estimates.

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