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Dimensions of Social and Environmental Change: Insights into Long-Term Poverty, Environmental Concern, and Urban Greenery

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Content

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Abstract

Our society faces numerous challenges that emerged at the turn of the millennium. In the wake of the 2007 financial crisis, reducing inequality and poverty has become a pressing issue not only in the Global South but also in Europe. Another significant challenge that emerged before the turn of the millennium but has since gained even greater importance is addressing climate change. Furthermore, the global urban population is increasing at an unprecedented rate, highlighting the importance of urban planning in creating safe, livable, and prosperous cities. The dissertation addresses these issues by empirically analyzing the drivers of these phenomena. The first article examines how long-term poverty has developed in 26 European countries after the financial crises and by what macro-level factors it is driven. The findings suggest that the long-term poverty rate stayed unchanged in 13 out of 26 European countries. GDP does not affect long-term poverty rates, but male employment rates and social welfare expenditure are negatively associated. The second article provides an overview of the development of environmental concern in 29 countries responsible for 71% of global CO_2 emissions over the past three decades. Moreover, the article examines the determinants of environmental concern at the individual level and country level. Compared to the previous measurement in 2010, environmental concern has increased in nearly all countries. Education, post-materialistic values, political attitudes, and trust in the news media and science are the main driving factors of environmental concern at the individual level. At the country level, environmental concern is predominately influenced by countries' GPD. The third article sheds light on the relationship between urban greenery, mixed land use and life satisfaction in Switzerland. Only older residents tend to benefit from a greener neighborhood. This relationship is mainly driven by trees and grass located in gardens and parks. In contrast, land use mixture is only positively associated with younger residents' life satisfaction, and the positive effect diminishes at higher ages.

Introduction and Summary

The advent of the new millennium was marked by the bursting of the dot-com bubble in March 2000, which precipitated a wave of layoffs in the technology sector. Seven years later, the bankruptcy of Lehman Brothers, the fourth-largest investment bank in the USA, marked the inception of one of the most far-reaching financial crises in history. The 2008 financial crisis resulted in a notable increase in unemployment rates across the globe. In the European Union, the rate rose from 7.4% in 2007 to 11.3% in the post-crisis period, while in the United States, it increased from 4.6% to 9.6% (The World Bank, 2023a). As governments were compelled to support struggling banks, national debt rose to unprecedented levels. In the United States, the national debt increased from 62% to 100% of the GDP (Federal Reserve Bank of St. Louis, 2024). This was surpassed by some European countries such as Ireland (141%) and Greece (175%) (Eurostat, 2024). The economic uncertainty, struggling financial institutions, higher unemployment, and reduced consumption lead to a downturn in the broader economy (Federal Reserve History, 2013). An economic downturn often leads to a precarious situation in the job market and hence can translate to poverty. As Peter Townsend (1979, p. 31) stated, poverty is more than just being deprived of money but “the resources [of the poor] are so seriously below those commanded by the average individuals or family that these are, in effect, excluded from ordinary living patterns, customs and activities”. Research has shown that poverty has negative effects on both individuals and society. These effects include shorter life expectancy (Chetty et al., 2016), poor health (e.g., Bor, Cohen, & Galea, 2017; Madden, 2015; Wagstaff, 2002), depression (Abbott & Wallace, 2014; Riumallo-Herl, Basu, Stuckler, Courtin, & Avendano, 2014), low educational performance (Blanden, 2004; Ferguson, Bovaird, & Mueller, 2007), and limited social and political participation (Mood & Jonsson, 2016).

A few years later, with the failure of the Kyoto Protocol, it became evident that society was facing yet another significant challenge: climate change. This issue tried to be addressed by follow-up conferences such as the COP21 in Paris, which resulted in a remarkable agreement to limit global warming to well below 2 °C. However, while CO_2 emissions per capita decreased by 1/3 European Union and 1/4 in the United States, respectively, they increased threefold in China and India in the last three decades. This has led to a continuous rise in global CO_2 emissions of 63% compared to 1990, calling for further action (Global Carbon Project, 2024). When addressing climate change, both enterprises and governments have a significant responsibility due to their high leverage. However, the literature suggests that the individual’s beliefs towards the environment can influence its political (e.g., Anderson, Böhmelt, & Ward, 2017; Bakaki, Böhmelt, & Ward, 2020; Franzen & Vogl, 2013; Vandeweerdt, Kerremans, & Cohn, 2016) as well as everyday behavior (e.g., Bamberg & Möser, 2007; Bouman et al., 2020; Bruderer Enzler & Diekmann, 2019; Diekmann & Preisendörfer, 2003; Gifford & Sussman, 2012; Hines, Hungerford, & Tomera, 1987; Kollmuss & Agyeman, 2002; Preisendörfer, 1999; Preisendörfer & Franzen, 1996; Steg & Vlek, 2009) and hence, their examination is of interest.

On November 15, 2022, a record was broken by the birth of the 8 billionth person on earth. This was the result of an unprecedented increase in the world population by around 30% in the first two decades of the millennium. (The World Bank, 2022). As a consequence of the ongoing process of globalization, the majority of the global population is engaged in industrial or service-related work. This work is frequently situated in urban areas, and in conjunction with population expansion, this has resulted in a global urban population that has reached 57% in 2022. According to The World Bank's (2023b) prediction, this number will increase to 70% by 2050. However, this is already a reality in Europe, and 75% of the inhabitants live in urban areas. Living in a city has numerous advantages, such as having a short commute and being close to cultural, culinary, nightlife, medical, or educational services. Nevertheless, studies (Dye, 2008; Sundquist, Frank, & Sundquist, 2004) suggest that cities became the epicenters of mental distress, which is due to anthropogenic noise and air pollution, crowdedness, and detachment from natural environments (Kaplan & Kaplan, 1989; Wilson, 1984). Due to the high urbanization rate, this negatively affects the well-being of a large part of Europe's population and will become a global issue with the rising global urbanization rate.

The challenges faced by our society in the first two decades of the millennium are numerous and ongoing. This dissertation aims to shed light on the development of crucial social concepts such as poverty, environmental concern, and the well-being of urban residents, as well as the drivers that can influence these concepts. Rigorous empirical analysis and novel machine-learning approaches are utilized to accomplish this.

The first article, "Poverty in Europe: How long-term poverty developed following the financial crisis and what drives it" co-authored by Axel Franzen (Franzen & Bahr, 2023), focuses on poverty, precisely the most severe form of it, which is long-term poverty. Cross-sectional poverty indicators tell us the proportion of households or individuals living in poverty in a given year. This is relevant information, but cross-sectional data cannot tell us how long someone stayed in poverty and whether they were able to leave this state again. It is evident that shorter periods of poverty exert a smaller impact on the individual's living conditions, as savings or financial aid from relatives can compensate for short periods of economic hardship. In contrast, longer or more frequent periods of poverty will diminish savings and poverty will exert a more pronounced effect on individuals' living conditions, health, and ability to participate in social life (Corcoran, 1995; Holmes & Kiernan, 2013; Whelan, Layte, & Maître, 2003). This highlights why long-term poverty should receive special attention in the field of poverty research. However, examining long-term poverty requires panel data, which is costly and scarce. Further, it is interesting to examine how long-term poverty is affected by key macro-economic characteristics such as economic growth, employment rates, and countries' social expenditure. So far, only one study by Ingensiep (2016) analyzes the relationship between macro-economic drivers and persistent poverty. She compares long-term poverty rates taking four 4-year periods from 2006 to 2012 using a cross-sectional approach. Nevertheless, panel regression estimators are more suitable with this data structure to test causal hypotheses (Brüderl & Ludwig, 2013; Wooldridge, 2010). This study overcomes the limitations of previous research and aims to comprehensively examine the development of long-term poverty in Europe and identify possible macro-level drivers by analyzing 26 countries between 2009 and 2018 using panel regression estimators. It reveals that in 13 out of 26 countries, long-term poverty stayed unchanged or even decreased. The results of panel regression analysis suggest that changes in the GDP per capita do not explain fluctuations in long-term poverty. In contrast, the male employment rate has a strong positive effect on long-term poverty. A 1% increase in the male employment rate decreases long-term poverty by 4%. Further, an increase in the social expenditures in % of the GDP reduces long-term poverty. Decomposing social expenditure into four subcategories reveals that this effect is mainly due to expenditures for survivors and old age pensions. Interestingly, long-term poverty is negatively associated with short-term poverty. This finding suggests that countries with a high level of short-term poverty do not necessarily have high levels of long-term poverty and vice versa. An explanation is that in dynamic societies, individuals quickly fall into poverty but manage to escape it as quickly, whereas in less dynamic societies, being long-term poor means staying long-term poor.

The second article, "The development of global environmental concern during the last three decades" co-authored by Axel Franzen (Franzen & Bahr, 2024), uses the International Social Survey Programme (ISSP) data to analyze the development of environmental concern from 1993 onwards as well as its individual-level and country-level drivers. This is an interesting question, as CO_2 emissions have increased by 63% over the last three decades (Global Carbon Project, 2024), and biodiversity measured by the Living Planet Index dropped by almost 50% (WWF, 2022) and it is unclear how these trends are reflected in people's environmental concern. As environmental concern is an important prerequisite for supporting pro-environmental friendly policies (Bakaki et al., 2020; Franzen & Vogl, 2013; Vandeweerdt et al., 2016) and studies have shown that it is linked to environmentally friendly behavior (e.g., see Bouman et al., 2020; Bruderer Enzler & Diekmann, 2019; Diekmann & Preisendörfer, 2003; Preisendörfer & Franzen, 1996; Steg & Vlek, 2009), observing the development produces precious information for decision-makers about the support they can expect for pro-environmental initiatives. The study builds on a unique dataset, the ISSP environment module, which is available at four points in time (1993, 2000, 2010, and 2020) and allows for the measurement of environmental concern over three decades in up to 33 participating countries. This allows for the first time to assess the development of countries' environmental concern over an extensive time period. A period where CO_2 emissions strongly increased, biodiversity substantially decreased, the COP21 climate change agreement was ratified by 175 countries, and new environmental youth movements emerged (e.g., "Fridays for Future, "Last Generation"). Furthermore, the ISSP has the advantage that it covers non-OECD countries like Russia, South Africa, the Phillippines, Thailand, Taiwan, as well as India and China for the first time. The inclusion of the two biggest emerging economies, India and China, in the 2020 wave allow to examine environmental concern in a set of 29 countries that are responsible for 71% of the global CO_2 emissions. The variety of environmental variables available in the data allows us to measure environmental concern using a two-dimensional index, which has been shown to be superior to the single-item (Franzen & Mader, 2021). The article reveals that environmental concern was the highest in Switzerland (61.8) and the lowest in Slovakia (40.4) in 2020. Further, after a drop in environmental concern in 2010, it rose on average from 49.5 to 52.8 in 2020 in the 29 participating countries. Distinguishing between OECD and non-OECD countries indicates that OECD countries have a higher level of environmental concern. However, both groups experienced a similar pattern, where concern decreased slightly in 2000 and 2010 and recovered in 2020 to the level of 1993. A separate analysis for the United States reveals that being affiliated with the Republicans leads to a by 0.61 standard deviation lower environmental concern than respondents affiliated with the Democrats. Further, trust in science and the news media is positively associated with environmental concern. Surprisingly, household income and education do not matter. The multi-level model can partially confirm the findings of the US case. In the international context, on the individual level, trust in others, the parliament, science, and news media are all positively correlated with environmental concerns. In addition, postmaterialistic values, left political orientation, a higher educational degree, and being female lead to a higher concern. On the country level, GDP per capita is strongly, and population density is moderately related to environmental concern. Every percent increase in the GDP per capita leads to a rise in concern by 0.34 standard deviations.

The third and last article, "The relationship between urban greenery, mixed land use and life satisfaction: An examination using remote sensing data and deep learning" was written in single-authorship and examined if urban greenery and mixed land use in the neighborhood affect residents' life satisfaction (Bahr, 2024). It expands on an extensive body of literature that suggests a positive effect of urban greenery on residents' life satisfaction (Ambrey & Fleming, 2014; Bertram & Rehdanz, 2015; Kley & Dovbishchuk, 2021; Krekel, Kolbe, & Wüstemann, 2016; White, Alcock, Wheeler, & Depledge, 2013; Wu, Tan, Wang, & Chen, 2023) and criticizes the heterogeneous measurement of urban green spaces in the literature. The article suggests a cost-efficient and unbiased approach to measure urban green areas using high-resolution satellite images in combination with deep learning segmentation models. This approach allows the derivation of nine green urban land types on a fine-grained level and matches them with the life satisfaction of Swiss urban residents via geo-coding. This is important evidence for Swiss urban planners as 2/3 of the population live in urbanized areas but empirical evidence on this relationship is lacking. Furthermore, some studies indicate that preferences for urban green spaces differ by age. They revealed that younger individuals value green spaces more if they can be used for physical activities or meeting others, whereas older residents value them more if they can relax, enjoy nature, or stay with children (Chiesura, 2004; Kabisch & Haase, 2014). The objective of this article is to investigate whether heterogeneous age-related preferences exert an influence on the effect of urban greenery on life satisfaction by age cohort. Finally, human-oriented smart neighborhoods represent a fundamental component of a liveable and sustainable urban environment. However, only a limited number of studies have examined the relationship between mixed land use neighborhoods and residents' life satisfaction. The findings are indeterminate in the global (Cao, 2016; Dong & Qin, 2017; Guo et al., 2021; McCarthy & Habib, 2018; Wu, Chen, Yun, Wang, & Gong, 2022) as well as the European context (Mouratidis, 2018; Olsen, Nicholls, & Mitchell, 2019) and the article aims to shed further light on this relationship. The empirical results indicate that there is no general relationship between urban green spaces within the walkable neighborhood and residents' life satisfaction in Switzerland. As postulated in the literature, age matters, and urban greenery exerts a positive effect on life satisfaction among individuals age over 65. Additionally, the heterogeneous findings for the nine examined green space types highlight the importance of analyzing them separately. The findings indicate that trees and grass in parks and gardens are the primary contributors to the positive impact of urban greenery on older residents. The strongest effect was observed for grass in gardens and parks. A one standard deviation increase in grass coverage (located in gardens and parks) leads to a 0.240 standard deviation increase in residents' life satisfaction. The contrary is the case for a high mixture of land use types in a neighborhood. Only younger individuals seem to benefit from a higher mixture and this positive effect decreases at higher ages. The findings have practical ramifications for future urban planning initiatives in Switzerland and other European countries. They underscore the necessity of incorporating the age distribution of neighborhoods into the planning process to optimize the beneficial effects of urban greenery and mixed land use on residents' life satisfaction.

To sum up, the three research articles address relevant issues our society has been facing since the beginning of the millennium. By applying rigorous and novel empirical methods, this thesis can provide a better understanding of the development and drivers of long-term poverty, environmental concern, and urban residents' life satisfaction. The COVID-19 pandemic and armed conflict in Ukraine put pressure on the economy of various countries. The good news is that long-term poverty is not directly linked to economic downturn. However, it is related to social expenditures, especially the expenditures for pensions. If social expenditures decrease due to the economic downturn, it might lead to higher long-term poverty rates in the long run. CO_2 emissions have been increasing inexorably in the last three decades. Unfortunately, environmental concern does not mirror this development and only recently reached the 1993 level after a downturn. It needs to be added that the data of the current wave has been collected in the aftermath of the COVID-19 pandemic, and health was the issue respondents worried about the most. This might change in the near future and possibly lead to higher environmental concern. Furthermore, the finding that education has a direct effect on environmental concern after controlling for a possible mediation by political orientation is reassuring. The importance of promoting education to foster environmental concern and abate climate change is further stressed by the finding that higher education is commonly associated with higher trust in the political system, science, and media (Roberts, Reid, Schroeder, & Norris, 2013; Ugur-Cinar, Cinar, & Kose, 2020), which themselves are positively related with the level of concern. The positive relation between GDP and environmental concern is encouraging as the emerging countries China and India are among the top three CO_2 emitters globally. However, the future will reveal if the relationship, which is positive on average, also holds for these countries. The thesis provides new empirical evidence to Swiss urban planners, regarding the creation of liveable urban neighborhoods. The findings highlight that age is an important determinant of the perception of the urban environment by its residents. It is, therefore, crucial to incorporate the neighborhood's age distribution in the planning process of new urban neighborhoods. However, as the positive effect of urban greenery on life satisfaction is nuanced it is far from being a silver bullet to enhance residents' life satisfaction on average. Instead, urban planners should focus on targeting specific age groups and their needs and accordingly promote particular urban green space types. This same approach should be applied to the land use mix in a neighborhood, as it is only younger individuals who stand to gain from it. To ensure higher life satisfaction among younger age groups, city planners should promote the construction of mixed-use buildings, where the ground floor is occupied by commercials, bars, restaurants, or public services, and the upper floors are inhabited by residents. However, noise and nuisance are often associated with these vibrant areas and might decrease the life satisfaction of older residents. This showcases the complex interdependence between different urban land types, their heterogeneous effects on different age groups, and the challenge they pose to urban planners in order to build urban areas liveable for all residents and avoid segregation.

In a perfect world, scientific evidence builds the foundation for future political actions. However, "[w]hen widely followed public figures feel free to say anything, without any fact-checking, we have a problem. It becomes impossible for a democracy to think intelligently about big issues — deficit reduction, health care, taxes, energy/climate […]" (Friedman, 2010).

Overview of published articles

1	Title	**Poverty in Europe: How long-term poverty developed following the financial crisis and what drives it**
	Authors	Axel Franzen and Sebastian Bahr
	Publication date	May, 21 2023
	Journal	International Journal of Social Welfare 33(2)
	Journal Impact Factor	1.2 (2023)
	DOI	https://doi.org/10.1111/ijsw.12614
2	Title	**The development of global environmental concern during the last three decades**
	Authors	Axel Franzen and Sebastian Bahr
	Publication date	July, 2 2024
	Journal	Current Research in Environmental Sustainability 8
	Journal Impact Factor	3.7 (2023)
	DOI	https://doi.org/10.1016/j.crsust.2024.100260
3	Title	**The relationship between urban greenery, mixed land use and life satisfaction: An examination using remote sensing data and deep learning**
	Authors	Sebastian Bahr
	Publication date	July, 24 2024
	Journal	Landscape and Urban Planning 251
	Journal Impact Factor	7.9 (2023)
	DOI	https://doi.org/10.1016/j.landurbplan.2024.105174

Note: Journal Impact Factor is derived from the Journal Citation Reports.

Article 1

Poverty in Europe: How long-term poverty developed following the financial crisis and what drives it

Joint work with Axel Franzen

"Their resources [of the poor] are so seriously below those commanded by the average individual or family that they are, in effect, excluded from ordinary living patterns, customs and activities"

Peter Townsend (1979)

Franzen, A., & Bahr, S. (2024). Poverty in Europe: How long-term poverty developed following the financial crisis and what drives it. International Journal of Social Welfare, 33(2), 482–494. https://doi.org/10.1111/ijsw.12614

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ORIGINAL ARTICLE

INTERNATIONAL JOURNAL OF SOCIAL WELFARE

Poverty in Europe: How long-term poverty developed following the financial crisis and what drives it

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Abstract
The purpose of this paper is to provide an update on the development of the long-term relative poverty rate in Europe. We use European Statistics on Income and Living Conditions data (EU-SILC) for 26 European countries between 2009 and 2018. In addition to describing the development of long-term poverty, we also analyse the drivers of poverty on the country level via fixed effects panel regression analysis. We are particularly interested in how economic growth, employment rates, social expenditure, and short-term poverty rates are related to long-term poverty. Overall, the results show that long-term poverty has increased in 13 out of 26 countries, but was unchanged or decreased in 13 countries. Gross domestic product growth is not related to the development of long-term poverty. However, we find that male employment and social welfare expenditure reduce poverty rates. Furthermore, short-term poverty is negatively associated with long-term poverty. Hence, short-term poverty and long-term poverty rather substitute than complement each other.

KEYWORDS
current poverty, EU-SILC data, fixed effects panel regression, long-term poverty, relative poverty

INTRODUCTION

Europe and the world have experienced almost constant economic growth in the past several decades. However, this is only one side of the coin. In academic, public, and political discussions, rising income inequality has become a major concern. For example, Nobel prize-winning economist Angus Deaton wrote 'While I do not believe that there is any statement about income inequality that is true in every country of the world—except that it is difficult to measure—it is clear that the general trend has been towards higher income inequality, especially in recent years' (Deaton, 2013, p. 259). Similar conclusions are drawn in many other studies on inequality (e.g., Keeley, 2015; Piketty & Saez, 2014; Wilkinson & Pickett, 2009). In this paper, we focus on the lower end of the income distribution—the poor, and particularly on that part of the population that remains in poverty for a longer period. We want to shed light on the most recent development of long-term poverty in the aftermath of the financial crisis in 2008. We use European Statistics on Income and Living Conditions (EU-SILC) data for 26 countries. The SILC data are gathered via personal or telephone interviews in a 4-year rotating panel. Hence, we can describe countries' poverty rates during seven 4-year time spells starting with 2009–2012 up to and including the period of 2015–2018.

Poverty research is relevant from a sociological perspective because it has major consequences on the living conditions of the affected individuals. Peter Townsend (1979, p. 31) wrote the 'resources [of the poor] are so seriously below those commanded by the average individual or family that these are, in effect, excluded from ordinary living patterns, customs and activities'. More particularly, poverty leads to shorter life expectancy (Chetty et al., 2016), bad health (e.g., Bor et al., 2017; Madden, 2015; Wagstaff, 2002), depression (Abbott & Wallace, 2014; Riumallo-Herl et al., 2014), low educational performance (e.g., Blanden & Gregg, 2004; Ferguson et al., 2007), and low social and political participation (Mood & Jonsson, 2016). Poverty not only creates problems for the affected individuals, but high levels of poverty—and therefore unequal living conditions—may also jeopardise the social order and cohesion of societies. Hence, countering poverty is a major goal of practically every Western welfare state as well as of the European Commission (European Commission, 2010).

Cross-sectional poverty indicators tell us how many households or individuals live in poverty in a given year. This information is of course interesting and informative, but it tells us only one part of the story. The other interesting question is how long households stay in poverty and whether or not they succeed in leaving this state again. Long-term poverty is often defined as households that stay in poverty for more than 2 years. A short period of poverty has a lower impact on the living conditions of individuals. Savings, assets, or financial aid from relatives can compensate for short periods of economic hardship. However, if spells of poverty become longer or more frequent, savings vanish and poverty will have a more serious impact on individuals' living conditions, health, and ability to participate in social life (Corcoran, 1995; Holmes & Kiernan, 2013; Whelan et al., 2003). This is one reason why long-term poverty should receive special attention. The other reason is that the current relative poverty rate is susceptible to small changes in income located around the poverty threshold. Hence, small changes in income may lead to shifts in the poverty rate without substantial changes in living conditions. A long-term poverty measure is more robust with regard to this problem since short periods of poverty do not affect it.

This article is structured into five sections. In the second section, we briefly discuss the literature concerning poverty rates, particularly long-term poverty rates in Europe. Furthermore, we discuss the main macroeconomic drivers of poverty as well as institutional differences as described in the literature. The third section describes the EU-SILC data we use. The fourth section presents the latest trends in long-term poverty for 26 European countries. Furthermore, the section describes the multivariate panel data analyses and presents the results concerning the main drivers of poverty rates. Finally, the last section summarises and discusses the main findings.

LITERATURE REVIEW

While there is a great deal of literature that describes and analyses absolute poverty rates (e.g., Bárcena-Martín et al., 2014; Dudek, 2019; Duiella & Turrini, 2014; Nelson, 2012; Nolan & Whelan, 2010; Whelan et al., 2004; Whelan & Maître, 2012), or relative poverty rates (e.g., Alper et al., 2021; Bosco & Poggi, 2020; Caminada et al., 2012; Cammeraat, 2020; Cantillon, 2011; Duiella & Turrini, 2014; Nelson, 2013), research devoted to long-term poverty is sparse. The existing articles present mainly descriptive results (Layte & Whelan, 2003; Maître et al., 2011; Vaalavuo, 2015), focus on the causes of entry into and exit from poverty at the individual level (Andriopoulou & Tsakloglou, 2016; Polin & Raitano, 2014; Şeker & Dayioğlu, 2015), or have used cross-sectional analysis to determine macro-level characteristics on poverty rates (Ingensiep, 2016). However, to date, there is no study examining macro-level effects on long-term poverty in Europe using a panel regression approach. The main reason for this gap is the lack of availability of longitudinal data. In the past, such data was available only for selected countries such as the USA, the UK, the Netherlands, or Germany. This situation improved when the European Statistical Office (Eurostat) started the European Community Household Panel Survey (ECHP) in 1994. The ECHP collected income data from representative samples of households over 8 years which allows the observation of household income dynamics. A first analysis of this data with respect to poverty was presented by Layte and Whelan (2003). One of their main findings is that many more households experience poverty during a 4-year time span as compared to the proportion falling under the current poverty definition in a given year. However, long-term poverty, that is, being poor for 3 or 4 years is relatively rare. Hence, a large number of households move in but also out of poverty during a 4-year period. Ingensiep (2016) uses EU-SILC data (the continued ECHP) from 2005 to 2012 to describe the development of long-term poverty rates. She concludes that long-term poverty increased during this period in every country besides Poland.

The purpose of our study is to replicate and extend the analysis of Layte and Whelan (2003) and Ingensiep

(2016). Layte and Whelan (2003) compare the poverty rates for 15 countries in the period 1994–1998. Ingensiep (2016) compares the long-term poverty rate of 19 countries for the period of 2005–2012. Our analysis extends former research by incorporating all 4-year spells of the EU-SILC data starting in 2009 after the financial crisis. Hence, we observe long-term poverty for seven 4-year spells in 26 countries. Because of the increased number of available time spells as well as the number of countries it is now also possible to analyse the data via fixed effects (FE) panel regressions at the country level. Such an analysis is better suited for a causal investigation of macro-economic effects on countries' poverty rates than ordinary OLS or logistic regression approaches.

As does most poverty research, we use a relative poverty definition and measure the proportion of individuals whose household equivalence income is below 60% of a country's median income (e.g., Krämer, 2000). In addition to describing the trend, we are also interested in how key macro-economic characteristics such as economic growth, employment rates, and countries' social expenditure influence poverty rates. The effect of economic growth on relative poverty rates is theoretically indeterminate and an empirical question. If all income groups profit proportionately from economic growth then relative poverty rates should remain unchanged with increasing gross domestic product (GDP). But if the income of the non-poor rises disproportionally more, GDP growth leads to a rise in poverty. Only if the poor benefit more than the non-poor, can relative poverty rates diminish. This scenario is also referred to as 'pro-poor growth' in the literature (e.g., Kakwani & Pernia, 2000). With respect to absolute poverty, empirical research mostly finds that economic growth decreases poverty (Bárcena-Martín et al., 2014; Dudek, 2019; Duiella & Turrini, 2014; Kraay, 2006; Škare & Pržiklas Družeta, 2016; Whelan & Maître, 2012).

Relative poverty rates are less responsive to growth than absolute poverty rates. Dollar and Kraay (2002) and Dollar et al. (2016) analyse more than 120 countries and find that the income of the poor benefit proportionately to the income of the non-poor during periods of economic growth. However, more recent panel studies of European countries show mixed evidence. Bosco (2019) uses a quantile regression approach for 31 European countries for the time span of 2002 until 2011. He uses the 'at risk of poverty and social exclusion' (AROPE) measure of Eurostat as the dependent variable which considers households falling either into relative poverty, absolute poverty, or low work intensity. He finds that income growth leads in all poverty quantiles to a reduction of the AROPE. Cammeraat (2020) applies a FE panel regression for 22 European countries from 1990 to 2015 and reports that a 1% GDP increase decreases relative poverty by 0.15%. He uses OECD data and 50% of the national median income as the relative poverty threshold. But there are also studies reporting zero effects. Caminada et al. (2012) find no effects of GDP on relative poverty rates for 22 OECD countries for the five-observation points of 1985, 1990, 1995, 2000, and 2005. This result is also confirmed by Duiella and Turrini (2014), Domonkos and Ostrihoň (2015), and Bosco and Poggi (2020). Summing up, evidence to date finds predominately no relation between GDP growth and relative poverty. Hence, we expect that this zero effect also holds true for the most recent time span of long-term poverty. This is hypothesis 1.

Unemployment is of course a major risk to fall into poverty. Accordingly, growth in employment should lead to reductions in relative poverty. However, an analysis by Cantillon (2011) between 2004 and 2008 for 27 EU countries did not find any relationship between employment and relative poverty. Cantillon (2011) concluded that jobless households were only sparsely affected by job growth, and that wealthy households profited more from employment growth. Moreover, if employment growth occurs predominantly in low-paid sections of the labour market, the newly created jobs may promote in-work poverty. Hence, the relationship between change in the rate of employment and poverty is not as straightforward as it appears at first glance. Marx et al. (2012) investigated the effects of employment on the poverty rate via a simulation study. Among others, they differentiate two scenarios: (1) the effect of an increase in the employment rate to 75% for the poverty rate of the working-age population (20–64), and (2) for the poverty rate of the whole population. In Scenario 1, the majority of the countries experience a fall in relative poverty rates. But in Scenario 2, almost half of the countries experience a rise in the relative poverty rate. Marx et al. (2012) conclude that newly employed individuals indeed move out of poverty. But this change in employment also affects the median income and hence the poverty threshold and deteriorates the relative position of others, for example, elderly people or people depending on social transfers. In a more recent study, Gábos et al. (2019) examine employment and poverty dynamics before and after the financial crisis. Their panel regression analysis reveals a negative relationship between employment and poverty in 27 EU countries from 2005 to 2012 for the population aged between 20 and 59. The results, therefore, support the simulation results of Marx et al. (2012) for Scenario 1. Also, Scenario 2 is supported by a recent panel analysis of 22 EU member states between 1990 and 2015 by Cammeraat (2020). His analysis uses the whole population and reveals no relationship between the unemployment rate and poverty.

Furthermore, the effect of employment depends on the type of employment. Previous research found a positive relationship between low-wage jobs and relative poverty (Alper et al., 2021; Crettaz, 2013; Lohmann & Gießelmann, 2010). A more recent panel analysis for Germany from 1992 to 2011 supports these findings. Brülle et al. (2019) find that relative poverty in Germany increased by 2 percentage points. Most of this increase (92%) is due to the increase in low-paid jobs. Hence, the effect of an employment increase on the relative poverty rate of the whole population depends on the type of jobs created in an economy. Employment growth can decrease poverty if the benefit to the poor is over-proportionate, and if the new jobs are created not only in low-wage sectors.

The reasoning that higher employment should decrease poverty rates applies also, or even more so, to the female employment rate. Assuming that the main breadwinners are still males in most European countries, one would expect that female labour market participation does not substitute male incomes but complements the household income. In particular, women in poor households have a higher need to participate in the labour market, and their additional income should improve the household income of the poor, in turn decreasing the poverty rate. Hence, the findings of the effects of employment on poverty are very mixed. The effects depend on the type of jobs that were created in a certain time period. The way how the European labour market changed after the financial crisis is highly speculative. Hence, we assume that both low-paid and high-paid employment increased proportionately in most countries leaving a neutral effect on poverty rates. Therefore, we hypothesize that there is on average no effect of employment on the long-term poverty rate. This is hypothesis 2.

Another important factor in poverty rates is the social security spending of governments. Social expenditures are implemented by welfare states to redistribute income from the rich to the poor. Hence, the more a country spends on social security the lower should be relative poverty rates. This hypothesis seems to be confirmed by the literature (e.g., Bosco & Poggi, 2020; Caminada et al., 2012; Jenkins, 2000). Notten and Guio (2019) find reductions in relative poverty rates of between 51.2% and 64.8% for Germany, Poland, Greece, and the UK by comparing household incomes before and after receiving social security funds. However, their analysis takes only direct transfers into account, not government spending on social services and institutions. Cammeraat (2020) uses countries' total social expenditure as a percentage of GDP and finds that an increase in social expenditures by 1% leads to a decrease in relative poverty of 0.337%.

So far, only the study by Ingensiep (2016) examines the relationship of macro-economic drivers on persistent poverty. Ingensiep (2016) conducts a cross-sectional analysis of the individual data and estimates the effects by assigning the macro characteristic (e.g., a country's social protection expenditure) to every individual in a given country. Taking four 4-year periods from 2006 to 2012 for 19 European countries into account, she finds that an increase of social protection expenditures by 1 percentage point of GDP decreases the probability of being persistently poor by between 0.011 and 0.024. However, her statistical model is not an optimal use of the data structure since causal hypotheses can be better tested via FE panel regressions (Brüderl & Ludwig, 2015; Wooldridge, 2010). Hence, we conduct FE panel regressions at the country level for seven 4-year periods from 2009–2012 to 2015–2018 in 26 European countries. In line with previous findings, we hypothesize that increases in social protection expenditures decrease long-term poverty rates. This is hypothesis 3.

To sum up, the purpose of this study is to investigate the trend in countries' long-term poverty rates and to identify the main macro-economic drivers of its development. Given previous research findings that increase in GDP are not related to relative current poverty rates, we expect that long-term poverty has also not decreased during the last 10 years. Hence, consistent with previous findings, we expect that GDP changes are not related to long-term poverty rates (Hypothesis 1). Concerning the effect of employment, previous research found different results depending on whether employment growth occurred predominantly in the low-paid sector or in the more well-paid parts of the labour market. Given these undetermined findings, we also expect to find no relation between employment rates and long-term poverty. As a matter of fact, individuals with long-term poverty should find it harder to return to the labour market. Hence, they should profit less from employment growth leaving long-term poverty rates unchanged (Hypothesis 2). Finally, the existing literature suggests that countries' spending on social welfare reduces poverty rates. This effect should be stronger for long-term poverty as compared to current poverty since individuals in long-term poverty are more dependent on social transfers (Hypothesis 3).

DATA AND METHODS

To describe and analyse the recent trend in long-term poverty we use the EU-SILC. EU-SILC is a coordinated survey on the income and living conditions of individuals in private households in 31 European countries. The data is collected in each country by the national statistical offices and is harmonised and provided by Eurostat. EU-SILC is designed as a rotational 4-year panel. Each year a random sample of private households is drawn and surveyed for four consecutive years. In some countries (Denmark, Finland, the Netherlands, Norway, Sweden, and Slovenia) some of the data (e.g., income) are retrieved from administrative sources, but in most countries, the data are obtained by survey interviews. The mode of data collection varies between the countries. In some countries, the surveys are conducted via personal interviews (face-to-face), while others use telephone interviews, and Germany conducts the data collection via a web-based online survey (for a critique of these differences in the data collection see Iacovou et al., 2012; Polin & Raitano, 2014).

Most countries use either simple random sampling (Denmark, Malta, and Norway) or stratified random sampling where the geographical region is the main stratification criterion. All members of the selected households aged 16 or older are surveyed. The individual response rates vary between 37% (Denmark in 2015) and 96% (Romania in 2014). Since EU-SILC is a rotational panel, the cross-section for each year consists of four groups; individuals who are interviewed for the first time, the second time, the third time, and the fourth time. Eurostat provides weights to account for selection probabilities, non-response rates, and characteristics of households and individuals (e.g., sex and age) (Eurostat, 2020). Generally, attrition is an issue in longitudinal data collection, and this is also true in some countries included in EU-SILC (see Jenkins & Van Kerm, 2017). This attrition can be incorporated by using an appropriate weight. However, in our case incorporating this weight does not influence the results and hence we are not using longitudinal weights.

The number of surveyed individuals varies in the longitudinal 4-year time periods from 1661 in Denmark (2010–2013) to 13,037 in France (2008–2011). The detailed number of observations is reported in the supplement (Table S3a–c). In each cross-section, the number of observed individuals differs from a minimum of 9283 in Cyprus in 2009 to a maximum of 56,447 in Greece in 2018 (see Table S4a–c). Since a description of the long-term poverty rate for the period of 2005–2012 is already contained in Ingensiep (2016), our analysis focuses on the development following the financial crisis until 2018. Therefore, we use seven sequential 4-year periods from 2009 to 2018 to obtain the long-term relative poverty rates. A more detailed description of the data structure is contained in Figure S5. Longitudinal data is available for 27 of the 31 countries in our observation period. However, for Germany data exists only for the most recent 4-year period, and hence, has only one observation period. Furthermore, robustness checks identified Hungary as a statistical outlier. Therefore, the panel analysis with respect to long-term poverty is based on 25 countries.

Because income is usually shared between household members, we use the households' equivalence income for each individual as provided by Eurostat. It is calculated by summing up all individual net incomes generated in a household and by dividing this sum by the weighted number of household members. Following the definition of the OECD, the first adult receives a weight of one, each additional household member aged 14 or older has a weight of 0.5, and each child below the age of 14 receives a weight of 0.3. The relative poverty rate is defined as the ratio of individuals who have less than 60% of the equivalent national median household income. We define individuals as long-term poor if they fall under this 60% threshold for 3 or 4 years in a 4-year time spell. In contrast, short-term poverty is defined as individuals being poor for 1 or 2 years.

Since we are interested in the macro-economic determinants of the long-term poverty rates our data consists of 25 countries (units of analysis) which are observed for seven 4-year time spells starting from 2009–2012 to 2015–2018. Hence, we have panel data consisting of 173 observations (24 countries times seven 4-year spells, plus Switzerland for which the data is only available for five 4-year time spells). The data structure allows us to differentiate between individuals who never fell into poverty during a given 4-year time spell, who went into poverty during 1 or 2 years (short-term poverty), or who spent 3 or 4 years in poverty (long-term poverty). Since we have panel data which describes the trend of the countries' poverty rate for the seven time spells we employ a FE panel regression approach. FE regressions only analyse the within-unit variances by demeaning the data as shown in (1):

$$y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)\beta + \varepsilon_{it} - \bar{\varepsilon}_i, \tag{1}$$

where y_{it} denotes a country's (i) poverty rate in year t and $\bar{y}_i$ the countries' average poverty rate for the whole observation period. x_{it} denotes the vector of the exogenous variables for country i in time t, and $\bar{x}_i$ the averages for the whole observation period. FE panel regressions have the advantage of taking only the within-country variation into account, and not the between-country differences. This avoids biased estimates due to unobserved heterogeneity between the countries. Furthermore, estimates can also be biased due to unobserved heterogeneity in time-varying variables (or different slopes or trends). The problem of different slopes can be taken into consideration by estimating FE individual slopes (FEIS) models. FEIS estimators are obtained by applying pooled OLS regression to the detrended data (Brüderl & Ludwig, 2015;

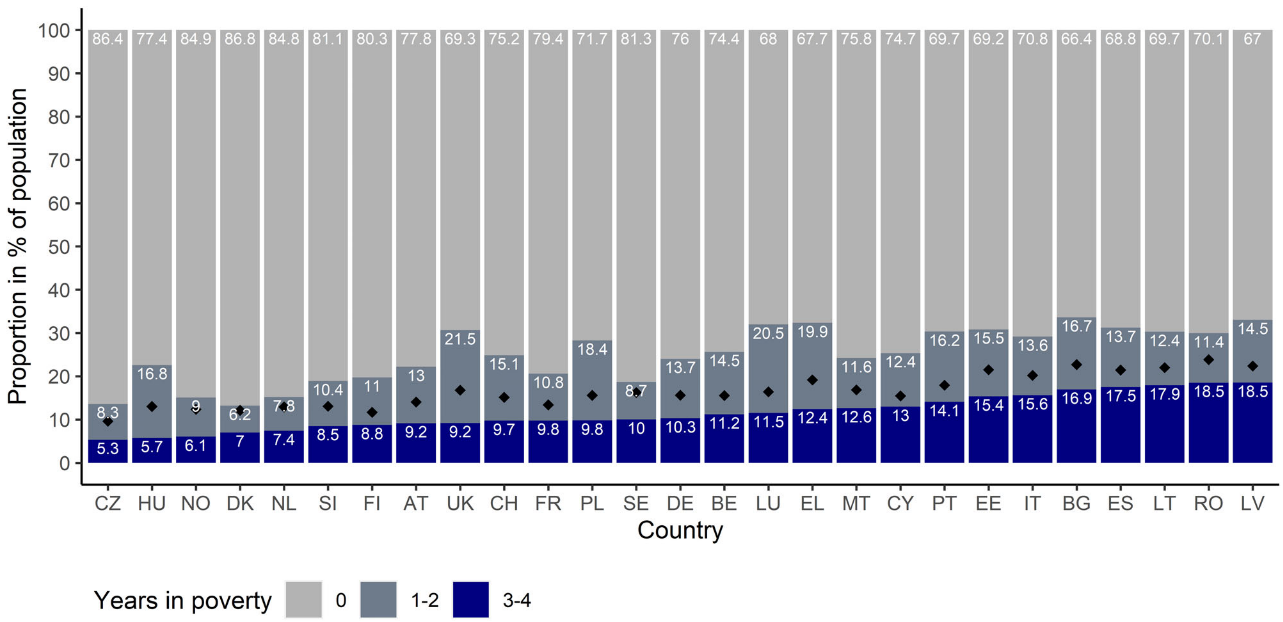

FIGURE 1 The proportion of the population in poverty by duration in the period 2015–2018. Note: Data base is the EU-SILC from 2016 to 2019 which refers to the income conditions in 2015 to 2018. Countries are ranked according to the proportion of individuals falling for three or four years under the 60% of median income poverty definition.

Rüttenauer & Ludwig, 2023; Wooldridge, 2010). The model can be written as

$$\tilde{y}_{it} = \tilde{x}_{it}\beta + \tilde{\varepsilon}_{it}, \tag{2}$$

where $\tilde{y}_{it}$ denotes the detrended values of the dependent variable and $\tilde{x}_{it}$ a vector of the detrended independent variables. We regress detrended poverty rates on detrended GDP, employment rates and countries' social protection expenditures. The effects can be causally interpreted under the assumption that none of the exogenous variables x_{it} is correlated with the error ε_{it}. The assumption is known as the strict exogeneity assumption. The data for countries' GDP, employment rates and social protection expenditures are provided by Eurostat (2021). The latter includes expenditures on old age pensions, sickness and healthcare benefits, social support for families and children, and unemployment payments. The statistical analyses are conducted with the software packages R 4.0.3 and STATA 16.0.

RESULTS

Figure 1 depicts the proportion of the population that falls under the relative poverty definition of having less than 60% of the median income from 2015 to 2018, which is the latest available 4-year spell. The graph describes the proportion of four different groups. First, the light grey section of the bars shows the proportion that experienced no poverty at all during the 4 years. Second, the dark grey bars show the proportion that experienced short-term periods of poverty by falling once or twice under the poverty threshold within the 4-year period. Third, the lower section of the bars depicts the proportion of inhabitants living in long-term poverty, that is, 3 or 4 years. Fourth, the black rhombus in each bar depicts the proportion that falls under the poverty definition in a given year termed current poverty. Cross-sectional data would only reveal this proportion. However, the panel data show that the proportion of those who report living in low-income conditions at least once during a 4-year time spell is larger than the cross-sectional proportion. For some countries, this difference is quite substantial. For instance, for the UK the cross-sectional data shows a poverty rate of 16% (average of the 4-year period), but 30.7% of the population experienced poverty at least once during the observed time span. The data also reveal that in most countries the long-term poverty rate is much lower than the short-term poverty rate. However, this is not true for the Baltic countries (Lithuania, Estonia, Latvia), some Eastern countries (Romania, Bulgaria), and some Southern countries (Italy and Spain) that experience high long-term poverty rates within Europe. The countries with the lowest long-term poverty are Hungary, the Czech Republic, and the Northern European countries, that is, Norway, Denmark, and the Netherlands. Overall, the

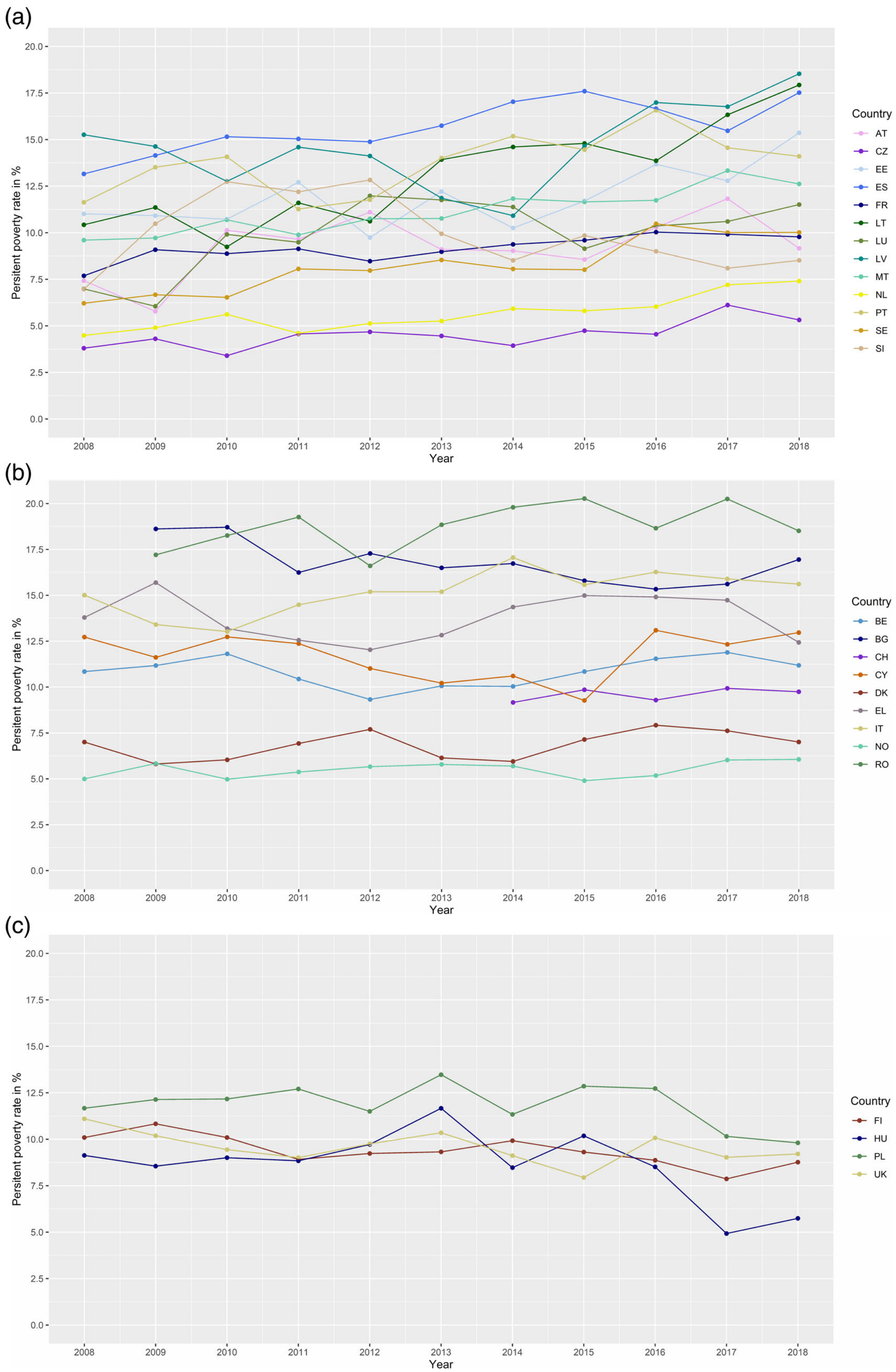

FIGURE 2 (a) Countries with increased long-term poverty rates. (b) Countries with unchanged long-term poverty rates. (c) Countries with decreased long-term poverty rates. Note: Data base is the EU-SILC from 2005 to 2019, referring to the income conditions in 2005 to 2018. Countries are grouped according to their trend in long-term poverty. We compared the first and the last year and assigned the countries to the various groups according to the results of a t-test.

TABLE 1 Panel regression analysis of current and long-term poverty rates.

	Current poverty rate FEIS estimator		Long-term poverty rate FEIS estimator		
	(1)	(2)	(3)	(4)	(5)
GDP per capita in 1000 EURO	−0.450*** (0.134)	−0.302+ (0.174)	0.396 (1.139)	−0.714 (0.847)	−0.646 (0.773)
Male employment rate	−0.041 (0.266)	0.129 (0.267)	−4.528** (1.622)	−4.718** (1.553)	−4.410** (1.393)
Female employment rate	−0.554 (0.321)	−0.538+ (0.320)	2.804+ (1.555)	1.240 (1.107)	1.738+ (1.048)
Social expenditures in % of GDP	−0.346** (0.114)		−1.136+ (0.583)		
Unemployment exp. in % of GDP		−0.035 (0.084)		0.070 (0.396)	0.070 (0.363)
Pension and survivor exp. in % of GDP		0.110 (0.252)		−3.260*** (0.860)	−2.248** (0.907)
Sickness and disability exp. in % of GDP		−0.230 (0.169)		0.270 (1.152)	−0.237 (1.088)
Family and child benefits in % of GDP		−0.064 (0.098)		0.128 (0.548)	0.205 (0.551)
Short-term poverty rate					−0.277*** (0.080)
Within R^2	0.18	0.18	0.06	0.13	0.20
n	30	30	25	25	25
$n \times T$	300	300	173	173	173

Note: Unstandardized regression coefficients of logarithmized variables with standard errors in brackets. The effects can be interpreted as elasticities. All standard errors are panel-robust. Iceland is an outlier and excluded in Models 1 and 2. Hungary is an outlier and excluded in Models 3–5. The data source is the EU-SILC Cross and Long UDB 2010–2019—version of 2021–3 for the poverty rates. GDP, employment rates, and social protection expenditures are from Eurostat (2021).

Abbreviations: FEIS = fixed effect individual slope; GDP = gross domestic product.

$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

distribution depicted in Figure 1 demonstrates that there are substantial differences in Europe with respect to long-term poverty ranging between 5% and 6% at the bottom of the distribution to 15% and 18% at the top.

Table S1a,b contains more detailed information and indicates the proportion of the population suffering from poverty by the exact number of years for the periods 2007–2010, 2011–2014, and 2015–2018.

Next, Figure 2 shows the trend of long-term poverty from 2008 to 2018. Each year represents the last year of the 4-year observation period. We grouped countries into those that experienced an increase in poverty, those with unchanged poverty rates, and those with decreased poverty rates. As can be seen from Figure 2, half (13/26) of the countries for which the data is available experienced an increase in long-term poverty, but nine experienced no change, and poverty rates decreased in four countries. All groups are fairly heterogeneous. For instance, the group with increasing rates contains mostly East and South European countries. Only five of the wealthy mid and northern European countries (Austria, France, Luxembourg the Netherlands, and Sweden) are in this group. The other middle and northern European countries experienced either no change in long-term poverty (Belgium, Switzerland, Denmark, and Norway) or even a decrease (Finland and the United Kingdom). 58% of the population of the 26 observed countries are located in countries with unchanged or decreased long-term poverty. Overall, the long-term poverty rate increased by 1.38 percentage points between the first observation point and the last. This increase is statistically not significant ($t = 1.25$, $N = 52$).

The results of the FEIS panel regressions are shown in Table 1. First, we analyze the current poverty rate in Models 1 and 2. Hence, Models 1 and 2 are a replication of Caminada et al. (2012), Duiella and Turrini (2014), Bosco (2019), and Cammeraat (2020). Models 3–5 estimate the effects of GDP, employment, and social expenditure on the long-term poverty rate. In Models 1 and 2, values of the independent variables (GDP, employment, and social expenditures) are used on a yearly basis. However, for the analysis of long-term poverty, we use the rolling 4-year averages of the periods for which we observe the long-term poverty rates. The analysis of the current poverty rate is based on 30 countries. We excluded Iceland from the regression because it causes non-robust coefficients. Model 1 shows that GDP is statistically significantly related to the countries' current poverty rate. Since we use the natural logarithm of all variables, all coefficients in Table 1 can be interpreted in terms of elasticities. Hence, the effect of GDP means that the current poverty rate diminished by 0.45% with every percentage increase in GDP in the decade from 2009 to 2018. This finding rejects Hypothesis 1 and supports the results of Bosco (2019) and Cammeraat (2020). It means that the lower incomes did profit over-proportionately from economic growth after the financial crisis.

Furthermore, the analysis (Model 1 in Table 1) shows that female and male employment rates have no statistically significant effects on current poverty rates which is in line with most evidence reported in the literature. Theoretically, employment rates only reduce current poverty if the incomes generated are above the 60% median income of a country. This was not the case in most European countries in the last decade, and employment seems to have benefited all labour market sectors (low-paid and otherwise) leaving the current poverty rate unchanged.

Countries' social welfare spending is associated with lower current poverty rates as expected by Hypothesis 3. Surprisingly, the relation of governmental social spending with the current poverty rate is relatively modest; a 1% increase in social expenditure (in terms of the proportion of GDP) is associated with a decrease in the current poverty rate by only 0.35%. Eurostat distinguishes social expenditures into six categories which in theory enables a more detailed analysis of the effect of different types of social expenditures. However, our analysis reveals that the decomposition of the expenditure variable does not produce any statistically significant effect for any subgroup (see Model 2 of Table 1). Hence, the beneficial effect of total social expenditure is due to the sum of the subcategories, and not caused by any specific subcategory.

Next, we repeat the analyses with the long-term poverty rate, that is with the proportion of the population that falls under the poverty rate for 3 or 4 years. First of all, GDP is not related to long-term poverty (Models 3–5 in Table 1). This finding is surprising since GDP is negatively associated with the current poverty rate. However, male employment rates and also social expenditure are negatively related to long-term poverty. The effect of male employment is strong; a 1% increase in employment decreases long-term poverty by more than 4%. Also, the dampening effect of social expenditure is much stronger with respect to long-term poverty as compared to current poverty. An increase in social expenditure by 1% decreases long-term poverty by 1.14%. Moreover, a decomposition of social expenditures suggests that the effect is due to expenditures for survivors and old age pensions. Finally, in Model 5 we investigate how short-term and long-term poverty are related. The result indicates a negative relation between the two. If short-term poverty increases long-term poverty decreases. At first glance, this effect looks counterintuitive, since one might think that short-term poverty leads to long-term poverty as is the case for individual poverty trajectories. But on the country level, it might be the case that a country has a large proportion of individuals living in long-term poverty, but only a small proportion with short poverty spells (see Romania), or vice versa. An example of the opposite pattern is the UK which has relatively high short-term poverty rates and relatively low long-term poverty rates. A good number of individuals fall into poverty, but they also manage to move out of it again, leading to low long-term poverty rates. The results of Model 5 in Table 1 says, that this pattern applies to most countries in Europe.

All estimates reported in Table 1 were tested extensively for robustness. First, all models were repeatedly analysed excluding one country each time from the regression. All results depicted in Table 1 remained robust, meaning that the results are not driven by a single country. Second, we trimmed the income distribution of all countries and for all years by the top 1% and the bottom 1%. All results displayed in Table 1 are robust to this trimming of the income distribution. Third, we repeated the analysis of Models 3–5 with weighted poverty measures, as suggested by Jenkins and Van Kerm (2017) and find only minor differences in the coefficients. Forth, all parameters are checked for non-linearity via penalised splines FEIS regressions (Ruppert et al., 2003). Fifth, we also controlled for possible autocorrelation and heteroscedasticity of standard errors by using panel-robust standard errors. Sixth, we conducted the Frank test (Frank et al., 2013) examining the proportion of cases that would have to change to make the effects insignificant. The proportion of cases necessary to change our results varies between 21% (for social expenditures in Model 5) and 48% (for social expenditures in Model 4). Hence, the results are very robust. Furthermore, we conducted the Hausman test (Croissant & Millo, 2008; Hausman, 1978) to find out if the estimates of the FE regression model differ from the estimates of a first-difference model. This is not the case and suggests that there are no substantial feedback effects. Finally, we also considered if the effects of employment and social expenditure depend on the proportion of the population above 65 years of age. For this purpose, we included a country's proportion of the elderly (>65) in the analysis. None of the coefficients reported in Table 1 changed due to this model extension. The same holds true if the models are controlled for the proportion of individuals receiving pensions. None of these model extensions changed the results reported in Table 1.

CONCLUSIONS AND DISCUSSION

This paper analyses the recent trend of long-term poverty in Europe since 2008. We find that long-term poverty increased in 13 out of 26 countries, but remained unchanged in 9, and decreased in 4 countries. Rises in long-term poverty are observed in southern and eastern European countries. But the majority of middle and northern European countries experienced unchanged or decreasing long-term poverty rates. In terms of the number of inhabitants, the majority of individuals surveyed by EU-SILC (58%) live in countries with unchanged or decreasing long-term poverty rates. Hence, the trend for the latest decade is much more optimistic than the trend from 2005 to 2012 reported by Ingensiep (2016), who found increasing long-term poverty rates.

With respect to the current poverty rate, we find that economic growth (GDP) is associated with decreases in poverty rates which refutes the findings of Caminada et al. (2012), Duiella and Turrini (2014), Domonkos and Ostrihoň (2015), Bosco and Poggi (2020), but confirms the findings of Bosco (2019) and Cammeraat (2020). Also, the employment rate does not affect the current poverty rate, which is in line with the results of Cammeraat (2020). Moreover, social expenditure is associated with decreases in the current poverty rate as is also shown by Caminada et al. (2012), Bosco and Poggi (2020), and Cammeraat (2020).

Concerning long-term poverty we do not find an association with GDP confirming Hypothesis 1. Increases in employment, however, do decrease long-term poverty rates. This result is surprising since it only applies to male employment and long-term poverty but not to current poverty rates. The result suggests that the poor are not permanently disconnected from the labour market.

In line with former research (Ingensiep, 2016), and confirming Hypothesis 3 we find that social protection expenditures are negatively related to long-term poverty as well as current poverty. Interestingly the association of social welfare spending with the long-term poverty rate is about three times as strong as the association with the current poverty rate. However, whether this effect can be interpreted causally is debatable. On one side it seems plausible that social expenditures reduce poverty rates. On the other side high poverty rates might also increase political pressure to increase social spending. Hence, the causal relationship remains undetermined by our analysis. However, reversed causality (e.g., poverty affects social spending) seems less convincing, because poverty rates would most likely not influence social expenditures instantly but with a certain time lag. But in our analysis, the poverty rate in a given year is regressed on the social expenditure of the same year which favours the first interpretation.

Finally, our analysis finds a negative relation between short-term and long-term poverty rates. This result is surprising at first glance since one might assume that a country's long-term poverty rate is positively associated with its short-term poverty rate. However, the association we find is negative. One possible interpretation is that high short-term poverty rates exist in more dynamic societies, in which individuals have a higher risk of falling into poverty, but also a better chance of leaving this state again. Separating the analysis into short-term and long-term periods of poverty as done in this paper makes this relation visible, whereas reporting only current spells of poverty conceals this interesting and relevant finding. Countries' welfare not only depends on the current poverty rate but also on the relationship between short-term and long-term periods of poverty. The long-term poverty rates should be small since they impact the well-being of individuals much more severely than short-term poverty.

However, the EU-SILC data also have some limitations. First of all, most countries gather the income of households via surveys (face-to-face or telephone) which are knowingly subject to social desirability. Hence, the rich might underreport and the poor might over-report their income. This would result in an underestimation of poverty rates. We do not think that this is very likely, but the data would of course be more reliable if all countries used registered data.

Furthermore, EU-SILC observes individuals only for 4 years. Therefore, individuals who report to be poor in the first or second wave, and who left poverty thereafter are classified as being short-term poor. However, since there is no information about the income situation before they participate in the survey, poverty rates are left-censored which means that we might underreport long-term poverty. The same problem occurs if a person falls into poverty during the last 2 years of his or her participation in the survey. If a respondent stays in poverty thereafter we would also underestimate long-term poverty. The short time spells of observations are a disadvantage of the EU-SILC data.

The poverty indicators we use only measure the proportion of people affected by poverty. This poverty measure does not include information about the income distribution of the poor and the depth of poverty, as done by other measures such as the Income Gap (I) (Kakwani, 1993), the Interval Measure (HI) (Atkinson, 1987), or the FGT index (Foster et al., 1984). Future research should shed light on the relationship between macro-economic drivers and these intensity measures of poverty.

Finally, the goal of this paper is to describe the development of long-term poverty and to examine possible explanations for it. Given that the estimates must be interpreted with caution it is not so obvious what the potential social policy implications are. If the effects can be interpreted causally, then an increase in social expenditures would dampen the poverty rate. Furthermore, employment reduces particularly the long-term poverty rate. But we think that further research is needed to give more precise social policy recommendations.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interests.

DATA AVAILABILITY STATEMENT

The data are available from the Statistical Office of the European Union (Eurostat): https://doi.org/10.2907/EUSILC2004-2019V.2.

ETHICS STATEMENT

No new data were collected for this research and the data are freely available from the Statistical Office of the European Union (Eurostat). Since this research uses freely available survey data no patient consent is required.

REFERENCES

Abbott, P., & Wallace, C. (2014). Rising economic prosperity and social quality the case of new member states of the European Union. *Social Indicators Research*, *115*, 419–439. https://doi.org/10.1007/s11205-012-9992-0

Alper, K., Huber, E., & Stephens, J. D. (2021). Poverty and social rights: Among the working age population in post-industrial democracies. *Social Forces*, *99*(4), 1710–1744. https://doi.org/10.1093/sf/soaa073

Andriopoulou, E., & Tsakloglou, P. (2016). *Mobility into and out of poverty in Europe in the 1990s and the pre-crisis period: The role of income, demographic and labour market events* (IZA Discussion Papers No. 9750). http://hdl.handle.net/10419/141509

Atkinson, A. B. (1987). On the measurement of poverty. *Econometrica*, *55*(4), 749–764. https://doi.org/10.2307/1911028

Bárcena-Martín, E., Lacomba, B., Moro-Egido, A. I., & Pérez-Moreno, S. (2014). Country differences in material deprivation in Europe. *Review of Income and Wealth*, *60*(4), 802–820. https://doi.org/10.1111/roiw.12030

Blanden, J., & Gregg, P. (2004). Family income and educational attainment: A review of approaches and evidence for Britain. *Oxford Review of Economic Policy*, *20*(2), 245–263. https://doi.org/10.1093/oxrep/grh014

Bor, J., Cohen, G. H., & Galea, S. (2017). Population health in an area of rising income inequality: USA 1980–2015. *Lancet*, *389*, 1475–1490. https://doi.org/10.1016/S0140-6736(17)30571-8

Bosco, B. (2019). One size does not fit all: Quantile regression estimates of cross-country risk of poverty in Europe. *Economic Analysis and Policy*, *62*, 280–299. https://doi.org/10.1016/j.eap.2019.04.003

Bosco, B., & Poggi, A. (2020). Middle class, government effectiveness and poverty in the EU: A dynamic multilevel analysis. *Review of Income and Wealth*, *66*(1), 94–125. https://doi.org/10.1111/roiw.12403

Brüderl, J., & Ludwig, V. (2015). Fixed-effects panel regression. In H. Best & C. Wolf (Eds.), *Regression analysis and causal inference* (pp. 327–358). Sage.

Brülle, J., Gangl, M., Levanon, A., & Saburov, E. (2019). Changing labour market risks in the service economy: Low wages, part-time employment and the trend in working poverty risks in Germany. *Journal of European Social Policy*, *29*(1), 115–129. https://doi.org/10.1177/0958928718779482

Caminada, K., Goudswaard, K., & Koster, F. (2012). Social income transfers and poverty: A cross-country analysis for OECD countries. *International Journal of Social Welfare*, *21*, 115–126. https://doi.org/10.1111/j.1468-2397.2011.00815.x

Cammeraat, E. (2020). The relationship between different social expenditure schemes and poverty, inequality and economic growth. *International Social Security Review*, *73*(2), 101–123. https://doi.org/10.1111/issr.12236

Cantillon, B. (2011). The paradox of the social investment state: Growth, employment and poverty in the Lisbon era. *Journal of European Social Policy*, *21*(5), 432–449. https://doi.org/10.1177/0958928711418856

Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., Bergeron, A., & Cutler, D. (2016). The association between income and life expectancy in the United States, 2001-2014. *JAMA*, *315*(16), 1750–1766. https://doi.org/10.1001/jama.2016.4226

Corcoran, M. (1995). Rags to rags: Poverty and mobility in the United States. *Annual Review of Sociology*, *21*(1), 237–267. https://doi.org/10.1146/annurev.so.21.080195.001321

Crettaz, E. (2013). A state-of-the-art review of working poverty in advanced economies: Theoretical models, measurement issues and risk groups. *Journal of European Social Policy*, *23*(4), 347–362. https://doi.org/10.1177/0958928713507470

Croissant, Y., & Millo, G. (2008). Panel data econometrics with R: The plm package. *Journal of Statistical Software*, *27*(2), 1–43. https://doi.org/10.18637/jss.v027.i02

Deaton, A. (2013). *The great escape: Health, wealth, and the origins of inequality*. Princeton University Press.

Dollar, D., Kleineberg, T., & Kraay, A. (2016). Growth still is good for the poor. *European Economic Review*, *81*, 68–85. https://doi.org/10.1016/j.euroecorev.2015.05.008

Dollar, D., & Kraay, A. (2002). Growth is good for the poor. *Journal of Economic Growth*, *7*, 195–225.

Domonkos, T., & Ostrihoň, F. (2015). Inclusive growth in selected central European countries. *Ekonomický Časopis*, *63*(9), 881–905.

Dudek, H. (2019). Country-level drivers of severe material deprivation rates in the EU. *Ekonomický Časopis*, *67*(1), 33–51.

Duiella, M., & Turrini, A. (2014). Poverty developments in the EU after the crisis: A look at main drivers. European Commission's Directorate-General for Economic and Financial Affairs. https://data.europa.eu/doi/10.2765/72447

European Commission. (2010). Europe 2020: A strategy for smart, sustainable and inclusive growth: Communication from the commission. https://eur-lex.europa.eu/legalcontent/en/ALL/?uri=CELEX%3A52010DC2020

Eurostat. (2020). EU statistic on income and living conditions (EU-SILC) methodology—Data quality. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU_statistics_on_income_and_living_conditions_(EU-SILC)_methodology

Eurostat. (2021). Database. https://ec.europa.eu/eurostat/data/database?node_code=tec00001

Ferguson, H. B., Bovaird, S., & Mueller, M. P. (2007). The impact of poverty on educational outcomes for children. *Paediatrics and Child Health*, *12*(8), 701–706. https://doi.org/10.1093/pch/12.8.701

Foster, J., Greer, J., & Thorbecke, E. (1984). A class of decomposable poverty measures. *Econometrica*, *52*(3), 761–766. https://doi.org/10.2307/1913475

Frank, K. A., Maroulis, S., Duong, M., & Kelcey, B. (2013). What would it take to change an inference? Using Rubin's causal model to interpret the robustness of causal interferences. *Educational Evaluation and Policy Analysis*, *35*(4), 437–460.

Gábos, A., Branyiczki, R., Binder, B., & Tóth, I. G. (2019). Employment and poverty dynamics before, during, and after the crisis. In B. Cantillon, T. Goedemé, & J. Hills (Eds.), *Decent incomes for all: Improving policies in Europe* (pp. 34–55). Oxford University Press.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica*, *46*(6), 1251–1271. https://doi.org/10.2307/1913827

Holmes, J., & Kiernan, K. (2013). Persistent poverty and children's development in the early years of childhood. *Policy and Politics*, *41*(1), 19–42. https://doi.org/10.1332/030557312X645810

Iacovou, M., Kaminska, O., & Levy, H. (2012). *Using EU-SILC data for cross-national analysis: Strengths, problems and recommendations*. (ISER Working Paper Series, No. 2012-03). http://hdl.handle.net/10419/65951

Ingensiep, C. (2016). Determinants of persistent poverty. Do institutional factors matter? In M. Heidenreich (Ed.), *Exploring inequality in Europe* (pp. 48–69). Edward Elgar.

Jenkins, S. P. (2000). Modelling household income dynamics. *Journal of Population Economics*, *13*, 529–567.

Jenkins, S. P., & Van Kerm, P. (2017). How does attrition affect estimates of persistent poverty rates? The case of European Union statistics on income and living conditions (EU-SILC). Publication Office of the European Union. https://doi.org/10.2785/86980

Kakwani, N. (1993). Statistical inference in the measurement of poverty. *The Review of Economics and Statistics*, *75*(4), 632–639.

Kakwani, N., & Pernia, E. M. (2000). What is pro-poor growth? *Asian Development Review*, *18*(1), 1–16.

Keeley, B. (2015). What's happening to income inequality? In *Income inequality: The gap between rich and poor*. OECD Publishing. https://doi.org/10.1787/9789264246010-4-en

Kraay, A. (2006). When is growth pro-poor? Evidence from a panel of countries. *Journal of Development Economics*, *80*, 198–227. https://doi.org/10.1016/j.jdeveco.2005.02.004

Krämer, W. (2000). *Armut in der Bundesrepublik: Zur Theorie und Praxis eines überforderten Begriffs*. Campus Verlag.

Layte, R., & Whelan, C. T. (2003). Moving in and out of poverty: The impact of welfare regimes on poverty dynamic in the EU. *European Societies*, *5*(2), 167–191. https://doi.org/10.1080/1461669032000072274

Lohmann, H., & Gießelmann, M. (2010). Armut von erwerbstätigen in Ost- und Westdeutschland: Die Bedeutung von niedrigen Löhnen und unterschiedlichen Erwerbsmustern. In P. Krause & I. Ostner (Eds.), *Leben in Ost- und Westdeutschland: Eine sozialwissenschaftliche Bilanz der deutschen Einheit 1990–2010* (pp. 299–311). Campus Verlag.

Madden, D. (2015). Health and wealth on the roller-coaster: Ireland 2003-2011. *Social Indicators Research*, *121*, 387–412. https://doi.org/10.1007/s11205-014-0644-4

Maître, B., Russel, H., & Watson, D. (2011). *Persistent at-risk-of-poverty in Ireland: An analysis of the survey on income and living conditions 2005–2008* (Social Inclusion Technical Paper, No. 1). http://www.socialinclusion.ie/publications.html

Marx, I., Vandenbroucke, P., & Verbist, G. (2012). Can higher employment levels bring down relative income poverty in the EU? Regression-based simulations of the Europe 2020 target. *Journal of European Social Policy*, *22*(5), 472–486. https://doi.org/10.1177/0958928712456577

Mood, C., & Jonsson, J. O. (2016). The social consequences of poverty: An empirical test on longitudinal data. *Social Indicators Research*, *127*, 633–652. https://doi.org/10.1007/s11205-015-0983-9

Nelson, K. (2012). Counteracting material deprivation: The role of social assistance in Europe. *Journal of European Social Policy*, *22*(2), 148–163. https://doi.org/10.1177/0958928711433658

Nelson, K. (2013). Social assistance and EU poverty thresholds 1990-2008. Are European welfare systems providing just and fair protection against low income? *European Sociological Review*, *29*(2), 386–401. https://doi.org/10.1093/esr/jcr080

Nolan, B., & Whelan, C. T. (2010). Using non-monetary deprivation indicators to analyze poverty and social exclusion: Lessons from Europe? *Journal of Policy Analysis and Management*, *29*(2), 305–325. https://doi.org/10.1002/pam.20493

Notten, G., & Guio, A. C. (2019). The impact of social transfers on income poverty and material deprivation. In B. Cantillon, T. Goedemé, & J. Hills (Eds.), *Decent incomes for all: Improving policies in Europe* (pp. 85–107). Oxford University Press.

Piketty, T., & Saez, E. (2014). Inequality in the long run. *Science*, *344*(6186), 838–843. https://doi.org/10.1126/science.1251936

Polin, V., & Raitano, M. (2014). Poverty transitions and trigger events across EU groups of countries: Evidence from EU-SILC. *Journal of Social Policy*, *43*(4), 745–772. https://doi.org/10.1017/S0047279414000270

Riumallo-Herl, C., Basu, S., Stuckler, D., Courtin, E., & Avendano, M. (2014). Job loss, wealth and depression during the great recession in the USA and Europe. *International Journal of Epidemiology*, *43*(5), 1508–1517. https://doi.org/10.1093/ije/dyu048

Ruppert, D., Wand, M. P., & Carroll, R. J. (2003). *Semiparametric Regression*. Cambridge University Press.

Rüttenauer, T., & Ludwig, V. (2023). Fixed effects individual slopes: Accounting and testing for heterogeneous effects in panel data or other multilevel models. *Sociological Methods & Research*, *52*, 43–84. https://doi.org/10.1177/0049124120926211

Şeker, S. D., & Dayioğlu, M. (2015). Poverty dynamics in Turkey. *Review of Income and Wealth*, *61*(3), 477–493. https://doi.org/10.1111/roiw.12112

Škare, M., & Pržiklas Družeta, R. (2016). Poverty and economic growth: A review. *Technological and Economic Development of Economy*, *22*, 156–175. https://doi.org/10.3846/20294913.2015.1125965

Townsend, P. (1979). *Poverty in the United Kingdom: A survey of household resources and standards of living*. University of California Press.

Vaalavuo, M. (2015). *Poverty dynamics in Europe: From what to why*. Publication Office of the European Union. https://doi.org/10.2767/956213

Wagstaff, A. (2002). Poverty and health sector inequalities. *Bulletin of the World Health Organization*, *80*(2), 97–105.

Whelan, C. T., Layte, R., & Maître, B. (2003). Persistent income poverty and deprivation in the European Union: An analysis of the first three waves of the European Community household panel. *Journal of Social Policy*, *32*(1), 1–18. https://doi.org/10.1017/S0047279402006864

Whelan, C. T., Layte, R., & Maître, B. (2004). Understanding the mismatch between income poverty and deprivation: A dynamic comparative analysis. *European Sociological Review*, *20*(4), 287–302.

Whelan, C. T., & Maître, B. (2012). Understanding material deprivation: A comparative European analysis. *Research in Social Stratification and Mobility*, *30*, 489–503. https://doi.org/10.1016/j.rssm.2012.05.001

Wilkinson, R., & Pickett, K. (2009). *The spirit level: Why equality is better for everyone*. Penguin Books.

Wooldridge, J. (2010). *Econometric analysis of cross section and panel data*. MIT Press.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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Poverty in Europe:
How long-term poverty developed after the financial crisis and what drives it

Supplement

Table S1a: Years in poverty during four-year period

	years	CZ	HU	NO	DK	NL	SI	FI	AT	UK	CH[1]	FR	PL	SE
2015-2018	0	86.4	77.4	84.9	86.8	84.8	81.1	80.3	77.8	69.3	75.2	79.4	71.7	81.3
	1	4.6	12.0	5.7	3.9	4.9	6.8	6.2	8.0	14.9	9.8	6.5	10.8	4.8
	2	3.7	4.9	3.4	2.3	2.8	3.6	4.8	5.1	6.5	5.3	4.4	7.7	3.8
	3	2.4	3.0	2.0	1.9	3.0	3.6	3.8	3.4	5.2	4.7	3.8	4.4	3.7
	4	2.9	2.7	4.0.	5.1	4.4	4.9	4.9	5.7	4.0	5.1	6.0	5.4	6.3
2011-2014	0	87	77.1	85.4	85.2	86.4	80.4	79.9	75.6	68.1	75.2	78.8	73.9	82.2
	1	6.4	8.8	6.0	5.8	4.6	6.6	6.0	8.2	14.8	9.2	7.4	9.0	6.8
	2	2.7	5.6	2.9	3.0	3.1	4.4	4.2	7.1	8.0	6.4	4.4	5.8	2.9
	3	1.6	3.8	2.7	2.0	2.8	3.4	3.7	3.6	5.5	4.2	4.1	4.4	2.5
	4	2.3	4.7	3.0.	4.00	3.1	5.1	6.2	5.5	3.7	4.9	5.3	6.9	5.6
2007-2010	0	85.9	77.1	86.7	87.5	85.4	78	80.7	78.4	66.4	n.a.	78.5	69.4	82.8
	1	7.3	8.4	5.4	4.1	5.7	6.0	5.2	7.2	15.0	n.a.	8.0	11.5	5.6
	2	3.4	5.6	2.9	2.3	3.3	3.3	4.0	4.2	9.2	n.a.	4.6	6.9	50
	3	1.3	4.2	1.9	20	2.2	3.8	3.7	3.8	5.4	n.a.	4.2	5.5	3.0
	4	2.1	4.8	3.1	4.1	3.5	8.9	6.4	6.3	4.1	n.a.	4.7	6.7	3.5

Countries sorted by long-term poverty rate (three or more years poor in indicated period) of the period 2015-2018 in increasing order. (1) For Switzerland, the 2019 data is not available and the period represents the survey period and not the reference one, which is lagged by a year. The data source is the EU-SILC Long UDB 2011, 2015, 2019 and 2010, 2014, 2018 for UK and CH – version of 2021-03.

Table S1b: Years in poverty during four-year period (table S1a continued)

	years	DE	BE	EL	MT	CY	PT	EE	IT	BG	ES	LT	RO	LV
2015-2018	0	76.0	74.4	67.7	75.8	74.7	69.7	69.2	70.8	66.4	68.8	69.7	70.1	67.0
	1	8.7	8.5	11.9	8.2	6.4	10.0	7.9	7.8	10.7	7.6	7.1	7.1	8.1
	2	5.0	6.0	8.0	3.4	6.0	6.2	7.6	5.8	6.0	6.1	5.3	4.4	6.4
	3	4.2	4.5	6.1	5.4	5.8	6.3	5.1	5.9	6.6	7.3	5.5	4.4	7.0
	4	6.1	6.7	6.4	7.2	7.1	7.8	10.3	9.8	10.4	10.2	12.4	14.1	11.5
2011-2014	0	n.a.	76.2	65.9	74.0.	73.6	69.9	70.5	70.9	68.9	67.4	73.0	69.9	71.5
	1	n.a.	8.1	12.1	7.8	10.2	9.1	11.5	7.0	9.6	7.8	7.8	6.2	10.5
	2	n.a.	5.6	7.7	6.4	5.6	5.8	7.7	5.0.	4.8	7.8	4.6	4.1	7.1
	3	n.a.	4.6	6.3	4.8	4.8	6.3	4.9	6.9	7.4	6.8	5.5	4.8	4.9
	4	n.a.	5.4	8.0	7.1	5.8	8.9	5.4	10.1	9.3	10.2	9.1	15.0	6.1
2007-2010	0	n.a.	76.6	66.8	75.3	75.3	69.9	70.3	70.5	64.4	69.5	63.6	69.8	60.7
	1	n.a.	7.6	13.6	9.8	7.9	10.1	11.0	9.3	10.7	9.0	16.8	6.9	13.1
	2	n.a.	4.0	6.4	4.2	4.1	5.9	8.0	7.2	6.2	6.4	10.4	5.1	13.4
	3	n.a.	5.3	4.6	4.7	3.5	5.4	4.7	5.9	6.4	6.4	3.8	4.8	6.0
	4	n.a.	6.5	8.6	6.0	9.3	8.7	6.1	7.1	12.3	8.8	5.5	13.4	6.7

Countries sorted by long-term poverty rate (three or more years poor in indicated period) of the period 2015-2018 in increasing order. The data source is the EU-SILC Long UDB 2011, 2015 and 2019 – version of 2021-03.

Table S2: Variable description of panel regression

Variable	mean	within $\bar{x}_i$ sd.	min.	max.	between $x_{it} - \bar{x}_i + \bar{\bar{x}}$ sd.	min.	max.	N (nxT)	n	Description
Relative poverty rate	16.29	0.96	12.15	18.36	3.63	9.49	23.48	300	30	Proportion of population with a household equivalence income below 60% of national median income. Unit: metric.
Long-term poverty rate	11.35	1.18	7.39	15.05	3.63	4.83	18.99	173	25	Proportion of population with a household equivalence income below 60% of national median income in 3 or 4 years in a 4 year period. Unit: metric.
GDP per capita in 1000 EURO	28.12	2.80	18.09	44.19	12.23	12.74	73.72	300	30	GDP per capita in 1000 EURO PPS 2020. Unit: metric.
Male employment rate	78.44	2.74	70.18	88.73	4.65	69.17	88.26	300	30	Male employment rate in % of male population. In the age category 25 to 64 years. Unit: metric.
Female employment rate	66.92	2.76	53.86	80.16	7.67	49.86	80.00	300	30	Female employment rate in % of female population. In the age category 25 to 64 years. Unit: metric.
Social expenditures in % of GDP	22.98	1.20	16.95	27.55	5.27	15.10	32.15	300	30	Social protection expenditures in % of GDP. Unit: metric
Unemploy-ment exp. in % of GDP	1.12	0.32	-0.23	2.20	0.74	0.22	3.04	300	30	Unemployment expenditures in % of GDP. Unit: metric
Pension and survivor exp. in % of GDP	8.37	0.47	6.48	9.98	2.28	4.30	12.16	300	30	Old age and survivor pensions in % of GDP. Unit: metric
Sickness and disability exp. in % of GDP	2.05	0.24	1.20	3.32	0.77	1.05	3.76	300	30	Expenditures for sickness, health and disability in % of GDP. Unit: metric
Family and child benefits in % of GDP	10.65	0.61	8.06	12.43	2.69	6.27	16.43	300	30	Expenditures for families and children in % of GDP. Unit: metric
Short-term poverty rate	13.49	1.33	9.97	18.47	3.75	7.99	21.79	73	25	Proportion of population with a household equivalence income below 60% of national median income in 1 or 2 years in a 4 year period. Unit: metric

Notes: Unlogarithmized values. All variables are included in the regression models by adding one and taking the natural logarithm allowing for the estimation of elasticities. The data source is the EU-SILC Cross and Long UDB 2005-2019 – version of 2021-3 for the poverty rates. GDP, employment rates, and social protection expenditures are from Eurostat (2021).

Table S3a: Observed number of individuals for the calculation of the current poverty rate per year and country

year	AT	BE	BG	CH	CY	CZ	DE	DK	EE	EL
2005	14882	14302	n.a.	n.a.	11069	17830	31639	14630	15778	15142
2006	16683	15455	12047	15914	10630	23059	31515	14823	14360	14742
2007	13621	15080	12180	16363	10025	26933	28792	14787	13023	16798
2008	13603	14686	14979	17523	9283	23300	28338	14859	13533	17901
2009	14085	14738	16323	17933	11088	21375	27944	14586	13450	17539
2010	13933	14282	17180	17573	11443	20628	28585	13076	13419	14995
2011	13910	13912	14508	17449	13379	20236	27901	13099	14240	13732
2012	13249	14615	12425	16893	13277	19101	26637	13338	15018	17910
2013	12982	14336	12184	15628	12027	18208	26260	14049	15002	20966
2014	13213	14191	12031	17149	11966	17701	26131	13952	14512	34248
2015	13044	13747	17788	17866	11236	18958	26612	13765	15169	43796
2016	12876	13996	17649	18679	11504	19198	26427	12687	15293	53612
2017	12749	13707	17022	15193	11108	18933	25108	11690	14860	56447
2018	12355	15501	17012	16648	10974	19149	23832	11996	15101	39598

Data source is the EU-SILC Cross UDB 2006-2019 – version of 2021-03.

Table S3b: Observed number of individuals for the calculation of the current poverty rate per year and country (table S3a continued)

year	ES	FI	FR	HR	HU	LT	IE	IT	LT	LU
2005	34491	28026	24919	n.a.	19859	12134	14632	54368	12134	10236
2006	34518	27448	25868	n.a.	22293	12775	13690	52617	12775	10412
2007	35902	26477	25504	n.a.	22352	12146	12549	52290	12146	10128
2008	36728	25151	25600	n.a.	25046	12847	12639	51124	12847	11392
2009	36870	27002	26507	9862	24748	13217	11583	47450	13217	13399
2010	34602	23011	27053	16889	29463	12470	11005	47778	12470	14843
2011	33444	25364	28524	15170	28423	12662	11891	47317	12662	16114
2012	32041	27904	26333	13879	25432	11744	12660	44509	11744	9966
2013	31508	27141	26779	14033	22706	11894	14073	47050	11894	9935
2014	32293	26431	26630	17173	18676	11002	13787	42860	11002	8745
2015	36308	25983	26625	19648	18771	10880	13182	48152	10880	10129
2016	34859	24813	25375	20081	18454	11123	12612	48771	11123	10784
2017	33678	23877	24669	21274	16835	11144	11130	45709	11144	10513
2018	39797	23160	26472	19562	15122	11346	10698	43345	11346	10494

Data source is the EU-SILC Cross UDB 2006-2019 – version of 2021-03.

Table S3c: Observed number of individuals for the calculation of the current poverty rate per year and country (table S3a and S3b continued)

year	LV	MT	NL	NO	PL	PT	RO	SE	SI	SK	UK
2005	10941	n.a.	23016	14697	45101	12071	n.a.	17114	31276	15141	25428
2006	11186	10244	25835	15104	42841	11691	19763	18107	28566	14849	23283
2007	13093	9580	25394	14165	41149	11786	19013	18795	28956	16535	21878
2008	14369	10212	23644	13844	38538	13013	18567	18400	29573	16129	20971
2009	15266	10370	24581	13240	37374	13368	18288	17843	29516	16300	19321
2010	15845	11193	25408	11715	36707	14662	17832	16638	28745	15335	18631
2011	15150	11922	24913	15515	37114	15965	17606	16565	28064	15457	18584
2012	14576	11957	24587	15302	36414	16410	17545	15192	27265	15456	23328
2013	14010	11802	24445	18399	36103	17221	17240	14010	27697	15691	23183
2014	13895	11249	23316	15684	33634	21965	17318	14227	26150	16181	22395
2015	13828	10738	29492	16889	32586	26565	17229	14047	25637	16480	21143
2016	13405	10146	29649	14928	34797	30007	17110	14591	26306	16013	22091
2017	12812	9815	27537	14291	39881	33935	17068	14372	25843	15714	28073
2018	11363	9552	29808	14682	50707	33081	16738	13442	25253	14646	38517

Data source is the EU-SILC Cross UDB 2005-2019 – version of 2021-03.

Table S4a: Observed number of individuals for the calculation of the long-term poverty rate per 4-year period and country

year	AT	BE	BG	CH	CY	CZ	DE	DK	EE	EL
2008	2439	2591	n.a.	n.a.	2177	6974	n.a.	2056	3114	3140
2009	2561	2631	2154	n.a.	2092	5135	n.a.	2272	2794	2696
2010	2389	2168	2154	n.a.	1814	3796	n.a.	2088	2742	3451
2011	2830	2347	3891	n.a.	1827	4774	n.a.	1992	2377	3186
2012	2756	2467	2963	n.a.	3487	5049	n.a.	1832	2700	2784
2013	2451	2415	2867	n.a.	2438	4620	n.a.	1661	2743	2557
2014	2492	2352	2564	3133	3121	3758	n.a.	2404	3043	2737
2015	2360	2803	7357	2943	2082	3861	n.a.	2380	2931	4851
2016	2557	2426	6977	2982	2597	3891	n.a.	2133	3094	5319
2017	2326	2532	6872	2840	2409	3957	n.a.	1667	2768	12428
2018	2587	4301	7346	2986	2514	4306	4612	1884	3053	10738

Note: The year indicates the last year of the four-year period. Data source is the EU-SILC Long UDB 2009-2019 – version of 2021-03.

Table S4b: Observed number of individuals for the calculation of the long-term poverty rate per 4-year period and country (table S4a continued)

year	ES	FI	FR	HU	IT	LT	LU	LV	MT	NL
2008	6499	3369	11138	4349	9581	2983	1045	2169	1885	2965
2009	6961	3121	11793	4490	9639	2941	777	2604	1852	4874
2010	7015	2983	11774	4297	8751	2489	6006	2955	1880	4543
2011	6643	2905	13037	5260	7442	2758	7061	2878	2428	4064
2012	5981	5307	12162	4425	6497	3052	1903	3010	2484	4526
2013	5271	5505	11936	7320	8332	2528	1675	2858	2592	4984
2014	5777	5110	12037	3470	8307	2575	1731	2758	2350	4255
2015	5757	5092	11774	3683	7969	2224	1706	2584	2488	4341
2016	5858	4825	11273	3313	7953	2741	1476	2537	2257	4197
2017	5868	4971	10792	3430	6204	1996	1009	2726	2145	3846
2018	5251	4540	10556	3135	9890	2348	2102	2660	2084	5633

Note: The year indicates the last year of the four-year period. Data source is the EU-SILC Long UDB 2009-2019 – version of 2021-03.

Table S4c: Observed number of individuals for the calculation of the long-term poverty rate per 4-year period and country (table S4a and S4b continued)

year	NO	PL	PT	RO	SE	SI	UK
2008	5484	8862	2218	n.a.	2736	4608	3649
2009	5313	8206	2501	4551	3479	4769	3150
2010	4784	7783	2494	4228	2695	5487	3157
2011	4655	7359	3239	4236	2706	5175	2929
2012	3462	7688	3127	4415	2498	4644	2687
2013	3268	7244	3499	4251	2144	4678	2763
2014	2161	7808	3610	4031	1875	4804	2841
2015	2245	7234	3777	4154	2009	4285	2841
2016	2047	7102	3680	4026	1956	4285	3098
2017	2008	5780	7704	4341	2248	3978	5163
2018	1981	6088	7530	3954	2057	4392	6526

Note: The year indicates the last year of the four-year period. Data source is the EU-SILC Long UDB 2008-2019 – version of 2021-03.

Figure S5: Description of the calculation of the current and long-term poverty rate by the example Austria

N	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	long-term poverty rate
2,439	W1	W2	W3	W4											7.42%
2,561		W1	W2	W3	W4										5.78%
2,389			W1	W2	W3	W4									10.13%
2,830				W1	W2	W3	W4								9.65%
2,756					W1	W2	W3	W4							11.10%
2,451						W1	W2	W3	W4						9.10%
2,492							W1	W2	W3	W4					9.03%
2,360								W1	W2	W3	W4				8.56%
2,557									W1	W2	W3	W4			10.29%
2,326										W1	W2	W3	W4		11.82%
2,587											W1	W2	W3	W4	9.16%

Note: The long-term poverty is calculated by using the green marked waves over four years. The current poverty is calculated by using the red marked waves at a certain point in time. Each four-year panel (W1-W4) is labeled by the last year of the panel (W4). In each four-year panel, the proportion of individuals suffering one or two years of poverty (short-term poverty) and three or four years of poverty (long-term poverty) is calculated. The indicated numbers are exemplarily for Austria. Data source is the EU-SILC Long UDB 2009-2019 – version of 2021-03.

Table S6: Panel regression analysis of current and long-term poverty rate

Dependent variables	Current poverty rate		Long-term poverty rate		
	FEIS estimator		FEIS estimator		
	(1)	(2)	(3)	(4)	(5)
GDP per capita in 1000 EURO	-9.257*** (2.545)	-6.695* (0.166)	5.946 (14.591)	-5.944 (10.827)	-5.238 (10.028)
Male employment rate	-1.205 (4.053)	1.675 (4.329)	-57.418** (19.543)	-59.208** (19.519)	-55.135** (17.307)
Female employment rate	-8.628+ (4.800)	-8.628+ (4.893)	32.156 (19.938)	15.188 (15.572)	21.664 (14.735)
Social expenditures in % of GDP	-7.148** (2.139)		-12.501 (9.190)		
Unemployment exp. in % of GDP		-0.543 (1.433)		1.250 (5.079)	1.212 (4.648)
Pension and survivor exp. in % of GDP		0.719 (4.258)		-34.465*** (9.806)	-25.438** (8.921)
Sickness and disability exp. in % of GDP		-3.484 (2.736)		0.637 (14.509	-5.891 (13.489
Family and child benefits in % of GDP		-1.513 (1.665)		2.177 (6.428)	3.224 (6.580)
Short-term poverty rate					-3.799*** (0.824)
Within R^2	0.21	0.20	0.09	0.15	0.25
n:	30	30	25	25	25
n x T:	300	300	173	173	173

Note: + = p < 0.10, * = p < 0.05, ** = p < 0.01, *** = p < 0.001. Unstandardized regression coefficients of logarithmized exogenous variables with standard errors in brackets. The effects can be interpreted as a one-percentage change in the exogenous variable that leads to a change of $\beta * \log(1.01)$ or $\approx \beta/100$ in the endogenous variable (poverty rate). All standard errors are panel-robust. Island is an outlier and excluded in model 1 and 2. Hungary is an outlier and excluded in model 3-5. The data source is the EU-SILC Cross and Long UDB 2010-2019 – version of 2021-3 for the poverty rates. GDP, employment rates, and social protection expenditures are from Eurostat (2021).

Article 2

The development of global environmental concern during the last three decades

Joint work with Axel Franzen

“We are the first generation to feel the effect of climate change and the last generation who can do something about it”

Former US president Barack Obama (2014)

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The development of global environmental concern during the last three decades

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ABSTRACT

The environmental concern of a country's population is an important prerequisite for addressing environmental problems, foremost reducing CO_2 emissions and limiting global warming. In this paper, we analyze the development of environmental concern by using the newest wave of the environmental module of the International Social Survey Programme (ISSP) for 29 countries. First, we discuss the measurement of environmental concern and construct a ranking of countries according to the 2020 survey results. Second, we analyze the determinants of environmental concern by employing multilevel models that take individual effects as well as context effects into account. The results show that environmental concern has increased in almost all nations since the last measurement in 2010. The country ranking is headed by European nations such as Switzerland, France and Germany. The USA takes a middle position and China ranks number 20. We observe more variance within countries at the individual level as compared to the differences between countries. At the individual level, environmental concern is closely related to education, post-materialistic values, political attitudes, and individuals' trust in the news media and in science. At the country level, the average environmental concern increases with the wealth of nations.

1. Introduction

Environmental problems, particularly global warming but also biodiversity loss, have dramatically increased during recent decades (IPCC, 2022; Cowie et al., 2020; Tilman et al., 2017). Given this environmental decline, an interesting question is how this development is reflected in people's concern about the environment. This paper provides the first analysis of a suvey on environmental concern that spans a quarter of a century. We analyze all four waves of the International Social Survey Programm's (ISSP) environmental modules which started in 1993 and were repeated in 2000, 2010 and 2020. The latest wave covers 29 countries, including the world's most populous nations (China, India, the USA, Japan), as well as many European countries. Together, the 29 countries represent 53% of the world population and are responsible for 71% of global CO_2 emissions.

According to a widely used definition, environmental concern refers to the belief that the natural environment is in danger and that environmental degradation is caused by human activity. Furthermore, this belief must be combined with a willingness to contribute to environmental protection (Diekmann and Preisendörfer, 2001; Dunlap and Jones, 2002; Franzen and Vogl, 2013a). Sociologists and psychologists often add a third dimension, namely that environmental destruction worries people. Hence, environmental concern can be conceptualized as consisting of three dimensions: the insight that the environment is endangered by human activities (cognitive component); the emotional reaction that finds environmental destruction threatening (affective component); and the willingness to do something about it (conative component).

Environmental concern is an important element of public opinion for two distinct reasons. First, it is an important prerequisite for supporting environmentally friendly policies to protect the environment and for voting in favor of pro-environmental political parties (e.g. Franzen and Vogl, 2013b; Vandeweerdt et al., 2016; Anderson et al., 2017; Bakaki et al., 2020). Second, much research has shown that pro-environmental attitudes increase everyday environmentally friendly behaviors, such as saving energy, participating in recycling programs, driving less and using public transportation (e.g., Hines et al., 1986/87; Preisendörfer and Franzen, 1996; Preisendörfer, 1999; Diekmann and Preisendörfer, 2003; Bamberg and Möser, 2007; Steg and Vlek, 2009; Kollmuss and Agyeman, 2010; Gifford and Sussman, 2012; Bruderer Enzler and

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Diekmann, 2019, Bouman et al., 2020). Given that environmental concern is a necessary (but certainly not sufficient) condition for voluntary pro-environmental behavior, as well as for supporting pro-environmental policies, observing its development is important, and this can inform decision makers on the amount of support they can expect for pro-environmental initiatives.

In this paper, we utilize the environmental module of the ISSP 2020 to describe and analyze changes in levels of environmental concern. In section two, we briefly summarize previous research and outline the research hypotheses. Section three describes how the data were collected and how the variables were measured. Section four presents the results of the measurement of environmental concern and provides a country ranking according to the new results. Moreover, we describe the development of environmental concern by comparing the new findings to the earlier results of the ISSP 1993, 2000 and 2010. Section four also investigates individual characteristics and country-level features that are correlated with environmental concern. In particular, previous research has demonstrated that environmental concern depends on individuals' age, gender, education and income, but also on post-materialistic values and trust in various institutions (Franzen and Meyer, 2010; Franzen and Vogl, 2013a). Furthermore, we incorporate some key country level differences, such as GDP per capital, and investigate how these micro- and macro-level differences are related to environmental concern. Finally, section five summarizes and discusses the results.

2. Previous research findings

Since its first wave in 1993 the ISSP has applied a three-dimensional definition of environmental concern and it contains nine items that measure the conative, affective and cognitive components of environmental concern. The questions referring to the conative component read "How willing would you be to accept cuts in your standard of living in order to protect the environment?", "How willing would you be to pay much higher prices in order to protect the environment?", and "How willing would you be to pay much higher taxes in order to protect the environment?" All three items are accompanied by a five-point Likert-type answer scale: "very willing", "fairly willing", "neither willing nor unwilling", "fairly unwilling", and "very unwilling". The affective component is covered by the following three items: "We worry too much about the future of the environment and not enough about prices and jobs", "People worry too much about human progress harming the environment", and "It is just too difficult for someone like me to do much about the environment". These three items have a five-point answer scale: "strongly agree", "fairly agree", "neither agree nor disagree", "fairly disagree", and "disagree strongly". Finally, the cognitive component is covered by the following three items: "In order to protect the environment, the country needs economic growth", "Modern science will solve our environmental problems with little change to our way of living", and "I do what is right for the environment, even when it costs more money or takes more time". These three items are also accompanied by a five-point answer scale, ranging from "agree strongly" to "disagree strongly".

Previous research has revealed that a factor analysis does not separate the three dimensions of environmental concern in the manner that was originally intended. Explorative principal component analysis extracts two components: one for the conative items and a second for the rest of the items. Hence, factor analysis does not separate the cognitive and affective components (Franzen and Vogl, 2013a). However, thorough tests of the scale suggest that the composite index has higher test-retest reliability as compared with a single item with five answer categories (0.80 vs 0.69), or a single item with 11 answer categories (0.80 vs 0.72). Moreover, the composite index is also more strongly related to donation behavior toward pro-environmental organizations than any of the single items, suggesting better external validity than a single item measurement (Franzen and Mader, 2021a).

In addition to describing the development of environmental concern, we also seek to identify the characteristics that determine – or are at least associated with – the level of environmental concern. Previous research has shown that socio-demographic variables, such as gender, age and education, are linked to environmental concern. With respect to gender, most studies have found that women display slightly higher levels of environmental concern than men (e.g., Zelezny et al., 2000; McCright and Xiao, 2014; Hartmann and Preisendörfer, 2021). This difference between the sexes is assumed to be due to different forms of socialization, and different social roles of women in many societies.

Previous findings regarding the effect of age on environmental concern are more mixed. Hartmann and Preisendörfer (2021) report that respondents over the age of 30 reported lower levels of environmental concern in the 1980s and 1990s, but the effect has changed – at least for Germany – in the last decade, with age having a positive effect on environmental concern. Recently, a number of environmental youth movements (e.g. "Fridays for Future", "Last Generation") have received public attention, suggesting that environmental concern once again might be stronger in younger generations as compared to older people. Hence, the effect of age on environmental concern in international comparisons is unclear. The effect may be positive, negative or u-shaped. However, we assume that it is a cohort effect, rather than an age effect.

Previous studies have often found strong effects of education on environmental concern (Combes et al., 2018; Franzen and Vogl, 2013a; Post and Meng, 2018). On the one hand, environmental topics and issues have found their way into the curricula of schools and universities, and the study of environmental issues also highlights concern about, and awareness of, environmental problems. On the other hand, education generally increases the level of interest in political issues. Those who are better educated are more interested in the news and read more newspapers, which are increasingly reporting environmental problems.

Higher incomes are also often found to correlate with environmental concern (Franzen and Vogl, 2013a; Hartmann and Preisendörfer, 2023). The reason for this is that economic concerns are often in competition with environmental concerns, and individuals under economic constraints tend to prioritize the former over the latter. In particular, the conative component of the environmental concern index, which addresses willingness to pay higher prices in order to protect the environment, is easier to accept for wealthier respondents.

In addition to socio-demographic variables, environmental concern is also found to correlate strongly with other values and political orientations (Franzen and Meyer, 2010; Franzen and Vogl, 2013a). Most importantly, past research has found that socialization in materially wealthy circumstances is closely related to environmental concern. The rationale for this correlation is that socialization shifts individuals' attention away from materialistic values toward post-materialistic values as defined by Inglehart (1990, 1995, 1997).

In most countries, conservative parties put more emphasis on economic development and less on environmental protection. Hence, individuals who lean further to the right on the political spectrum are expected to show less environmental concern than those leaning further to the left. Following previous research, we also incorporate different measures of trust in others and in political institutions into the analyses. Information about environmental changes and threats are usually communicated through governmental agencies and news media, and by scientists. Hence, individuals who have more trust in these institutions are also expected to show higher levels of environmental concern (Meyer and Liebe, 2010; Smith and Mayer, 2018). Moreover, trusting others should also be positively related to general concern for the social welfare of society, and should highlight concern for the maintenance of public goods, including the environment.

Finally, previous research has shown that there is also variation between countries. More specifically, earlier findings suggest that individuals living in affluent countries have a higher preference for environmental protection (Franzen and Vogl, 2013a; Franzen and Vogl, 2013c). The reason behind this finding is that populations in more wealthy countries can more easily focus on improving the environment compared to populations in less wealthy countries, where improvement of the economy is often the priority. Furthermore, we also consider population density, inequality and the proportion of the population living in cities compared to rural areas. Environmental problems (e.g. relating to air and water quality) should be more severe in more densely populated countries, and this might increase environmental concern. Similarly, the population in rural areas usually faces fewer environmental problems and therefore is likely to have a lower level of environmental concern. Next to nations' wealth, which is measured by GDP per capita, the distribution of that wealth might also affect environmental concern. Countries with high inequality might be more concerned with economic topics and redistribution than with environmental issues.

3. Data and methods

The core questionnaire of the ISSP 2020 contains 60 questions which are suggested by expert teams of the ISSP member countries. For the purpose of comparison 40 questions were taken from the survey in 2010, and 20 questions were newly integrated into the 2020 survey. All questions and the final questionnaire must be agreed upon by all ISSP member countries (see Hadler and Schweighardt, 2023). The ISSP puts a very strong emphasis on random sampling. The data collection was based on simple random sampling in Australia, Denmark, Iceland, Norway, Sweden, Thailand and the USA. All other countries included in the ISSP 2020 (Austria, China, Croatia, Finland, France, Germany, Hungary, India, Italy, Japan, Lithuania, New Zealand, Philippines, the Russian Federation, Slovakia, Slovenia, South Africa, South Korea, Spain, Switzerland, Taiwan, and the UK) used multistage random sampling. In some countries, the samples were restricted to citizens (Australia, China, India, Italy, Philippines, Sweden, Thailand and South Africa). All other countries included respondents who permanently live in the specific country. All samples only included individuals aged 18 and above. The data collection took place between February 2020 and May 2023 and lasted between one and seven months in most countries. The exceptions were Russia and the Philippines, where the data collection lasted for seven and four days, respectively. Most countries used mixed methods for the data collection. 41% of data collection was conducted via face-to-face interviews (CAPI and PAPI) (e.g. in China, India), 37% of the interviews were collected via self-administered online-questionnaires (CAWI) (e.g. in the USA and Switzerland), 19% took the form of self-administered paper and pencil questionnaires (e.g. Japan, Germany), and 3% of the interviews were conducted via telephone interviews. The response rates range from 12% in the UK to 81% in South Africa with a median of 42% (ISSP Research Group, 2023).

The measurement of the socio-demographic variables of gender and age is straightforward (see Table S1 in the appendix for the description of all variables). Education is measured in nine categories in the ISSP, which we collapsed into four groups: primary schooling, secondary schooling, lower tertiary degrees, and higher tertiary degrees. We measure income by calculating individuals' household equivalence income. For this we divided the sum of household members' incomes by the square root of the number of household members (see OECD, 2013). For comparative purposes we calculate the individuals' standard deviations from the specific country mean.

Post-materialism is measured in the ISSP by asking respondents what the highest priority and second highest priority should be of the country they live in. Respondents prioritizing "Give people more say in government decisions" and "Protect freedom of speech" over "fight rising prices" and "maintain order in the nation" rank higher on post-materialistic values and are expected to also assign more importance to environmental protection. Hence, the variable runs from 0 (no post-materialistic goals named) to 2 (naming two post-materialistic goals). Political orientation is measured in the ISSP on an 11-point scale ranging from left to right.

The ISSP 2020 measures trust in others and in different institutions in a more detailed way than in former rounds. For general trust in other people, the question reads: "Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people?" which is followed by a five-point scale running from (1) "You can't be too careful" to (5) "Most people can be trusted". This item is an exact repetition of former rounds.

Trust in institutions is measured by the question: "On a scale of 0 to 10, how much do you personally trust each of the following institutions?" Four institutions are named: the national parliament, the news media, university research centers, business and industry. The measurement of trust in these institutions (besides national parliaments) is new in the ISSP 2020.

Since the ISSP collects individual data in different countries it has a two-level data structure of individuals (level one) in different countries (level two). For this type of data, hierarchical linear regression analysis (or multilevel analysis) is a suitable statistical tool. Such models allow the simultaneous estimation of the effect of individual characteristics and of country characteristics (Gelman and Hill, 2007; Rabe-Hesketh and Skrondal, 2008; Snijders and Bosker, 1999). Following former research, we take four variables at the country level into consideration: GDP per capita, adjusted for purchasing power, which is the standard indicator of countries' wealth; income inequality, in the form of the Gini coefficient; countries' population density; and the proportion living in urban aeras. These four macro indicators are taken from the World Bank. We apply a varying-intercept model and estimate the coefficients via restricted maximum likelihood because of the small number of countries (Kenward and Roger, 1997). We used the statistical software R 4.2.2.

4. Results

Table 1 presents the results of the nine-item composite index of environmental concern for the three largest economies that have participated in the ISSP since 1993. These are the USA, Japan and Germany. An explorative principal component analysis (PCA) extracts two factors for the three countries in every year. Factor 1 consists of Items 1–3, and 8, and explains 36% of the variance for the USA in 2020, 29% of the variance for Japan and 28% of the variance for Germany. Factor 2 consists of Items 4–7, and 9, and explains 20%, 24%, and 25% of the variance for the USA, Japan and Germany, respectively. Factor 1 clearly mirrors the conative component of environmental concern. Factor 2 is a mixture of the affective component (Items 4, 5 and 6) and the cognitive component (items 7 and 9). Hence, the index in Table 1 does not exactly mirror all three dimensions of the definition of environmental concern. However, the index has the same factor results for 25 of the 29 countries in the ISSP 2020 (the exceptions are Hungary, India, Thailand and the Philippines), which demonstrates its comparability across different countries. Furthermore, the same factor structure can also be replicated using confirmatory factor analysis (see Fig. S1 in the supplement). Moreover, the index displays high reliability, as shown by a Cronbach's alpha of 0.82, 0.74 and 0.79 for the USA, Japan and Germany, respectively. Overall, the analysis using the new ISSP 2020 data replicates former ISSP results (Franzen and Vogl, 2013a).

The proportion of inhabitants agreeing and disagreeing with statements has not changed much in the USA over the last 30 years (Table 1). The overall change in environmental concern can best be assessed when the values of the additive index (originally ranging from 9 to 45) are standardized to range from 0 to 100. For the USA, the standardized mean was 54.7 in 1993, dropped to 50.3 in 2010 but rose back to 54.2 in 2020. Similar observations apply to Japan. The index started in 1993 with a value of 58.5, dropped in 2010 to 53.9 but recovered to 57.1 in 2020. The story is similar in Germany: the index started at 56.5 in 1993, dropped in 2000 and 2010, but rose back to 58.2 in 2020.

Table 2 displays the standardized index for all countries in all four years and ranks countries according to the 2020 results. The ranking of

Table 1
Environmental concern in the USA, Japan and Germany (percentage agreement/disagreement).

Questions	USA				Japan				Germany			
	1993	2000	2010	2020	1993	2000	2010	2020	1993	2000	2010	2020
1) How willing would you be to accept cuts in your standard of living in order to protect the environment? (% fairly and very willing)	34	29	36	35	44	41	28	33	52	40	41	59
2) How willing would you be to pay much higher prices in order to protect the environment? (% fairly and very willing)	52	45	46	42	53	53	40	48	46	34	38	48
3) How willing would you be to pay much higher taxes in order to protect the environment? (% fairly and very willing)	40	32	32	34	44	37	23	27	31	19	23	25
4) We worry too much about the future of the environment and not enough about prices and jobs (% disagree fairly and strongly)	44	44	39	49	47	47	35	53	50	50	51	57
5) People worry too much about human progress harming the environment (% disagree fairly and strongly)	50	49	41	50	48	51	41	53	57	48	47	57
6) It is just too difficult for someone like me to do much about the environment (% disagree fairly and strongly)	60	51	54	50	56	56	50	47	54	55	48	69
7) Modern science will solve our environmental problems with little change to our way of living (% disagree fairly and strongly)	59	48	48	51	75	76	65	74	43	45	44	61
8) I do what is right for the environment, even when it costs more money or takes more time (% fairly and very willing)	57	51	54	53	59	53	40	47	60	55	52	61
9) In order to protect the environment, the country needs economic growth (% disagree fairly and strongly)	26	25	20	20	17	18	7	10	32	28	28	40
Cronbach's alpha	0.76	0.74	0.73	0.82	0.71	0.68	0.71	0.74	0.75	0.65	0.70	0.79

Note: Data source is the ISSP 2020. All items have five-point Likert-type answer categories ranging from 1 = not all willing to 5 = very willing (Items 1–3, and Item 8) and 1 = strongly disagree to 5 = agree strongly (Items 4–7, and Item 9). For descriptive purposes, the table shows the percentage of respondents who answered very or fairly willing and agree fairly and strongly.

countries according to the level of environmental concern in 2020 is also shown in Fig. 1

As can be seen, the index varies from 61.8 in Switzerland, which has consistently received the first rank since 1993, to 40.4 in Slovakia. Most of the countries that participated in the 2020 survey reported a higher mean environmental concern compared to 2010. There are only three exceptions: in Russia, the mean dropped slightly from 41.4 to 40.7 (n.s.); in Slovakia, the mean dropped substantially from 45.5 to 40.4; and in South Korea, the mean decreased slightly from 53.9 to 52.5 (n.s.). However, overall, the measure indicates that environmental concern has increased on average from 49.5 in 2010 to 52.8 in 2020 for the 29 participating countries.

The development of environmental concern since 1993, separately for OECD countries and non-OECD countries, is depicted in Fig. 2. Since 1993, OECD countries show consistently higher levels of environmental concern as compared to non-OECD countries. However, the trend of a slight decrease in 2000 and 2010 and a recovery in 2020 to the level of 1993 can be observed for both groups of countries. Fig. 2 also contains the trend for global CO_2 emissions. Global CO_2 emissions were at about 22 Gt at the start of the observation period in 1993 and doubled to almost 40 Gt in 2020. Furthermore, Fig. 2 contains the Living Planet Index (LPI) which measures biodiversity (WWF, 2022). The Index varies between 1 (highest biodiversity) and 0 (lowest biodiversity) and dropped during the observation period by half, from 0.58 to 0.31. Hence, both trends demonstrate the degradation of the environment. At the same time the social reflection in terms of environmental concern did not increase accordingly but remained basically stable over the whole observation period. There are different interpretations for this paradox. One possibility is that environmental concern reached the maximum possible level in 1993 in most countries, and there is little potential for further increases. Another interpretation is that the economic recession in the aftermath of the banking crisis in 2008 shifted attention away from environmental problems toward economic issues. A similar shift of attention might have happened in 2020. Here, the COVID-19 pandemic might have shifted attention from environmental issues toward concern for public health. Hence, the occurrence of other global crises around the last two rounds of the ISSP might have influenced the results, preventing further increases in environmental concern.

Next, we analyze the variance of environmental concern via ordinary least squares (OLS) regressions. We do this in various steps by first analyzing the data for the USA and then for all ISSP countries via multilevel models. We chose the USA because it is the largest economy of the world with a large share (13%) of global CO_2 emissions. Model 1 in Table 3 presents the standardized regression results of the standardized environmental concern index for the USA. Gender, age and income are not statistically significantly related to environmental concern in the USA. Surprisingly, this also applies to education. What matters in the USA are post-materialistic values (Inglehart, 1990, 1995, 1997), trust in science, trust in news media, trust in business and industry, and, most importantly, party affiliation. A standard deviation of increase in trust in science increases environmental concern by almost 0.3 standard deviations, trust in news media increases environmental concern by 0.27 standard deviations, and respondents who said they trust business and industry have a lower environmental concern of 0.25 standard deviations.

These effects are all moderately strong and in the expected direction. Respondents who affiliate with the Republican Party report on average a lower level of environmental concern, by 0.61 standard deviations, as compared to respondents who affiliate with the Democrats. This latter result mirrors previous findings that environmental attitudes in the USA are very much polarized and dominated by affiliation with either the Republican or the Democratic Party (McCright et al., 2014; Clark et al., 2019). The effect of party affiliation overrides socio-demographic differences in the USA. Different trust variables and party affiliations explain almost 50% of the observed variance in environmental concern.

Next, we analyze the data for all 29 countries via multilevel regression models that take country differences in addition to individual variables into account (Snijders and Bosker, 1999; Gelman and Hill, 2007; Hox et al., 2017). Since the reliability of the measurement of environmental concern (Cronbach's alpha) is extremely low for India ($\alpha = 0.16$) it is excluded from the multilevel analysis. Most importantly, at the country level we add GDP per capita, the Gini index, population density, as well as the percentage of respondents living in urban areas. We calculated two multilevel-models, Model 2 and 3. The variable political party affiliation contains many missing values in the data. Particularly, the question about left-right orientation was not asked in China and Taiwan. Hence, to keep these countries in the analysis, Model 2 does not include party affiliation. However, since party affiliation is important and has a large effect in the USA, we ran Model 3 including party affiliation and using a lower number of countries and observations within countries. First, the ICC coefficient of the models indicates that most of the observed variance lies within countries and between

Table 2
Mean environmental concern per country and per year.

Country	1993		2000		2010		2020	
	N	Concern	N	Concern	N	Concern	N	Concern
Switzerland (CH)	3019	60.9	1006	61.0	1212	60.2	4280	61.8[c]
France (FR)					2253	50.8	1520	58.6[c]
Germany (DE)	2106	56.5	1501	51.6	1407	51.9	1702	58.2[b,c]
Norway (NO)	1414	58.0	1452	54.4	1382	52.1	1131	58.0[b,c]
Great Britain (GB)	1261	53.9	972	52.5	928	46.6	2344	57.6[a,b,c]
Sweden (SE)			1067	54.9	1181	54.1	1921	57.3[b,c]
Finland (FI)			1528	57.0	1211	54.8	1137	57.2[c]
Japan (JP)	1305	58.5	1180	59.3	1307	53.9	1491	57.1[b,c]
Iceland (IS)					798	50.8	1150	56.8[c]
Australia (AU)	1779	57.1			1946	50.1	1147	56.6[c]
Denmark (DK)			1069	57.9	1305	55.3	1198	55.9
Austria (AT)			1011	54.8	1019	50.8	1261	55.9[c]
Slovenia (SI)	1032	52.0	1077	52.0	1082	50.0	1102	55.1[a,b,c]
New Zealand (NZ)	1271	57.7	1112	54.7	1172	51.7	993	54.9[a,c]
United States (US)	1557	54.7	1276	52.6	1430	50.3	1847	54.2[c]
Taiwan (TW)					2209	52.6	1822	54.1
South Korea (KR)					1576	53.9	1205	52.5
Spain (ES)	1208	52.6	958	52.6	2560	50.4	2254	51.3
India (IN)							1421	51.2
China (CN)							2741	50.8
Italy (IT)	1000	55.2					1138	49.3[a]
Croatia (HR)					1210	42.0	1000	45.4[c]
Lithuania (LT)					1023	40.4	1200	44.8[c]
Hungary (HU)	1167	40.7					1001	44.3[a]
South Africa (ZA)					3112	38.5	2844	42.9[c]
Philippines (PH)	1200	43.1	1200	42.9	1200	39.3	1500	41.2[a,b,c]
Russia (RU)	1931	48.5	1705	44.0	1619	41.4	1583	40.7[a,b]
Thailand (TH)							1498	40.4
Slovakia (SK)					1159	45.5	1013	40.4[c]
Canada (CA)	1467	59.8	1115	55.9	985	56.5		
Netherlands (NL)	1852	60.2	1609	58.0	1472	53.1		
Chile (CL)			1503	45.4	1436	50.6		
Belgium (BE)					1142	49.4		
Israel (IL)	1198	51.7	1205	49.0	1216	47.4		
Portugal (PT)			1000	38.5	1022	47.0		
Mexico (MX)			1262	48.7	1637	46.4		
Argentina (AR)					1130	44.8		
Turkey (TR)					1665	44.1		
Czech Republic (CZ)	1005	45.6	1244	44.7	1428	42.9		
Latvia (LV)			1000	42.3	1000	39.8		
Bulgaria (BG)	1183	42.0	1013	38.7	1003	38.7		
Ireland (IE)	957	46.7	1232	52.3				
Poland (PL)	1641	48.3						

Note: The second, fourth, sixth and eight columns report the number of cases per country in the dataset. We report the standardized mean (between 0 and 100) of the environmental concern index.

[a] Significant difference between 1993 and 2020.
[b] Significant difference between 2000 and 2020.
[c] Significant difference between 2010 and 2020.

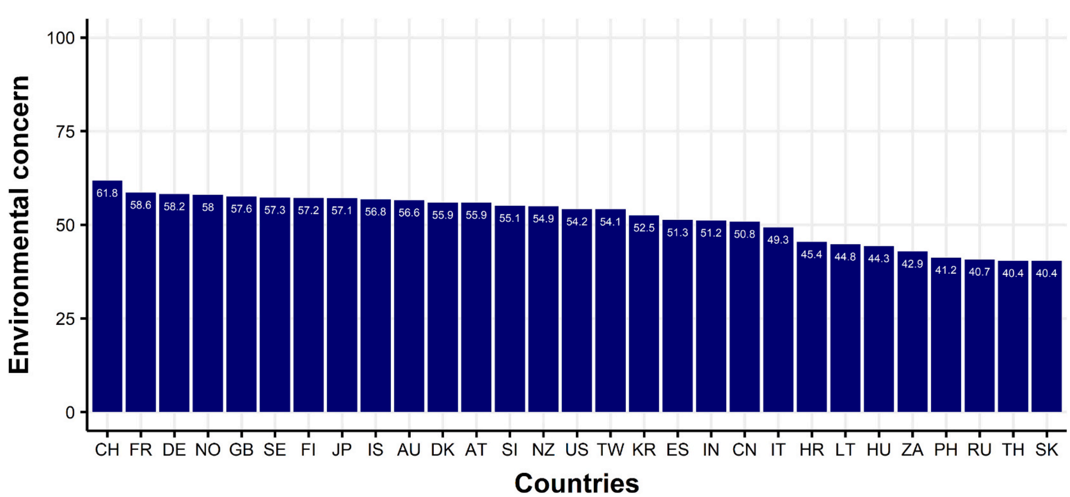


Fig. 1. Country ranking according to environmental concern 2020.

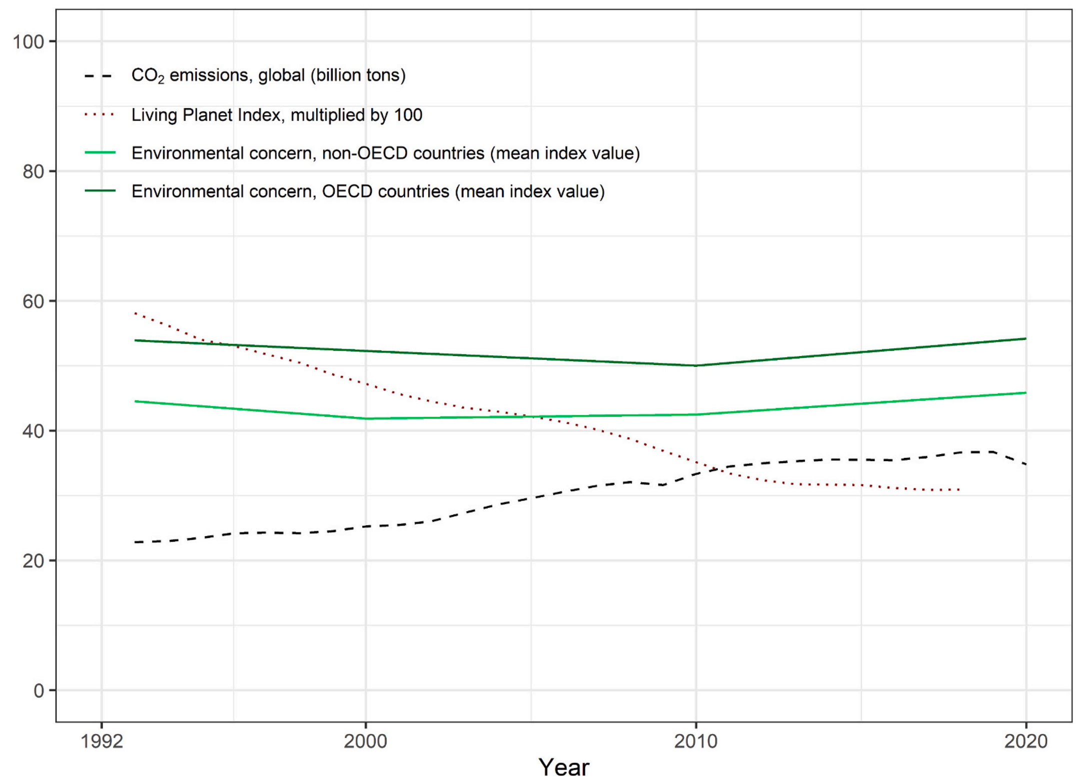


Fig. 2. CO_2 emissions, biodiversity and environmental concern.
Note: The dark green line presents the mean environmental concern of the OECD countries that participated in the ISSP at least once. Three countries are observed at only one point in time, 12 at two points in time, nine at three points in time and nine at four points in time. The depicted trend does not change if only countries with all four observation points are analyzed. The light green line depicts the mean environmental concern of non-OECD countries. Four countries are observed once, three twice, one three times and two four times. In tendency, this trend remains the same if we only consider the two countries observed four times. The other two lines depict the development of global CO_2 emissions and the Living Planet Index (LPI) which shows the decrease in biological diversity.

individuals. Only 18% (ICC = 0.18) of the total variance can be observed between countries. Looking first at individual differences, the results show in both models that, in the international context, female respondents show a slightly higher level of environmental concern than men. The age effect is also statistically significant. Environmental concern first increases with age, reaches a maximum at the age of 50 and decreases thereafter. Moreover, education has a strong effect on environmental concern. Respondents show more environmental concern the higher their educational degree. Furthermore, post-materialistic values, as well as an individual's trust in other people, the national parliament, science, news media, and business and industry, are all associated with environmental concern. Hence, there are profound differences between the USA and the international context, particular with respect to socio-demographic variables and education. Trust in science and the media are also internationally importantly associated with environmental concern, but less strongly than in the US. The importance of trust in others and in various institutions is in line with previous studies showing that trust in others increases pro-social attitudes and cooperative behavior (Yamagishi et al., 1999; Sonderskov, 2009; Balliet and Van Lange, 2013). Generally, a more conservative political orientation is also relevant in international comparisons, but the effect is much smaller compared to the effect of party affiliation in the USA (see Model 3).

At the macro level of country differences, GDP per capita is strongly related with environmental concern. For every percent increase in GDP, environmental concern increases by 0.34 standard deviation (Model 2). In Model 3, where China and Taiwan are excluded from the sample, the effect doubles in size. Population density increases environmental concern by 0.09 respectively by 0.15 standard deviations. None of the other macro variables (inequality, as measured by the Gini index, and the percentage of urban population) show any significant relation with environmental concern. The strong effect of GDP is depicted in Fig. 3, which shows the bivariate relation between GDP and environmental concern for the 29 countries that participated in the ISSP 2020. The bivariate correlation is 0.75, suggesting that wealth makes it easier for respondents to shift attention to environmental problems.

The results reported in Table 3 were extensively checked for robustness. First, we tested for potential interviewing mode effects. For the USA (Model 1) the mode effect is statistically significant (−0.25) for conducting the interviews per telephone instead of self-administered web-surveys. However, excluding the mode effect does not bias any of the other estimates. Thus, to keep the model concise and since there is no obvious reason for the mode effect, we decided not to include it in Model 1. Moreover, we did not find any mode effects for models 2 and 3. Second, the results reported in models 2 and 3 are robust with respect to excluding one country at a time. Hence, the results are not driven by any one single country. The results also remain stable if all four countries in which the measurement of environmental concern does not closely fit a two-factorial structure (Philippines, Hungary, South Africa, and Thailand) are excluded from the analysis. Third, the results do not depend on whether the independent variables are regressed only on the first factor of environmental concern (the conative component of Items 1–3, and 8, see Table S2 in the supplement). Fourth, since many respondents did not report their income, we also imputed the income variable using a machine learning approach suggested by Chen and Guestrin (2016). The results of the model using the imputed data do not differ from the results of the models that listwise exclude those observations with missing data (see Table S3 in the supplement). Fifth, the multilevel Models 2 and 3 reported in Table 3 are random intercept models, assuming that the effects for the macro-level variables have different intercepts but the same slope. We also calculated all models

Table 3
Determinants of environmental concern.

	Model 1 USA	Model 2 all countries	Model 3 all countries
Individual-level variables			
Sex (1 = female)	0.078	0.132***	0.134***
	(0.057)	(0.025)	(0.022)
Age in years (18–80)	−0.004	0.008*	0.010*
	(0.013)	(0.003)	(0.004)
Squared age	0.00004	−0.0001**	−0.0001**
	(0.0001)	(0.00003)	(0.00004)
Reference: Primary degree			
Secondary degree	0.223	0.120***	0.096**
	(0.161)	(0.031)	(0.033)
Low tertiary degree	0.199	0.275***	0.229***
	(0.179)	(0.040)	(0.038)
Tertiary degree	0.265	0.412***	0.366***
	(0.162)	(0.039)	(0.039)
Relative income within country[a]	0.053	0.018*	0.012
	(0.034)	(0.009)	(0.012)
Post-materialism	0.059*	0.116***	0.103***
	(0.029)	(0.012)	(0.009)
Trust in others	0.019	0.103***	0.102***
	(0.033)	(0.011)	(0.012)
Trust in parliament	0.033	0.109***	0.115***
	(0.034)	(0.021)	(0.021)
Trust in science	0.286***	0.144***	0.152***
	(0.038)	(0.027)	(0.035)
Trust in news media	0.172***	0.063***	0.066**
	(0.044)	(0.019)	(0.022)
Trust in industry	−0.252***	−0.164***	−0.187***
	(0.034)	(0.032)	(0.025)
Party affiliation[b]	−0.615***		−0.175***
	(0.085)		(0.026)
Country-level variables			
Log GDP per capita (PPP)		0.341***	0.622***
		(0.099)	(0.094)
Proportion urban population		0.071	0.008
		(0.053)	(0.046)
Population density		0.090**	0.150**
		(0.032)	(0.054)
Gini index		−0.039	0.074
		(0.041)	(0.041)
Explained variance			
Country level		0.04	0.04
Individual level		0.70	0.69
Intraclass correlation (ICC)			
Null model		0.18	0.18
Model with covariates		0.06	0.06
R^2 adjusted	0.49		
Number of countries	1	28	26
Number of observations	753	24,436	13,496

Note: $^+ = p < 0.10$, $* = p < 0.05$, $** = p < 0.01$, $*** = p < 0.001$. Standardized regression coefficients with heteroscedasticity and cluster-robust standard errors in parentheses. Dependent variable is the standardized composite index of environmental concern as presented in Table 1. [a] = absolute household equivalence income in Model 1. [b] = dummy for affiliating with the Republican Party for the USA in Model 1. In Model 3, political affiliation is measured on a five-point Likert scale ranging from 1 = far left to 5 = far right. In Models 2 and 3, India is excluded due to the low reliability of the environmental concern index (Cronbach's alpha = 0.16). Model 3 also excludes China and Taiwan because the left–right scale was not included in the questionnaire.

using random slopes for all macro-level variables. This variation did not change the results.

5. Discussion

The results of the fourth environmental module of the ISSP 2020 reveal that environmental concern had increased in most of the 29 participating countries as compared to 2010. However, the increase in environmental concern was small. The measurement started in 1993 with a standardized value of 52.7 and returned in 2020 to 51.9, after a decrease in 2000 to 51.0 and to 48.5 in 2010. Thus, environmental concern has not changed much on average over the last three decades. These small changes in environmental concern are surprising, since many environmental problems have increased in intensity during this period, particularly greenhouse gas emissions. One reason for the small increase might be the COVID-19 pandemic. Data collection in most countries took place in 2020 or 2021, during or shortly after the pandemic, which might have distracted attention from environmental issues. This interpretation is also supported by respondents' answers to the question of the nation's biggest problem at the time. Respondents in most countries answered "health". The exceptions were Australia, where most respondents named "the environment", and Japan, Spain, Croatia, South Korea, and Thailand, where respondents mentioned "the economy". In India, participants named "poverty" as the nation's biggest problem.

At the individual level, the analysis confirms former findings regarding the relation of gender, age and education with environmental concern. Females show slightly higher values of environmental concern. Moreover, environmental concern increases with age until the age of 50 and decreases thereafter. The more respondents lean toward the right of the political spectrum, the lower their level of environmental concern. Trust in others, the national parliament, news media and science increases environmental concern. At the macro level, environmental concern is strongly related to GDP, explaining 65% of the between country variance. This result is in strong contrast to the higher levels of CO_2 emissions of more wealthy countries (Franzen and Mader, 2021b). The finding contains a paradoxical twist: those who pollute the most are also the ones who are the most concerned about protecting the environment. Overall, the analysis of the 2020 ISSP data essentially confirms the results found using the data from former waves (Franzen and Meyer, 2010; Franzen and Vogl, 2013a). In addition, the ISSP 2020 contains more detailed information on trust in institutions than former rounds. Trust in institutions, and particularly in science, matters and has a strong impact on environmental concern in the US, and a moderate influence internationally.

The ISSP 2020 environmental module has some strength but also some weaknesses. The biggest strength is certainly that it enables international comparative research for almost three decades. It started data collection in 1993 in 21 countries. 25 countries participated in 2000, and the number of participating nations increased to 36 in 2010. Unfortunately, the survey in 2020 suffered from the COVID-19 pandemic which reduced the number of the participating countries to 29. Another strength of the ISSP is also the thorough design of the questionnaire keeping many key questions unchanged for the whole observation period. Moreover, the ISSP encourages strict random sampling for the participating countries, enabling the inference from the samples to populations. Furthermore, the ISSP invests great care ensuring accurate translations of the original English questionnaire into the different languages of the participating nations.

One of the weaknesses of the ISSP 2020 is the reduced number countries and delay of the data provision due to the COVID-19 pandemic. Another drawback is that countries do not participate continuously in each wave but interrupt participation for various reasons in certain years. Furthermore, the ISSP contains many more OECD countries as compared to non-OECD countries. Together, the relatively small number of participating nations, the dominance of the data from OECD countries, and the interrupted trend for many countries compromise the generalizability of the results. Moreover, it should be kept in mind that surveys contain naturally self-reported data. Such self-reports might be influenced by socially desirable answering behavior. This problem might be particularly pronounced in countries with stronger restrictions on the freedom of speech than in other countries. Another characteristic of the ISSP is that the questionnaires are short and contain about 60 questions. The rules of the ISSP stipulate that a new wave can only contain 20 new questions in exchange for 20 old ones. The advantage of this is that it ensures comparability of some survey questions over a long time period. However, it also limits the

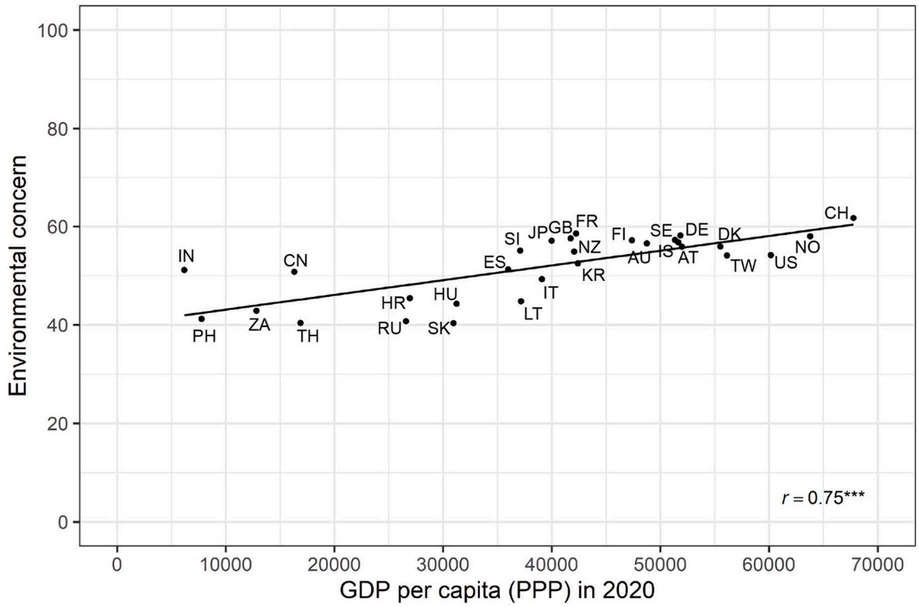


Fig. 3. Bivariate correlation between GDP and environmental concern.

possibility to incorporate new questions into the surveys and to acquire new trend data. Fortunately, this problem does not apply to our analysis of environmental concern since these items are contained in the surveys since 1993.

Possible avenues for future research analyzing the determinants of environmental concern should pay more attention on the interplay of education, political attitudes, and trust in science and media. These concepts are measured rather rudimentarily in the ISSP. For instance, the concept "trust in science" refers to science in general but does not differentiate between different scientific institutions or subjects. Similarly, "trust in media" does not differentiate between different types of media such as print media or television. Furthermore, it might be advisable to consider the role of social media for the development of environmental concern. Similar considerations apply to the measurement of education which is very general in our analysis and does not separate between different contents of school curricula.

6. Conclusion

This paper describes and analyses the trend of environmental concern in the countries that participated in the ISSP environmental module which started in 1993. The repeated measure of environmental concern in 2000, 2010 and 2020 reveals that the average level of countries` environmental concern first decreased until 2010 but recovered in 2020 to the level observed in 1993. Thus, the increasing environmental degradation did not have much impact on individuals` environmental attitudes. Reasons for this might be that survey participants were predominately concerned about the economic condition in the aftermath of the banking crisis in 2008. The survey in 2020 might have been influenced by the COVID-19 pandemic, giving health issues high priority. Both events were global affecting every country and might have prevented a stronger increase in environmental concern. Comparing countries environmental concern depends on the wealth of nations. Countries with higher GDP per capita tend to rank higher in terms of environmental concern. At the individual level, environmental concern is closely related to education, post-materialistic values, political attitudes, and individuals' trust in the news media and in science.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crsust.2024.100260.

References

Anderson, B., Böhmelt, T., Ward, H., 2017. Public opinion and environmental policy output: a cross-national analysis. Environ. Res. Lett. 12, 1–10.

Bakaki, Z., Böhmelt, T., Ward, H., 2020. The triangular relationship between public concern for environmental issues, policy output, and media attention. Environment. Politic. 29, 1157–1177.

Balliet, D., Van Lange, P.A.M., 2013. Trust, conflict, and cooperation: a meta-analysis. Psychol. Bull. 139, 1090–1112.

Bamberg, S., Möser, G., 2007. Twenty years after Hines, Hungerford, and Tomera: a new Meta-analysis of psycho-social determinants of pro-environmental behaviour. J. Environ. Psychol. 27, 14–25.

Bouman, Thijs, Verschoor, Mark, Albers, Casper J., Böhm, Gisela, Fisher, Stephen D., Poortinga, Wouter, Whitmarsh, Lorraine, Steg, Linda, 2020. When worry about climate change leads to climate action: how values, worry and personal responsibility relate to various climate actions. Glob. Environ. Chang. 62, 102061.

Bruderer Enzler, H., Diekmann, A., 2019. All talk and no action? An analysis of environmental concern, income and greenhouse gas emissions in Switzerland. Energy Res. Soc. Sci. 51, 12–19.

Chen, T., Guestrin, C., 2016. XGBOOST: A scalable tree boosting system *KDD '16*. In: The 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. https://doi.org/10.48550/arXiv.1603.02754. San Francisco, United States.

Clark, A., Justwan, F., Carlisle, J.E., Clark, M., 2019. Polarization politics and hopes for a green agenda in the United States. Environment. Politic. 29, 719–745.

Combes, J.L., Hamit-Haggar, M., Schwartz, S., 2018. A multilevel analysis of the determinants of willingness to pay to prevent environmental pollution across countries. Soc. Sci. J. 55, 284–299.

Cowie, R.H., Bouchet, P., Fontaine, B., 2020. The sixth mass extinction: fact, fiction or speculation? Biol. Rev. 97, 640–663.

Diekmann, Andreas, Preisendörfer, Peter, 2001. Umweltsoziologie: Eine Einführung. Rowohlt, Reinbek bei Hamburg.

Diekmann, A., Preisendörfer, P., 2003. Green and greenback: the behavioral effects of environmental attitudes in low-cost and high-cost situations. Ration. Soc. 15, 441–472.

Dunlap, R.E., Jones, R.E., 2002. Environmental concern: conceptual and measurement issues. In: Dunlap, R.E., Michelson, W. (Eds.), Handbook of Environmental Sociology. Greenwood Press, Westport.

Franzen, A., Mader, S., 2021a. Testing the measurement of environmental concern: How do single items perform in comparison to multi-item scales? In: Franzen, Axel, Mader, Sebastian (Eds.), Research Handbook on Environmental Sociology. Edward Elgar Publishing, Cheltenham, UK.
Franzen, A., Mader, S., 2021b. The development of global CO2 emissions. In: Franzen, Axel, Mader, Sebastian (Eds.), Research Handbook on Environmental Sociology, Edward Elgar Publishing, Cheltenham, UK.
Franzen, A., Meyer, R., 2010. Environmental attitudes in cross-National Perspective: a multilevel analysis of the ISSP 1993 and 2000. Eur. Sociol. Rev. 26, 219–234.
Franzen, A., Vogl, D., 2013a. Two decades of measuring environmental attitudes: a comparative analysis of 33 countries. Glob. Environ. Chang. 23, 1001–1008.
Franzen, A., Vogl, D., 2013b. Time preferences and environmental concern: an analysis of the Swiss ISSP 2010. Int. J. Sociol. 43, 39–62.
Franzen, A., Vogl, D., 2013c. Acquiescence and the willingness to pay for environmental protection: a comparison of the ISSP, WVS, and EVS. Soc. Sci. Q. 94, 637–659.
Gelman, A., Hill, J., 2007. Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge University Press, Cambridge.
Gifford, R., Sussman, R., 2012. Environmental Attitudes. In: Clayton, S.D. (Ed.), The Oxford Handbook of Environmental and Conservation Psychology. Oxford University Press, New York, pp. 65–80.
Hadler, M., Schweighardt, M., 2023. Report on Questionnaire Development. Accessed 2024 June 19. https://access.gesis.org/dbk/74754.
Hartmann, J., Preisendörfer, P., 2021. Development and structure of environmental worries in Germany 1984–2019. Z. Soziol. 50, 322–337.
Hartmann, J., Preisendörfer, P., 2023. The relationship between ecology and economy in German public opinion, 1984–2019. Environment. Politic. https://doi.org/10.1080/09644016.2023.2178358.
Hines, J.M., Hungerford, H.R., Tomera, A.N., 1986. Analysis and synthesis of research on responsible environmental behaviour: a meta- analysis. J. Environ. Educ. 18, 1–8.
Hox, J.J., Moerbeek, M., Van der Schoot, R., 2017. Multilevel Analysis: Techniques and Applications. Routledge, New York.
Inglehart, R., 1990. Culture Shift in Advanced Industrial Society. Princeton University Press, Princeton.
Inglehart, R., 1995. Public support for environmental protection: objective problems and subjective values in 43 societies. Polit. Sci. Polit. 28, 57–72.
Inglehart, R., 1997. Modernization and Postmodernization: Cultural, Economic and Political Change in 43 Societies. Princeton University Press, Princeton.
IPCC, 2022. Summary for policymakers. In: Pörtner, H.-O., Roberts, D.C., Poloczanska, E. S., Mintenbeck, K., Tignor, M., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A. (Eds.), Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press, Cambridge and New York, pp. 3–33. https://doi.org/10.1017/9781009325844.001.
ISSP Research Group, 2023. International Social Survey Programme: Environment IV - ISSP 2020. GESIS, Köln. ZA7650 Data File Version 2.0.0. https://doi.org/10.4232/1.14153.
Kenward, M.G., Roger, J.H., 1997. Small sample inference for fixed effects from restricted maximum likelihood. Biometrics 53, 983–977.
Kollmuss, A., Agyeman, J., 2010. Mind the gap: why do people act environmentally and what are the barriers to pro-environmental behavior? Environ. Educ. Res. 8, 239–260.
McCright, A.M., Xiao, C., 2014. Gender and environmental concern: insights from recent work and for future research. Soc. Nat. Resour. 27, 1109–1113.
McCright, A.M., Xiao, C., Dunlap, R.E., 2014. Political polarization on support for government spending on environmental protection in the USA, 1974–2012. Soc. Sci. Res. 48, 251–260.
Meyer, R., Liebe, U., 2010. Are the affluent prepared to pay for the planet? Explaining willingness to pay for public and quasi-private environmental goods in Switzerland. Popul. Environ. 32, 42–65.
OECD, 2013. OECD Framework for Statistics on the Distribution of Household Income, Consumption and Wealth. OECD Publishing, Paris.
Post, D., Meng, Y., 2018. Does schooling foster environmental values and action? A cross national study of priorities and behaviors. Int. J. Educ. Dev. 60, 10–18.
Preisendörfer, P., 1999. Umwelteinstellungen Und Umweltverhalten in Deutschland. Leske und Budrich, Opladen.
Preisendörfer, P., Franzen, A., 1996. Der schöne Schein des Umweltbewusstseins. Kölner Zeitschrift für Soziol. Sozialpsychol. 36, 219–244.
Rabe-Hesketh, S., Skrondal, A., 2008. Multilevel and Longitudinal Modeling Using Stata, 2nd ed. Stata Press, College Station, Texas.
Smith, E.K., Mayer, A., 2018. A social trap for the climate? Collective action, trust and climate change risk perception in 35 countries. Glob. Environ. Chang. 49, 140–153.
Snijders, T.A., Bosker, R.J., 1999. Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling. Sage, London.
Sonderskov, K.M., 2009. Different goods, different effects: exploring the effects of generalized social trust in large-N collective action. Public Choice 140, 145–160.
Steg, L., Vlek, C., 2009. Encouraging pro-environmental behaviour. An integrative review and research agenda. J. Environ. Psychol. 29, 309–317.
Tilman, D., Clark, M., Williams, D.R., Kimmel, K., Polasky, S., Packer, C., 2017. Future threats to biodiversity and pathways to their prevention. Nature 546, 73–81.
Vandeweerdt, C., Kerremans, B., Cohn, A., 2016. Climate voting in the US congress: the power of public concern. Environment. Politic. 25, 268–288.
WWF, 2022. In: Almond, R.E.A., Grooten, M., Juffe Bignoli, D., Petersen, T. (Eds.), Living Planet Report 2022 – Building a Nature- Positive Society. WWF, Gland, Switzerland.
Yamagishi, T., Kikuchi, M., Kosugi, M., 1999. Trust, gullibility, and social intelligence. Asian J. Soc. Psychol. 2, 145–161.
Zelezny, L.C., Chua, P.P., Aldrich, C., 2000. Elaborating on gender differences in environmentalism. J. Soc. Issues 56, 443–457.

The development of global environmental concern during the last three decades

Supplement

Table S1: Data description

	Min.	Max.	Mean.	Sd.	Description	Source
Endogenous variables						
Environmental concern	0	100	52.6	16.1	The index is built out of the items 1 to 9 of Table 1. It is rescaled between 0 and 100.	ISSP (2020)
Environmental concern items 1 to 4	0	100	50.0	22.0	The index is built out of the items 1 to 4 of Table 1. It is rescaled between 0 and 100.	ISSP (2020)
Exogenous variables						
Individual level variables						
Sex	0	1	0.5		0 = male, 1 = female.	ISSP (2020)
Age	18	80	49.4	16.5	Age in years.	ISSP (2020)
Education	1	4			Education is classified into 4 categories: 1 = primary degree, 2 = secondary degree, 3 = low tertiary degree, 4 = tertiary degree.	ISSP (2020)
Relative household income	-2.4	28.1	0.0	1.0	Household income divided by the square root of the number of persons living in the household, z-transformed.	ISSP (2020)
Post-materialism	0	2	0.9	0.6	Number of post-materialistic goals a country should have from a list of four[a].	ISSP (2020)
Trust in others	1	5	2.9	1.3	5-point Likert scale from 1 = you can't be too careful to 5 = most people can be trusted[b].	ISSP (2020)
Trust in parliament	0	10	4.9	2.9	10-point Likert scale form 1 = not at all to 10 = complete trust to the question "How much do you personally trust the country's national parliament".	ISSP (2020)
Trust in science	0	10	6.7	2.4	10-point Likert scale form 1 = not at all to 10 = complete trust to the question "How much do you personally trust university and research centers".	ISSP (2020)
Trust in news media	0	10	4.7	2.6	10-point Likert scale form 1 = not at all to 10 = complete trust to the question "How much do you personally the news media".	ISSP (2020)
Trust in industry	0	10	5.2	2.2	10-point Likert scale form 1 = not at all to 10 = complete trust to the question "How much do you personally trust businesses and industry".	ISSP (2020)
Party affiliation	1	5	3.0	1.0	1 = far left, 2 =left, 3 center/ liberal, 4 = right / conservative, and 5 = far right.	ISSP (2020)
Country level variables						
Log GDP per capita (PPP)	8.7	11.1	10.4	0.6	Logarithm of per capita GDP 2020 converted to measure the purchasing power in each country in 2017 international US$.	World Bank
Proportion urban population	34.9	93.9	73.2	13.7	Proportion of population living in areas classified as urban according to the criteria used by each country in 2020.	World Bank
Population density	3.3	652.0	170.6	162.4	Number of inhabitants per square kilometer of country's land area in 2020.	World Bank
Gini index	23.2	66.0	35.9	10.3	The country's Gini index in 2020.	World Bank

Note: [a] = the four goals are freedom of speech, democratic participation, fight rising prices, and maintain order in the nation. The first two goals represent post-materialistic values. [b] = In China general trust was measured on a 4-point Likert scale. The values are recoded to their corresponding values on the 5-point Likert scale by leaving out the middle category.

Table S2: Determinants of environmental concern (willingness to pay, items 1-3, and 8)

	Model 4 USA	Model 5 all countries	Model 6 all countries
Individual-level variables			
Sex (1 = female)	0.011	0.063**	0.062***
	(0.058)	(0.022)	(0.018)
Age in years (18-80)	-0.018	-0.003	-0.005
	(0.014)	(0.003)	(0.004
Squared age in years (18-80)	0.0002	0.00005	0.00006^{+}
	(0.0001)	(0.00003)	(0.00003)
Reference: Primary degree			
Secondary degree	0.087	0.116***	0.099*
	(0.185)	(0.033)	(0.040)
Low tertiary degree	0.116	0.228***	0.181***
	(0.201)	(0.043)	(0.048)
Tertiary degree	0.154	0.312***	0.293***
	(0.184)	(0.045)	(0.046)
Relative income within country[a]	(0.051	0.021**	0.020^{+}
	(0.033)	(0.007)	(0.010)
Post-materialism	0.053^{+}	0.113***	0.108***
	(0.030)	(0.010)	(0.010)
Trust in others	0.015	0.095***	0.102***
	(0.035)	(0.011)	(0.012)
Trust in parliament	0.106*	0.162***	0.167***
	(0.044)	(0.021)	(0.024)
Trust in science	0.242***	0.107***	0.101*
	(0.040)	(0.024)	(0.031)
Trust in news media	0.160***	0.072***	0.065***
	(0.048)	(0.017)	(0.019)
Trust in industry	-0.185***	-0.089***	-0.103***
	(0.035)	(0.025)	(0.019)
Party affiliation[b]	0.574***		-0.141***
	(0.094)		(0.016)
Country-level variables			
Log GDP per capita (PPP)		0.194*	0.452***
		(0.082)	(0.053)
Proportion urban population		0.037	-0.018
		(0.046)	(0.037)
Population density		0.119***	0.171***
		(0.026)	(0.019)
Gini index		0.046	0.157***
		(0.036)	(0.036)
Explained variance			
Country level		0.10	0.10
Individual level		0.89	0.90
Intraclass correlation (ICC)			
Null model		0.10	0.10
Model with covariates		0.03	0.02
R^2 adjusted	0.35		
Number of countries	1	28	26
Number of observations	782	25,939	14,284

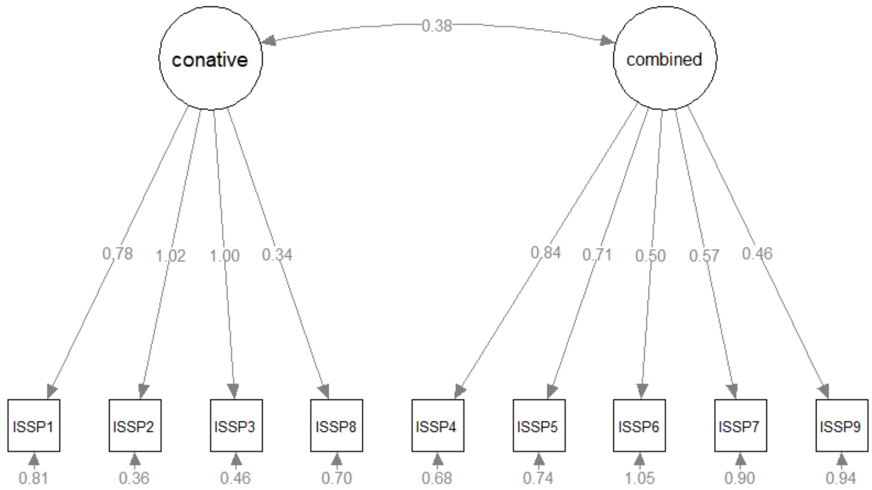
Note: $^{+}$ = $p < 0.10$, * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$, [a] = absolute household equivalence income in model 1. [b] = dummy that indicates affiliation to the Republicans in model 4. Standardized regression coefficients with heteroscedasticity and cluster-robust standard errors in parentheses. The environmental concern is measured by creating an index out of the items 1-3, and 8. In model 5 and 6 India is excluded due to poor data quality (Cronbach's alpha = 0.16).

Table S3: Determinants of the environmental concern (income imputed)

	Model 7 all countries	Model 8 all countries
Individual-level variables		
Sex (1 = female)	0.132***	0.137***
	(0.024)	(0.022)
Age in years (18-80)	0.007*	0.010**
	(0.003)	(0.004)
Squared age in years (18-80)	-0.00008**	-0.0001**
	(0.00002)	(0.00003)
Reference: Primary degree		
Secondary degree	0.125***	0.117**
	(0.030)	(0.037)
Low tertiary degree	0.271***	0.239***
	(0.038)	(0.042)
Tertiary degree	0.418***	0.379***
	(0.037)	(0.045)
Relative income within country (imputed)[a]	0.020*	0.013
	(0.010)	(0.012)
Post-materialism	0.115***	0.103***
	(0.012)	(0.008)
Trust in others	0.101***	0.099***
	(0.011)	(0.012)
Trust in parliament	0.103***	0.103***
	(0.020)	(0.022)
Trust in science	0.115***	0.164***
	(0.028)	(0.035)
Trust in news media	0.068***	0.078**
	(0.022)	(0.025)
Trust in industry	-0.170***	-0.193***
	(0.031)	(0.024)
Party affiliation		-0.171***
		(0.025)
Country-level variables		
Log GDP per capita (PPP)	0.333***	0.605***
	(0.100)	(0.100)
Proportion urban population	0.071	0.016
	(0.054)	(0.049)
Population density	0.093**	0.154**
	(0.032)	(0.056)
Gini index	-0.036	0.072
	(0.041)	(0.044)
Explained variance		
Country level	0.17	0.18
Individual level	0.82	0.82
Intraclass correlation (ICC)		
Null model	0.17	0.18
Model with covariates	0.06	0.06
R^2 adjusted		
Number of countries	28	26
Number of observations	30,575	16,547

Note: $^+$ = $p < 0.10$, * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$. [a] = the relative income was imputed using Extreme Gradient Boost that was trained on the remaining data. Standardized regression coefficients with heteroscedasticity and cluster-robust standard errors in parentheses. The environmental concern is measured by creating an index out of the items 1 to 9. In model 7 and 8 India is excluded due to poor data quality (Cronbach's alpha = 0.16).

Figure S1: Confirmatory Factor Analysis for the whole sample of the ISSP 2020



Note: The fit statistics CFI = 0.960, RMSEA = 0.058, SRMR = 0.039 all indicate a good fit according to the cutoff criteria of CFI > 0.95, RMSEA < 0.06, and SRMR < 0.08 (Hu and Bentler 1999).

Article 3

The relationship between urban greenery, mixed land use and life satisfaction: An examination using remote sensing data and deep learning

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"If you invite more cars, you get more cars. If you make more streets better for cars you get more traffic. If you make more bicycle infrastructure you get more bicycles. If you invite people to walk more and use public spaces more, you get more life in the city. You get what you invite."

Jan Gehl (2019)

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Research Paper

The relationship between urban greenery, mixed land use and life satisfaction: An examination using remote sensing data and deep learning

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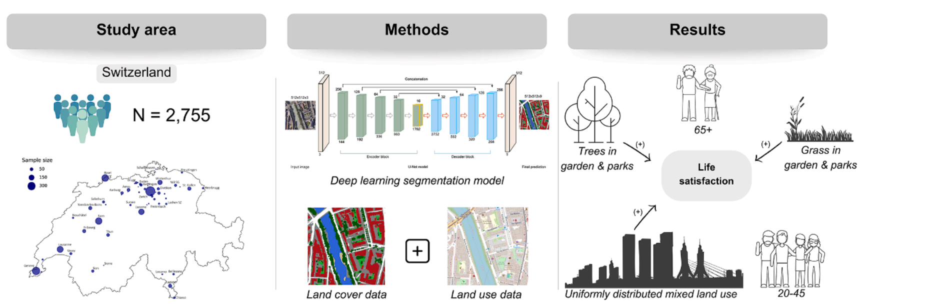
HIGHLIGHTS

- With regard to life satisfaction in Switzerland, only residents aged above 65 appear to benefit from urban greenery.
- Trees and grass situated in parks and gardens are the main drivers of this positive relationship.
- A greater land use mix is positively associated with life satisfaction solely for younger individuals.

GRAPHICAL ABSTRACT



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ABSTRACT

Most Europeans reside in urban areas. Due to anthropogenic air and noise pollution, as well as crowdedness, urban residents experience lower levels of well-being and life satisfaction. The literature indicates that greening urban spaces can help to mitigate these negative effects on life satisfaction. This study employs a deep learning approach in conjunction with high-resolution satellite imagery and land use data to obtain the distribution of different green space types in the residents' neighborhood and examine their effect on life satisfaction. Furthermore, the study sheds light on the indeterminate relationship between mixed urban land use and life satisfaction. In both cases, the study considers heterogeneous age group effects. The empirical results reveal that in Switzerland, (1) solely older residents' life satisfaction is positively affected by a greener neighborhood; (2) trees and grass located in gardens and parks are the primary drivers of this effect; and (3) the positive association between land use mixture and life satisfaction decreases with age, with no association found for older individuals. These findings provide practical implications for future city planning in Switzerland and other European countries and highlight the importance of considering the neighborhood's age distribution in this process to maximize the positive impact of urban greenery and mixed land use on residents' life satisfaction.

1. Introduction

The global rise in population has led to a substantial increase in the urban population. In 1960, only 34 % of the world's population resided in cities, whereas by 2022, this number had almost doubled to 57 %. The World Bank (2023) projects that this trend will continue, with an estimated urban population of 70 % by 2050. The European Union has already reached this level, as evidenced by the fact that 75 % of its population resided in urbanized areas in 2022. Studies suggest that urban areas have become the epicenters of mental distress (Dye, 2008;

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Sundquist, Frank, & Sundquist, 2004) and that this is partly due to the detachment from the natural environments in which humans evolved (Kaplan & Kaplan, 1989; Wilson, 1984). Due to the growing population in urban areas and the negative effects of these areas on humans, urban planning has become increasingly vital in maintaining residents' mental and physical health. This is acknowledged by the European Commission (2020) and its EU Biodiversity Strategy 2030, which aims to promote investments in green infrastructure as well as the systematic integration of healthy ecosystems, green infrastructure, and nature-based solutions into urban planning. These efforts are supported by a substantial body of literature, which suggests that people living in greener urban environments tend to have better health and higher levels of well-being (e.g., see Hartig, Mitchell, De Vries, & Frumkin, 2014; Reyes-Riveros et al., 2021; Yang et al., 2021 for reviews). However, limited space in cities, along with a range of stakeholders with divergent land usage objectives, complicates urban planning decisions and puts strain on the limited green urban areas.

Besides various other urban planning objectives, such as reducing air and water pollution, traffic noise, and congestion, building human-oriented smart cities has been increasingly promoted in the past. Consequently, they have become an essential dimension of planning livable cities alongside greening urban landscapes. As advocated by the new urbanism movement (Garde, 2020), this concept promotes neighborhoods that comprise a high mix of different land use classes. The proximity of residential areas to workplaces, grocery stores, public transportation, commercial, educational, health, leisure, sports, and cultural facilities creates a multitude of amenities, reduces the necessity for residents to commute, and tends to result in a higher satisfaction among residents. (Dong & Qin, 2017; Mouratidis, 2018).

Nowadays, urban greenery and mixed land use neighborhoods play a major role in designing livable and smart growing cities. While many studies have examined the relationship between urban greenery and well-being, there is little consensus about measuring urban green spaces. Although multiple approaches have been used to do so, a thorough operationalization of green spaces is inevitable to correctly estimate its effect on residents' well-being. Earlier studies (Ambrey & Fleming, 2014; Bertram & Rehdanz, 2015; Krekel, Kolbe, & Wüstemann, 2016; White, Alcock, Wheeler, & Depledge, 2013) relied on land usage data, whereas more recent studies (Kwon et al., 2021; Taylor, Hahs, & Hochuli, 2018; Tsurumi, Imauji, & Managi, 2018) shifted to using remote sensing imagery and measured green space by calculating the Normalized Difference Vegetation Index (NDVI), which measures the amount and vigor of vegetation. The emergence of deep learning and the facilitated access to street-level imagery led to a rising number of studies using street-level imagery in combination with segmentation models to quantify urban greenness (e.g., see Seiferling, Naik, Ratti, & Proulx, 2017; Stubbings, Peskett, Rowe, & Arribas-Bel, 2019) and some of them used it to examine the relationship with residents' life satisfaction (Wu, Chen, Yun, Wang, & Gong, 2022; Wu, Tan, Wang, & Chen, 2023). I argue that the mentioned approaches have significant limitations and suggest a procedure that combines deep learning with publicly available high-resolution satellite images and land use data. This produces a very detailed and spatially fine-grained measurement of the distribution of urban green space types.

The contribution of the article is fourfold. First, it contributes to the field of urban planning by presenting a novel measurement of urban greenery. It enables scholars and urban planners to select from an extensive set of green space types and use them in examinations. Second, it contributes to the literature by using the proposed measurement and disentangling the association between urban greenery and residents' life satisfaction in a case study in Switzerland, by examining nine different green space types in the analysis. As the suggested approach allows it to easily obtain the proportion of green space types in any selected area, all densely populated areas in Switzerland, a country where 2/3 of its population live in urbanized areas, but comprehensive evidence is lacking, are analyzed. Third, some studies suggest that the preferences for urban greenery components differ by age. They showed that younger individuals value green spaces more if they can be used for physical activities or meeting others, whereas older people value them more if they can relax, stay with children, and enjoy nature (Chiesura, 2004; Kabisch & Haase, 2014). The article acknowledges these findings by considering heterogeneous age subgroup effects in the association between urban greenery and life satisfaction. The provided evidence indicates to urban planners which types of green spaces are most promising to be promoted in a neighborhood, given its age distribution, to enhance residents' life satisfaction. Fourth, while human-oriented smart neighborhoods are an essential pillar of a livable and sustainable city, only a limited number of studies examine the relationship between mixed land use neighborhoods and residents' life satisfaction. This study aims to contribute further evidence on this relationship.

2. Literature review

2.1. Life satisfaction and urban green space

Self-reported subjective well-being is a comprehensive tool to assess the impact of green spaces on respondents' lives and is used in a growing number of studies as a proxy for well-being (e.g., see Bertram & Rehdanz, 2015; MacKerron & Mourato, 2013; Tsurumi, Imauji, & Managi, 2018; White et al., 2013). Since it indicates overall satisfaction with one's life, it is often considered to be synonymous with happiness or life satisfaction (Diener, Oishi, & Lucas, 2003).

Previous research has identified three main mechanisms with regard to how urban greenery is linked to well-being. First, green spaces result in environmental benefits such as reductions of anthropogenic noise (Gaudon, McTavish, Hamberg, Cray, & Murphy, 2022), air pollution (Nowak, Hirabayashi, Doyle, McGovern, & Pasher, 2018; Selmi et al., 2016), and heat islands (Aram, Higueras García, Solgi, & Mansournia, 2019) which contribute to a better life experience and better well-being. Second, public green spaces such as parks or recreation areas encourage residents to pursue physical activities and social interactions (Akpinar, 2016). Evidence from Hong Kong suggests that even street greenery fosters physical activities and cycling behavior (Lu, 2019; Lu, Yang, Sun, & Gou, 2019). This can lead to better health and higher levels of well-being. Third, natural environments can help with relaxation by providing a mental escape and thereby reducing mental distress, as evidenced by studies in Australia (Shanahan et al., 2016), England (White et al., 2013), and the Netherlands (De Vries, Verheij, Groenewegen, & Spreeuwenberg, 2003; Maas et al., 2009; Van Den Berg, Maas, Verheij, & Groenewegen, 2010).

Existing research mainly examines the relationship between availability (e.g., see Ambrey & Fleming, 2014; Bertram & Rehdanz, 2015; Kley & Dovbishchuk, 2021; Krekel et al., 2016; White et al., 2013; Wu, Tan, Wang, & Chen, 2023), or proximity (e.g., see Bertram & Rehdanz, 2015; Fleming, Manning, & Ambrey, 2016; Krekel et al., 2016; Wu, Chen, Yun, Wang, & Gong, 2022) of green space and residents' subjective well-being in a predefined buffer zone created around the residents' home. The majority of these studies find a positive relationship between green space and subjective well-being in the urban context. However, in Beijing, a number of studies found no evidence that the distance to urban parks is associated with higher life satisfaction (Ma, Dong, Chen, & Zhang, 2018; Wu et al., 2022), and an analysis of 33 cities located in six countries did not reveal any association between green land cover and residents' subjective well-being (Brown, Oueslati, & Silva, 2016).

Previous research has applied different approaches to measure urban greenery. However, I argue that they suffer from significant limitations. Bertram and Rehdanz (2015), Olsen et al. (2019), and Krekel et al. (2016) used the European Urban Atlas, which contains land usage data for all European urbanized areas with more than 50,000 inhabitants and with a minimum mapping unit size of 0.25 ha. It has the disadvantage that data on densely populated areas with less than 50,000 inhabitants are not available, and due to the moderate resolution, the data does not contain information on private or small green areas such as gardens, playgrounds, or tree canopies. However, it is plausible that these small green spaces create amenities and can influence well-being positively. Hence, they are an essential part of the analysis and should not be neglected. Assessing green cover using the NDVI is simple; however, it comes at the cost that the input images need to contain a near-infrared band. Most studies (e.g., Kwon et al., 2021; Taylor et al., 2018) use Landsat 8 satellite imagery because it includes all the necessary color bands for calculating the NDVI. However, the data is only available at a 30-meter per pixel resolution. Li, Saphores, and Gillespie (2015) provided evidence that the resolution matters and the economic benefits of tree canopy cover and grass measured with medium- (30 m) and high- (0.6 m) resolution satellite images only correlate weakly. Tsurumi et al. (2018) expanded the literature by utilizing QuickBird satellite images to assess the NDVI in high resolution (0.61 m per pixel). They combined the NDVI score of an image pixel with the land use type it is located in, e.g., residential area, park, or roadside. This measure is subsequently used to examine the association between green spaces and well-being in Tokyo. They found that only urban green in residential areas and along roads was positively associated with well-being, but not green space in parks or public facilities, which is surprising. The main limitation of using the NDVI to assess urban green spaces is that it is measured at a low resolution, which can be overcome by using QuickBird images. However, the mission ended in 2015, and no recent high-resolution data is available. In addition, the NDVI measures the amount and vigor of plants but cannot differentiate between different vegetation types, such as grass, meadows, or trees. This issue can only be partly addressed by adding information on the land use type in which an image pixel is located. For instance, it cannot be distinguished if a pixel with a high NDVI score inside a park belongs to a tree or a grass field.

However, a strain of literature indicates that these nuances matter when it comes to the effect of urban greenery on residents' life satisfaction (Ayala-Azcárraga, Diaz, & Zambrano, 2019; Syrbe et al., 2021; Wu et al., 2023). Evidence for Mexico City suggests that the prevalence of trees is a significant factor influencing the utilization of parks. Additionally, the height of trees and the melodies of birds inhabiting them are associated with the well-being of park visitors (Ayala-Azcárraga et al., 2019). An examination in two Czech cities and one German city revealed that residents prefer natural (less intensively maintained) green spaces with safe, clean, and accessible pathways (Syrbe et al., 2021). These findings underscore the importance of considering not only the proportion and proximity of urban green spaces when investigating their effect on residents' well-being but also their composition. The composition of urban greenery is often measured by survey data, which has the disadvantage of being costly to generate, resulting in a small study area, and being prone to survey bias. A more recent case study conducted in Beijing (Wu et al., 2023) revealed that the quantity (availability, accessibility) and quality (attractiveness, natural aesthetics) of urban greenery exert heterogeneous effects on well-being. The relationship between attractiveness and natural aesthetics was found to be more pronounced compared to the quantitative dimensions, indicating that the quality of urban green spaces is of great importance when assessing its relationship with life satisfaction. The study employed a manual rating system to determine the attractiveness and natural aesthetics of green spaces. This involved rating 200 street-view images, after which a deep learning segmentation model was trained to predict these characteristics on the remaining street-view images. Differentiating urban greenery into their components, such as trees, hedges, and grass fields, and rating their quality by applying segmentation models is a promising approach. However, it should be noted that street-view data has some limitations over high-resolution satellite data. This is because street-view data is limited to areas adjacent to streets and mostly neglects green spaces in residential areas. Moreover, buildings or other vegetation, such as tree canopies or hedges, may obscure green space located behind them, particularly in urban settings. Tong et al. (2020) support this by demonstrating a weak correlation between greenery measured through street-level imagery and satellite imagery in residential and industrial neighborhoods. Furthermore, street imagery does not provide information on the size of the vegetated area, which is an essential determinant of the relationship between urban greenery and subjective well-being (Krekel et al., 2016; Tsurumi et al., 2018).

This study proposes a novel approach to measure the various components of urban green spaces and their association with residents' life satisfaction. It builds on evidence (Ayala-Azcárraga et al., 2019; Syrbe et al., 2021; Wu et al., 2023) indicating varying assessment and usage of these components, which may result in heterogeneous effects on life satisfaction. It employs high-resolution and publicly available satellite imagery combined with a deep learning semantic segmentation model to derive nine distinct urban green space components. This procedure allows the study to consider the proportion and type of green spaces and comprehensively answers the question (Q1) if different types of urban green spaces located in the walkable neighborhood have heterogeneous effects on residents' life satisfaction in urban areas in Switzerland.

2.2. Life satisfaction and mixed land use

The urban environment affects residents' subjective well-being not solely through urban greenery; the access to various goods and amenities in the neighborhood is also critical. A mixed land use neighborhood is defined by the presence of different stores, businesses, and services in the area of interest. From a theoretical perspective, a neighborhood environment that provides a large variety of services such as education, the provision of daily goods and public services, cultural and culinary activities, sports, and recreation should increase the livability of that area and positively affect residents' subjective well-being. This is due to greater social cohesion, more social engagement, economic vibrancy, and better accessibility, which is especially relevant for older people. While the examination of the relationship between urban green spaces and subjective well-being has been given a lot of attention in the literature, there are just a limited number of studies (Cao, 2016; Dong & Qin, 2017; Guo et al., 2021; McCarthy & Habib, 2018; Mouratidis, 2018; Olsen, Nicholls, & Mitchell, 2019; Wu et al., 2022) focusing on the relationship between mixed land use and residents' subjective well-being. Case studies examining the direct effect of mixed land use on residents' well-being conducted in Beijing (Dong & Qin, 2017) and Nova Scotia, Canada (McCarthy & Habib, 2018) could not find any effect. In contrast, evidence from Minneapolis-St. Paul, Minnesota, indicates that a greater mix of land use types leads to better accessibility but also to increased nuisance due to crowdedness, noise, and pollution. Accessibility was positively associated, and nuisance was negatively associated with life satisfaction, resulting in an insignificant total effect (Cao, 2016). Guo et al. (2021) found no direct effect of land use mix on subjective well-being. However, a mediation analysis revealed that the neighborhood's perceived age-friendliness and sense of community in Hong Kong mediates the relationship. Further evidence from China (Beijing) that operationalizes mixed land use by calculating the land use entropy in an area indicates that a higher mixture is not only positively associated with residents' life satisfaction but that this relationship is more substantial in areas with more green space (Wu et al., 2022). Evidence from Europe is somewhat mixed. A study conducted in 66 European cities revealed a weak negative effect of the area covered by continuous urban fabric (at least 80 % building coverage) and residents' subjective well-being. However, they found no evidence that land cover diversity or evenness is related to subjective well-being (Olsen et al., 2019). Contrarily, results from Oslo (Norway) suggest that the number of cafés, restaurants, and bars in an area positively affects residents' satisfaction with their relationships, by enabling them to have larger social networks and more frequent social interactions (Mouratidis, 2018). Since the effect of mixed land use on residents' subjective well-being is empirically indeterminate, this study aims to shed further light on this relationship by answering the question (Q2) whether in Switzerland residents' life satisfaction is positively associated with a higher mix of land use types in the walkable neighborhood.

2.3. Heterogeneous age effects

People's preferences change over their life course, as do the residents' preferences for urban green spaces. Syrbe et al. (2021) discovered that older individuals residing in Dresden, Germany, and two Czech cities tend to hold a more favorable opinion of parks than forests. Conversely, middle-aged residents in these cities express greater appreciation for forests and playgrounds. This aligns with previous findings from Berlin (Kabisch & Haase, 2014) and Amsterdam (Chiesura, 2004), which indicate that younger age groups primarily visit green spaces for recreational purposes, including sports, sunbathing, and social gatherings. In contrast, older individuals sought out environments that offered opportunities for relaxation and appreciation of nature. The utilization of green spaces for social gatherings is of greater significance to younger individuals in Denmark as well. Nevertheless, the most prevalent reason for visiting green spaces across all age groups was "enjoy the weather and get fresh air". In contrast to other studies, relaxation and stress relief were more prevalent reasons for visiting urban greenery among younger age groups (Schipperijn et al., 2010). A series of studies conducted in Germany and Basel, Switzerland, examined the interaction effect of urban greenery and age groups on residents' life satisfaction. Both studies yielded evidence that green spaces have a more substantial effect on life satisfaction among older age groups. (Jeong et al., 2022; Krekel et al., 2016). This work contributes to the existing body of literature by investigating the interaction between age and different urban green spaces and addressing the question (Q3) whether there are heterogeneous effects in the association between various types of urban greenery and life satisfaction by age group.

3. Methodology

3.1. Study area

Switzerland lies in the center of Europe, and the Alps and the Jura Mountains cover 70 % of its area. The remaining 30 % is covered by the Swiss Plateau region, which reaches from Lake Geneva to St. Gallen and Lake Constance, and holds 2/3 of the country's population. This area is characterized by a medium to high population density of 400 inhabitants per km^2 and, due to federalism, many small to medium-sized municipalities (Federal Department of Foreign Affairs, 2023). The DEGURA typology developed by Eurostat (2018) and adopted by the Swiss Federal Statistical Office classifies areas as urban centers when they have a population density of at least 1500 inhabitants per km^2 and a minimum population of 50,000. However, as only ten Swiss cities have more than 50,000 inhabitants, using this classification would limit the study area and hamper the study's generalizability. Since the study aims to examine the effect of urban greenery and mixed land use on life satisfaction in a densely built and urbanized context, I argue that high population density is the main distinct feature of these areas and less so population size. Therefore, an adapted version of the DEGURA typology is used, and the analysis is restricted to postcodes with a population density of 1500 people per km^2.

3.2. Data

3.2.1. Residents' life satisfaction

The subjective well-being approach is used in this study to ensure comparability with previous research and to assess the effect the built environment has on the resident's overall life. As in other studies, the terms subjective well-being and life satisfaction are used interchangeably. The residents' life satisfaction data was obtained from the Swiss Household Panel Wave 23 conducted in 2021 and 2022 (individual level response rate = 77%). In the survey, life satisfaction was measured on an 11-point Likert scale by asking the respondents, "In general, how satisfied are you with your life if 0 means not at all satisfied and 10 means completely satisfied". The households were selected using stratified random sampling, and where possible, all individuals of a household aged 16 years and over were interviewed. A total of 11,890 individuals aged between 20 and 85 years, clustering in 7,816 households, answered the life satisfaction question. After restricting the sample to highly urbanized postcodes and excluding records with missing values on any control variable, a total of 2,755 individuals based in 1,867 households located in 206 postcodes, which are part of 57 cities, remained and formed the final sample. The spatial distribution of the interviewed households is depicted in Fig. 1. As expected, most surveyed households reside in the densely populated Swiss Plateau. The respondents indicated an average life satisfaction value of 7.94 (SD = 1.46). To obtain the neighborhood characteristics related to greenery and mixed land use the exact geo-location of the household is added to the data.

3.2.2. Urban green space

To measure green land cover, this study uses satellite images of the households' neighborhood environment in combination with a deep learning semantic segmentation model. A 1260 m × 1260 m tile was created for every household, with the household at the center. This corresponds to an approximate 10-minute walking distance. Each tile represented the area (neighborhood) of interest and was split into nine sub-tiles, as can be seen in Fig. 2A. For every sub-tile, a satellite image with a size of 1024 × 1024 pixels (0.42 m per pixel) was scraped from the Google Static Maps API (see Fig. 2B). Semantic segmentation models offer the unique opportunity to separate an image into different categories. For the case at hand, this method allows the detection of up to eight different land cover classes on a satellite image (see Fig. 2C), enabling the study to differentiate between different green land cover types. One advantage of semantic segmentation models is that their prediction is mostly based on the structure and shape of an object and less on its color. This makes the model robust to changes in the saturation and luminosity of colors, as it could be due to changing lighting conditions or seasons at which the satellite imagery was collected. The model was trained on the publicly available OpenEarthMap (Xia, Yokoya, Adriano, & Broni-Bediako, 2022) dataset. It contains around 5,000 high-resolution satellite images with manually annotated 8-class land cover labels, covering 97 regions from 44 countries across 6 continents. Due to its high generalizability, it can be applied to tasks worldwide. All images were split into sub-images of 512 × 512 pixels to reduce the computational load. As annotations were absent in the dataset for some images, this procedure resulted in 9,278 images, 39 % from developed and 61 % from developing countries. The data was randomly split into five folds (Fig. 2E). This allows the evaluation of the performance of the model on different data and gives a better understanding of how the performance can vary on different datasets. In the first step, the semantic segmentation model consisting of a U-Net architecture (Ronneberger, Fischer, & Brox, 2015) with an Efficient Net B4 (Tan & Le, 2020) encoder was trained on an NVIDIA GeForce RTX 3090. In the encoder part, the U-Net compresses the information contained in the input image by reducing height and width and increasing the depth of the feature map. The decoder tries to upsample and rebuild the input image based on that information. However, instead of outputting the RGB values of a pixel, it predicts the segmentation class it belongs to (see Fig. 2D). In the training process, the model learned to assign the following eight land cover classes to the input satellite image: bareland, rangeland (grass, shrubs, gardens, and parks), trees, agricultural land, roads, developed space (pavements, parking lots or other paved areas), buildings, and water. Test time augmentation (TTA) is used to enhance the generalization performance of the model. Since the model is used for predictions in Switzerland, it is evaluated solely on images from developed countries. As Fig. 2E depicts, the optimal hyperparameters of the model were assessed on dataset 1. This set of hyperparameters was used to train four separate U-Nets on the four remaining datasets (2–5). Each

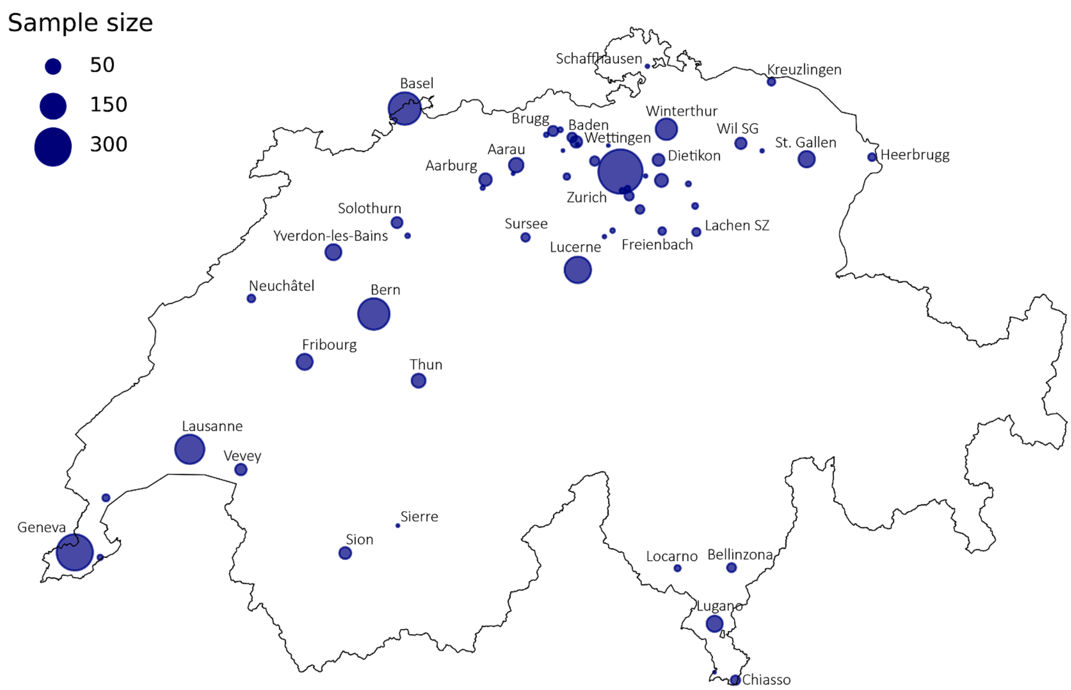

Fig. 1. Map of sample locations. The circle size is proportional to the sample size. The sample size varies from 2 in Sierre to 569 in Zurich, with a mean of 48. A circle represents either a single postcode if it is considered an independent municipality or multiple postcodes if they belong to one city. All postcodes have a population density of at least 1,500 inhabitants per km^2.

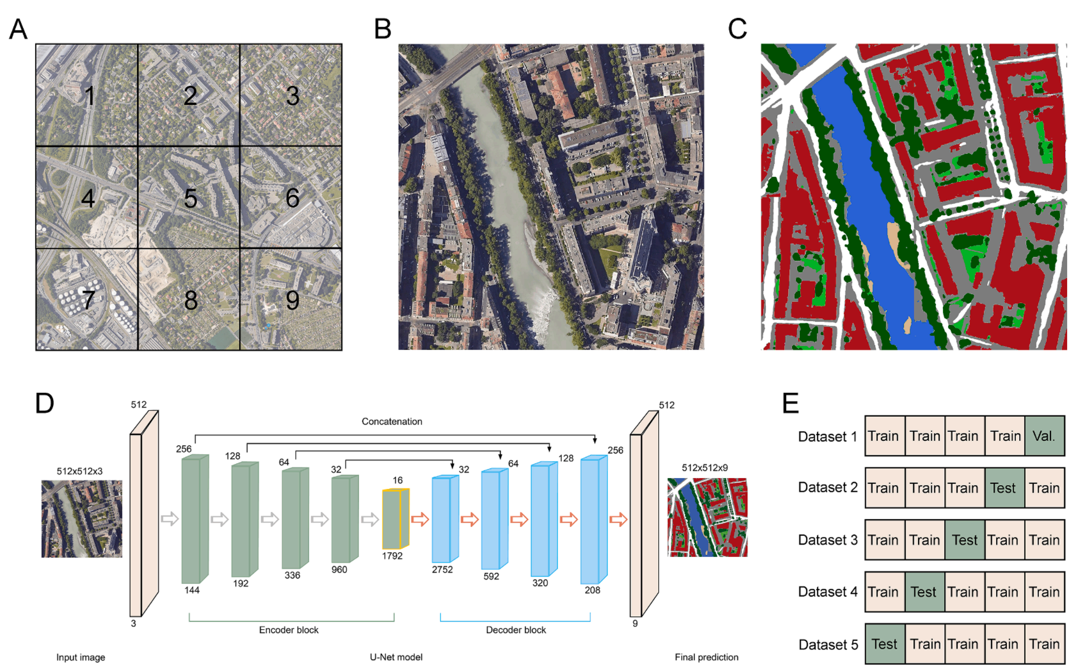

Fig. 2. Satellite image sampling process, example input and output image, model architecture, and training procedure. A Depicts a neighborhood of 1260 m × 1260 m, split into 9 sub-tiles, each representing 420 m × 420 m and consisting of 1024 × 1024 pixels. B Example satellite image of size 512 × 512 pixels is provided as input to the segmentation model. C Land cover classes predicted by the model, based on the input image. Red depicts buildings, gray developed space, white roads, light green grass, dark green trees, and blue water. D Overview of the U-Net architecture and the size of the feature maps. The green parts represent the encoder that compresses the input image into a lower dimensional space (512 × 512 × 3 → 16 × 16 × 1792). The decoder is colored in blue. It up-samples the compressed image to the size of the input, and predicts the segmentation classes instead of the RGB values. E Overview of the training, validation, and test procedure. The model is trained on 4/5 of the data and validated or tested on the remaining part. This gives better insights into the generalization capability of the model. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

model was trained on 4/5 of the data and evaluated on 1/5. The models achieved an average pixel accuracy of 95 % ± 1 %. However, some land cover classes are more frequent than others, and accuracy as a performance metric is biased towards the performance of the frequent classes. Metrics like the intersection over union (IoU) or the F1-score are less affected by class imbalance. Nevertheless, the good model performance is confirmed by an F1-score of 0.766 ± 0.01 (ranges from 0 to 1, the higher, the better) and an IoU of 0.691 ± 0.01 (ranges from 0 to 1, a value of 0.5 is considered good). A more in-depth overview of the model performance is depicted in Table S1 (supplement). As all five models were trained on slightly different data, they may have learned different patterns, and combining them into a model ensemble should increase the generalizability of the predictions. Accordingly, to the previously learned patterns, the model ensemble assigned each pixel of the satellite image to one of the eight land cover classes. This approach would only allow for the differentiation between three urban green space types (trees, grass, and agricultural land). However, the effect of grass or trees in a park or garden differs from that of a wild meadow or a tree canopy next to a road. Hence, the three green land cover types are matched with freely available land usage data from OpenStreetMap (OSM) for detailed separation. This allows a more sophisticated answer to the first research question (Q1). Out of the three existing, nine new classes are built by differentiating land cover based on its land usage. E. g., trees located in forests are recoded as *trees forest,* and trees in parks or gardens as *trees garden & park*. The nine following categories were created: trees forest, trees garden & park, trees other, grass garden & park, grass recreation, grass playground, grass other, allotments, agriculture other (see Table 1 for an overview of their composition). These classes are referred to as *green land types* in the following to avoid confusion with the terms land cover and land use. Because the area of analysis is identical in size for all observed households, the coverage of each neighborhood tile by a *green land type* can be compared between neighborhoods. The coverage C_i for *green land type i* is calculated by dividing the total number of pixels in the neighborhood tile by the number of pixels belonging to *green land type i* (Eq. (1)). The coverage ranges from 0 to 1. It is used as an exogenous variable in the analysis. Table S2 (supplement) contains a description of the distribution of all *green land type* variables.

$$C_i = \frac{N_i}{\sum_{i=1}^{n} N_i} \tag{1}$$

3.2.3. Mixed land use

To examine the effect of mixed land use on residents' life satisfaction an extensive set of 172 land use classes in the resident's neighborhood are obtained from OSM. They are assigned to five broader categories, based on the service or amenity they are creating for the residents, namely *residential, commercial or groceries*, *recreation*, *public services*, and the class *culinary, culture, and events (CCE)*. As a result, the created land use categories consist of green as well as build-up areas. A detailed overview of the assignment procedure can be found in Table S3 (supplement). The literature suggests multiple approaches to measure mixed land use (Song, Merlin, & Rodriguez, 2013), such as the proportion of a particular land use type, the relative proportion of different land use types (entropy), the interaction between two land use types (exposure index), the land use diversity (Atkinson or Herfindahl-Hirschman index) or the evenness of two different land use classes (Gini index). Each of the measures provides a distinct perspective on the land use mixture. However, this study opts for the entropy measure as with this approach, multiple land use classes can be considered simultaneously. Further, it is symmetrical to the proportion of land use types. Therefore, the distribution 50/30/20 and the distribution 30/20/50 result in the same entropy score. In addition, entropy can measure the evenness and diversity of land use classes concurrently and reaches its maximum value 1 only if all k classes are evenly distributed (Song et al., 2013). Entropy is calculated as denoted in Eq. (2), whereas P_j is the percentage or proportion of a land use category j in the neighborhood of a surveyed household. The proportion is measured as the number of pixels in a resident's neighborhood covered by a specific land use category. This is done for all five land use types (residential, commercial or groceries, recreation, public services, and CCE). $k = 5$ as it is the number of considered land use classes.

$$Entropy = \frac{-\left[\sum_{j=1}^{k} P_j \ln(P_j)\right]}{\ln(k)} \tag{2}$$

The surveyed individuals live in neighborhoods with an average entropy of 0.7 (SD = 0.15). For simplicity, entropy is referred to as mixed land use in the following sections.

3.2.4. Confounding covariates

The relationship between urban greenery, land use mixture and life satisfaction is directly and indirectly affected by various factors at the individual, household, and neighborhood levels. As households were not assigned randomly to their neighborhoods but directly or indirectly selected themselves into them, self-selection into the treatment is an issue and would cause spurious correlations. This issue can be solved by including the confounding variables in the statistical model and controlling for them, assuming no unobserved heterogeneity remains. For instance, wealthier households have the financial ability to move to greener and more vibrant neighborhoods. Further, the preferences of individuals and households for their neighborhood environment differ. Younger individuals prefer a vibrant and built-up environment, whereas public services such as schools and playgrounds matter more for families with children. Older people, on the other hand, can be limited in their freedom of movement due to health issues and might prefer to live in areas with nearby green spaces. The different preferences and financial constraints likely cause self-selection of specific individuals into greener and more vibrant neighborhoods. Because household income and the presence of children are also related to life satisfaction (Ambrey & Fleming, 2014; Krekel et al., 2016; Wu et al., 2022), they act as confounders and must be controlled for. As the literature suggests heterogeneous effects of urban greener on life satisfaction by age groups, the age variable is split into four categories. Each group represents different life courses and should theoretically result in similar green space preferences. These categories are young adults (20–29 years), middle-aged adults possibly sharing a household with their children (30–49), older adults where possible children recently moved out (50–65), and older people (65+). Covariates like the residence type (apartment or detached house), the ownership of the accommodation, the population density of the resident's postcode, the distance to the city center, and the language region (French, Italian, or German) the accommodation is located in are likely related to the amount of green space or the land use mix in the resident's neighborhood. Theoretically, these covariates also affect life satisfaction, which the literature could confirm for some of them (Ambrey & Fleming, 2014; Krekel et al., 2016; Wu et al., 2022). Therefore, the analysis controls for these confounding variables. Further control variables that are considered are sex, civil status, education, and

Table 1
Composition of land types.

Land type	Land cover	Land use
Trees forest	Trees	Forest
Trees garden & park		Park, public, or private garden
Trees other		Single trees, canopies, or not available
Grass garden & park	Rangeland	Park, pavilion, flowerbed, public or private garden
Grass recreation		Recreation area and sports ground
Grass playground		Playground
Grass other		Meadows, greenfields, shrubs, hedges, or not available
Allotments	Agricultural land	Allotments
Agriculture other		Farmland, vineyard, greenhouse, farm, orchard, or not available

occupation.

3.2.5. Statistical modeling approach

The units of analysis are individuals, and they cluster in households. Therefore, cluster robust standard errors on the household level are applied to all analyses. However, one could argue that households are nested in cities and life satisfaction varies strongly between cities, which would favor using a multilevel model. However, the data does not confirm this. Only 2 % of the total variance can be explained at the city level, and using an ordinary least-squares regression approach with cluster robust standard errors is therefore appropriate. By applying this approach, the direct effect of greenery and mixed land use variables (exogenous) on life satisfaction (endogenous) can be estimated considering confounding variables. The model can be formulated as shown in Eq. (3). LS_i is the stated level of life satisfaction, LT_i the proportion of a *green land type* or the land use entropy in the neighborhood, X_i includes all individual-level characteristics of the respondent, Z_i contains all households and V_i all neighborhood characteristics. Equation (4) depicts the modeling approach of an interaction effect between a *green land type* or the land use entropy (LT_i) and age (Age_i). Since the *green land type* trees garden & park is strongly correlated with grass garden & park (r = 0.93) the *green land type* categories related to trees, grass and agriculture are analyzed independently to avoid multicollinearity.

$$LS_i = \beta_0 + \beta_{lt} LT_i + \beta_x X_i + \beta_z Z_i + \beta_v V_i + \varepsilon_i \tag{3}$$

$$LS_i = \beta_0 + \beta_{lt} LT_i + \beta_{age} Age_i + \beta_{lt*age} LT_i{*}Age_i + \beta_x X_i + \beta_z Z_i + \beta_v V_i + \varepsilon_i \tag{4}$$

To illustrate the interaction effect of mixed land use and age on life satisfaction (Fig. 4) a random forest machine learning model (Breiman, 2001) is trained on the data using the same variables as included in Model 6 (Table 2). The advantage of using a random forest over a linear regression is its ability to model non-linear patterns without overfitting the data. Similar to obtaining conditional expected values from a regression model, the fitted random forest model can be used to predict the endogenous variable $\widehat{Y}_i$ conditional on selected X_i values and control variables C_i. A random forest is an ensemble of uncorrelated decision trees. A decision tree tries to split the data on variable values that result in the most homogeneous subgroups, groups that have similar Y-values. This process is repeated until a certain level of homogeneity is reached.

All files are available at the GitHub repository: https://github.com/sebastianbahr/urban-environment-CH.

4. Results

Model 1 (Table 2) aims to answer the question of whether there is an association between green spaces in general and life satisfaction. Therefore, an additive index of all tree and grass-related *land types* is created. However, Model 1 suggests no relationship between urban greenery within the walkable neighborhood and residents' life satisfaction. As indicated in the literature, age groups value different amenities of urban green spaces. Therefore, an interaction effect is introduced in Model 2 (Table 2) to model heterogeneous age group effects. The analysis indicates that the association between urban greenery and life satisfaction differs between age groups. Nevertheless, only for

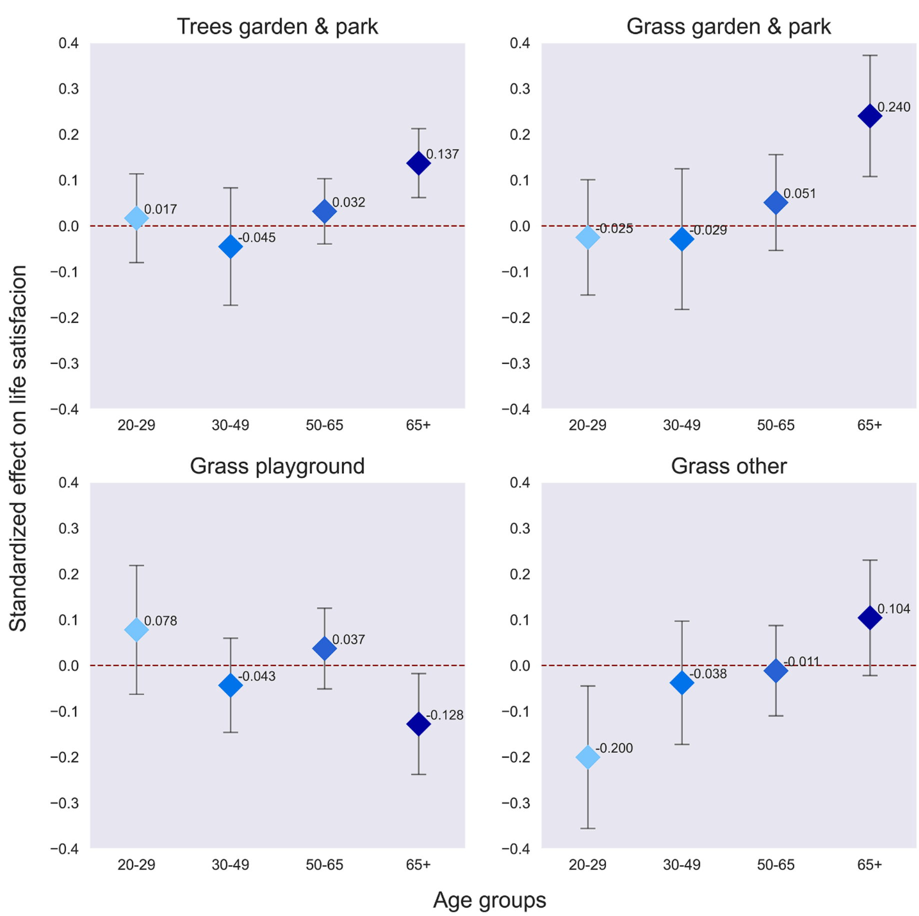

Fig. 3. Standardized effect of different urban green types on residents' life satisfaction by age category (buffer 1260 m). The rhombus depicts the change in life satisfaction in standard deviations if the green space type increases by one standard deviation. The displayed values are the main effect of the interaction between the green space type and the categorized age variable when the corresponding age group is set as the reference category. Similar to Model 3 and Model 4 in Table 2, a linear OLS model is used for estimation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

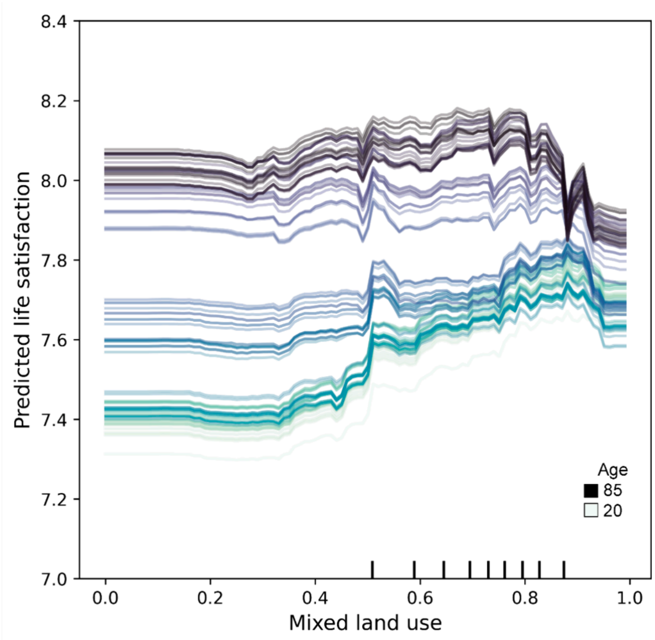

Fig. 4. Predicted life satisfaction value based on the interaction effect of mixed land use and age. Light green lines depict younger and black older age groups. The bars on the x-axis depict the distribution of mixed land use in quantiles. Predictions were performed by using a random forest machine learning model (hyperparameters: estimators = 1,000, max depth = 10). The depicted predicted life satisfaction values are based on 1,000 different ages and mixed land use combinations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

individuals aged above 65 the effect is significantly more positive than for the reference category (20–29 years). To better understand which components of urban green spaces matter for life satisfaction and to answer research question Q1, tree-, grass-, and agricultural-related *land types* are separately examined in Models 3 to 5 (Table 2). Notably, none of the green space types located in the walkable neighborhood are significantly associated with the life satisfaction of residents aged between 20 and 29. An exception is grass located in land use categories other than the specified ones, which exhibits an inverse relationship with life satisfaction among this age group. In contrast, for individuals aged above 65, trees and grass located in gardens and parks are positively associated with life satisfaction (Models 3 and 4). Fig. 3 provides a more intuitive understanding of the total effects (main + interaction effect). It shows that only in the age group 65+ an increase of trees located in gardens and parks by one standard deviation is associated with a significant increase in life satisfaction by 0.137 standard deviations. The same is true for grass located in gardens and parks. For the oldest age category, a one-standard-deviation increase in this *green land type* is associated with a 0.240-standard-deviation increase in life satisfaction. In contrast, a rise in grass located on playgrounds reduces the life satisfaction of older individuals. Model 4 (Table 2) suggests that the negative effect ($\beta = -0.200$) of grass located in any other than the specified *green land types*, is less negative or even positive for the age categories 50–65 and 65+ compared to the reference category (aged 20–29). However, as depicted in Fig. 3, the total effect does not differ significantly from zero. A rise in agricultural land other than allotments in the age group 30–49 is associated with a positive rather than a negative association with life satisfaction when compared to the age reference category (Model 5 Table 2). Nevertheless, the total effect for this group of residents does not differ from zero. ($\beta = 0.043, SE = 0.032$).

The next step evaluates the association between mixed land use and life satisfaction. Mixed land use is not related to life satisfaction if heterogeneous age group effects are not modeled ($\beta = 0.012, SE = 0.021$). The same holds if the previously utilized age categories are used. It appears that the information loss imposed by the categorization of age prevents the accurate capturing of the interaction between age and mixed land use. Consequently, a continuous age variable is employed in the interaction. The coefficient of mixed land use indicates the impact of mixed land use on life satisfaction at an age of zero. As no observations in the sample have an age of zero and to allow a more meaningful and robust estimation and interpretation of the effect, age is centered at 25 years. Correspondingly, an increase in mixed land use in the walkable neighborhood by one standard deviation increases life satisfaction by 0.079 standard deviations among the residents aged 25 (Model 6 Table 2). Estimating this effect is repeated by splitting age into 5-year and 10-year buckets, which did not substantially alter the previous findings. The negative interaction effect of mixed land use and age indicates that the positive association between the two variables diminishes with increasing age. This interaction is graphically represented in Fig. 4. The colored lines illustrate the predicted values for life satisfaction at a specified age, contingent upon the degree of mixed land use. The light green lines represent the predicted values for younger individuals, while the dark black lines represent those for older individuals. It can be demonstrated that an increase in mixed land use is associated with higher predicted life satisfaction values for younger residents. Conversely, the predicted life satisfaction remains unchanged for varying mixed land use values at older ages.

Recent evidence from Beijing shows a positive interaction effect between mixed land use and urban greenery, suggesting that promoting both concurrently has beneficial effects on residents' life satisfaction (Wu et al., 2022). To acknowledge these findings, the previous interaction between mixed land use and age is extended by an interaction with an additive index of all tree- and grass-related *land types*. Model 7 (Table 2) indicates that at age 25, an increase in greenery reduces the positive effect of mixed land use on life satisfaction. However, since a three-way interaction is not straightforward to interpret, the colored rhombus in Fig. 5 depicts the association between mixed land use in the resident's walkable neighborhood and life satisfaction conditioned on the greenness level of the neighborhood and different age values. A positive relationship between mixed land use and life satisfaction is observed at ages 25 and 35. This relationship is most pronounced among individuals residing in urban areas with limited access to green spaces and diminishes in neighborhoods with more extensive green infrastructure. A comparable tendency can be observed in residents aged 45. Nevertheless, the effects are not statistically significant. In accordance with the findings of Model 6 (Table 2), there is no correlation between mixed land use and life satisfaction at older ages (55, 65, and 75). It appears neither deprivation nor abundance of urban greenery can alter this unrelatedness. A notable exception is the 75-year-old cohort, where mixed land use is negatively associated with life satisfaction in areas with limited green space (10 % and 20 % percentile). It can be observed that an increase in green space tends to reduce this negative effect.

The results are tested for robustness. First, some *green land type* variables contain up to 1/3 of zero values. Because the effect of not-having to *having* a land type class in the neighborhood might differ from the effect a one-unit increase has, a control dummy is added to the model. None of the dummies were significant, and the linear effects did not change. Second, for around 300 respondents, the household equivalence income is missing. To avoid a bias that could have occurred due to the exclusion of these observations, the household equivalence income is imputed using a machine learning approach (Breiman, 2001). The re-analysis did not lead to a substantial difference in the coefficients. The only exception is the interaction effect of pooled green spaces with the age group 65+ (Model 2 Table 2). Third, all models are estimated using multilevel models with city random intercepts, which did not change the results. Fourth, instead of examining the neighborhood environment within 10 min' walking distance (1260 m × 1260 m), just the immediate environment, located in a tile of size 420 m × 420 m, is

Table 2
OLS model of land types and life satisfaction (buffer 1260 m).

Life satisfaction	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Control variables [a]	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Age groups: 20–29		*Ref.*	*Ref.*	*Ref.*	*Ref.*		
30–49		−0.034 (0.079)	−0.042 (0.079)	−0.049 (0.120)	−0.027 (0.078)		
50–65		0.015 (0.082)	0.013 (0.083)	0.030 (0.125)	0.017 (0.083)		
65+		0.171 (0.124)	0.163 (0.124)	0.261 (0.187)	0.175 (0.124)		
Age continuous [b]	0.004 (0.002)					0.004 (0.002)	0.008* (0.003)
Environmental variables							
Green (trees & grass, age 20–29) [c, d]	−0.001 (0.022)	−0.082 (0.049)					−0.013 (0.066)
× age group (30–49)		0.092 (0.059)					
× age group (50–65)		0.071 (0.055)					
× age group (65+)		**0.125*** (0.062)					
Trees (forest, age 20–29)			−0.021 (0.041)				
× age group (30–49)			−0.029 (0.054)				
× age group (50–65)			0.090 (0.053)				
× age group (65+)			0.049 (0.049)				
Trees (garden & park, age 20–29)			0.017 (0.049)				
× age group (30–49)			−0.062 (0.080)				
× age group (50–65)			0.015 (0.053)				
× age group (65+)			**0.120*** (0.060)				
Trees (other, age 20–29)			−0.034 (0.051)				
× age group (30–49)			0.096 (0.060)				
× age group (50–65)			−0.005 (0.057)				
× age group (65+)			0.003 (0.064)				
Grass (garden & park, age 20–29)				−0.025 (0.064)			
× age group (30–49)				−0.004 (0.101)			
× age group (50–65)				0.076 (0.075)			
× age group (65+)				**0.265*** (0.089)			
Grass (recreation, age 20–29)				−0.097 (0.092)			
× age group (30–49)				0.099 (0.096)			
× age group (50–65)				0.078 (0.099)			
× age group (65+)				0.045 (0.126)			
Grass (playground, age 20–29)				0.078 (0.072)			
× age group (30–49)				−0.121 (0.090)			
× age group (50–65)				−0.041 (0.084)			
× age group (65+)				**−0.206*** (0.092)			
Grass (other, age 20–29)				**−0.200*** (0.079)			
× age group (30–49)				0.163 (0.097)			
× age group (50–65)				**0.189*** (0.088)			
× age group (65+)				**0.304**** (0.096)			
Allotments (age 20–29)					−0.007 (0.072)		
× age group (30–49)					0.063 (0.098)		
× age group (50–65)					0.020 (0.082)		
× age group (65+)					−0.032 (0.084)		
Other agricultural land (age 20–29)					−0.118 (0.067)		
× age group (30–49)					**0.161*** (0.072)		
× age group (50–65)					0.122 (0.067)		
× age group (65+)					0.109 (0.076)		
Mixed land use						**0.079*** (0.039)	**0.148*** (0.069)
Mixed land use × age [b]						**−0.002*** (0.001)	**−0.004*** (0.002)
Green (trees & grass) × age [b]							0.001 (0.001)
Green (trees & grass) × Mixed land use							**−0.106*** (0.046)
Mixed land use × Green (forest & grass) × age [b]							**0.004*** (0.002)

(*continued on next page*)

Table 2 (*continued*)

Life satisfaction	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
N	2755	2755	2755	2755	2755	2755	2755
Adj. R2	0.10	0.10	0.11	0.11	0.10	0.10	0.10

Note: * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$. [a] The coefficients of the control variables are depicted in Table S4 of the supplement. [b] Age is centered at 25 years to enhance the interpretability of the main effect of mixed land use in Models 6 and 7. [c] In Model 1, the Green (trees & grass) effect incorporates all age groups and is not restricted to individuals aged 20–29. [d] Green effect at age 25 in Model 7. Life satisfaction, population density, distance to the city center, mixed land use, and all tree-, grass- and agriculture-related variables are z-standardized. For these variables, the coefficient depicts the change of the endogenous variable in standard deviations if the exogenous variable increases by one standard deviation. Household cluster robust and heteroscedasticity robust standard errors in parenthesis. Source: Swiss Household Panel (SHP) and author's data.

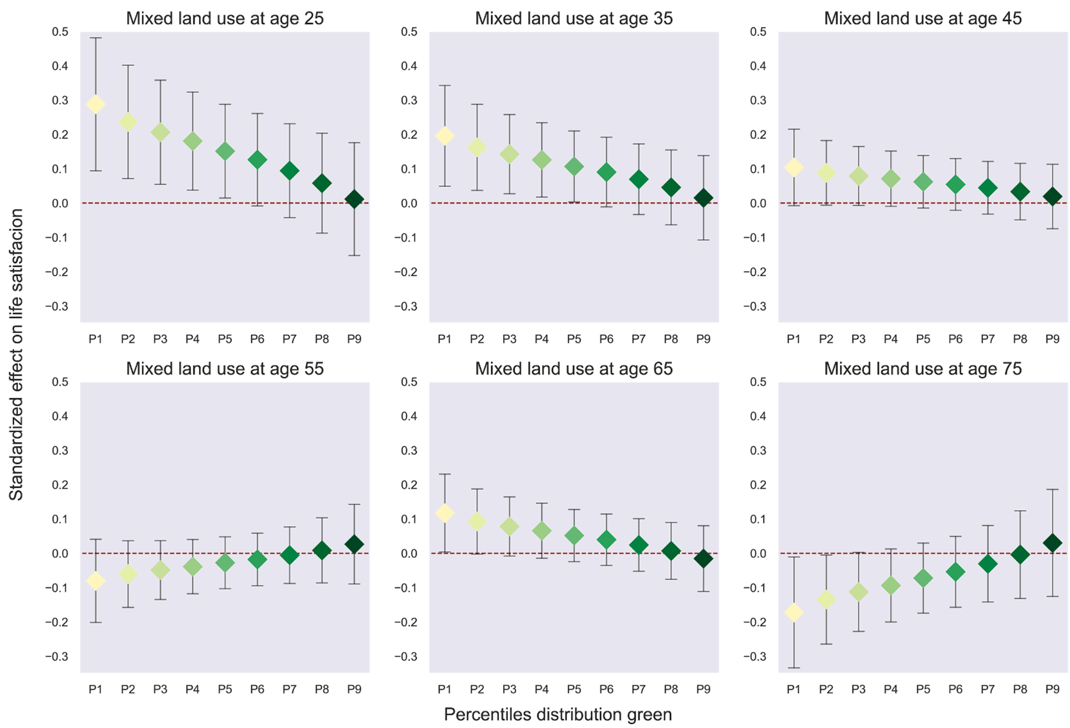

Fig. 5. Standardized effect of mixed land use on residents' life satisfaction at specified urban greenery percentiles and ages (buffer 1260 m). Urban greenery is an additive index of all tree- and grass-related green space types. The rhombus depicts the change in life satisfaction in standard deviations if mixed land use increases by one standard deviation conditioned on the stated urban greenery percentile and age. The displayed values are the main effect of the interaction between mixed land use, age, and urban greenery when the corresponding urban greenery percentile and age are set as the reference category. The same control variables as in Model 7 in Table 2 are introduced, and a linear OLS model is used for estimation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

analyzed. Changing the area of analysis reduces the effect size of *grass garden & park* but does not alter the main findings (Fig. 6).

5. Discussion

This study examined how different urban green space types and the land use mixture in the walkable neighborhood are related to residents' life satisfaction in Switzerland, with a particular focus on age-related differences in these relationships. Previous research indicates heterogeneous preferences and usage patterns of urban green spaces by different age groups (Chiesura, 2004; Kabisch & Haase, 2014; Schipperijn et al., 2010; Syrbe et al., 2021). Additionally, a stronger positive relationship was found between urban greenery and life satisfaction among older individuals (Jeong et al., 2022; Krekel et al., 2016). In light of the third research question (Q3), the study finds varying effects of urban greenery on residents' life satisfaction by age and corroborates evidence from Basel, Switzerland (Jeong et al., 2022). There it was found that greenery has a negative effect on the youngest age group (20–29), but the effect diminishes and becomes positive for older age cohorts. A similar pattern emerges in this study when examining all urban areas in Switzerland. However, the negative effect of the youngest age cohort is not significant, and only for residents over the age of 65 is greenery positively associated with their life satisfaction. Differences in preferences and spatial mobility can explain this. As the literature suggests, younger individuals use urban green spaces predominantly for social interactions and physical activities (Chiesura, 2004; Kabisch & Haase, 2014). Pursuing sports requires larger green areas covered with groomed lawns, markings, and equipment such as goals. Given the high cost of maintaining such areas, they are typically situated in close proximity to leisure centers and rarely in the vicinity of residential areas. Similarly, social gatherings can only be held in green areas with cut and groomed lawns, which must also be located away from busy and noisy roads. Consequently, it is probable that younger individuals are compelled to leave their neighborhood in order to engage in these activities. Their good health and high mobility allow them to easily access these green spaces, reducing their reliance on such areas in their vicinity. In contrast, older people visit urban green spaces to relax and appreciate nature (Chiesura, 2004; Kabisch & Haase, 2014). Green areas

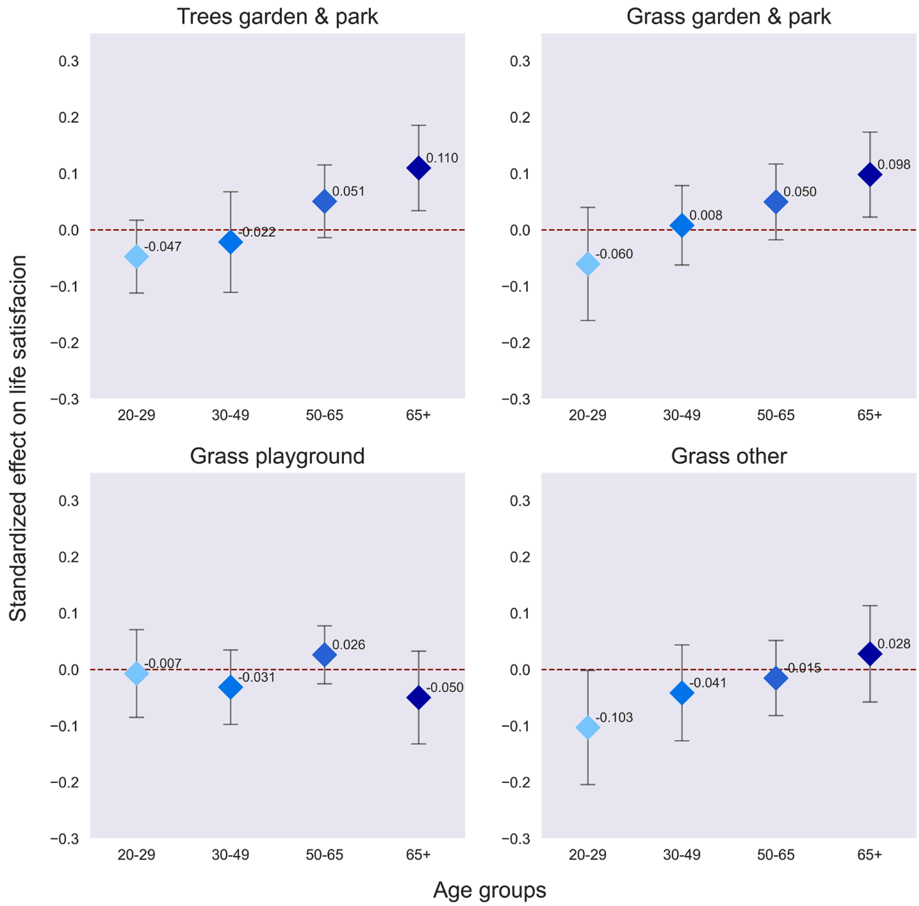

Fig. 6. Standardized effect of different urban green types on residents' life satisfaction by age category (buffer 420 m). The rhombus depicts the change in life satisfaction in standard deviations if the green space type increases by one standard deviation. The displayed values are the main effect of the interaction between the green space type and the categorized age variable when the corresponding age group is set as the reference category. Similar to Model 3 and Model 4 in Table 2, a linear OLS model is used for estimation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

that are smaller, less well-maintained, or private, such as tree canopies, small parks, or private gardens, can provide these amenities. Hence, urban greenery in their immediate neighborhood likely satisfies these needs. Accordingly, due to their constrained area of movement, caused by their health condition, a lack of sufficient green spaces in the vicinity can result in reduced life satisfaction.

The partitioning of green spaces within a resident's neighborhood into subgroups allows urban planners to gain a more nuanced understanding of the types of urban greenery that should be prioritized in future city planning to improve dwellers' life satisfaction. The heterogeneous findings for different green urban areas in the analysis support these claims empirically (Q1). Solely trees and grass fields located in gardens and parks are positively associated with the life satisfaction of older residents. Whereas, the effect of grass is almost twice as much as the effect of trees. In contrast, trees situated in forests or other land use categories are not correlated. This suggests that trees should be incorporated into a more diverse and versatile green area, such as parks or gardens, to be associated with life satisfaction. Theoretically, forests would fulfill this requirement. However, they usually lack seating possibilities and paved paths, which makes them less appealing to older individuals (Syrbe et al., 2021). Grass located on recreation sides is not related to life satisfaction at all, which is especially surprising for younger individuals, as older tend to pursue fewer physical activities in general. This discrepancy may be attributed to the heterogeneous interest in pursuing physical activities and their type. Some residents may engage in no sports at all, while others may participate in a specific sport that is not permitted on the recreation grounds in their neighborhood. These varying preferences may result in a lack of perceived value for some residents. On the contrary, playgrounds equipped with larger grass fields reduce the life satisfaction of people aged over 65. Their association with noise might be an explanation. Grass situated in unspecified land use types of a neighborhood is negatively associated with the life satisfaction of younger adults. As this *green land type* encompasses a variety of urban green spaces it is hard to provide an explanation for this relationship. Possibly, greener neighborhoods are located in smaller and less vibrant cities, with limited nightlife and social and cultural events.

In both the European case (Mouratidis, 2018; Olsen et al., 2019) and the global case (Cao, 2016; Dong & Qin, 2017; McCarthy & Habib, 2018; Wu et al., 2022), the evidence of the relationship between mixed land use and life satisfaction is indeterminate. Mouratidis (2018) shows a positive association between mixed land use and life satisfaction in Oslo (Norway). This study tends to corroborate these findings, but the results in Switzerland are more nuanced, and the positive relationship only exists among younger individuals (Q2). The land use entropy provides insight into the uniformity of the distribution of the five analyzed land use categories within a resident's neighborhood. Due to their limited mobility, older individuals tend to utilize a greater range of services in their local area, including shopping, health care, social services, and culture (between variety). Nonetheless, it is probable that they are already satisfied with a lower number of the same service, and younger individuals might value the versatility of the same service (within variety), e.g., one bar vs. five bars. Hence, the needs of younger residents are better met if services are uniformly distributed. Further, in contrast to younger individuals, older individuals tend to value fewer services from the land use category *culture, culinary, and events (CCE)* and *recreation* as they visit fewer bars, pubs, nightclubs, sports venues, sports centers, fitness centers, water parks, swimming pools, or bowling alleys. Consequently, despite the presence of these land use categories in their neighborhood, resulting in a higher entropy score, it is more probable that older individuals derive less benefit from their existence. Furthermore, the noise and pollution generated by a vibrant nightlife can, in fact, diminish the positive impact of the amenities created by a neighborhood with a high land use mixture. This phenomenon is indeed observed in the sample, as an increase in the land use category *CCE* is associated with an increase in life satisfaction among younger residents but a decrease among older residents. In contrast to the findings of Wu et al. (2022), higher green coverage does not amplify the positive effect of mixed land use on life satisfaction in Swiss urban areas. Instead, it decreases the positive mixed land use effect at younger ages. The reason might be that the residents' life satisfaction is influenced by a myriad of factors, one of which is the living environment. However, this particular factor exerts only a limited influence on life satisfaction. Hence, it is probable that the marginal utility resulting from improvements in the neighborhood environment diminishes in more livable areas. This could explain why mixed land use has a more pronounced influence on life satisfaction among young residents deprived of green. Conversely, in greener areas, urban greenery and the amenities it provides have already increased life satisfaction attributed to the neighborhood environment, and the influence of other environmental factors, such as mixed land use, diminish. Moreover, green spaces like parks or sports fields can provide amenities comparable to those offered by certain land use classes, e.g., bars, pubs, or sports centers. This substitution is likely to weaken the influence of mixed land use. As noted, older residents tend not to benefit from a more uniformly distributed land use mix due to their specific set of needs, which can be satisfied at lower entropy levels. Therefore, it is reasonable that a rise in urban greenery does not affect the amenities provided by different land use classes and consequently does not alter the zero effect of mixed land use. Furthermore, the results from the megacity Beijing, with 21 million inhabitants, can hardly be compared with the findings of a country where the largest city has 1 million inhabitants, and residents' neighborhoods tend to be rather green on average ($\overline{x} = 39\%; \widetilde{x} = 38\%$ green coverage) compared to Beijing with an average green coverage of 29 % in 2020 (Cao, Li, & Huang, 2023). Nevertheless, the theoretical rationale for this phenomenon is not yet fully identified, and further research is required to better explain the underlying mechanisms.

The contributions of this work are multifold. First, it implements a new approach to measure the distribution of urban greenery in a more detailed and unbiased way. The fine-grained measurement ensures that all components of urban green spaces are considered when analyzing their impact on residents' life satisfaction. Second, the applied measurement approach not only guarantees a more fine-grained measurement but also allows splitting urban green spaces into nine subcategories. This provides urban planners with new empirical evidence on what green space types to focus on to influence residents' life satisfaction positively. Third, by acknowledging a strain of literature that suggests heterogeneous preferences for urban green space types based on residents' age, this work generates new evidence on how these different preferences affect the relationship between urban greenery and life satisfaction. Lastly, the work sheds light on a relatively new research field inspired by the claims of the new urbanism movement to build human-oriented smart neighborhoods (Garde, 2020). This field examines the effect of mixed land use on residents' life satisfaction; however, current evidence is indeterminate. The empirical results of this work propose that an equal mix of different land use types can enhance residents' life satisfaction in tendency and support the claims of the new urbanism movement and findings from Oslo (Mouratidis, 2018). Nevertheless, the association is more nuanced in Switzerland and only holds for younger individuals and vanishes at higher ages. This is precious information for Swiss city planners when determining the mixture of land use types in newly built urban areas. Additionally, these findings should encourage future research in other countries to account for heterogeneous age group effects. Regarding urban green spaces, the empirical results are much more subtle than those of former studies (e.g., see Bertram & Rehdanz, 2015; Krekel et al., 2016; White et al., 2013). They suggest that greener neighborhoods are not, per se, associated with higher life satisfaction in Switzerland. Instead, they underline the importance of considering heterogeneous age effects when examining the relationship between urban greenery and life satisfaction. These findings expand prior work that suggests varying preferences for urban green spaces among age groups by showcasing how these preferences influence the effect of urban greenery on residents' life satisfaction. Finally, to the best of the author's knowledge, no other study analyzes urban green spaces in such detail and incorporates the vegetation type and the land usage class in which it is located. The heterogeneous effects of different *green land types* on life satisfaction highlight the importance of this disentanglement. For the first time, this provides city planners with comprehensive information on what urban green types to focus on, given the neighborhoods' age distribution, to positively influence residents' life satisfaction. As urbanization continues unabated, these findings might become even more valuable for planning livable urban neighborhoods in the future.

It is important to highlight that the study solely examines the association of urban greenery, mixed land use, and their interaction with age on life satisfaction in the walkable neighborhood of residents in Switzerland. Consequently, claims outside the study area and generalizations to other countries must be made with caution. The study faces some limitations. First, the individuals were surveyed between September 2021 and March 2022. In the warmer season, residents profit more from amenities offered by green spaces, which could lead to an underestimation of the effect of greenery in winter. However, a *t*-test ($t = 0.32, N = 2755$) did not reveal any difference in life satisfaction between individuals surveyed in fall and winter. Second, the segmentation model performs well but still misclassifies pixels, potentially leading to biased results. Third, land usage types are assigned by volunteers at OpenStreetMap, and they need to follow a predefined classification methodology. Plausibility checks were performed for some analyzed neighborhoods, but there is still a margin of error. Fourth, by controlling for variables that cause self-selection, the study tries to alleviate this issue. However, only the usage of panel data would fully prevent self-selection.

6. Conclusion

This study examined how different urban green space types and the neighborhood's land use mixture are related to residents' life satisfaction in Switzerland. Thereby, it particularly focuses on age-related differences in these relationships. The study employed a deep learning approach to assess urban green spaces at a granular level and to identify a comprehensive set of green space types. The findings indicate that age groups value green spaces differently. For residents aged above 65, trees and grass located in parks and gardens are positively associated with life satisfaction. In contrast, green areas on playgrounds are negatively associated with this age group. A more uniform distribution of land use types appears to be more valuable for younger individuals and its positive association with life satisfaction decreases at higher ages. Insights gained from this research provide valuable information to city planners in Switzerland and expand prior findings in the literature.

CRediT authorship contribution statement

Sebastian Bahr: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The Swiss Household Panel data is upon request at FORS. Land cover and usage data can be obtained from the GitHub repository: https://github.com/sebastianbahr/urban-environment-CH

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2024.105174.

References

Akpinar, A. (2016). How is quality of urban green spaces associated with physical activity and health? *Urban Forestry & Urban Greening, 16*, 76–83. https://doi.org/10.1016/j.ufug.2016.01.011

Ambrey, C., & Fleming, C. (2014). Public greenspace and life satisfaction in urban Australia. *Urban Studies*, *51*(6), 1290–1321. JSTOR. Retrieved from JSTOR.

Aram, F., Higueras García, E., Solgi, E., & Mansournia, S. (2019). Urban green space cooling effect in cities. *Heliyon, 5*(4), e01339. https://doi.org/10.1016/j.heliyon.2019.e01339

Ayala-Azcárraga, C., Diaz, D., & Zambrano, L. (2019). Characteristics of urban parks and their relation to user well-being. *Landscape and Urban Planning, 189*, 27–35. https://doi.org/10.1016/j.landurbplan.2019.04.005

Bertram, C., & Rehdanz, K. (2015). The role of urban green space for human well-being. *Ecological Economics, 120*, 139–152. https://doi.org/10.1016/j.ecolecon.2015.10.013

Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Brown, Z. S., Oueslati, W., & Silva, J. (2016). Links between urban structure and life satisfaction in a cross-section of OECD metro areas. *Ecological Economics, 129*, 112–121. https://doi.org/10.1016/j.ecolecon.2016.05.004

Cao, X.(Jason) (2016). How does neighborhood design affect life satisfaction? Evidence from Twin Cities. *Planning for Quality of Life, 5*, 68–76. https://doi.org/10.1016/j.tbs.2015.07.001

Cao, Y., Li, G., & Huang, Y. (2023). Spatiotemporal evolution of residential exposure to green space in Beijing. *Remote Sensing, 15*(6), 1549. https://doi.org/10.3390/rs15061549

Chiesura, A. (2004). The role of urban parks for the sustainable city. *Landscape and Urban Planning, 68*(1), 129–138. https://doi.org/10.1016/j.landurbplan.2003.08.003

De Vries, S., Verheij, R. A., Groenewegen, P. P., & Spreeuwenberg, P. (2003). Natural environments—Healthy environments? An exploratory analysis of the relationship between greenspace and health. *Environment and Planning A: Economy and Space, 35*(10), 1717–1731. https://doi.org/10.1068/a35111

Diener, E., Oishi, S., & Lucas, R. E. (2003). Personality, culture, and subjective well-being: Emotional and cognitive evaluations of life. *Annual Review of Psychology, 54*(1), 403–425. https://doi.org/10.1146/annurev.psych.54.101601.145056

Dong, H., & Qin, B. (2017). Exploring the link between neighborhood environment and mental wellbeing: A case study in Beijing, China. *Landscape and Urban Planning, 164*, 71–80. https://doi.org/10.1016/j.landurbplan.2017.04.005

Dye, C. (2008). Health and urban living. *Science, 319*(5864), 766–769. https://doi.org/10.1126/science.1150198

European Commission (2020). EU Biodiversity Strategy for 2030. Retrieved from https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A52020DC0380.

Eurostat (2018). Territorial typologies manual. Retrieved from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Territorial_typologies_manual.

Federal Department of Foreign Affairs (2023). Geography - Facts and Figures. Retrieved from https://www.eda.admin.ch/aboutswitzerland/en/home/umwelt/geografie/geografie—fakten-und-zahlen.html.

Fleming, C. M., Manning, M., & Ambrey, C. L. (2016). Crime, greenspace and life satisfaction: An evaluation of the New Zealand experience. *Landscape and Urban Planning, 149*, 1–10. https://doi.org/10.1016/j.landurbplan.2015.12.014

Garde, A. (2020). New urbanism: Past, present, and future. *Urban Planning, 5*(4), 453–463. https://doi.org/10.17645/up.v5i4.3478

Gaudon, J. M., McTavish, M. J., Hamberg, J., Cray, H. A., & Murphy, S. D. (2022). Noise attenuation varies by interactions of land cover and season in an urban/peri-urban landscape. *Urban Ecosystems, 25*(3), 811–818. https://doi.org/10.1007/s11252-021-01194-4

Guo, Y., Liu, Y., Lu, S., Chan, O. F., Chui, C. H. K., & Lum, T. Y. S. (2021). Objective and perceived built environment, sense of community, and mental wellbeing in older adults in Hong Kong: A multilevel structural equation study. *Landscape and Urban Planning, 209*, Article 104058. https://doi.org/10.1016/j.landurbplan.2021.104058

Hartig, T., Mitchell, R., De Vries, S., & Frumkin, H. (2014). Nature and health. *Annual Review of Public Health, 35*(1), 207–228. https://doi.org/10.1146/annurev-publhealth-032013-182443

Jeong, A., Galliker, F., Imboden, M., Keidel, D., de Hoogh, K., Vienneau, D., & Probst-Hensch, N. (2022). Residential exposure to greenspace and life satisfaction in times of COVID-19: A cross-sectional analysis of 9444 participants from a population-based study in Basel-Stadt and Basel-Landschaft [Application/pdf]. *Swiss Medical Weekly*, 34. https://doi.org/10.3929/ETHZ-B-000559214

Kabisch, N., & Haase, D. (2014). Green justice or just green? Provision of urban green spaces in Berlin, Germany. *Landscape and Urban Planning, 122*, 129–139. https://doi.org/10.1016/j.landurbplan.2013.11.016

Kaplan, R., & Kaplan, S. (1989). *The experience of nature: A psychological perspective.* Cambridge University Press.

Kley, S., & Dovbishchuk, T. (2021). How a lack of green in the residential environment lowers the life satisfaction of city dwellers and increases their willingness to relocate. *Sustainability, 13*(7), 3984. https://doi.org/10.3390/su13073984

Krekel, C., Kolbe, J., & Wüstemann, H. (2016). The greener, the happier? The effect of urban land use on residential well-being. *Ecological Economics, 121*, 117–127. https://doi.org/10.1016/j.ecolecon.2015.11.005

Kwon, O.-H., Hong, I., Yang, J., Wohn, D. Y., Jung, W.-S., & Cha, M. (2021). Urban green space and happiness in developed countries. *EPJ Data Science, 10*(1), 28. https://doi.org/10.1140/epjds/s13688-021-00278-7

Li, W., Saphores, J.-D.-M., & Gillespie, T. W. (2015). A comparison of the economic benefits of urban green spaces estimated with NDVI and with high-resolution land cover data. *Landscape and Urban Planning, 133*, 105–117. https://doi.org/10.1016/j.landurbplan.2014.09.013

Lu, Y. (2019). Using Google Street View to investigate the association between street greenery and physical activity. *Landscape and Urban Planning, 191*, Article 103435. https://doi.org/10.1016/j.landurbplan.2018.08.029

Lu, Y., Yang, Y., Sun, G., & Gou, Z. (2019). Associations between overhead-view and eye-level urban greenness and cycling behaviors. *Cities, 88*, 10–18. https://doi.org/10.1016/j.cities.2019.01.003

Ma, J., Dong, G., Chen, Y., & Zhang, W. (2018). Does satisfactory neighbourhood environment lead to a satisfying life? An investigation of the association between neighbourhood environment and life satisfaction in Beijing. *Cities, 74*, 229–239. https://doi.org/10.1016/j.cities.2017.12.008

Maas, J., Verheij, R. A., de Vries, S., Spreeuwenberg, P., Schellevis, F. G., & Groenewegen, P. P. (2009). Morbidity is related to a green living environment. *Journal of Epidemiology and Community Health, 63*(12), 967. https://doi.org/10.1136/jech.2008.079038

MacKerron, G., & Mourato, S. (2013). Happiness is greater in natural environments. *Global Environmental Change, 23*(5), 992–1000. https://doi.org/10.1016/j.gloenvcha.2013.03.010

McCarthy, S., & Habib, M. A. (2018). Investigation of life satisfaction, travel, built environment and attitudes. *Journal of Transport & Health, 11*, 15–24. https://doi.org/10.1016/j.jth.2018.09.007

Mouratidis, K. (2018). Built environment and social well-being: How does urban form affect social life and personal relationships? *Cities, 74*, 7–20. https://doi.org/10.1016/j.cities.2017.10.020

Nowak, D. J., Hirabayashi, S., Doyle, M., McGovern, M., & Pasher, J. (2018). Air pollution removal by urban forests in Canada and its effect on air quality and human health. *Wild Urban Ecosystems: Challenges and Opportunities for Urban Development, 29*, 40–48. https://doi.org/10.1016/j.ufug.2017.10.019

Olsen, J. R., Nicholls, N., & Mitchell, R. (2019). Are urban landscapes associated with reported life satisfaction and inequalities in life satisfaction at the city level? A cross-sectional study of 66 European cities. *Social Science & Medicine, 226*, 263–274. https://doi.org/10.1016/j.socscimed.2019.03.009

Reyes-Riveros, R., Altamirano, A., De La Barrera, F., Rozas-Vásquez, D., Vieli, L., & Meli, P. (2021). Linking public urban green spaces and human well-being: A systematic review. *Urban Forestry & Urban Greening, 61*, Article 127105. https://doi.org/10.1016/j.ufug.2021.127105

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In N. Navab, J. Hornegger, W. M. Wells, & A. F. Frangi (Eds.), *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015* (pp. 234–241). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-24574-4_28.

Schipperijn, J., Ekholm, O., Stigsdotter, U. K., Toftager, M., Bentsen, P., Kamper-Jørgensen, F., & Randrup, T. B. (2010). Factors influencing the use of green space: Results from a Danish national representative survey. *Landscape and Urban Planning, 95*(3), 130–137. https://doi.org/10.1016/j.landurbplan.2009.12.010

Seiferling, I., Naik, N., Ratti, C., & Proulx, R. (2017). Green streets − Quantifying and mapping urban trees with street-level imagery and computer vision. *Landscape and Urban Planning, 165*, 93–101. https://doi.org/10.1016/j.landurbplan.2017.05.010

Selmi, W., Weber, C., Rivière, E., Blond, N., Mehdi, L., & Nowak, D. (2016). Air pollution removal by trees in public green spaces in Strasbourg city, France. *Urban Forestry & Urban Greening, 17*, 192–201. https://doi.org/10.1016/j.ufug.2016.04.010

Shanahan, D. F., Bush, R., Gaston, K. J., Lin, B. B., Dean, J., Barber, E., & Fuller, R. A. (2016). Health benefits from nature experiences depend on dose. *Scientific Reports, 6*(1), 28551. https://doi.org/10.1038/srep28551

Song, Y., Merlin, L., & Rodriguez, D. (2013). Comparing measures of urban land use mix. *Computers, Environment and Urban Systems, 42*, 1–13. https://doi.org/10.1016/j.compenvurbsys.2013.08.001

Stubbings, P., Peskett, J., Rowe, F., & Arribas-Bel, D. (2019). A hierarchical urban forest index using street-level imagery and deep learning. *Remote Sensing, 11*(12), 1395. https://doi.org/10.3390/rs11121395

Sundquist, K., Frank, G., & Sundquist, J. (2004). Urbanisation and incidence of psychosis and depression: Follow-up study of 4.4 million women and men in Sweden. *British Journal of Psychiatry, 184*(4), 293–298. https://doi.org/10.1192/bjp.184.4.293

Syrbe, R.-U., Neumann, I., Grunewald, K., Brzoska, P., Louda, J., Kochan, B., & Bastian, O. (2021). The value of urban nature in terms of providing ecosystem services related to health and well-being: an empirical comparative pilot study of cities in Germany and the Czech Republic. *Land, 10*(4), 341. https://doi.org/10.3390/land10040341

Tan, M., & Le, Q. V. (2020, September 11). *EfficientNet: Rethinking model scaling for convolutional neural networks*. arXiv. Retrieved from http://arxiv.org/abs/1905.11946.

Taylor, L., Hahs, A. K., & Hochuli, D. F. (2018). Wellbeing and urban living: Nurtured by nature. *Urban Ecosystems, 21*(1), 197–208. https://doi.org/10.1007/s11252-017-0702-1

The World Bank (2023). Urban Development. Retrieved from https://www.worldbank.org/en/topic/urbandevelopment/overview#:~:text=Globally%2C%20over%2050%25%20of%20the,housing%20their%20expanding%20populations%20need.

Tong, M., She, J., Tan, J., Li, M., Ge, R., & Gao, Y. (2020). Evaluating street greenery by multiple indicators using street-level imagery and satellite images: A case study in Nanjing, China. *Forests, 11*(12), 1347. https://doi.org/10.3390/f11121347

Tsurumi, T., Imauji, A., & Managi, S. (2018). Greenery and subjective well-being: Assessing the Monetary value of greenery by type. *Ecological Economics, 148*, 152–169. https://doi.org/10.1016/j.ecolecon.2018.02.014

Van Den Berg, A. E., Maas, J., Verheij, R. A., & Groenewegen, P. P. (2010). Green space as a buffer between stressful life events and health. *Social Science & Medicine, 70*(8), 1203–1210. https://doi.org/10.1016/j.socscimed.2010.01.002

White, M. P., Alcock, I., Wheeler, B. W., & Depledge, M. H. (2013). Would you be happier living in a greener urban area? A fixed-effects analysis of panel data. *Psychological Science, 24*(6), 920–928. https://doi.org/10.1177/0956797612464659

Wilson, E. O. (1984). *Biophilia*. Harvard University Press. https://doi.org/10.2307/j.ctvk12s6h.

Wu, W., Chen, W. Y., Yun, Y., Wang, F., & Gong, Z. (2022). Urban greenness, mixed land-use, and life satisfaction: Evidence from residential locations and workplace settings in Beijing. *Landscape and Urban Planning, 224*, Article 104428. https://doi.org/10.1016/j.landurbplan.2022.104428

Wu, W., Tan, W., Wang, R., & Chen, W. Y. (2023). From quantity to quality: Effects of urban greenness on life satisfaction and social inequality. *Landscape and Urban Planning, 238*, Article 104843. https://doi.org/10.1016/j.landurbplan.2023.104843

Xia, J., Yokoya, N., Adriano, B., & Broni-Bediako, C. (2022, October 19). *OpenEarthMap: A Benchmark Dataset for Global High-Resolution Land Cover Mapping*. arXiv. Retrieved from http://arxiv.org/abs/2210.10732.

Yang, B.-Y., Zhao, T., Hu, L.-X., Browning, M. H. E. M., Heinrich, J., Dharmage, S. C., & Dong, G.-H. (2021). Greenspace and human health: An umbrella review. *The Innovation, 2*(4), Article 100164. https://doi.org/10.1016/j.xinn.2021.100164

The relationship between urban greenery, mixed land use and life satisfaction: An examination using remote sensing data and deep learning

Supplement

Table S1: Model performance in developed countries

Metric	Accuracy	IoU	F1
Bareland	0.997 ± 0.01	0.950 ± 0.01	0.953 ± 0.01
Rangeland	0.891 ± 0.01	0.444 ± 0.02	0.572 ± 0.02
Trees	0.945 ± 0.01	0.639 ± 0.03	0.754 ± 0.02
Agriculture	0.973 ± 0.01	0.835 ± 0.03	0.858 ± 0.03
Roads	0.966 ± 0.01	0.609 ± 0.03	0.716 ± 0.03
Developed Space	0.895 ± 0.01	0.475 ± 0.03	0.603 ± 0.03
Buildings	0.965 ± 0.01	0.786 ± 0.01	0.860 ± 0.01
Water	0.997 ± 0.01	0.793 ± 0.01	0.809 ± 0.01
Avg.	0.953 ± 0.01	0.691 ± 0.01	0.766 ± 0.01

Note: Model performance evaluated on four hold-out folds.

Table S2: Descriptive statistics of all variables

Variable	Min	Max	Mean	SD	N	Description
Life satisfaction	0.00	10.00	7.94	1.46	2755	Metric: "In general, how satisfied are you with your life if 0 means not at all satisfied and 10 means completely satisfied."
Sex	0.00	1.00	0.53		2755	Binary: 0 = male, 1 = female
Age	20.00	85.00	52.38	17.18	2755	Metric: Age of the respondent.
Civil status	1.00	3.00			2755	Categorical: 1 = single, 2 = married or partnership, 3 = separated, divorced or widowed.
Education	1.00	3.00			2755	Completed education. Categorical: 1 = primary, 2 = secondary, 3 = tertiary.
Occupation	1.00	6.00			2755	Current occupation. Categorical: 1 = full-time work, 2 = part-time work, 3 = education, 4 = unemployed, 5 = retired, 6 = other.
Children toddler	0.00	1.00	0.07		2755	Dummy: 0 = no children aged 4 or younger, 1 = at least one child aged 4 or younger.
Children school age	0.00	1.00	0.17		2755	Dummy: 0 = no children aged between 5 and 17, 1 = at least one child aged between 5 and 17.
Children adult	0.00	1.00	0.45		2755	Dummy: 0 = no children aged 18 or older, 1 = at least one child aged 18 or older.
Household equivalence income	2000	797600	79196	49802.8	2755	Metric: Household income weighted by the OECD weighting scheme.
Accommodation owner	0.00	1.00	0.37		2755	Binary: 0 = accommodation not owner, 1 = accommodation owned.
Residence type	1.00	3.00			2755	Categorical: 1 = Apartment, 2 = detached or semi-detached, 3 = other.
Regions	1.00	3.00			2755	Region of Switzerland the respondent is located in. Categorical: 1 = French, 2 = Italien, 3 = German.
Population density	1502.00	26266.00	4407.00	3540.94	2755	Metric: Population density of respondents' postcode in inhabitants per km^2
Distance to city center	60.34	15351.38	3104.69	2333.55	2755	Metric: Distance to the city center (train station) in meters.
Green (trees & grass)	0.04	0.90	0.39	0.04	2755	Metric: Additive index of all tree and grass related green types.
Trees (forest)	0.00	0.49	0.02	0.04	2755	Metric: Proportion of neighborhood covered by trees being located in a forest.
Trees (garden & park)	0.00	0.23	0.01	0.03	2755	Metric: Proportion of neighborhood covered by trees located in a private or public garden or park.
Trees (other)	0.02	0.78	0.15	0.09	2755	Metric: Proportion of neighborhood covered by trees with unknown land-use type.
Grass (recreation)	0.00	0.12	0.004	0.008	2755	Metric: Proportion of neighborhood covered by grass located in a recreation ground.
Grass (garden & parks)	0.00	0.17	0.01	0.03	2755	Metric: Proportion of neighborhood covered by grass located in a private or public garden or park.
Grass (playground)	0.00	0.005	0.0006	0.0007	2755	Metric: Proportion of neighborhood covered by grass located in a playground.
Grass (other)	0.01	0.53	0.18	0.09	2755	Metric: Proportion of neighborhood covered by grass with unknown land-use type.
Allotments	0.00	0.007	0.0001	0.0006	2755	Metric: Proportion of neighborhood covered by allotments.
Other agricultural land	0.00	0.76	0.07	0.11	2755	Metric: Proportion of neighborhood covered by agricultural land with unknown land-use type.
Mixed land use	0.00	0.99	0.70	0.15	2755	Metric: Entropy of the proportion of five land-use types in the neighborhood.

Source: Swiss Household Panel (SHP) and author's data.

Table S3: Land usage categories and corresponding subcategories from OpenStreetMap

	Residential		
Residential	House	Detached	Terrace
Semidetached	Dormitory	Inhabited	
	Culture, culinary, and events (CCE)		
Bar	Biergarden	Café	Fast food
Food court	Ice cream	Pub	Restaurant
Arts centre	Casino	Cinema	Event venues
Music venues	Nightclub	Theatre	Outdoor seating
Stadium	Bleachers	Grandstand	Bandstand
Museum	Castle		
	Recreation		
Recreation	Sports centre	Sports hall	Ice rink
Water park	Paddling pool	Dance	Fitness centre
Sauna	Swimming pool	Riding hall	Sport hall
Bowling alley	Trampoline park	Pavilion	
	Public services		
College	Kindergarten	Library	Toy library
Training	Music school	School	University
Atm	Bank	Clinic	Dentist
Doctors	Hospital	Nursing home	Pharmacy
Social facility	Veterinary	Community centre	Social centre
Post office	Townhall	Parcel locker	Recycling
Playground	Public	Train station	Railway
Transportation	Chapel	Civic	Church
Meadow	Park	Fire station	Schoolyard
Religious	Cathedral	Temple	Synagogue
Mosque	Public transport	Hospice	Monastery
Public services	Place of worship	Government	Police
	Commercial and groceries		
Commercial	Car wash	Fuel	Department store
General	Kiosk	Mall	Interior decoration
Boutique	Clothes	Fabric	Shoes
Tailor	Watches	Wool	Charity
Second hand	Variety store	Beauty	Chemist
Cosmetics	Hairdresser	Optician	Perfumery
Appliance	Do it yourself	Electrical	Florist
Garden centre	Hardware	Paint	Furniture
Electronics	Mobile phone	Bicycle	Car
Outdoor	Sports	Art	Books
Stationary	Dry cleaning	Retail	Supermarket
Toys	Groceries	Marketplace	Alcohol
Bakery	Beverages	Butcher	Cheese
Coffee	Confectionery	Convenience	Deli
Dairy	Farm	Frozen food	Greengrocer
Health food	Pasta	Pastry	Seafood
Spices	Tea	Wine	Food

Table S4: Coefficients of control variables of the models in Table 2 (buffer 1260 m)

Life satisfaction	Model1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Individual-level characteristics							
Sex	0.024	0.020	0.021	0.032	0.023	0.027	0.043
	(0.037)	(0.037)	(0.037)	(0.056)	(0.037)	(0.037)	(0.056)
Civil status: Single	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Married or partnership	0.159**	0.178**	0.184**	0.267**	0.172**	0.161**	0.244**
	(0.057)	(0.058)	(0.057)	(0.087)	(0.057)	(0.058)	(0.087)
Separated, divorced, or	0.048	0.075	0.070	0.114	0.067	0.053	0.080
widowed	(0.078)	(0.078)	(0.077)	(0.118)	(0.078)	(0.079)	(0.118)
Education: Primary education	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Secondary	0.087	0.082	0.079	0.099	0.085	0.087	0.131
	(0.098)	(0.098)	(0.097)	(0.148)	(0.098)	(0.099)	(0.148)
Tertiary	0.065	0.059	0.060	0.066	0.062	0.061	0.085
	(0.100)	(0.100)	(0.100)	(0.151)	(0.100)	(0.101)	(0.150)
Occupation: Full-time	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Part-time	-0.023	-0.017	-0.023	-0.034	-0.022	-0.023	-0.035
	(0.047)	(0.047)	(0.047)	(0.071)	(0.047)	(0.047)	(0.071)
Education	0.151	0.090	0.072	0.142	0.076	0.150	0.217
	(0.091)	(0.093)	(0.094)	(0.140)	(0.093)	(0.092)	(0.138)
Unemployed	-0.917***	-0.921***	-0.928***	-1.390***	-0.905***	-0.912***	-1.369***
	(0.210)	(0.210)	(0.210)	(0.317)	(0.212)	(0.215)	(0.320)
Retired	0.117	0.060	0.058	0.084	0.069	0.114	0.170
	(0.072)	(0.095)	(0.095)	(0.143)	(0.095)	(0.072)	(0.108)
Other	-0.026	-0.024	-0.030	-0.039	-0.038	-0.022	-0.031
	(0.118)	(0.118)	(0.118)	(0.177)	(0.117)	(0.117)	(0.175)
Household characteristics							
Children toddler	0.233**	0.227**	0.213**	0.340**	0.245**	0.237**	0.363**
(<5 years)	(0.078)	(0.079)	(0.079)	(0.120)	(0.081)	(0.078)	(0.117)
Children school age	0.056	0.075	0.073	0.123	0.078	0.062	0.101
(≥5 and <18 years)	(0.057)	(0.061)	(0.061)	(0.093)	(0.061)	(0.057)	(0.086)
Children adult	0.084	0.093	0.082	0.132	0.095	0.082	0.118
(≥18 years)	(0.055)	(0.056)	(0.056)	(0.084)	(0.055)	(0.055)	(0.083)
Log household	0.312***	0.320***	0.307***	0.473***	0.323***	0.315***	0.477***
equivalence income	(0.044)	(0.044)	(0.044)	(0.066)	(0.044)	(0.044)	(0.065)
Accommodation owned	0.141**	0.145**	0.153**	0.228**	0.143**	0.143**	0.212**
	(0.050)	(0.050)	(0.050)	(0.076)	(0.050)	(0.051)	(0.076)
Residence type: Apartment	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Detached or semi-	-0.063	-0.064	-0.076	-0.118	-0.062	-0.057	-0.087
detached	(0.054)	(0.054)	(0.054)	(0.081)	(0.053)	(0.054)	(0.082)
Other	0.072	0.079	0.078	0.152	0.074	0.076	0.116
	(0.130)	(0.130)	(0.128)	(0.196)	(0.127)	(0.133)	(0.198)
Neighborhood characteristics							
Regions: French	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Italian	0.141	0.146*	0.158*	0.287*	0.135	0.141*	0.215
	(0.073)	(0.073)	(0.080)	(0.113)	(0.071)	(0.073)	(0.111)
German	0.088	0.087	0.122*	0.212**	0.084	0.084	0.122
	(0.048)	(0.047)	(0.052)	(0.078)	(0.047)	(0.048)	(0.072)
Population density	-0.034	-0.032	-0.045	-0.073	-0.034	-0.032	-0.055
	(0.024)	(0.024)	(0.024)	(0.040)	(0.025)	(0.024)	(0.037)
Distance to city center	0.009	0.012	0.012	0.017	0.013	0.012	0.016
	(0.020)	(0.020)	(0.020)	(0.030)	(0.020)	(0.019)	(0.029)
N	2755	2755	2755	2755	2755	2755	2755
Adj. R2	0.10	0.10	0.11	0.11	0.10	0.10	0.10

Source: Swiss Household Panel (SHP) and author’s data.

References

Abbott, P., & Wallace, C. (2014). Rising Economic Prosperity and Social Quality the Case of New Member States of the European Union. Social Indicators Research, 115(1), 419–439. https://doi.org/10.1007/s11205-012-9992-0

Ambrey, C., & Fleming, C. (2014). Public Greenspace and Life Satisfaction in Urban Australia. Urban Studies, 51(6), 1290–1321. JSTOR. Retrieved from JSTOR.

Anderson, B., Böhmelt, T., & Ward, H. (2017). Public opinion and environmental policy output: A cross-national analysis of energy policies in Europe. Environmental Research Letters, 12(11), 114011. https://doi.org/10.1088/1748-9326/aa8f80

Bahr, S. (2024). The relationship between urban greenery, mixed land use and life satisfaction: An examination using remote sensing data and deep learning. Landscape and Urban Planning, 251, 105174. https://doi.org/10.1016/j.landurbplan.2024.105174

Bakaki, Z., Böhmelt, T., & Ward, H. (2020). The triangular relationship between public concern for environmental issues, policy output, and media attention. Environmental Politics, 29(7), 1157–1177. https://doi.org/10.1080/09644016.2019.1655188

Bamberg, S., & Möser, G. (2007). Twenty years after Hines, Hungerford, and Tomera: A new meta-analysis of psycho-social determinants of pro-environmental behaviour. Journal of Environmental Psychology, 27(1), 14–25. https://doi.org/10.1016/j.jenvp.2006.12.002

Bertram, C., & Rehdanz, K. (2015). The role of urban green space for human well-being. Ecological Economics, 120, 139–152. https://doi.org/10.1016/j.ecolecon.2015.10.013

Blanden, J. (2004). Family Income and Educational Attainment: A Review of Approaches and Evidence for Britain. Oxford Review of Economic Policy, 20(2), 245–263. https://doi.org/10.1093/oxrep/grh014

Bor, J., Cohen, G. H., & Galea, S. (2017). Population health in an era of rising income inequality: USA, 1980–2015. The Lancet, 389(10077), 1475–1490. https://doi.org/10.1016/S0140-6736(17)30571-8

Bouman, T., Verschoor, M., Albers, C. J., Böhm, G., Fisher, S. D., Poortinga, W., … Steg, L. (2020). When worry about climate change leads to climate action: How values, worry and personal responsibility relate to various climate actions. Global Environmental Change, 62, 102061. https://doi.org/10.1016/j.gloenvcha.2020.102061

Bruderer Enzler, H., & Diekmann, A. (2019). All talk and no action? An analysis of environmental concern, income and greenhouse gas emissions in Switzerland. Energy Research & Social Science, 51, 12–19. https://doi.org/10.1016/j.erss.2019.01.001

Brüderl, J., & Ludwig, V. (2013). Fixed-effects panel regression. In C. Wolf & H. Best (Eds.), Regression analysis and causal inference (pp. 327–358). London: Sage.

Cao, X. (Jason). (2016). How does neighborhood design affect life satisfaction? Evidence from Twin Cities. Planning for Quality of Life, 5, 68–76. https://doi.org/10.1016/j.tbs.2015.07.001

Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., … Cutler, D. (2016). The Association Between Income and Life Expectancy in the United States, 2001-2014. JAMA, 315(16), 1750. https://doi.org/10.1001/jama.2016.4226

Chiesura, A. (2004). The role of urban parks for the sustainable city. Landscape and Urban Planning, 68(1), 129–138. https://doi.org/10.1016/j.landurbplan.2003.08.003

Corcoran, M. (1995). Rags to Rags: Poverty and Mobility in the United States. Annual Review of Sociology, 21(1), 237–267. https://doi.org/10.1146/annurev.so.21.080195.001321

Diekmann, A., & Preisendörfer, P. (2003). Green and Greenback: The Behavioral Effects of Environmental Attitudes in Low-Cost and High-Cost Situations. Rationality and Society, 15(4), 441–472. https://doi.org/10.1177/1043463103154002

Dong, H., & Qin, B. (2017). Exploring the link between neighborhood environment and mental wellbeing: A case study in Beijing, China. Landscape and Urban Planning, 164, 71–80. https://doi.org/10.1016/j.landurbplan.2017.04.005

Dye, C. (2008). Health and Urban Living. Science, 319(5864), 766–769. https://doi.org/10.1126/science.1150198

Eurostat (2024). Quarterly government debt. Retrieved from https://ec.europa.eu/eurostat/databrowser/view/GOV_10Q_GGDEBT__custom_9497724/default/line?lang=en

Federal Reserve Bank of St. Louis (2024). Federal Debt: Total Public Debt as Percentage of Gross Domestic Product. Retrieved from https://fred.stlouisfed.org/series/GFDEGDQ188S

Federal Reserve History (2013). The Great Recession and Its Aftermath. Retrieved from https://www.federalreservehistory.org/essays/great-recession-and-its-aftermath

Ferguson, H., Bovaird, S., & Mueller, M. (2007). The impact of poverty on educational outcomes for children. Paediatrics & Child Health, 12(8), 701–706. https://doi.org/10.1093/pch/12.8.701

Franzen, A., & Bahr, S. (2023). Poverty in Europe: How long-term poverty developed following the financial crisis and what drives it. International Journal of Social Welfare, 33(2), 482–494. https://doi.org/10.1111/ijsw.12614

Franzen, A., & Bahr, S. (2024). The development of global environmental concern during the last three decades. Current Research in Environmental Sustainability, 8, 100260. https://doi.org/10.1016/j.crsust.2024.100260

Franzen, A., & Mader, S. (2021). Testing the measurement of environmental concern: How do single items perform in comparison to multi-item scales? In A. Franzen & S. Mader (Eds.), Research handbook on environmental sociology (pp. 63–78). Cheltenham UK: Edward Elgar Publishing.

Franzen, A., & Vogl, D. (2013). Two decades of measuring environmental attitudes: A comparative analysis of 33 countries. Global Environmental Change, 23(5), 1001–1008. https://doi.org/10.1016/j.gloenvcha.2013.03.009

Friedman, T. L. (2010). Too Good to Check. Retrieved from https://www.nytimes.com/2010/11/17/opinion/17friedman.html?src=tptw

Gifford, R., & Sussman, R. (2012). Environmental Attitudes. In S. D. Clayton (Ed.), The Oxford Handbook of Environmental and Conservation Psychology (pp. 65–80). New York: Oxford University Press.

Global Carbon Project (2024). Explore the latest GCB data. Retrieved from https://explore.globalcarbonbudgetdata.org/timeseries.html

Guo, Y., Liu, Y., Lu, S., Chan, O. F., Chui, C. H. K., & Lum, T. Y. S. (2021). Objective and perceived built environment, sense of community, and mental wellbeing in older adults in Hong Kong: A multilevel structural equation study. Landscape and Urban Planning, 209, 104058. https://doi.org/10.1016/j.landurbplan.2021.104058

Hines, J. M., Hungerford, H. R., & Tomera, A. N. (1987). Analysis and Synthesis of Research on Responsible Environmental Behavior: A Meta-Analysis. The Journal of Environmental Education, 18(2), 1–8. https://doi.org/10.1080/00958964.1987.9943482

Holmes, J., & Kiernan, K. (2013). Persistent poverty and children’s development in the early years of childhood. Policy & Politics, 41(1), 19–42. https://doi.org/10.1332/030557312X645810

Ingensiep, C. (2016). Determinants of persistent poverty. Do institutional factors matter? In M. Heidenreich (Ed.), Exploring Inequality in Europe. Edward Elgar Publishing. https://doi.org/10.4337/9781783476664.00007

Kabisch, N., & Haase, D. (2014). Green justice or just green? Provision of urban green spaces in Berlin, Germany. Landscape and Urban Planning, 122, 129–139. https://doi.org/10.1016/j.landurbplan.2013.11.016

Kaplan, R., & Kaplan, S. (1989). The experience of nature: A psychological perspective. Cambridge University Press.

Kley, S., & Dovbishchuk, T. (2021). How a Lack of Green in the Residential Environment Lowers the Life Satisfaction of City Dwellers and Increases Their Willingness to Relocate. Sustainability, 13(7), 3984. https://doi.org/10.3390/su13073984

Kollmuss, A., & Agyeman, J. (2002). Mind the Gap: Why do people act environmentally and what are the barriers to pro-environmental behavior? Environmental Education Research, 8(3), 239–260. https://doi.org/10.1080/13504620220145401

Krekel, C., Kolbe, J., & Wüstemann, H. (2016). The greener, the happier? The effect of urban land use on residential well-being. Ecological Economics, 121, 117–127. https://doi.org/10.1016/j.ecolecon.2015.11.005

Madden, D. (2015). Health and Wealth on the Roller-Coaster: Ireland, 2003–2011. Social Indicators Research, 121(2), 387–412. https://doi.org/10.1007/s11205-014-0644-4

McCarthy, S., & Habib, M. A. (2018). Investigation of life satisfaction, travel, built environment and attitudes. Journal of Transport & Health, 11, 15–24. https://doi.org/10.1016/j.jth.2018.09.007

Mood, C., & Jonsson, J. O. (2016). The Social Consequences of Poverty: An Empirical Test on Longitudinal Data. Social Indicators Research, 127(2), 633–652. https://doi.org/10.1007/s11205-015-0983-9

Mouratidis, K. (2018). Built environment and social well-being: How does urban form affect social life and personal relationships? Cities, 74, 7–20. https://doi.org/10.1016/j.cities.2017.10.020

Olsen, J. R., Nicholls, N., & Mitchell, R. (2019). Are urban landscapes associated with reported life satisfaction and inequalities in life satisfaction at the city level? A cross-sectional study of 66 European cities. Social Science & Medicine, 226, 263–274. https://doi.org/10.1016/j.socscimed.2019.03.009

Preisendörfer, P. (1999). Umwelteinstellungen und Umweltverhalten in Deutschland. Opladen: Leske und Budrich.

Preisendörfer, P., & Franzen, A. (1996). Der schöne Schein des Umweltbewusstseins. Kölner Zeitschrift Für Soziologie Und Sozialpsychologie, 36, 219–244.

Riumallo-Herl, C., Basu, S., Stuckler, D., Courtin, E., & Avendano, M. (2014). Job loss, wealth and depression during the Great Recession in the USA and Europe.

International Journal of Epidemiology, 43(5), 1508–1517. https://doi.org/10.1093/ije/dyu048

Roberts, M. R., Reid, G., Schroeder, M., & Norris, S. P. (2013). Causal or spurious? The relationship of knowledge and attitudes to trust in science and technology. Public Understanding of Science, 22(5), 624–641. https://doi.org/10.1177/0963662511420511

Steg, L., & Vlek, C. (2009). Encouraging pro-environmental behaviour: An integrative review and research agenda. Environmental Psychology on the Move, 29(3), 309–317. https://doi.org/10.1016/j.jenvp.2008.10.004

Sundquist, K., Frank, G., & Sundquist, J. (2004). Urbanisation and incidence of psychosis and depression: Follow-up study of 4.4 million women and men in Sweden. British Journal of Psychiatry, 184(4), 293–298. https://doi.org/10.1192/bjp.184.4.293

The World Bank (2022). Population total. Retrieved from https://data.worldbank.org/indicator/SP.POP.TOTL

The World Bank (2023a). Unemployment, total (% of total labor force). Retrieved from https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS

The World Bank (2023b). Urban Development. Retrieved from https://www.worldbank.org/en/topic/urbandevelopment/overview

Townsend, P. (1979). Poverty in the United Kingdom: A Survey of Household Resources and Standards of Living. University of California Press. https://doi.org/10.1525/9780520325760

Ugur-Cinar, M., Cinar, K., & Kose, T. (2020). How Does Education Affect Political Trust?: An Analysis of Moderating Factors. Social Indicators Research, 152(2), 779–808. https://doi.org/10.1007/s11205-020-02463-z

Vandeweerdt, C., Kerremans, B., & Cohn, A. (2016). Climate voting in the US Congress: The power of public concern. Environmental Politics, 25(2), 268–288. https://doi.org/10.1080/09644016.2016.1116651

Wagstaff, A. (2002). Poverty and health sector inequalities. Bulletin of the World Health Organization, 80(2), 97–105.

Whelan, C. T., Layte, R., & Maître, B. (2003). Persistent Income Poverty and Deprivation in the European Union: An Analysis of the First Three Waves of the European Community Household Panel. Journal of Social Policy, 32(1), 1–18. https://doi.org/10.1017/S0047279402006864

White, M. P., Alcock, I., Wheeler, B. W., & Depledge, M. H. (2013). Would You Be Happier Living in a Greener Urban Area? A Fixed-Effects Analysis of Panel Data. Psychological Science, 24(6), 920–928. https://doi.org/10.1177/0956797612464659

Wilson, E. O. (1984). Biophilia. Harvard University Press. https://doi.org/10.2307/j.ctvk12s6h

Wooldridge, J. (2010). Econometric analysis of cross section and panel data. MIT Press.

Wu, W., Chen, W. Y., Yun, Y., Wang, F., & Gong, Z. (2022). Urban greenness, mixed land-use, and life satisfaction: Evidence from residential locations and workplace settings in Beijing. Landscape and Urban Planning, 224, 104428. https://doi.org/10.1016/j.landurbplan.2022.104428

Wu, W., Tan, W., Wang, R., & Chen, W. Y. (2023). From quantity to quality: Effects of urban greenness on life satisfaction and social inequality. Landscape and Urban Planning, 238, 104843. https://doi.org/10.1016/j.landurbplan.2023.104843

WWF (2022). Living Planet Report 2022 - Building a Nature Positive Society. Almond, R.E.A., Grooten, M., Juffe Bignoli, D. & Petersen, T. (Eds). WWF, Gland, Switzerland.

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