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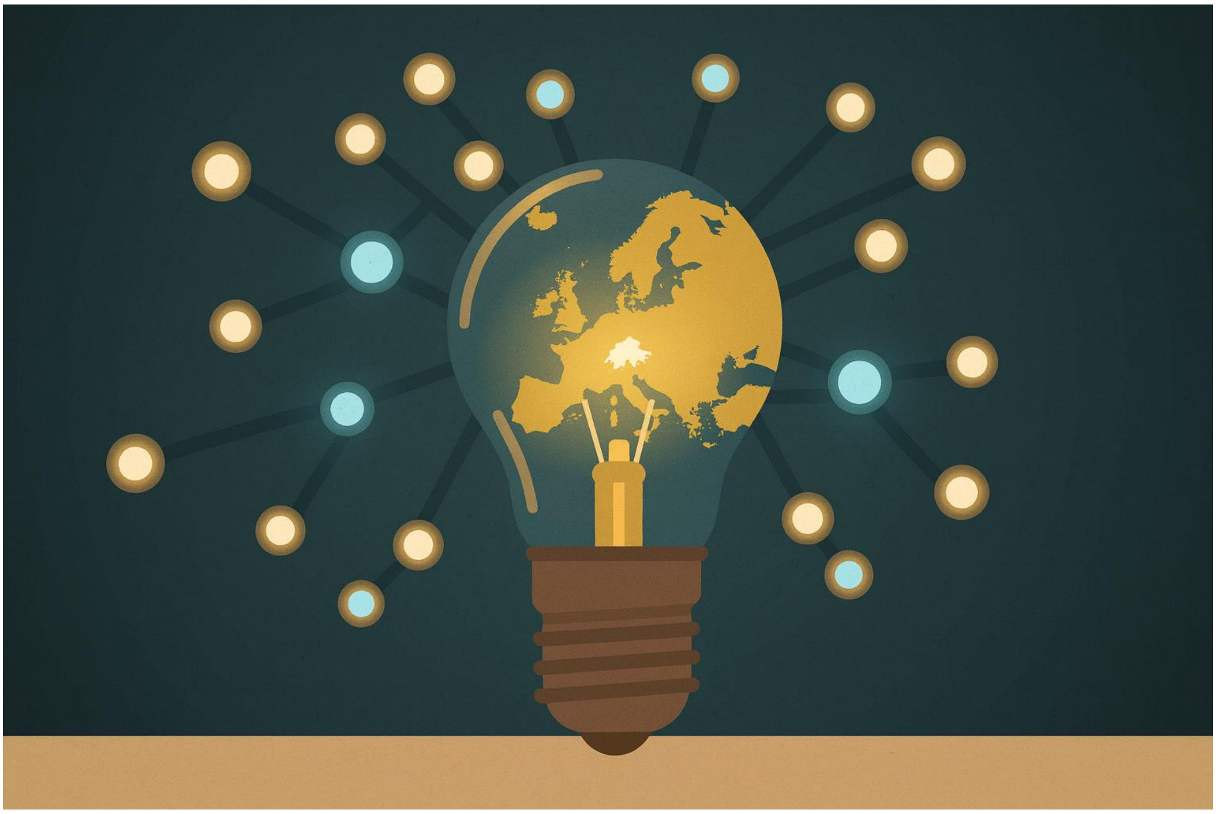
Distribution of energy related living expenditures and likelihood of living in polluted areas: An analysis using European data



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Summary

In recent years, rising prices for electricity, heating fuels, and other energy products have increased attention to household energy expenditures and their potential distributional implications. At the same time, concerns about air pollution and its health impacts continue to feature prominently in environmental and energy policy discussions. Against this background, this project examines how energy-related living expenditures and exposure to air pollution vary across population groups. The analysis focuses on whether household energy expenditures differ systematically by socio-demographic characteristics and whether the likelihood of living in polluted areas varies across income and demographic groups. The empirical analysis covers Switzerland and a selection of European countries.

The first work package analyses the distribution of housing-related energy expenditures in Switzerland and places the findings in a European context. Using data from the Swiss Household Budget Survey (HBS) and the European Household Budget Survey (EHBS), we document energy expenditure patterns across income quintiles and apply commonly used indicators of energy poverty, such as the Ten-Percent Rule, which classifies households as energy poor if they spend more than ten percent of their income on energy-related expenditures. In addition, we assess the distributional properties of energy expenditures using measures of regressivity, including the Degree of Convexity, the Kakwani Index, and Energy Lorenz curves, and decompose expenditure concentration by socio-demographic characteristics. The results show that, compared to many EU countries, Swiss households spend a smaller share of their income on energy expenditures across all income groups. In several EU countries, the energy expenditure share of high-income households exceeds that of low-income households in Switzerland. Furthermore, according to the Ten-Percent energy poverty indicator, the share of households in the HBS classified as energy poor in Switzerland is the lowest in a European comparison. While the distribution of energy expenditures in Switzerland is regressive, the degree of regressivity is broadly comparable to that observed in other European countries.

The second work package examines the distribution of air pollution exposure and differences between measured and perceived air quality. For Switzerland, we combine population data from Population and Households Statistics (STATPOP) with high-resolution $PM_{2.5}$ concentration data from Atmospheric Composition Analysis Group (ACAG) and Copernicus Atmosphere Monitoring Service (CAMS) to analyse exposure patterns, and use EU Statistics on Income and Living Conditions (EU-SILC) data to study *perceived* pollution through logistic regression models. Because Swiss data do not allow measured and perceived pollution to be linked at a granular level, we complement the analysis with data from the United Kingdom, drawing on Understanding Society survey data matched with air pollution data from Department for Environment, Food & Rural Affairs (DEFRA). This allows for a more accurate assessment of the relationship between $PM_{2.5}$ exposure and pollution perception. Potential endogeneity is addressed using a linear probability model with wind speed as an instrument. The results indicate that Switzerland occupies a middle position in the European distribution of $PM_{2.5}$ concentrations, although average levels remain above current world health organization (WHO) guidelines. In contrast, the share of households reporting that they feel affected by air pollution is consistently among the lowest in Europe. Pollution exposure is higher in urban areas, a pattern that is also reflected in perceived pollution by households. Perceived air pollution is negatively correlated with income while the education status is positively correlated with both measured and perceived pollution. Evidence from the UK suggests that although $PM_{2.5}$ exposure has declined over time, awareness of air pollution has increased, likely influenced by visible policy measures and information campaigns. These findings highlight the importance of considering both objective exposure and subjective perception when analysing environmental conditions and their distribution across population groups. Overall, the findings highlight the relevance of both measured exposure and perceived air pollution, since both may influence how environmental policies are received, implemented, and ultimately how effective they are.

Zusammenfassung

In den letzten Jahren haben steigende Preise für Strom, Heizenergie und andere Energieprodukte die Aufmerksamkeit auf die Höhe der energiebezogenen Haushaltsausgaben und deren mögliche Verteilungswirkungen gelenkt. Gleichzeitig spielen Fragen der Luftverschmutzung und ihrer gesundheitlichen Auswirkungen weiterhin eine zentrale Rolle in energie- und umweltpolitischen Diskussionen. Vor diesem Hintergrund untersucht das vorliegende Projekt, wie sich energiebezogene Lebenshaltungskosten sowie die Belastung durch Luftverschmutzung zwischen verschiedenen Bevölkerungsgruppen unterscheiden. Der Fokus der Analyse liegt darauf, ob sich Haushaltsausgaben für Energie systematisch entlang sozio-demografischer Merkmale unterscheiden und ob die Wahrscheinlichkeit, in Gebieten mit Luftverschmutzung zu leben, je nach Einkommens- und Bevölkerungsgruppe variiert. Die empirische Analyse umfasst die Schweiz sowie eine Auswahl europäischer Länder.

Im ersten Teilprojekt wird die Verteilung der Haushaltsenergieausgaben in der Schweiz analysiert und in einen europäischen Kontext eingeordnet. Auf Basis der Schweizerischen Haushaltsbudgeterhebung (HABE) und der Europäischen Haushaltsbudgeterhebung (EHBS) wird die Verteilung der Energieausgaben entlang von Einkommensquintilen dokumentiert und gängige Indikatoren zur Messung von Energiearmut angewendet. Darüber hinaus wird die Regressivität der Energieausgaben mithilfe verschiedener Maße untersucht, darunter der Degree of Convexity, der Kakwani-Index sowie Energie-Lorenz-Kurven. Die Ergebnisse zeigen, dass die in der Umfrage beinhalteten Schweizer Haushalte im Vergleich zu vielen Haushalten in EU-Ländern über alle Einkommensgruppen hinweg einen geringeren Anteil ihres Einkommens für Energie ausgeben. In mehreren EU-Ländern liegt der Einkommensanteil für Energieausgaben selbst bei Haushalten mit hohen Einkommen über jenem einkommensschwacher Haushalte in der Schweiz. Gemäß der Zehn-Prozent-Regel (wonach Haushalte als energiearm gelten, wenn sie mehr als zehn Prozent ihres Einkommens für energiebezogene Ausgaben aufwenden), ist der Anteil der in der HABE als energiearm klassifizierten Haushalte in der Schweiz im europäischen Vergleich am niedrigsten. Gleichzeitig sind Energieausgaben regressiv, wobei der Grad der Regressivität in etwa jenem anderer europäischer Länder entspricht.

Das zweite Teilprojekt untersucht die Verteilung der Belastung durch Luftverschmutzung sowie Unterschiede zwischen gemessener und wahrgenommener Luftverschmutzung. Für die Schweiz verwenden wir Bevölkerungsdaten aus der Statistik der Bevölkerung und der Haushalte (STATPOP) mit $PM_{2.5}$-Konzentrationsdaten mit hoher räumlichen Auflösung von Atmospheric Composition Analysis Group (ACAG) und Copernicus Atmosphere Monitoring Service (CAMS). Zur Untersuchung der wahrgenommenen Luftverschmutzung werden Daten von den EU Statistics on Income and Living Conditions (EU-SILC) mittels logistischer Regressionsmodelle ausgewertet. Da in der Schweiz gemessene und wahrgenommene Luftverschmutzung nicht auf einer ausreichend detaillierten Ebene verknüpft werden können, wird die Analyse durch Daten aus dem Vereinigten Königreich ergänzt, wobei die Understanding Society Umfrage mit Luftverschmutzungsdaten vom Department for Environment, Food & Rural Affairs (DEFRA) kombiniert wird. Dies erlaubt eine genauere Analyse des Zusammenhangs zwischen $PM_{2.5}$-Belastung und der Wahrnehmung von Luftverschmutzung. Die Ergebnisse zeigen, dass die Schweiz im europäischen Vergleich eine mittlere Position hinsichtlich der $PM_{2.5}$-Konzentrationen einnimmt, obwohl die durchschnittlichen Werte weiterhin über den aktuellen Richtlinien der Weltgesundheitsorganisation (WHO) liegen. Im Gegensatz dazu gehört der Anteil der befragten Haushalte, die angeben, sich durch Luftverschmutzung betroffen zu fühlen, in der Schweiz konstant zu den niedrigsten in Europa. Die Belastung durch Luftverschmutzung ist in städtischen Gebieten höher, ein Muster, das sich auch in der Wahrnehmung der Haushalte widerspiegelt. Die wahrgenommene Luftverschmutzung ist negativ mit dem Einkommen korreliert, während der Bildungsstand sowohl mit der gemessenen als auch mit der wahrgenommenen Luftverschmutzung positiv zusammenhängt. Evidenz aus dem Vereinigten Königreich deutet darauf hin, dass trotz rückläufiger $PM_{2.5}$-Belastung die Wahrnehmung der Luftverschmutzung zugenommen hat, was unter anderem auf sichtbare politische Maßnahmen und Informationskampagnen zurückzuführen sein dürfte.

Insgesamt zeigen die Ergebnisse, dass sowohl objektive Umweltbelastungen als auch subjektive Wahrnehmungen berücksichtigt werden sollten, da beide beeinflussen, wie umweltpolitische Maßnahmen wahrgenommen, umgesetzt und letztlich wirksam werden.

Résumé

Ces dernières années, la hausse des prix de l'électricité, des combustibles de chauffage et d'autres produits énergétiques a accru l'attention portée aux dépenses énergétiques des ménages et à leurs éventuelles implications distributives. Parallèlement, les préoccupations liées à la qualité de l'air et à ses effets sur la santé occupent une place importante dans les débats de politique énergétique et environnementale. Dans ce contexte, le présent projet analyse la manière dont les dépenses énergétiques liées au logement et l'exposition à la pollution atmosphérique varient selon les groupes de population. L'analyse examine si les dépenses énergétiques des ménages diffèrent systématiquement en fonction de caractéristiques socio-démographiques et si la probabilité de vivre dans des zones où la qualité de l'air est plus dégradée varie selon le revenu et d'autres caractéristiques démographiques. L'analyse empirique porte sur la Suisse ainsi que sur une sélection de pays européens.

Le premier lot de travail analyse la répartition des dépenses énergétiques liées au logement en Suisse et situe les résultats dans un contexte européen. À partir des données de l'Enquête suisse sur le budget des ménages (ESBM) et de l'Enquête européenne sur le budget des ménages (EEBM), nous documentons les profils de dépenses énergétiques par quintile de revenu et appliquons des indicateurs couramment utilisés pour mesurer la précarité énergétique, notamment la règle des dix pour cent, selon laquelle un ménage est considéré comme en situation de précarité énergétique lorsqu'il consacre plus de dix pour cent de son revenu aux dépenses énergétiques. En outre, nous évaluons les propriétés distributives des dépenses énergétiques à l'aide de différentes mesures de régressivité, telles que le degré de convexité, l'indice de Kakwani et les courbes de Lorenz appliquées aux dépenses énergétiques, et nous décomposons la concentration des dépenses selon des caractéristiques socio-démographiques.

Les résultats montrent que, par rapport à de nombreux pays de l'Union européenne, les ménages suisses consacrent une part plus faible de leur revenu aux dépenses énergétiques, et ce pour l'ensemble des groupes de revenu. Dans plusieurs pays de l'UE, la part du revenu consacrée à l'énergie par les ménages à revenu élevé dépasse celle des ménages à faible revenu en Suisse. En outre, selon l'indicateur de précarité énergétique basé sur la règle des dix pour cent, la proportion de ménages classés comme en situation de précarité énergétique dans les données de ESBM est la plus faible en comparaison européenne. Bien que la répartition des dépenses énergétiques en Suisse soit de nature régressive, le degré de régressivité observé est globalement comparable à celui constaté dans d'autres pays européens.

Le deuxième lot de travail examine la répartition de l'exposition à la pollution atmosphérique ainsi que les différences entre la qualité de l'air mesurée et perçue. Pour la Suisse, nous combinons des données de population issues de Statistique de la population et des ménages (STATPOP) avec des données de concentration de $PM_{2.5}$ à haute résolution provenant d'Atmospheric Composition Analysis Group (ACAG) et de Copernicus Atmosphere Monitoring Service (CAMS) afin d'analyser les profils d'exposition, et nous utilisons les données EU statistics on income and living conditions (EU-SILC) pour étudier la pollution perçue au moyen de modèles de régression logistique. Étant donné que les données suisses ne permettent pas de relier de manière suffisamment fine la pollution mesurée et la pollution perçue, l'analyse est complétée par des données du Royaume-Uni, en combinant l'enquête Understanding Society avec des données sur la qualité de l'air provenant de Department for Environment, Food & Rural Affairs (DEFRA). Cette approche permet une évaluation plus précise de la relation entre l'exposition aux $PM_{2.5}$ et la perception de la pollution atmosphérique.

Les résultats indiquent que la Suisse occupe une position intermédiaire dans la distribution européenne des concentrations de $PM_{2.5}$, bien que les niveaux moyens restent supérieurs aux valeurs guides

actuelles de l'Organisation Mondiale de la Santé (WHO). En revanche, la proportion de ménages déclarant se sentir affectés par la pollution atmosphérique figure systématiquement parmi les plus faibles en Europe. L'exposition à la pollution est plus élevée dans les zones urbaines, un schéma qui se reflète également dans la perception des ménages. La pollution atmosphérique perçue est négativement corrélée au revenu, tandis que le niveau d'éducation est positivement corrélé à la fois à la pollution mesurée et perçue. Les résultats pour le Royaume-Uni suggèrent que, bien que l'exposition aux $PM_{2.5}$ ait diminué au fil du temps, la sensibilisation à la pollution atmosphérique s'est accrue, probablement sous l'effet de mesures politiques visibles et de campagnes d'information. Ces résultats soulignent l'importance de prendre en compte à la fois l'exposition objective et la perception subjective lors de l'analyse des conditions environnementales et de leur répartition entre les groupes de population.

Dans l'ensemble, les résultats soulignent l'importance conjointe de l'exposition mesurée et de la pollution atmosphérique perçue, dans la mesure où l'une comme l'autre influencent la manière dont les politiques environnementales sont perçues, mises en œuvre et, en définitive, leur efficacité.

Main findings («Take-Home Messages»)

- **Low energy poverty:** Shares of income spent on energy are comparably low in Switzerland along the whole income distribution, including for low-income households.
- **Moderate regressivity**: While the distribution of energy expenditures in Switzerland is regressive, the degree of regressivity is broadly comparable to that observed in other European countries.
- **Stable air pollution perceptions and disparities in perceptions**: The share of surveyed Swiss households who report feeling affected by air pollution declined steadily from 2007 until around 2013, and stabilised thereafter until 2023. Throughout the period, lower-income groups consistently report a higher likelihood of feeling affected by air pollution than higher-income groups, and this gap remains relatively stable over time.
- **Air pollution misperception?** Although Switzerland's average $PM_{2.5}$ levels place it in the middle of the European distribution, Swiss households consistently report some of the lowest *perceived* pollution levels, suggesting that air quality is viewed more positively than objective exposure alone would justify**.**
- **Socioeconomic disparities differ for exposure and perception:** More educated individuals both experience and report higher pollution, reflecting their concentration in larger urban centres and greater environmental awareness. Income, however, is negatively correlated with *perceived* pollution, indicating that wealthier households feel less affected even when objective differences are small.

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List of abbreviations

SFOE	Swiss Federal Office of Energy
2M	Twice the Median Criterion
2SLS	Two Stage Least Squares

ACAG	Atmospheric Composition Analysis Group
AURN	Automatic Urban and Rural Network
BFS	Swiss Federal Statistical Office
CAMS	Copernicus Atmosphere Monitoring Service
CHF	Swiss Franc
CI	Concentration Index
DEFRA	Department for Environment, Food & Rural Affairs
DOC	Degree of Convexity
EH	Household Energy
EL	Electricity
ET	Total Energy
EU	European Union
EU SILC	European Union Statistics on Income and Living Conditions
FE	Fixed Effects
FSO	Federal Statistical Office
FU	Fuel
HBS	Household Budget Survey
KI	Kakwani Index
LPM	Linear Probability Model
LSOA	Lower Layer Super Output Area
PCM	Pollution Climate Mapping
$PM_{2.5}$	Particulate Matter ≤ 2.5 µm
SES	Socio Economic Status
STATPOP	Statistik der Bevölkerung und der Haushalte
TPR	Ten Percent Rule
UK	United Kingdom
US	Understanding Society
WHO	World Health Organization

1 Introduction

1.1 Context and motivation

The transformation of energy systems has economic, social, and environmental impacts. While governments globally prioritize both income redistribution as well as environmental concerns, practical challenges arise in addressing both simultaneously. Policies aimed at internalising environmental externalities—such as carbon pricing—can affect electricity or heating costs, but the extent to which such changes translate into distributional impacts is ultimately an empirical question. Rising energy prices following the Ukraine conflict have heightened these distributional concerns.

Air pollution constitutes another dimension of interest in this context. It remains a major global environmental and public health concern, with many cities worldwide exceeding WHO air quality guidelines. These exceedances are associated with substantial health and economic costs, including more than four million premature deaths annually at the global level and around 200,000 in Europe (Fuller et al., 2022; EEA, 2024). Although Switzerland is not typically seen as highly polluted, a study commissioned by the Swiss Federal Office for the Environment (Castro et al., 2023) estimates around 2,300 premature deaths each year due to air pollution. Whether and to what extent such impacts differ across population groups—for example due to differences in housing conditions, urban location, or occupational exposure—remains an open empirical question..

Taken together, these considerations motivate an analysis of energy-related living expenditures and exposure to air pollution from a distributional perspective, with the aim of documenting patterns.

A further motivation for this project relates to the relationship between *measured* and *perceived* air pollution. Previous research shows that subjective assessments of environmental conditions often diverge from objective indicators (Kim & Kwan, 2021; Song & Kwan, 2023). Such divergences may influence individual behaviour, for example by shaping precautionary responses or perceptions of environmental risk. Evidence from China suggests that improved monitoring and information provision can affect behavioural responses to air pollution (Greenstone et al., 2022), highlighting the potential relevance of accurate environmental information as a public good. At the same time, the degree to which perceptions align with measured exposure varies across contexts and populations.

While Swiss $PM_{2.5}$ levels place the country mid-range in the European context, perceptions of air pollution rank among the lowest. This “perception gap” complicates the interpretation of survey-based assessments of environmental burden and influences how households respond to policy measures or pollution episodes. However, Swiss data sources do not allow measured and perceived pollution to be linked at the household level, limiting the insights that can be drawn. A comparative perspective using detailed UK microdata—where both dimensions can be matched—allows us to better understand the drivers of this gap and its implications for environmental justice.

Finally, these analytical questions arise alongside ongoing policy discussions in Europe and Switzerland that increasingly consider the distributional aspects of climate and energy policies. The planned introduction of EU ETS 2 in the European Union from 2027, together with the accompanying Social Climate Fund, illustrates how distributional considerations are being incorporated into policy design. Against this background, empirical evidence on energy expenditures, pollution exposure, and perceptions can provide a useful basis for informing policy discussions.

1.2 Project objectives

Energy policies commonly aim to achieve multiple objectives, including emissions reduction, the promotion of renewable energy, and the enhancement of energy efficiency. However, the implementation of these diverse policies often encounters resistance, primarily due to concerns within the population regarding potential equity consequences. Therefore, this project is designed to gain a better understanding about the distribution of household energy expenditures among different population groups. To this end, the first part of the project analyses the distribution of household energy expenditures in Switzerland. We quantify energy-related living expenditures across income quintiles and assess their distributional properties using several complementary measures, including indicators of regressivity**.** The objective is to document observed patterns in energy expenditures and to place them in a broader European context, thereby facilitating an informed assessment of the potential distributional implications of energy policy measures.

Building on this analysis, the second part of the project examines the distribution of pollution-related exposure among households. Specifically, we analyse how the likelihood of living in environmentally burdened conditions—such as exposure to pollution or grime—varies across socio-demographic characteristics. A key element of this analysis is the distinction between *measured* and *perceived* air pollution, as these two dimensions may not coincide. This distinction enables a more nuanced analysis of how environmental quality and its perception differ across population groups.

1.3 Structure of the report

In Work Package 1 (WP1), we analyse energy-related living expenditures in Switzerland and examine their distribution using several complementary measures. To contextualise these findings, we compare results for Switzerland with data from multiple European countries. The research conducted in WP1 has been published in a peer-reviewed academic journal, where the methodological approach, empirical results, and an extended discussion are presented in full detail. We therefore refer to this publication mentioned also in the list of references for further details.

In WP2, we examine how socio-demographic characteristics are correlated with both *measured* and *perceived* air pollution, drawing on detailed data for Switzerland as well as a comparative perspective across European countries. We additionally compare perceived pollution with measured exposure to assess how closely perceptions align with actual pollution levels, using high-resolution UK data to conduct analyses that are not feasible with Swiss datasets. As no publicly available working paper accompanies this part of the report, we provide a description of the methodological approach and empirical models applied.

2 Approach, method, results and discussion

2.1 WP1: Distribution of energy related living expenditures

For this project, we employ cross-national, household-level survey microdata to examine the distributional implications of energy expenditures. The availability of survey data from a large number of European countries (including Switzerland) over multiple years enables us to exploit variation in energy-related housing expenditures. Countries differ in their power generation mix, energy taxation, and predominant heating sources, all of which translate into heterogeneity in energy prices and, consequently, in household spending on electricity and heating. Leveraging this variation, we identify the socio-demographic characteristics that shape the distribution of energy-related housing expenditures across the income distribution, as well as across degrees of urbanisation or tenure types. For Switzerland specifically, we further investigate how these patterns differ across linguistic regions. The Swiss Household Budget Survey (HBS) provides detailed information on energy-related housing expenditures, income, household appliances, and a wide range of socio-demographic variables for the periods 2006–2008, 2009–2011, 2012–2014, 2015–2017, 2018–2019, and 2020–2021.

We begin our analysis by assessing the prevalence of energy poverty in Switzerland and contextualizing it through a comparison with European Union member states. To identify energy-poor households, we apply two established expenditure-based criteria. The first classifies a household as energy poor if its energy expenditure exceeds twice the national median (the 2M indicator), consistent with the methodology of the Energy Poverty Observatory. The second criterion, the Ten-Percent Rule (TPR), designates households as energy poor when their energy expenditure amounts to more than 10% of their income (Churchill et al., 2020).

In the next step, we assess the regressivity of energy expenditures by comparing the proportion of income devoted to energy expenditures by households in the lowest and highest income groups. This provides an initial indication of the distributional burden of energy costs. We then extend the analysis by examining energy expenditure shares across the entire income distribution and by calculating the *Degree of Convexity (DOC)*. The DOC captures an additional dimension of regressivity, indicating *how steeply* expenditure shares decline between the lowest and highest income brackets.

Finally, we scrutinize the degree of regressivity of energy expenditures by computing "Housing Energy Expenditures Concentration and Kakwani" indices (Kakwani, 1997) and depict the corresponding energy expenditure Lorenz curves. The indicators reflect the housing related energy expenditure inequality by showing the distribution of energy expenditures in the population for different countries (including Switzerland) and years and comparing the energy expenditure concentration with the concentration of income to quantify the regressivity of energy expenditures. Such energy/electricity related Kakwani coefficients have not been computed in this form for Switzerland yet. Lastly, we decompose the concentration of energy expenditures by various covariates.[1]

Energy Poverty

From Table 1, we observe that energy poverty has decreased using information on the surveyed households when considering the Ten-Percent Rule (TPR) criterion by around 5 percentage points between 2006 and 2021. The 2M measure displays almost no change, which is plausible given that median values tend to change gradually, reflecting shifts near the maximum observed levels. Consequently, in 2021, around 17% of surveyed households had energy expenditures exceeding twice the sample median at the country level. According to the TPR, 6.4% of surveyed households in 2021 spent more than 10% of their income on energy.

Table 1: Energy poverty in Switzerland

Year	TPR	2M
2006	0.116	0.173
2007	0.100	0.174
2008	0.106	0.175
2009	0.083	0.185
2010	0.094	0.177
2011	0.102	0.186
2012	0.105	0.175
2013	0.100	0.175
2014	0.100	0.161
2015	0.085	0.173
2016	0.074	0.165
2017	0.079	0.168
2018	0.085	0.169
2019	0.066	0.154

[1] All methodological details, including data sources, analytical procedures, and model specifications, are described in detail in the published study by Ackermann, I., & Radulescu, D. (2026). *Unveiling the energy price tag – Assessing the burden of household energy expenditures among European countries. Energy Policy, 208,* 114919. https://doi.org/10.1016/j.enpol.2025.114919 and the working paper *Energy Burdens Unveiled: A Comparative Study of Household Energy Expenditure Inequality in Switzerland and EU Countries* from July 30, 2024 submitted to the SFOE.

2020	0.047	0.169
2021	0.064	0.172

In terms of energy poverty measured by the TPR (Ten Percent Rule), Switzerland and Luxembourg feature the smallest proportion of households with energy expenditures exceeding 10% of their income (see Table 9). However, when applying the 2M (twice the median) criterion, 17% of households in Switzerland report energy expenditures that are more than double the median, a rate higher than in most analysed EU countries. This discrepancy is explained by the fact that many surveyed households in these countries report high energy expenditures, which raises the national median and consequently results in a smaller proportion of households surpassing the twice-median threshold.

Energy expenditure regressivity

A first approximation of the regressivity of energy expenditures can be obtained by comparing the share of income spent on energy between the lowest and highest income quintiles. In 2021, in Switzerland, surveyed households in the poorest quintile allocated 8.0% of their equivalised disposable income to household energy expenditures, whereas households in the richest quintile spent only 2.4%. Figure 8 in the Appendix illustrates the development of income shares spent on energy. All income quintiles saw an increase in disposable income until 2014, with stronger growth among higher quintiles. Afterwards, whereas the positive trend continues for the highest income households it reverses for the poorest. Energy expenditures declined for all income groups but more pronounced for the top two, likely due to greater investments in energy efficiency and self-generation, such as solar panels. The bottom panel shows that the share of income spent on energy was largely stable over time, with higher-income groups spending a markedly smaller share than lower-income groups. Figure 9 in the Appendix shows that households with a car spend about 3 percentage points more of their income on energy than those without. Retired households also devote a larger income share to energy, mainly because of their lower disposable income. Differences appear across linguistic regions as well, with the highest shares in Ticino and the lowest among German-speaking households.

Furthermore, the difference of less than 6 percentage[2] points between the burden for the poorest and richest households in the survey is among the smallest compared to the analysed EU countries where the difference can even reach 19 percentage points (Croatia). One possible explanation for these pronounced differences is the influence of heating type. For instance, in Croatia, the share of coal heating is almost 5 percentage points higher among households belonging to the lowest income quintile compared to those in the fifth income quintile in 2020, whereas in Belgium, one of the countries with the lowest difference in the burden, heating systems of all types are very evenly distributed among income groups. Furthermore, we compute the average cost associated with each heating type for each country in 2020. Thus, Croatian households using coal heating in 2020 face an average expenditure share of 23.4%, which is the highest among all heating types. Hence, this descriptive evidence suggests that low-income households are more likely to employ heating systems that command higher expenditure shares.

With the degree of convexity, we capture another dimension of the regressivity of energy expenditure shares. Table 2 presents the results for the convexity of energy expenditure shares. Notably, for nearly all years and countries, the values are negative, indicating an abrupt decrease in energy expenditure shares as income increases. However, in 2020 only Greece features a higher absolute value than the value of -0.223 we compute for Switzerland for 2021. This suggests that in the majority of the analysed 19 European Union countries the rate at which energy expenditure shares decline with income is less pronounced and hence the degree of regressivity lower.

2 In Figure 10, we also examine the share of expenditures spent on energy across income groups and find less pronounced differences.

Table 2: Degree of convexity of energy expenditure shares in EU countries

Country	2010	2015	2020
AT	-0.058	-0.060	
BE	-0.179	-0.120	-0.083
BG	-0.098	-0.108	0.002
CY	-0.125	-0.023	-0.023
CZ	-0.103	0.062	
DE	-0.076	-0.062	-0.122
DK	-0.126	-0.061	-0.025
EE	-0.136	-0.188	-0.044
EL	-0.179	-0.229	-0.232
ES	-0.098	-0.073	-0.057
FI	-0.081	-0.114	
FR	-0.125	-0.143	-0.143
HR	-0.099	0.008	0.053
HU	-0.080	-0.179	-0.162
IE	-0.201	-0.165	
LT	-0.117	-0.094	-0.044
LU	-0.131	-0.202	-0.068
LV	-0.099	-0.075	-0.101
MT	-0.111	-0.131	-0.131
NL	-0.217	-0.210	-0.202
PL	-0.098	-0.043	
PT	-0.074	-0.147	
RO	0.003	-0.001	
SE	0.038	0.037	
SI	-0.183	-0.110	-0.127
SK	0.108	-0.061	-0.113
UK	-0.094		

Note: Own calculations. Further details regarding the methods are available in the referenced published paper. The degree of convexity reflects the average deviation of the share of income spent on energy from the linear trend spanning the lowest to the highest income group. Negative values indicate that the shares decline at a disproportionately high rate.

The Kakwani index also allows for a consistent comparison of regressivity across countries and over time.Tables 3 and 4 show a considerable variation in the degree of regressivity measured by means of the Kakwani index among the studied countries, with Luxembourg (-0.26 in 2020), Spain (-0.2 in 2020), and Switzerland (-0.21 in 2021) exhibiting the most pronounced regressivity and Bulgaria displaying the least degree of regressivity (-0.07 in 2020). A crucial aspect emphasized in our analysis is that assessing inequality in the distribution of the energy expenditure burden among households requires a more nuanced approach than solely focusing on the fraction of income spent on energy or on energy poverty.

As illustrated, the countries with the lowest or highest share of equivalent disposable income spent on energy expenditures differ from those with the lowest or highest degree of regressivity, underscoring the importance of a comprehensive examination of these dynamics.

Table 3: Summary statistics – Kakwani indices in EU states

Kakwani Total	2010	2015	2020
Min	-0.24	-0.24	-0.26
Mean	-0.14	-0.14	-0.15
Median	-0.15	-0.15	-0.16
Max	-0.03	-0.06	-0.07

Note: Own calculations. Further details regarding the methods are available in the referenced published paper. The Kakwani index compares the concentration index, which captures the distribution of energy expenditures across the income distribution, with the Gini index, which measures income inequality. Negative values indicate that the concentration of energy expenditures is lower than the concentration of income, suggesting a regressive pattern in energy expenditures.

The survey data also enables us to distinguish between various categories of energy expenditures. The fuel category encompasses spending on gasoline and diesel, while there is a separate category for electricity expenditures. The household energy category includes spending on gas, district heating, and electricity. Our analysis consistently reveals the regressive nature of energy expenditures. The numbers in Table 4 show that the degree of regressivity stayed constant over the 2006-2021 period. The table also underscores that the most pronounced regressivity occurs with respect to housing-related energy expenditures, encompassing expenditures on electricity and heating. Once again, this may simply reflect the fact that a large share of the population does not own a car and the share of low-income households without a car exceeds the share of high-income households owning a car.

Table 4: Gini index, Concentration and Kakwani indices for different energy categories for Switzerland

Year	Gini	CI ET	CI EH	CI EL	CI FU	KI ET	KI EH	KI EL	KI FU
2006	0.26	0.07	0.04	0.01	0.15	-0.19	-0.22	-0.25	-0.11
2010	0.27	0.08	0.04	0.03	0.14	-0.19	-0.23	-0.24	-0.13
2015	0.27	0.07	0.03	0.02	0.12	-0.20	-0.24	-0.25	-0.15
2020	0.28	0.07	0.05	0.01	0.11	-0.21	-0.23	-0.27	-0.17
2021	0.28	0.07	0.05	0.03	0.09	-0.21	-0.23	-0.26	-0.19

Note: Own calculations. Further details regarding the methods are available in the referenced published paper. CI = Concentration Index, KI = Kakwani Index, ET = Total energy, EH = Household energy, EL = Electricity, FU = Fuel.

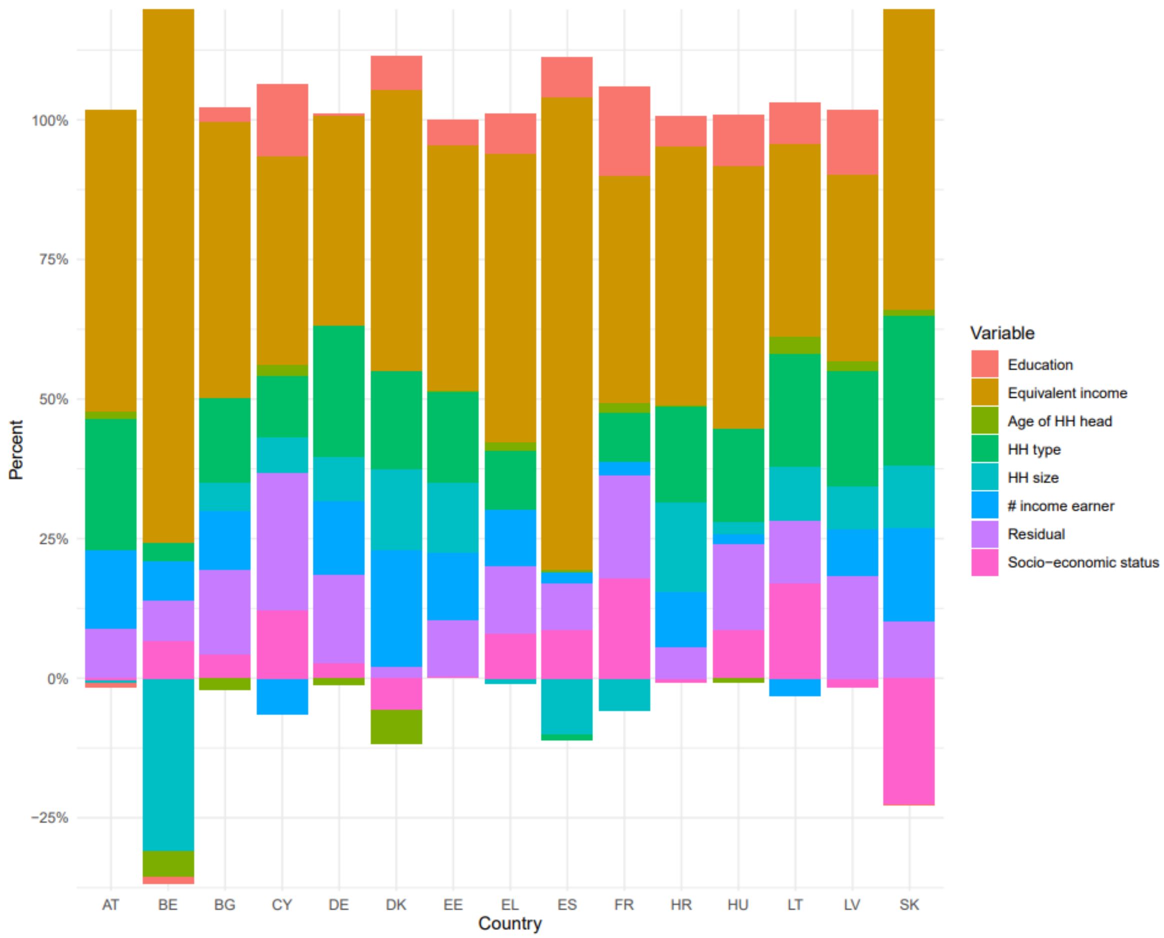
Finally, we examine the contribution of various socio-demographic variables to the overall concentration index of energy expenditures (see Figure 1). Equivalent income emerges as the main contributor to explaining the concentration of overall household energy expenditures; however, its contribution varies to a large extent. In Switzerland equivalent income alone explains more than 50% of the overall energy expenditure concentration index, but only 33% in Latvia or even 85% in Spain. However, we also find that, for some countries, variables such as household size or socio-economic status may even feature a negative contribution to the concentration of energy expenditures, thus counteracting the effect of the other variables and yielding more equally distributed energy expenditures along the income distribution. Understanding the contribution of these drivers is important in view of potential appropriate policy instruments that can be employed to address the potential adverse effects of higher energy prices.

Table 5: Contribution of various socio-demographic variables for Switzerland in 2021

Variable	Contribution	Percent
Concentration index	0.072	100.0
Equivalent income	0.040	55.6
HH size	0.006	7.7
HH type	0.007	10.3
# income earner	0.012	16.4
Residual	0.007	9.9

Note: Own calculations. Further details regarding the methods are available in the referenced published paper.

Figure 1: Decomposition of energy expenditure concentration by socio-demographic variable for European countries in 2020



Note: Own calculations. Further details regarding the methods are available in the referenced published paper.. With this decomposition we calculate the share of the energy expenditure concentration that is explained by the respective socio-demographic variable. For methodical background, see the published paper in *Energy Policy*.

2.2 WP2: Likelihood of living in polluted areas

Data and methods

Our empirical strategy draws on several complementary datasets that together allow us to examine the relationship between measured and perceived air pollution, and how both correlate with socioeconomic status (SES). A central challenge for Switzerland is that no dataset jointly provides high-resolution pollution data and household-level perception data. As a result, the associations between SES and measured pollution must be estimated separately from those between SES and perceived pollution. The Swiss case therefore relies on parallel analyses, which we subsequently contextualize using a unified dataset from the United Kingdom.

Measured Pollution and Socioeconomic Conditions in Switzerland

To quantify actual exposure to fine particulate matter ($PM_{2.5}$), we combine air quality data from two sources with detailed municipality-level socioeconomic records.

First, we use gridded $PM_{2.5}$ estimates from the Copernicus Atmosphere Monitoring Service (CAMS). CAMS provides modelled $PM_{2.5}$ concentrations at a spatial resolution of 0.1° × 0.1° (roughly 10 × 10 km), based on an ensemble of eleven state-of-the-art atmospheric models. We rely on annual averages from 2013–2022, which offer consistent coverage across Switzerland and Europe and thereby support comparative analyses.The focus on $PM_{2.5}$—widely used as a proxy for human exposure to ambient air pollution—reflects its strong and well-documented association with long-term health impacts.

Second, to obtain a more granular view of exposure within Switzerland, we incorporate the Atmospheric Composition Analysis Group (ACAG) dataset, which provides annual $PM_{2.5}$ levels at a resolution of 0.01° × 0.01° (approximately 1 × 1 km). These estimates combine satellite-derived aerosol optical depth, chemical transport modelling, and ground-based observations. We use the ACAG data primarily for Switzerland, where municipal-level socioeconomic data allow precise matching of pollution exposure with local characteristics, and CAMS data for broader European comparisons.

These pollution data are merged with the STATPOP population and household statistics of the Swiss Federal Statistical Office. STATPOP provides yearly demographic information at the municipal level, including age distribution, nationality, household size, and residential structure. To approximate socioeconomic status, we augment these data with income information derived from social insurance records and the Swiss Structural Survey (Strukturerhebung), which adds indicators such as education and employment. The resulting dataset allows us to study SES–pollution correlations with far greater spatial precision than in typical cross-national studies, although still not at the household level.

Perceived Pollution in Switzerland and Europe: EU-SILC

To analyse how pollution is perceived rather than measured, we turn to the European Union Statistics on Income and Living Conditions (EU-SILC). EU-SILC is a harmonized, nationally representative household survey conducted annually in Switzerland and 31 European countries. It provides detailed socioeconomic information—including income, education, employment, financial vulnerability, and household composition—as well as key contextual variables such as degree of urbanization (urban, suburban, rural).

Perceived air pollution is captured by the question:

> *"In the area where you live, do you have pollution, grime, or other environmental problems caused, among others, by traffic or industry?"*

This measure has been widely used as a proxy for subjective air pollution exposure in cross-country research. Although broad in wording, it reliably captures whether respondents consider their local environment to be polluted and has been shown to correlate with objective pollution levels when high-resolution spatial matching is feasible. In Switzerland, however, EU-SILC data are only available at the NUTS-2 regional level, which prevents accurate linkage with local $PM_{2.5}$ concentrations and thus precludes joint analysis of measured and perceived pollution.

This limitation is methodologically consequential: while we can estimate SES gradients in perceived pollution for Switzerland, we cannot determine whether perceptions align with actual exposure for the same households.

Linking Measured and Perceived Pollution: The UK Case

To overcome the limitations of the Swiss data—where measured and perceived pollution cannot be assigned to the same households—we incorporate a third dataset that allows full spatial matching: the Understanding Society (US) longitudinal household study from the United Kingdom.

The survey includes detailed socioeconomic information and a perception question closely aligned with EU-SILC. Most importantly, the dataset contains Lower Layer Super Output Area (LSOA) identifiers, enabling precise geographic linkage with British air quality data.

To measure actual pollution exposure in the UK, we use fine-resolution $PM_{2.5}$ estimates provided by the UK Department for Environment, Food & Rural Affairs (DEFRA). The DEFRA system integrates ground measurements from the Automatic Urban and Rural Network (AURN) with modelled pollution fields from the Pollution Climate Mapping (PCM) framework, resulting in annual $PM_{2.5}$ concentrations mapped at approximately 1 × 1 km resolution. All data are quality-assured and publicly available via the UK-AIR platform.

The DEFRA dataset is essential for our analysis because it allows us to match each surveyed household in Understanding Society to a high-resolution pollution estimate in the corresponding LSOA. This level of spatial precision is not achievable in Switzerland, where EU-SILC provides only NUTS-2 regional identifiers and STATPOP offers no pollution-perception data. As a result, the UK data provide the only environment in which we can jointly analyse SES, measured pollution, and perceived pollution for the same households.

A central motivation for combining these datasets is to examine the “perception gap”—the divergence between objectively measured pollution levels and the pollution individuals believe they are exposed to. In Switzerland, this gap cannot be quantified directly because measured pollution and perceived pollution are observed in entirely separate datasets. The analysis therefore proceeds in two steps: first, estimating the SES gradient in measured pollution using STATPOP–CAMS/ACAG; and second, estimating the SES gradient in perceived pollution using EU-SILC. Because these gradients pertain to different households, they cannot reveal whether individuals with certain socioeconomic profiles systematically under- or overestimate their own exposure. The UK dataset resolves this limitation by allowing measured and perceived pollution to be matched for the same households at a fine spatial scale, making it possible to directly estimate the perception gap and its determinants.

Methods

Our empirical approach is structured around the perception gap: the mismatch between actual pollution exposure and the subjective assessment of local air quality. Because the Swiss data do not permit joint estimation of measured and perceived pollution for the same households, we estimate two separate models—one for measured exposure and one for perceived exposure. These models describe socioeconomic gradients but cannot quantify the perception gap itself. The UK case study supplements this limitation by enabling a unified model in which perceptions can be regressed directly on DEFRA-measured pollution levels.

Measured Pollution and SES in Switzerland

To examine how pollution exposure varies with socioeconomic conditions, we estimate linear regressions of the form:

$$PM_{\{2.5_i\}} = \sum_j \beta_j \cdot SES_{\{ij\}} + \lambda_t + \varepsilon_i$$

where $PM_{2.5}$ is either the CAMS or ACAG annual concentration assigned to the municipality. The vector SES includes income, education, foreign-born status, employment, household structure, and municipality type (urban/suburban/rural). The dummy for the year controls for common shocks.

Because we cannot observe household-level locations, the SES–exposure relationship reflects municipal averages and may understate within-area inequality. These regressions are therefore interpreted as descriptive associations rather than causal effects.

Perceived Pollution and SES in Switzerland and Europe

To analyse subjective reports of pollution, we estimate logistic regressions using EU-SILC:

$$Pr\ (PerceivedPollution_i = 1) = \frac{1}{\left(1\ + exp\ \left(-\left(\Sigma_j \beta_j \cdot SES_{ij} + \lambda_t\right)\right)\right)}$$

The SES vector mirrors variables used in the Swiss exposure regressions. Because we cannot link perceptions to actual pollution levels for the same households in Switzerland, these results reveal SES differences in perception rather than misalignment between perception and exposure.

Linking Measured and Perceived Pollution: UK Models

The UK data allow us to estimate a linear probability model that combines both components (pollution exposure and perceived air pollution):

$$PerceivedPollution_{it} = \alpha + \theta\ PM2.5_{it} + \Sigma_j \beta_j\ X_{itj} + \Sigma_k \gamma_k\ C_{atk} + \lambda_t + \delta_a + \varepsilon_{it}$$

where $PerceivedPollution_{it}$ is a binary variable equal to one if individual *i* living in area *a* at time t reports being affected by air pollution. The coefficient θ captures the effect of measured $PM_{2.5}$ exposure on the probability of perceiving local pollution. X_{it} is a vector of socioeconomic characteristics, including income, education, employment status, and age. C_{at} represents weather controls—specifically average temperature and precipitation. λ_t are year fixed effects accounting for unobserved time-specific factors, and δ_a are Lower Layer Super Output Area (LSOA) fixed effects controlling for time-invariant local characteristics.

However, the OLS estimate of θ may be biased due to two sources of endogeneity. First, sorting of households may occur if environmentally aware individuals self-select into cleaner neighbourhoods, leading to a downward bias in the estimated relationship between exposure and perceived pollution

(Chay & Greenstone, 2005; Banzhaf & Walsh, 2008). Second, measurement error arises because $PM_{2.5}$ data are available at a 1 × 1 km spatial resolution, whereas household locations are observed only at the broader LSOA level, introducing potential misclassification of true exposure and attenuation bias in OLS estimates.

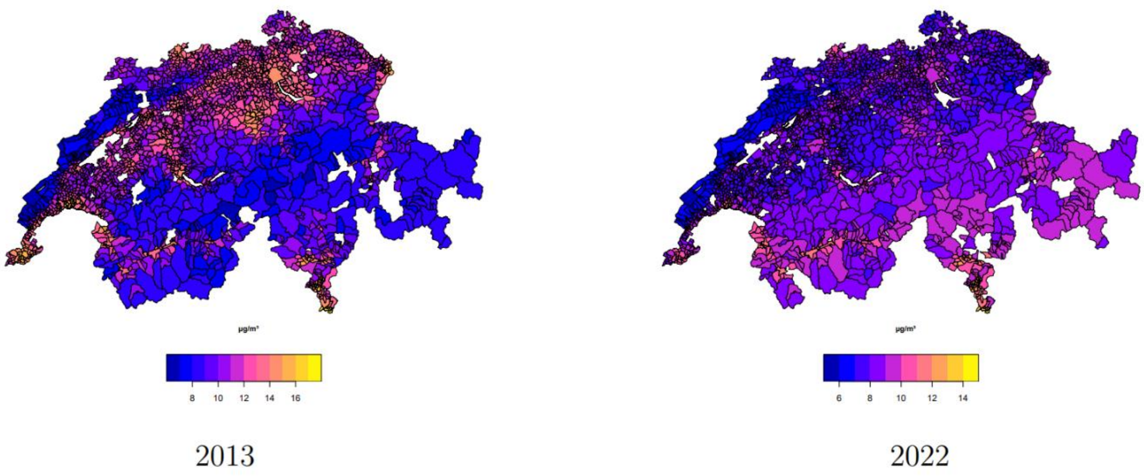
To address these issues, we estimate a two-stage least squares (2SLS) specification using wind speed as an instrumental variable for local $PM_{2.5}$ concentrations. Higher wind speeds increase atmospheric dispersion, thereby reducing local pollution levels (Sarmiento, 2022).[3] Conditional on weather controls and fixed effects, wind speed is plausibly exogenous to individual perceptions of air pollution, providing a valid source of exogenous variation in $PM_{2.5}$ exposure.

Before turning to the results, it is important to highlight how the data constraints in Switzerland shape our interpretation. Because we cannot observe measured and perceived pollution for the same households, the Swiss results speak to the socioeconomic patterning of exposure and perception separately, but not to their alignment. This alignment—i.e., the perception gap—is examined directly only in the UK case, where measured and perceived pollution can be matched. The UK findings therefore contextualize Swiss patterns and offer insight into whether, and for whom, perceptions deviate from reality.

Results

Figure 2 reveals that air pollution concentrations are particularly high in urban areas and Alpine valleys. In contrast, rural areas appear to be largely unaffected—at least when looking at annual municipal averages. This pattern confirms the well-documented association in the literature between urbanity and elevated levels of air pollution. Looking at absolute values, we observe that in 2013, average PM2.5 exposure significantly exceeded the former WHO guideline of 10 µg/m^3 in many municipalities. On average, the PM2.5 concentration was 12.6µg/m^3. By 2022, the situation had improved, yet numerous municipalities still report values above the 10 µg/m^3 threshold; the average concentration fell to 9.1 µg/m^3. Because the WHO has since tightened its recommended guideline to 5 µg/m^3, even today's lower pollution levels remain well above what is considered health-protective**.**

Figure 2: Spatial distribution of the average measured air pollution in CH for 2013 and 2022

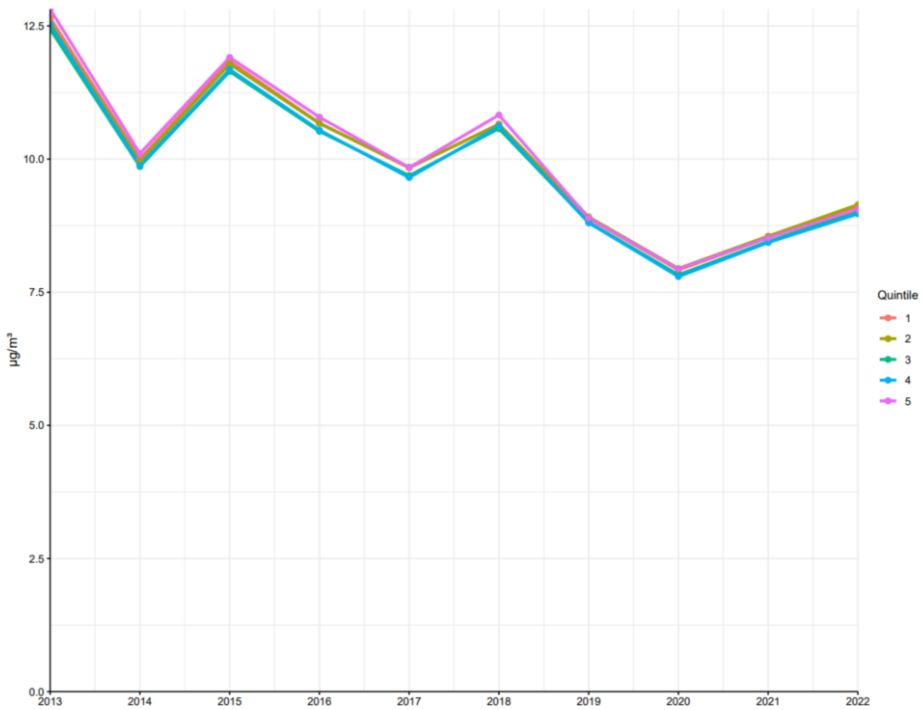


Note: Own illustration based on data from ACAG and FSO.

[3] We check the validity of the instrument in Table 12 in the appendix. The high F-statistic shows that the instrument is relevant. We find the expected negative correlation between wind speed and air pollution exposure.

This overall downward trend in $PM_{2.5}$ is also evident in Figure 3, which plots annual average exposure by income quintile. Yet despite the decline in pollution, we observe virtually no separation between income groups—the lines for all quintiles run nearly parallel across the entire period. One possible explanation is that the data linkage was performed at a relatively aggregated level, potentially masking variation in exposure by income. Even though the matching was carried out at the finest spatial resolution available, it is still possible that the exposure assignment is not sufficiently precise. In this setting, even modest measurement error arising from within-grid variation in $PM_{2.5}$ concentrations can attenuate true socioeconomic gradients, making it appear as though exposure is evenly distributed across income groups. Future research would benefit from access to more granular data, provided such data become available.

Figure 3: Development of the average measured air pollution by income quintile in CH 2013- 2022



Note: Own illustration based on data from ACAG and FSO.

Building on this initial descriptive evidence, we now turn to regression-based analyses of the relationship between socioeconomic status and measured $PM_{2.5}$ concentrations. Table 6 reports the results for both the ACAG and CAMS data sources. The estimations use a sample restricted to individuals with positive income. Unsurprisingly, urban and suburban areas experience higher levels of air pollution. PM2.5 concentration is positively correlated with income. PM2.5 levels are also positively correlated with being a foreign-born individual and higher educational attainment, whereas it is negatively correlated with having children and being employed. The positive correlation between measured PM2.5 and income or education stands in contrast to findings in the existing literature. However, we need to emphasize that the data linkage may be insufficiently precise, and these results should not be interpreted as evidence of causal relationships. Even though we control for urbanity, we still fall short to control for other unobserved differences between regions such as the city size. For example, Zürich is more polluted than some urban labelled areas in other cities and the income level in Zürich is much higher than in other urban areas causing omitted variable bias. This precludes a causal interpretation. When municipality fixed effects are included to account for time-invariant, area-specific heterogeneity, the association between pollution and income becomes statistically insignificant, whereas the association with education becomes significantly negative. The estimates reported in Table 10 in the Appendix thus align more closely with the prevailing findings in the existing literature (Hajat et al., 2015).

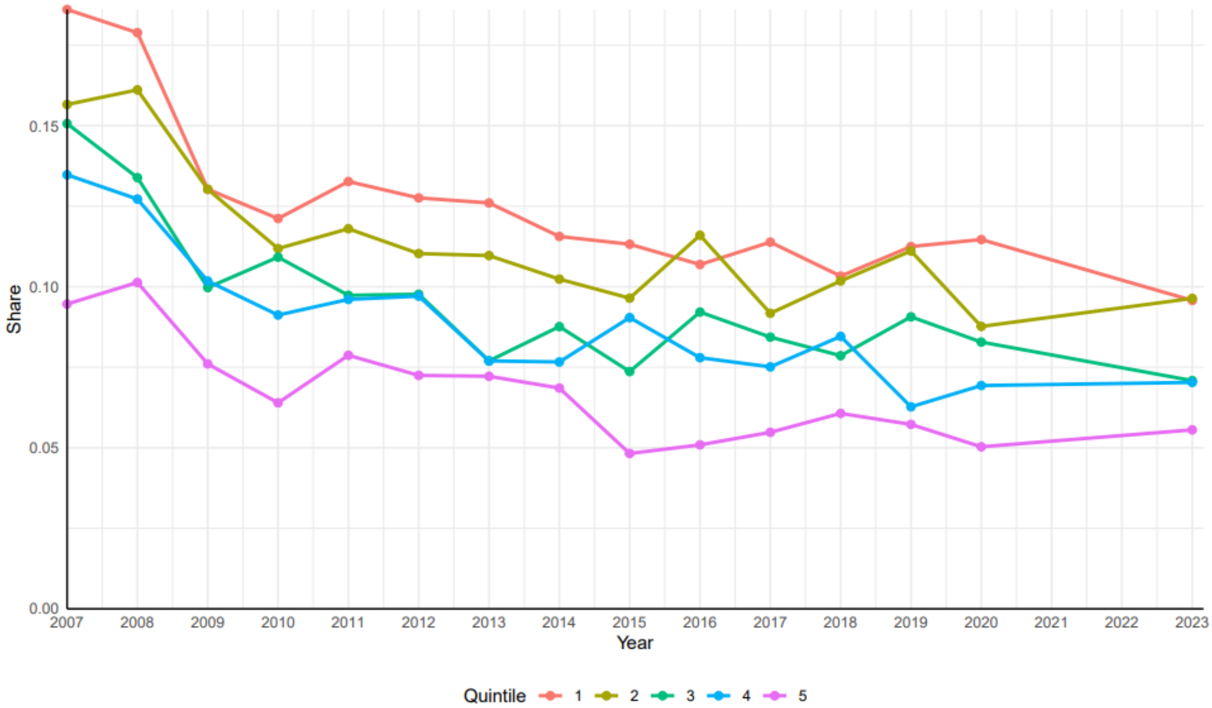
Table 6: Measured pollution and socioeconomic characteristics

	Dependent variable:	
	ACAG	CAMS
	(1)	(2)
Log income	0.003***	0.049***
	(0.001)	(0.001)
Work	−0.088***	−0.114***
	(0.002)	(0.003)
Education	0.109***	0.150***
	(0.002)	(0.002)
Foreigner	0.179***	0.215***
	(0.002)	(0.002)
HH size	0.002**	−0.009***
	(0.001)	(0.001)
Urban	1.791***	0.948***
	(0.002)	(0.003)
Suburban	0.513***	0.395***
	(0.003)	(0.004)
Age	0.0003***	0.001***
	(0.0001)	(0.0001)
Children	−0.033***	0.020***
	(0.002)	(0.003)
Observations	2,297,766	2,308,559
Year FE	Yes	Yes
Note: Normal standart errors.	Data: 2013-2022, Observations with positive income.	*p<0.1; **p<0.05; ***p<0.01

The distribution of *perceived* air pollution between income groups is illustrated in Figure 4. It reveals several key findings: First, the share of survey households reporting that they feel affected by air pollution has been decreasing over time. This decline mirrors the documented improvement in objective air quality, suggesting that households generally register improvements in environmental conditions. Second, lower income quintiles consistently report a higher share of affected households.[4] Third, the gap between income quintiles remains more or less stable throughout the observation period. In 2020, the difference between the share of respondents who report to feel affected by pollution and grime in the lowest and highest income quintile amounts to approximately 7 percentage points. This persistent disparity can be interpreted in two ways. It may reflect genuine differences in exposure that are not captured in the aggregated pollution data used for Switzerland, or it may indicate that lower-income households are more likely to perceive and report environmental problems. The latter explanation is less intuitive, as there is little conceptual or empirical foundation for assuming that lower-income individuals systematically overreport their exposure. Instead, the pattern suggests that the descriptive estimates of measured pollution—showing no substantial differences across income groups—may be masking within-municipality disparities that the available data cannot detect. The divergence between the flat socioeconomic gradient in measured pollution and the pronounced gradient in perceived pollution is therefore informative: it highlights the presence of a perception gap in Switzerland and points to limitations in the spatial precision of the measured exposure data. This gap motivates further investigation using data environments, such as the UK, where measured and perceived pollution can be matched for the same households at a finer spatial scale.

[4] The thresholds of the equivalized disposable income quintiles are 32 '834, 45' 174, 58 '084, 77' 383 Euro.

Figure 4: Development of the share of the population feeling affected by air pollution in Switzerland by income quintile



Note: Own illustration based on data from Eurostat.

In the following we present the results of logistic regressions on the correlation between socioeconomic characteristics and the probability to feel subject to pollution and grime. Column 2 in Table 7 presents the resulting coefficients for Switzerland. These results should once again be interpreted as correlations and do not imply any causal relationships. Households living in urban or suburban areas of Switzerland report feeling more affected by air pollution. This aligns with findings in the literature and with our analysis of PM2.5 exposure. This pattern suggests that individuals living in more polluted environments not only experience higher exposure but are also more aware of local environmental conditions. Income is negatively associated with perceived air pollution. Foreign-born individuals, tenants, individuals who report difficulties in paying their bills, and households with older household heads are more likely to report feeling affected by air pollution. These patterns are broadly consistent with findings in environmental justice research, which often documents higher perceived environmental burdens among socioeconomically vulnerable groups. In contrast to much of the existing literature, we find a positive correlation between education and perceived air pollution. This result mirrors the unexpected positive correlation between education and measured exposure. One plausible explanation is that individuals with higher educational attainment in Switzerland are disproportionately concentrated in major metropolitan areas—such as Zürich, Basel, or Geneva—where pollution levels are structurally higher than in smaller urban centres. As a result, the education coefficient may partly reflect spatial sorting rather than sensitivity or awareness. Taken together, the results for Switzerland reveal both parallels and discrepancies between measured and perceived pollution. Some SES variables, such as urban residence, foreign nationality, and financial strain, show similar signs across both dimensions; others, such as income, differ markedly. Crucially, however, these patterns must be interpreted in light of the data limitation that measured and perceived pollution are observed in entirely different datasets and for different households. This structural separation prevents direct assessment of how individual perceptions align with actual exposure in Switzerland.

Table 7: Perceived pollution and socioeconomic characteristics

	Dependent variable: Pollution									
	EU	CH	DE	IT	PL	BG	ES	RO	SE	NO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log income	−0.129***	−0.253***	−0.044***	0.005	0.099***	−0.242***	−0.014	0.099***	0.169***	−0.034
	(0.002)	(0.021)	(0.014)	(0.009)	(0.013)	(0.019)	(0.013)	(0.016)	(0.028)	(0.027)
Education	0.046***	0.043*	0.024*	0.120***	−0.080***	−0.081***	0.097***	−0.072***	0.190***	−0.047*
	(0.004)	(0.024)	(0.015)	(0.014)	(0.021)	(0.026)	(0.018)	(0.026)	(0.026)	(0.026)
Foreigner	−0.010	0.072**	−0.162***	−0.250***	−0.123	−0.033	−0.188***	0.032	−0.298***	0.002
	(0.007)	(0.030)	(0.047)	(0.028)	(0.163)	(0.147)	(0.037)	(0.355)	(0.064)	(0.062)
Tenant	0.165***	0.231***	0.168***	0.118***	0.220***	−0.002	0.067***	0.200***	0.454***	−0.011
	(0.004)	(0.026)	(0.016)	(0.015)	(0.029)	(0.056)	(0.023)	(0.063)	(0.028)	(0.039)
HH size	0.032***	−0.013	−0.028***	0.061***	0.008	0.161***	−0.003	0.010	−0.138***	−0.109***
	(0.002)	(0.013)	(0.009)	(0.006)	(0.006)	(0.009)	(0.008)	(0.009)	(0.015)	(0.015)
Urban	0.941***	0.566***	0.916***	1.577***	0.928***	1.274***	1.082***	1.039***	0.862***	0.334***
	(0.004)	(0.034)	(0.023)	(0.018)	(0.017)	(0.026)	(0.021)	(0.021)	(0.030)	(0.029)
Suburban	0.447***	0.174***	0.330***	0.744***	0.522***	0.436***	0.537***	0.570***	0.240***	0.109***
	(0.005)	(0.034)	(0.023)	(0.019)	(0.020)	(0.035)	(0.026)	(0.029)	(0.035)	(0.034)
Age	−0.001***	0.009***	−0.011***	0.003***	−0.0002	−0.010***	−0.004***	−0.003***	−0.002**	−0.001*
	(0.0001)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rate rich	0.258***	−0.144	0.097	0.381***	1.078***	−0.106	0.055	−0.015	−0.141	−0.162
	(0.019)	(0.096)	(0.083)	(0.051)	(0.134)	(0.173)	(0.075)	(0.400)	(0.154)	(0.139)
Children	−0.075***	−0.055	−0.018	−0.097***	0.033	−0.092***	0.072***	0.153***	0.212***	0.048
	(0.005)	(0.038)	(0.024)	(0.017)	(0.021)	(0.033)	(0.021)	(0.029)	(0.042)	(0.042)
No financial cushion	0.223***	0.491***	0.246***	0.233***	0.360***	0.218***	0.373***	0.271***	0.252***	0.497***
	(0.004)	(0.028)	(0.017)	(0.013)	(0.016)	(0.027)	(0.018)	(0.019)	(0.034)	(0.032)
Observations	3,282,145	101,692	130,707	270,868	208,754	83,087	192,863	103,868	102,993	98,431

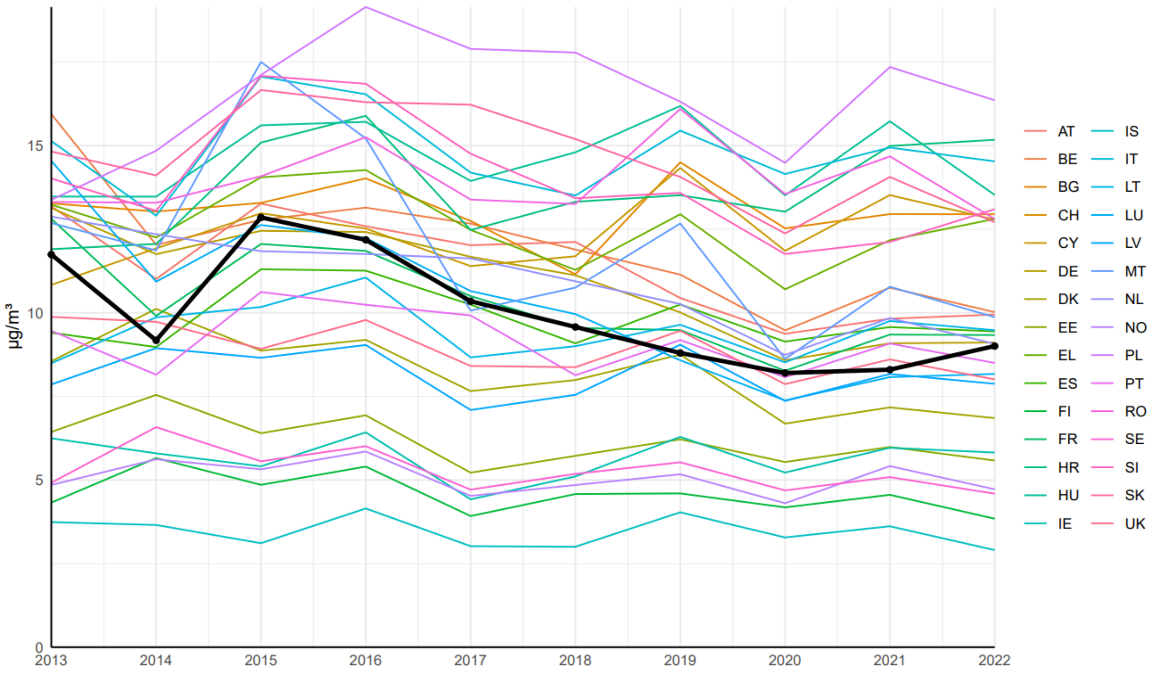
Note: normal standard errors in brackets *p<0.1; **p<0.05; ***p<0.01

Turning to the broader European context, we find that the correlations between socioeconomic status (SES) and reported exposure are largely consistent between Switzerland and the EU sample. As shown in Table 7, the main determinants of our dependent variable of interest—urbanity, income, tenant status and education—exhibit the same sign and similar statistical significance in both column (1) and column (2). The coefficients for urban and suburban residence are substantially larger in the EU sample, which likely reflects the presence of large metropolitan regions—such as Paris, Milan, or Warsaw—where pollution levels and perceived environmental burdens are considerably higher than in Swiss urban areas. The EU regression results further show that household size is positively associated with perceived pollution, while having children is negatively associated. Interestingly, the positive association between foreign nationality and perceived pollution observed in Switzerland does not generalize to the EU aggregate, nor to most individual countries, highlighting the importance of national context in shaping environmental percepti**n.** To provide a more nuanced comparison, we also examine country-specific regressions. While effect sizes and significance levels vary substantially across countries, some patterns are remarkably consistent. Urban and suburban households almost universally report higher perceived pollution. Moreover, **a** lack of financial security tends to be strongly and positively correlated with perceived environmental problems, reinforcing the view that socioeconomic vulnerability heightens both environmental exposure and the subjective experience of environmental risk. This finding is notable because individuals facing financial hardship may have fewer resources and less capacity to monitor, interpret, or mitigate environmental conditions, yet still perceive their surroundings as more burdensome.

Comparing $PM_{2.5}$ concentrations in Switzerland (marked in black in Figure 5) with those in other European countries shows that Switzerland occupies a middle position in terms of air pollution exposure. Figure 5 illustrates that this relative position has remained fairly stable from 2012 to 2022. The figure is not intended to single out particular countries but rather to situate Switzerland within the wider European distribution of air quality. Even so, several clear patterns emerge. Scandinavian countries consistently anchor the lower end of the distribution, with Iceland and Finland exhibiting the lowest $PM_{2.5}$ levels, followed by Norway and Sweden. At the other extreme, Poland reports the highest pollution levels throughout most of the period, with Italy and Hungary also regularly appearing among the most polluted countries.

The cross-country spread in 2022 is considerable. Iceland recorded a $PM_{2.5}$ concentration of 2.90 µg/m³—a value well below even the most stringent WHO guidelines—whereas Poland reported 16.36 µg/m³, far above both the former and revised WHO recommendations. Switzerland's average concentration of 9.01 µg/m³ places it 12th lowest among the 30 European countries for which data are available. This ranking underscores that while Switzerland performs relatively well in a European comparison, its $PM_{2.5}$ levels remain nearly double the latest WHO guideline of 5 µg/m³, indicating that there is still room for further improvement from a public health perspective.

Figure 5: Average PM2.5 exposure in Switzerland compared to European countries in 2013-2022



Note: Own illustration based on data from CAMS.

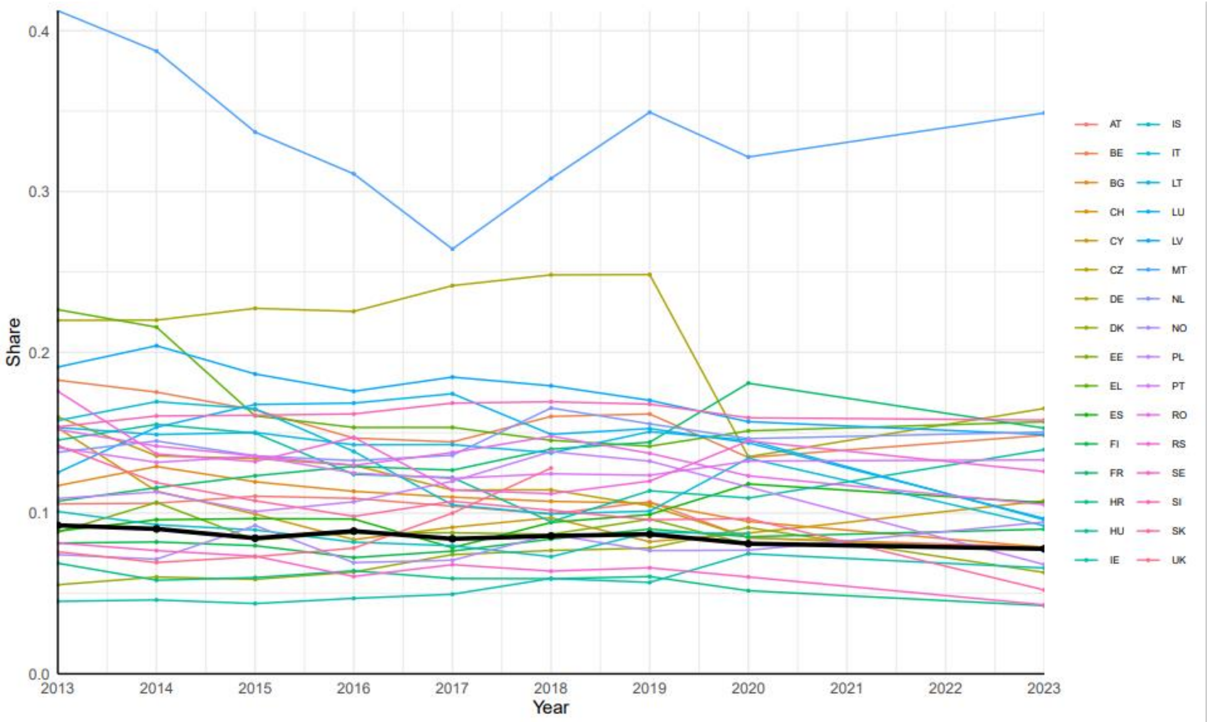
Focusing on perceived air pollution reveals notable deviations from the patterns observed for measured $PM_{2.5}$ concentrations. Figure 6 shows that between 2013 and 2020, the share of respondents reporting that they feel affected by air pollution remained broadly stable in several countries (such as Switzerland and Ireland) and even declined in others (such as Germany or Latvia). Throughout the entire period, Switzerland consistently ranks among the countries with the lowest levels of *perceived* pollution. In some years, Ireland, Croatia, and the Scandinavian countries report even lower values, but Switzerland remains firmly positioned in the lower segment of the distribution.

At the opposite end, Malta reports the highest perceived pollution levels year after year, while Germany also displays persistently elevated values. In 2023, the share of respondents who stated that they were affected by air pollution ranged from 4.2% to 34.9% across Europe. Switzerland's value of 7.8% places it eight lowest among all countries, reinforcing its position as one of the least environmentally burdened according to subjective assessments.

When comparing these perceptions with objectively measured $PM_{2.5}$ concentrations, however, a perception gap emerges. Switzerland's subjective ranking is more favourable than what its actual pollution levels would predict, suggesting that Swiss residents tend to overestimate the cleanliness of their local air in a European comparison. A similar pattern appears in Croatia. Conversely, countries such as Malta and Germany appear to underestimate their relative position: residents perceive themselves as more affected than national exposure levels alone would imply.

The Scandinavian countries, by contrast, exhibit close alignment between objective exposure and subjective perception; they report both the lowest measured pollution and the lowest perceived pollution. This correspondence reflects the categorization proposed by Chiarini et al. (2021), who distinguish between countries that overestimate, underestimate, or accurately assess their air quality. Our results place countries in the same broad categories: Switzerland and Croatia as overestimators; Malta and Germany as underestimators; and the Scandinavian countries as consistent realists with both low exposure and low perceived pollution.

Figure 6: Development of the share of the population feeling affected by air pollution in Switzerland compared to European countries in 2013-2023



Note: Own illustration based on data from Eurostat.

As previously discussed, comparing air pollution exposure and perception in Switzerland—and their correlation with socioeconomic status (SES)—is constrained by inconsistencies in the underlying datasets and by limited spatial granularity. To address these limitations, we turn to the United Kingdom, where individual-level survey data can be matched to high-resolution $PM_{2.5}$ measurements. This setting enables a more direct and conceptually consistent examination of how actual exposure shapes perceived pollution. As a result, the UK case study offers valuable insight into the relationship between exposure and perception in a Western European country with data structures that allow both to be analysed jointly.

Table 8 reports the results from linear probability models (LPMs) estimating the relationship between measured $PM_{2.5}$ concentrations and the probability of reporting local air pollution. In the baseline model without area fixed effects (column 1), the coefficient on $PM_{2.5}$ is positive and significant: a 1 µg/m³ increase in $PM_{2.5}$ is associated with a 2.2-percentage-point increase in the likelihood of reporting pollution. This suggests that individuals in more polluted locations tend to recognize and report their exposure—a finding consistent with the sorting literature discussed earlier.

Once Lower Layer Super Output Area (LSOA) fixed effects are included (column 2), the coefficient becomes negative and substantially smaller in magnitude. This reversal reflects the difference between cross-sectional and within-area variation: with LSOA fixed effects, identification comes only from changes in pollution within the same neighbourhood over time. The negative sign therefore indicates that year-to-year fluctuations within an area do not translate straightforwardly into changes in perceived pollution. Put differently, the positive cross-sectional association (column 1) reflects differences between locations, whereas the fixed-effects specification captures a distinct mechanism—how individuals respond to temporal variation in their own area.

The 2SLS results (column 3), using wind speed as an instrument for $PM_{2.5}$, further illustrate this point. The magnitude of the coefficient becomes more negative while the statistical significance weakens, implying that correcting for measurement error and potential sorting reduces the precision of the estimate. Economically, the estimated effects are small: in the fixed-effects specification, a 10% increase in $PM_{2.5}$ raises the probability of reporting pollution by only about 0.4 percentage points, while the IV estimate is not statistically significant at the 5% level. These findings underscore the difficulty of interpreting within-area variation, especially when long-term awareness trends and environmental policies evolve concurrently with pollution levels.

Table 8: Effect of $PM_{2.5}$ exposure on perceived air pollution

	(1) LPM	**(2) LPM**	**(3) 2SLS**
$PM_{2.5}$	0.022***(0.001)	-0.004**(0.002)	-0.012*(0.006)
SES controls	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
LSOA FE	No	Yes	Yes
Observations	83,171	83,171	83,171

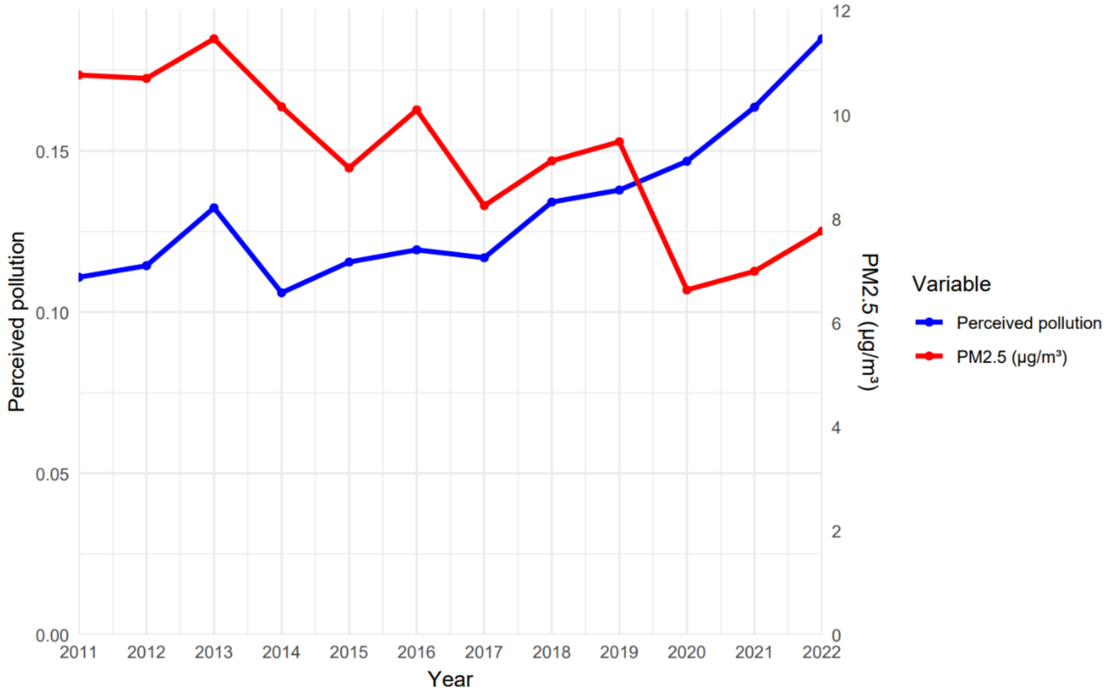
*Clustered (LSOA) standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

Figure 7 helps rationalize these patterns. While actual exposure has declined markedly over time, perceived pollution has increased. This growing awareness likely reflects the visibility of environmental policy interventions—such as the expansion of low-emission zones, the phase-out of coal power plants, and the implementation of London's air pollution alert system—which improve objective air quality but simultaneously heighten the salience of air pollution as a public issue.

This dynamic is not uniform across areas, and this heterogeneity matters for the estimation. Although year fixed effects control for nationwide temporal trends, differential trajectories across LSOAs may still bias estimates if awareness and exposure evolve differently in high- and low-pollution areas. In many UK cities, air quality improvements have been most pronounced in neighbourhoods starting from higher pollution baselines, where public awareness campaigns and regulatory interventions were concentrated.

Suggestive evidence for this interpretation is presented in Table 11 in the Appendix. The effect of $PM_{2.5}$ on perceived air pollution is positive in low-pollution areas but negative in high-pollution areas. This indicates that individuals in cleaner neighbourhoods respond to short-term variations in pollution, whereas the negative estimates in highly polluted areas may reflect the combined influence of environmental policies that not only reduce pollution but also amplify awareness. In these areas, declining pollution and rising concern about air quality may move in opposite directions, generating the negative within-area correlations observed in the fixed-effects and IV models.

Figure 7: Development of air pollution exposure and perception in the UK in 2011-2022



Note: Own illustration based on data from Understanding Society and DEFRA.

3 Conclusions and outlook

3.1 WP1: Distribution of energy related living expenditures

Switzerland exhibits one of the lowest household energy expenditure burdens in Europe, with energy spending representing only 8.0% of disposable income for the poorest surveyed households and 2.4% for the richest surveyed households in 2021. This difference of less than six percentage points is among the smallest in Europe—far below countries like Croatia, where the gap reaches 19 percentage points. Energy expenditure shares are relatively uniform across Swiss regions, though slightly higher in the French- and Italian-speaking areas. The low overall energy burdens are also evident from the low levels of energy poverty according to the Ten Percent Rule. In terms of regressivity, Switzerland's energy expenditure pattern remains notably regressive (Kakwani index around -0.21), but is broadly comparable to that observed in other European countries.

Policy implications suggest that while Swiss households are relatively shielded from energy cost shocks, inequalities in the energy burden persist. Targeted support for vulnerable households, energy-efficiency investments, and continued monitoring of regional disparities could help mitigate future distributional impacts of rising energy prices.

3.2 WP2: Likelihood of living in polluted areas

Even though air pollution levels in European countries are far below those observed in the most affected regions of the world, they remain a public health concern. The absolute levels still exceed WHO thresholds of annual average concentrations of 5 µg/m^3, especially in urban areas. Switzerland has a $PM_{2.5}$ concentration of 9.01 µg/m^3 which ranks 12th lowest among the 30 European countries in the sample.

Perceived air pollution tells a different story.The share of respondents who report to feel subject to pollution in Switzerland is consistently among the lowest in Europe. In some years, Ireland, Croatia, and several Scandinavian countries report even lower levels, but Switzerland remains in the lower tail of the distribution. In 2023, perceived pollution ranged from 4.2% to 34.9% of surveyed households across Europe; Switzerland stood at 7.8%, the eight lowest value in the sample. This gap between objective exposure and subjective assessment suggests that Switzerland tends to view its air quality more positively than its measured $PM_{2.5}$ levels alone would indicate.

In our analysis for Switzerland, we find that $PM_{2.5}$ concentrations are positively correlated with income and higher educational attainment—results that stand in contrast to much of the international literature. Given the coarse spatial resolution of available Swiss data and the need to link pollution and socioeconomic information at the municipal level, these correlations must be interpreted cautiously. Spatial aggregation and omitted variable bias likely play a substantial role, particularly because high-income and highly educated households are concentrated in larger urban centres where pollution levels are structurally higher.

Perceived pollution patterns, by contrast, are broadly in line with expectations. Households in urban and suburban municipalities report higher perceived exposure, reflecting their objectively higher pollution levels. Perceived pollution declines with income, indicating that wealthier households feel less burdened by air quality issues. Foreign-born individuals report higher perceived pollution, which may reflect either higher exposure, heightened risk awareness, or different expectations regarding environmental quality. Education is positively associated with both measured and perceived pollution, suggesting that more educated individuals may be more attuned to environmental issues, even when differences in objective exposure are modest.

The inability to precisely match individual-level perceptions with individual-level exposure remains a central challenge in the Swiss context. Without household-level air pollution measurements, it is difficult to assess how accurately residents perceive their own environmental conditions, a limitation that affects both research and policy design. Accurate perceptions matter: they shape protective behaviour during pollution episodes and influence willingness to pay for cleaner air, which in turn informs regulatory and infrastructural decisions.

Preliminary evidence from the United Kingdom—where individual survey data can be linked to high-resolution pollution measurements—indicates that people are generally aware of whether their local area is more or less polluted. However, once local characteristics are controlled for, the relationship between year-to-year variation in pollution and perceptions becomes more nuanced. Individuals appear to register broad differences in average pollution levels, but environmental policy interventions, such as low-emission zones, coal phase-outs, and targeted information campaigns like the London Air Pollution Alert, have simultaneously reduced exposure and heightened awareness. These dynamics can lead to a divergence between measured improvements in air quality and rising concern about pollution.

Further research should explore these relationships within Switzerland. Improving the availability, granularity, and accessibility of local air quality information would help support environmental and energy justice, particularly because awareness of pollution tends to be higher among more educated individuals. Ensuring that information is communicated in a clear, accessible, and locally relevant manner could help narrow perception gaps and enable all population groups—not only the well-informed—to take appropriate protective actions and participate meaningfully in environmental decision-making.

4 National and international cooperation

Ivan Ackermann will conduct a three-month research visit at UC Berkeley (Haas School of Business) from March to May 2026, to work with Prof. Reed Walker. This research visit will be partly funded by the UniBE Short Travel Grants Funding Programme.

5 Publications and other communications

The findings of the first part of the project have been presented at the SURED conference, the Annual Conference of the Swiss Society of Economics and Statistics, the Annual Conference of EAERE and the Annual Conference of IIPF between June and August of 2024. The research on the first part of the project resulted in a publication:

Ackermann, Ivan and Radulescu, Doina, Unveiling the energy price tag - Assessing the burden of household energy expenditures among European countries (2026). Energy Policy Volume 208

Link: https://doi.org/10.1016/j.enpol.2025.114919

The findings of the second part of the project have been presented at the Annual Conference of the Swiss Society of Economics and Statistics, the Annual Conference of EAERE and the Swiss workshop on "Environmental, Resource and Energy Economics" between June and November of 2025.

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7 Appendix

Table 9: Energy poverty indices for European countries in 2020

Country	TPR	2M
AT	0.228	0.150
BE	0.216	0.139
BG	0.760	0.094
CY	0.565	0.121
DE	0.317	0.100
DK	0.204	0.184
EE	0.370	0.194
EL	0.620	0.132
ES	0.322	0.185
FR	0.287	0.209
HR	0.801	0.116
HU	0.694	0.096
LT	0.571	0.173
LU	0.082	0.137
LV	0.666	0.139
MT	0.258	0.152
NL	0.144	0.097
SI	0.686	0.093
SK	0.635	0.095

Table 10: Measured pollution and socioeconomic characteristics

	Dependent variable:	
	ACAG	CAMS
	(1)	(2)
Log income	0.001*	−0.000
	(0.001)	(0.001)
Work	−0.002*	0.002
	(0.001)	(0.001)
Education	−0.003***	−0.010***
	(0.001)	(0.003)
Foreigner	−0.002*	0.000
	(0.001)	(0.002)
HH size	−0.002***	−0.002***
	(0.000)	(0.001)
Age	0.000*	−0.000*
	(0.000)	(0.000)
Children	0.001	0.001
	(0.001)	(0.001)
Observations	2,297,766	2,308,559
Year FE	Yes	Yes
Area FE	Yes	Yes

Clustered standard errors on municipality level. *Data: 2013-2022, Observations with positive income.* *p<0.1; **p<0.05; ***p<0.01

Table 11: Effect of $PM_{2.5}$ exposure on perceived air pollution by pollution level

	2SLS
$PM_{2.5}$	0.032*(0.019)
$PM_{2.5}$ x high pollution area	-0.032**(0.013)
SES controls	Yes
Weather controls	Yes
Year FE	Yes
LSOA FE	Yes
Observations	83,171

*Clustered (LSOA) standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

Table 11: First stage - Effect of wind speed on $PM_{2.5}$ exposure

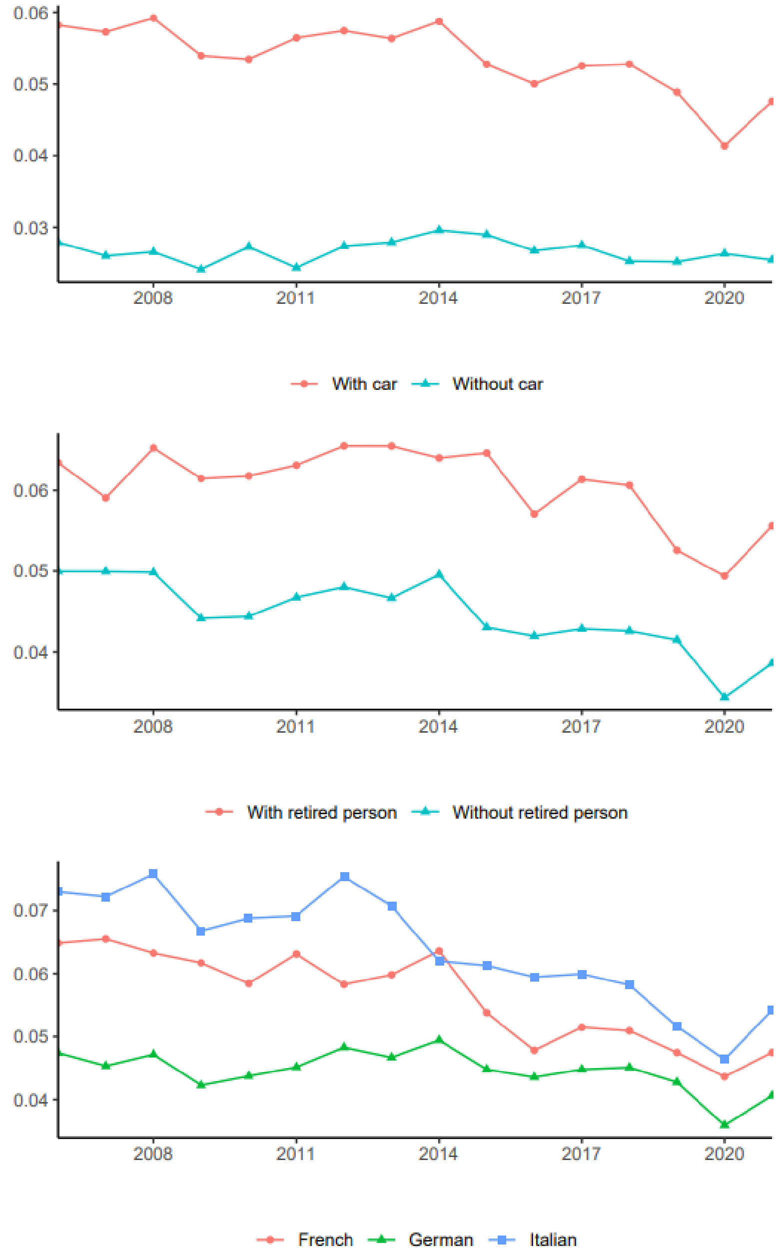
Wind speed	-1.43* (0.031)
Socioeconomic controls	Yes
Weather controls	Yes
Year FE	Yes
LSOA FE	Yes
Observations	83,171
F-statistic	6,599

*Clustered standard errors (at LSOA level) in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Figure 8: Development of average income, average energy expenditures, and share of income spent on energy by quintile

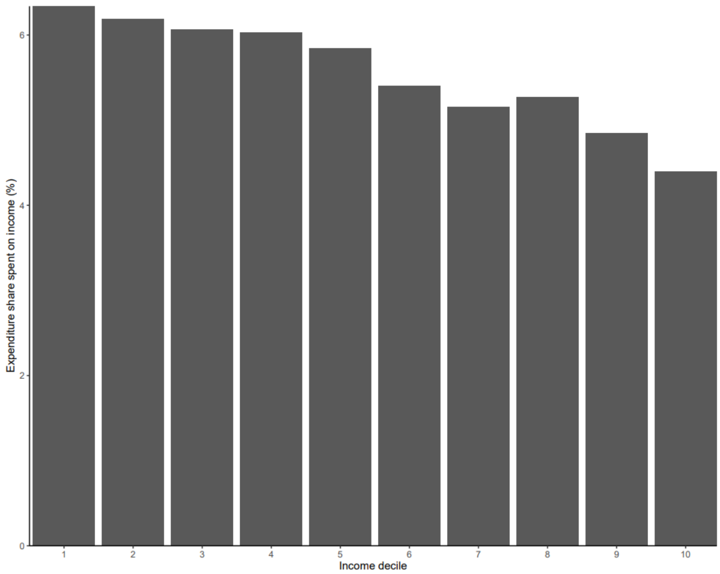
Note: Own illustration based on data from FSO.

Figure 9: Share of income spent on energy for different household compositions



Note: Own illustration based on data from FSO.

Figure 10: Share of expenditures spent on energy by income decile (2021)



Note: Own illustration based on data from FSO.

Energy Burdens Unveiled: A Comparative Study of Household Energy Expenditure Inequality in Switzerland and EU Countries*

Ivan Ackermann† Doina Radulescu‡

July 30, 2024

Abstract

Recent years have seen increased interest in the distribution of household energy expenditure burdens across income levels. Using data from the Swiss Household Budget Survey (2006-2017) and the European Household Budget Survey (2010, 2015, 2020), we quantify energy poverty and assess the regressivity of household energy expenditures, including the impact of recent energy price surges.

In 2017, the energy expenditure shares of equivalent income were 8.6% for the lowest income quintile and 2.6% for the highest in Switzerland, placing it among the lowest burdened compared to most EU economies. Energy poverty, defined as households with energy expenditures exceeding 10% of their income, is lowest in Switzerland and Luxembourg. However, using the criterion of expenditures exceeding twice the national median, Switzerland had one of the highest values at 17%.

We also examined the inequality of the energy expenditure burden. Switzerland shows relatively high values for the convexity of energy expenditure shares and Kakwani index implying a higher degree of regressivity compared to the majority of the EU counterparts.

Equivalent income was the primary factor in energy expenditure inequality, contributing over 50% to the overall concentration index. Age of household head and household size contributed negatively. This suggests that policies beyond income-based transfers may be necessary to address the adverse effects of an increasing energy expenditure burden.

Furthermore, our findings underscore the importance of using multiple measures to accurately assess the allocation of energy expenditure burdens within the population.

Keywords: Energy prices; energy expenditures; inequality; regressivity; Kakwani.
JEL Codes: D31; H23; Q48

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1 Introduction

In the current landscape, addressing climate change and ensuring energy security stands out as crucial priorities for policymakers globally. Post-pandemic and in the wake of geopolitical events like the Ukraine-Russia conflict, the intricate dance between demand and supply forces in energy markets has resulted in substantial price hikes. The equity dimension of these soaring energy prices takes center stage in the realms of climate change research and the ongoing transition of modern energy systems towards renewable sources.

Particularly noteworthy is the intersection of policies aimed at mitigating negative environmental impacts, such as carbon pricing, with the potential to escalate the costs of energy and downstream goods. This dynamic often triggers unintended consequences on individual welfare, casting a shadow on the acceptability of such policies. The energy sector, in particular, faces scrutiny due to the potential equity issues stemming from escalating energy taxes and regulatory measures.

These developments impact households differently, contingent on their income and other socio-demographic characteristics. Numerous studies on climate change mitigation and the shift to renewable energy underscore the equity concerns arising from energy price hikes (Hassett et al., 2009). The disproportionate impact on low-income households, which allocate a higher share of their disposable income to energy consumption, emphasizes the need to comprehend the redistributional implications of energy policies. This entails, on the one hand, understanding the challenges related to energy poverty, defined as a situation where households struggle to access energy products and services, which may be exacerbated by high energy prices and inefficient housing conditions. On the other hand, it also calls for a careful scrutinization of the allocation of energy expenditures along the income distribution. The latter aspect becomes particularly stringent in view of the energy transition and decarbonisation of economies which increasingly relies on policy instruments such as taxes and CO_2 prices that ultimately raise end-user energy prices. This begs the question as to whom bears the costs of the energy transition, calling for a careful assessment of the regressivity of housing-related energy expenditures.

We analyse household energy expenditure inequality with a special focus on Switzerland, but also within the context of other major European Union countries. We compute energy poverty and energy expenditure inequality indices and measures of the degree of regressivity of energy expenditures leveraging data from the Swiss (SHBS) and European Household Budget Survey (EHBS). We evaluate these indicators also for the seven different Swiss administrative regions (Lake Geneva region, Espace Mittelland, Northwestern Switzerland, Eastern Switzerland, Zurich, Central Switzerland and Ticino), for the different linguistic regions households belong to (German, French and Italian) as well as for different types of energy expenditures - energy expenditures related to mobility or housing. Furthermore, we assess the effects of the recent price increases on the distribution of energy expenditures among households.

First, we calculate the average shares of income households spend on energy by income quintile in each country. Second, we compute different expenditure based measures of energy poverty. Third, we construct energy expenditure concentration curves — akin to income Lorenz curves — that illustrate the cumulative proportion of energy expenditures against the cumulative proportion of the sample. Fourth, we calculate the degree of convexity of energy expenditure shares along the income distribution as well as Kakwani indices in order to assess the degree of regressivity of energy expenditures. Last, we decompose the energy concentration indices to understand the contribution of various socio-demographic characteristics to overall energy expenditure inequality.

This paper contributes to the literature on the repercussions of energy prices on the regressivity of energy expenditures. While our findings may not directly pertain to climate policy measures and their influence on energy price dynamics, our analysis offers valuable insights into the potential distributional effects of such policies since environmental taxes or regulatory policies also contribute to the escalation of energy prices.

Our findings unveil a pattern of regressive energy expenditures in all European countries analyzed including Switzerland. However, significant disparities in the shares of income allocated to energy expenses exist. With a share of household energy expenditures in equivalent income in 2017 of 8.6% and 2.6% for the first and fifth income decile respectively, Swiss households face a much lower burden compared to their counterparts in the majority of EU countries. Thus, in 2020, the poorest households in Croatia stand out with the largest proportion of income spent on energy (30%), nearly four times higher than Luxembourg's. Conversely, among the wealthiest households, Bulgaria records the highest expenditure proportion, exceeding that of Luxembourg by more than fourfold. The largest gap in expenditure shares between the top and bottom income quintiles is featured in Croatia in 2020, with a substantial difference of 19 percentage points, while Luxembourg exhibited the smallest difference at 4.7 percentage points, smaller than that of Switzerland in 2017.

In 2017, around 8% of surveyed households spent more than 10% of their income on energy[1], a figure projected to rise to approximately 10% by 2023. Despite this increase, these percentages are among the lowest of the 19 European countries analyzed. However, when energy poverty is assessed by comparing households' energy expenditures to twice the national median, 17% of Swiss households in 2017 had energy costs exceeding this threshold. Most European Union countries show lower percentages using this alternative measure, appearing better in terms of energy poverty. This discrepancy arises because many households in the EU have high energy expenditures, which elevates the national median and consequently reduces the number of households with expenses above the median.

Furthermore, in all countries and years the cumulative share of energy expenditures consistently surpasses the cumulative share of household income, resulting in regressive energy expenditures. In Switzerland, the degree of regressivity is among the highest compared to the analysed countries even though the income shares spent on energy are among the lowest. Within the realm of housing-related energy expenditures, which include costs for heating

[1] We thereby consider both housing as well as fuel expenditures under household energy expenditures.

and electricity, the highest degree of regressivity is observed. In addition, the expected or announced energy prices do not considerably increase energy expenditure inequality and thus have only a minor effect on regressivity.

Hence, focusing solely on the fraction of income spent on energy is not a definitive indicator of the degree of regressivity. The countries with the highest or lowest shares in this regard differ from those with the lowest or highest degrees of regressivity, adding complexity to the overall picture.

Furthermore, while we project an increase in energy poverty due to recent price hikes, we do not find significant changes in the regressivity of energy expenditures. However, this finding heavily depends on the assumed energy price elasticities for different income groups.

Lastly, the decomposition of the concentration index for energy expenditures reveals the specific contributions of household socio-demographic characteristics to overall inequality in energy spending. In Switzerland, equivalent income emerges as the primary factor influencing energy expenditure inequality, accounting for 50% of the concentration index. Conversely, household size and the age of the household head contribute negatively to the concentration index, leading to a more equal distribution of energy expenditures across the income distribution. This finding suggests that more specifically designed policies, beyond purely income-based transfers, may be necessary to address the increasing energy expenditure burden on the population.

The remainder of this paper is structured as follows: Section 2 reviews the related literature, Section 3 provides an overview of the data and employed methods, and Section 4 concludes.

2 Literature

The empirical literature on the distributional impact of climate policies, energy poverty, and the energy transition provides valuable insights into the regressive nature of such measures, particularly in the context of the United States. Studies such as Burtraw et al. (2009), Hassett et al. (2009), and Fullerton et al. (2011) present evidence highlighting the regressive effects of US climate policy. Examining electricity prices, Borenstein (2012) demonstrates that utilities adopt non-marginal increasing block prices and inefficiently low access fees to protect low-income customers. Levinson & Silva (2022) find that energy utilities concerned about inequality charge lower-than-efficient fixed costs and higher-than-efficient volumetric charges. Considering mark-ups on electricity prices, Feger & Radulescu (2020) employ data from the Swiss canton of Bern and delve into the implications in terms of taxes and network tariffs, showing that inequity aversion and environmental externalities can shift end-user electricity prices upwards.

The contribution by Vona (2021) offers an overview of the literature on the distributional effects of environmental policies, including those related to energy. Overall, these papers consistently identify regressive effects on income. For the case of Switzerland, Landis (2019) employs a computable general equilibrium model and finds that in the absence of revenue recycling, emission taxation leads to a regressive distribution of policy cost.

In the specific domain of energy inequality and its intersection with efficient energy provision, inequality, and environmental awareness, emerging literature is gaining traction. Menyhert et al. (2022) provide a preliminary assessment of the potential social consequences of increasing energy and consumer prices in the EU. While their focus encompasses all living cost increases and purchasing power losses, our study narrows in on housing and fuel-related energy expenditures, employing the Kakwani index to assess the degree of regressivity. Energy poverty, closely linked to energy inequality, has been scrutinized by various researchers, including Drescher & Janzen (2021), Wu et al. (2017), and Halkos & Gkampoura (2021). Two expenditure based methods are commonly applied in the literature to assess if households should be regarded as energy poor. First, the Ten-Percent-Rule (TPR) and second the Low Income High Costs indicator (LIHC). Under the first metric, suggested by Boardman (1991) and Boardman (2009), households are energy poor if their share of income spent on energy exceeds 10%. The second indicator captures whether households' actual energy expenditures exceed the median and if their residual income net of energy costs is below the official national income poverty line (Hills (2012)). For example, Drescher & Janzen (2021) use German SOEP data to reveal that, in 2019, 17% of households spent more than 10% of their income on domestic energy[2], with 4.5% to 14% experiencing persistent energy poverty. Wu et al. (2017) demonstrate a nearly 50% increase in energy poverty in the United States from 1990 to 2015, while Bouzarovski & Tirado Herrero (2017) and Halkos & Gkampoura (2021) emphasize the role of electricity prices in driving energy poverty in Europe. Our findings for Switzerland reveal that in terms of the TPR, Siwtzerland is clearly at the lower end of the distribution with low shares of households whose energy expenditures exceed 10% of their income.

Previous studies concerned with energy expenditure inequality employ Gini coefficients to illustrate energy expenditure inequality among households, with Jacobson et al. (2005) and Oswald et al. (2020) providing examples for various countries. However, we argue that the other indices such as the Kakwani index are better suited , since computing a Gini type index just offers information on the cumulative share of energy expenditures across the population, which is meaningful in the analysis of energy access, however it does not relate this to the distribution of income. The Kakwani index though, also captures this latter aspect. The index, initially designed to assess the progressivity of tax payments, has found applications in health economics to analyze the distribution of health expenditures, as evidenced by studies such as A. Wagstaff & van Doorslaer (1994), E. v. D. Wagstaff A. & P.Paci (1989), Kakwani & van Doorslaer (1997), and E. v. D. Wagstaff A. & Watanabe (2003). Huang (2022) employs the Kakwani index to illustrate electricity expenditure inequality in Taiwan, marking a notable exception in the literature's use of this index for assessing energy expenditure inequality.

We contribute to this literature by quantifying the degree of regressivity in household energy-related expenditures and decomposing energy expenditure inequality by various socio-

[2]Excluding fuel related mobility expenses.

demographic characteristics. Additionally, we develop and compute a new metric that determines the degree of convexity of energy expenditure shares along the income distribution, illustrating the rate at which these shares decrease with higher incomes compared to a system where they decrease proportionally.

3 Data and methods

3.1 Data and energy expenditure projection

We employ data from different waves of the HBS provided by the Swiss Federal Statistical Office. The survey contains detailed information about the persons living in the household, household income and household expenditures for the sample surveys conducted in 2006-2008, 2009-2011, 2012-2014, and 2015-2017 for which we have 9,919, 9,734, 9,367, and 9,955 observations, respectively. Since survey participants report information on the administrative and linguistic region they live in, we can also compute the different measures for the seven administrative and three linguistic regions. For 2017 the survey counts 6,780 households living in the German part, 2,078 in the French part, and 1,097 in the Italian region. To ensure comparability across households, we compute equivalised values for the disposable income. Disposable income is defined as gross income minus expenditures on mandatory social security, taxes, basic health insurance premiums, and regular transfer payments to other households. Equivalised income is obtained by dividing the disposable income by the number of equivalent adults in the household, adhering to the OECD equivalence scale. This scale assigns a weight of 1 for the first adult, 0.5 for each additional household member aged 14 and above, and 0.3 for each additional household member under 14. The SHBS datasets provides pertinent information on housing-related energy expenditures, encompassing electricity, gas, district heating, and fuel categories such as diesel and gasoline. [3]

Data for European Union countries is retrieved from the EHBS, provided by Eurostat.

[3] We also compute equivalised expenditures using the approach described above.

Our analysis focuses on sample surveys conducted in 2010, 2015, and 2020, encompassing between 275'259 and 208'519 observations.[4]

Given that the SHBS only provides data up to 2017 and EHBS up to 2020, we need to undertake projections to gauge the ramifications of recent escalations in energy prices on energy expenditures. This analysis illustrates the potential repercussions on energy expenditure inequality and the regressive effects of such price hikes. Even though Europe at large is in this process of energy transition, recent energy price developments differ considerably between countries. Additionally, the impact of increased energy prices on households' budgets varies to a large extent depending on the national energy strategies and the resulting compositions of the energy mix as well as geopolitical inter-dependencies. For example, countries such as Germany where natural pipeline gas imported from Russia represented a large fraction of total energy consumption, are more prone to natural gas shortages and the associated energy price increases compared to Spain, which imports its natural gas mainly as LNG from suppliers other than Russia (Holz et al., 2022).

The calculation of the projected energy expenditures in 2023, requires information on the corresponding prices in the base year (P_o - 2017 for Switzerland and 2020 for EU countries) and in 2023, as well as estimates of the price elasticities (η) by energy carrier and income

[4]From this extensive pool, 361'181 observations were meticulously selected for analysis. The exclusion criteria were primarily based on the presence of missing values in crucial categories, such as income and energy expenditures, as well as the geographical context of the respective country. Furthermore, to ensure the reliability and representativeness of our findings, we systematically eliminate observations that did not fall within the range of a household's share of income spent on energy between 0 and 1.

group. [5]

$$\exp_n = P_n \times Q_n = P_n \times (\eta \times \frac{P_n - P_o}{P_o} \times Q_o + Q_o) \tag{1}$$

$$\eta = \frac{\frac{dQ}{Q_o}}{\frac{dP}{P_o}}$$

Price information for the year 2023 is retrieved from the following sources. Information about Swiss electricity prices is provided by the Federal Electricity Commission (ElCom)[6] The expected price for gasoline, diesel, gas, and the respective changes are calculated with indices of the *Landesindex der Konsumentenpreise* (2022). We collect country-specific electricity and gas price development data from Eurostat and gasoline, diesel and heating oil prices are collected from the International Energy Agency (IEA). [7] . [8] As the HBS does not distinguish between diesel and gasoline expenditures in the general fuel category, we approximate fuel prices with weighted average of diesel and gasoline prices where the weights represent the share of registered cars with the respective engine type in each country. This information is obtained from the European Automobile Manufacturers' Association (ACEA).[9]

[5]This approach features however a downside. To be more specific, we cannot quantify the true adjustment of household energy consumption following a marked price increase for the following reason. The interpretation of price elasticities is based on marginal price changes. Therefore, low-income households are expected to be more price sensitive compared to higher-income groups. Furthermore, according to eq. (1), simply plugging in the corresponding values may result in negative energy consumption for some income groups and energy sources (especially gas) in some countries (i.e. Hungary) in 2023. This can happen if the price change, multiplied by the respective price elasticity, is below -1. Since this is unrealistic, we assume a minimum baseline gas consumption of 360 kWh per household annually for those households already utilizing gas in 2020. This figure aligns with the minimum electricity consumption deemed necessary for survival by the World Bank. Since there is no direct equivalent for minimum gas consumption, we approximate it using information on electricity consumption. However, this approximation may be conservative, as developed countries typically have higher minimum consumption levels than those defined by the World Bank for developing nations. Thus, assuming a subsistence level of energy consumption (in particular gas) beyond which energy consumption cannot be reduced, may imply that higher income-groups may appear to be more price elastic.

[6]The median prices for electricity for households amount to 20.2 Rp./kWh and 26.95 Rp./kWh for 2017 and 2023 respectively. We calculate a weighted average electricity price for each linguistic region where the weights are represented by the number of residents.

[7]We compute the mean of the two half-yearly average prices from 2020 and the latest available energy prices in the first half of 2022 to approximate the electricity and gas prices for 2020 and 2023.

[8]EU average gas price information is used for Finland, Malta and Cyprus and EU average oil prices for Sloavkia because of missing data on the national level.

[9]The missing values for Bulgaria and Malta are substituted with the EU average.

The price for solid fuels and liquefied hydrocarbons is approximated with UK prices from the Office for National Statistics (ONS). The heat price index is provided by the German Federal Statistical Office (Destatis). These energy prices only vary over time but not by country. Income projections are calculated with country-specific labor indices from the OECD. All price developments are presented in Table A4 in the Appendix.

Second, we retrieve estimates for price elasticities of energy demand for different income groups from the relevant literature. Feger et al. (2022) estimate price elasticities of electricity demand by income quintile for the Swiss Canton of Bern. We match these for the different income quintiles using the following cut-off values from the SHBS data: 69, 114, 166, 248 CHF. Auffhammer & Rubin (2018) provide two different estimates of gas demand elasticities, for the lower 45 income percentiles and the 55 higher income percentiles respectively. Gasoline expenditure elasticity estimates are obtained from the study by Wadud et al. (2010). Trotta et al. (2022) provide values for the price elasticity for district heating for different income quartiles. Table 1 reports the employed values for the different elasticities. We compare these values with the meta-analysis of Labandeira et al. (2017) who provide short- and long-run price elasticities of energy demand by energy type, albeit not according to income category. Still, the estimates we employ are within the range of these values. These price elasticities are also trustworthy in the context of the recent price spike. Peersman & Wauters (2022) report an average price elasticity of -0.22 using survey evidence on reported spending in hypothetical energy price shock scenarios.[10] Projected income for Switzerland for 2023 is obtained by scaling the 2017 values from the SHBS by the wage index of the Federal Statistical Office until 2021 and by expected nominal wage changes from the annual Credit Suisse report (*Lohnrunde 2023: Was ist zu erwarten?*, 2022) for 2022 and 2023.

It is important to acknowledge that there can be significant variation in the extent to which individuals are exposed to energy price increases, both across as well as within

[10]Since we did not find suitable estimates of the price elasticities of solid fuel, liquid fuel or liquefied hydrocarbon, we approximate the values by the price elasticities of natural gas. We argue that the energy carriers mentioned and natural gas are used in a comparable manner to heat living space.

Table 1: Energy price elasticities (η) for different source of energy

Energy	η	η	η	η	η	**Split**	**Reference**
Gas	-0.24				-0.14	income (45% / 55%)	Auffhammer & Rubin (2018)
Fuel	-0.63	-0.47	-0.37	-0.29	-0.21	expenditure quintiles	Wadud et al. (2009)
RDH*	-0.607		-0.598		-0.232	income quarters (1/4,2/4,1/4)	Trotta et al. (2022)
Electricity	-0.166	-0.103	-0.074	-0.063	-0.081	income quintiles	Feger et al. (2022)

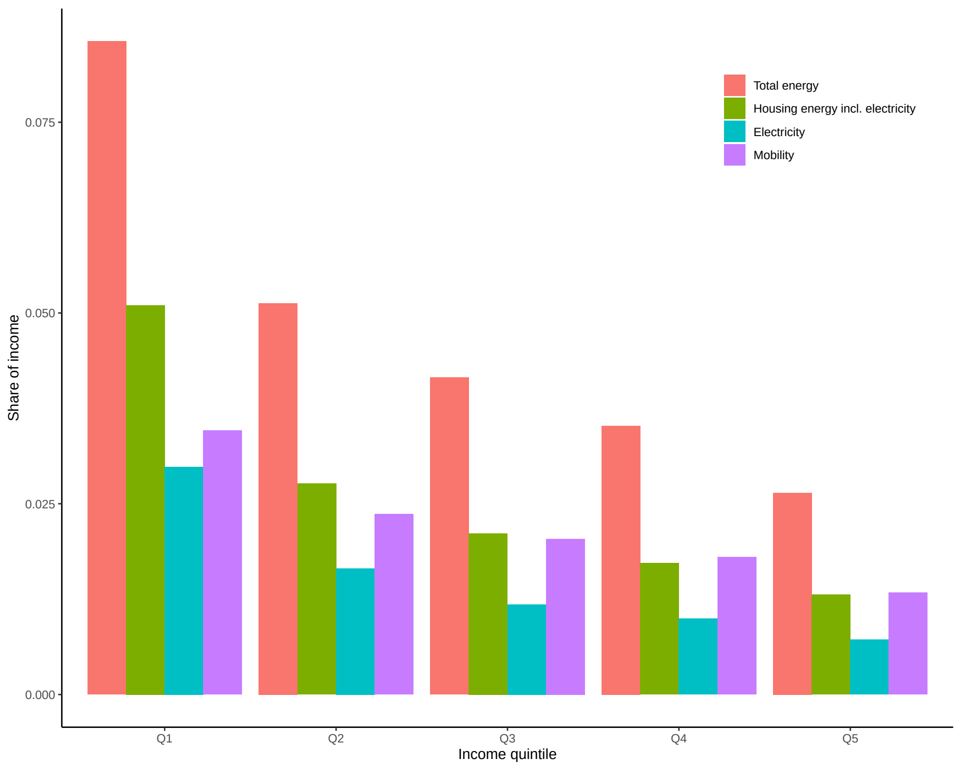
***Residential district heating**

countries. Therefore, our approximation of households' reactions to increased energy prices performs better for countries that faced no or little variation. To be more specific, the approximation for heat price indices can be less precise because the price of heat differs greatly depending on the type of energy source used. For example, district heating prices from providers using waste heat from data centers will not vary as much compared to those using natural gas. Lastly, we observe no cross-country price variation for solid fuel, liquefied hydrocarbon and district heat, as we lack any country specific information. However, a large part of the HBS sample does not provide specific information on expenditures on these energy sources with some countries featuring only a small corresponding number of users. Therefore, we conjecture only a negligible bias that affects the subsequent projections that arises since we employ for these latter prices only a single price index.

3.2 Regressivity of energy expenditures - energy expenditure as a share of income

Figure 1 depicts energy expenditures as a share of income for income quintiles for the year 2017 in Switzerland. Whereas the share of overall energy expenditures in equivalent disposable income is 8.6% for the first income quintile (for households with monthly equivalised net income <= 2,666 CHF), it is around 2.6% for households belonging to the fifth income quintile. The largest discrepancies arise for energy expenditures related to housing (including heating and electricity), whereas the share of mobility related energy expenditures and electricity feature less heterogeneity among households expressed in percentage points. In relative terms, the expenses for fuel are less unequally distributed compared to those for housing energy and electricity.

Figure 1: Share of income spent on energy for different income quintiles in 2017



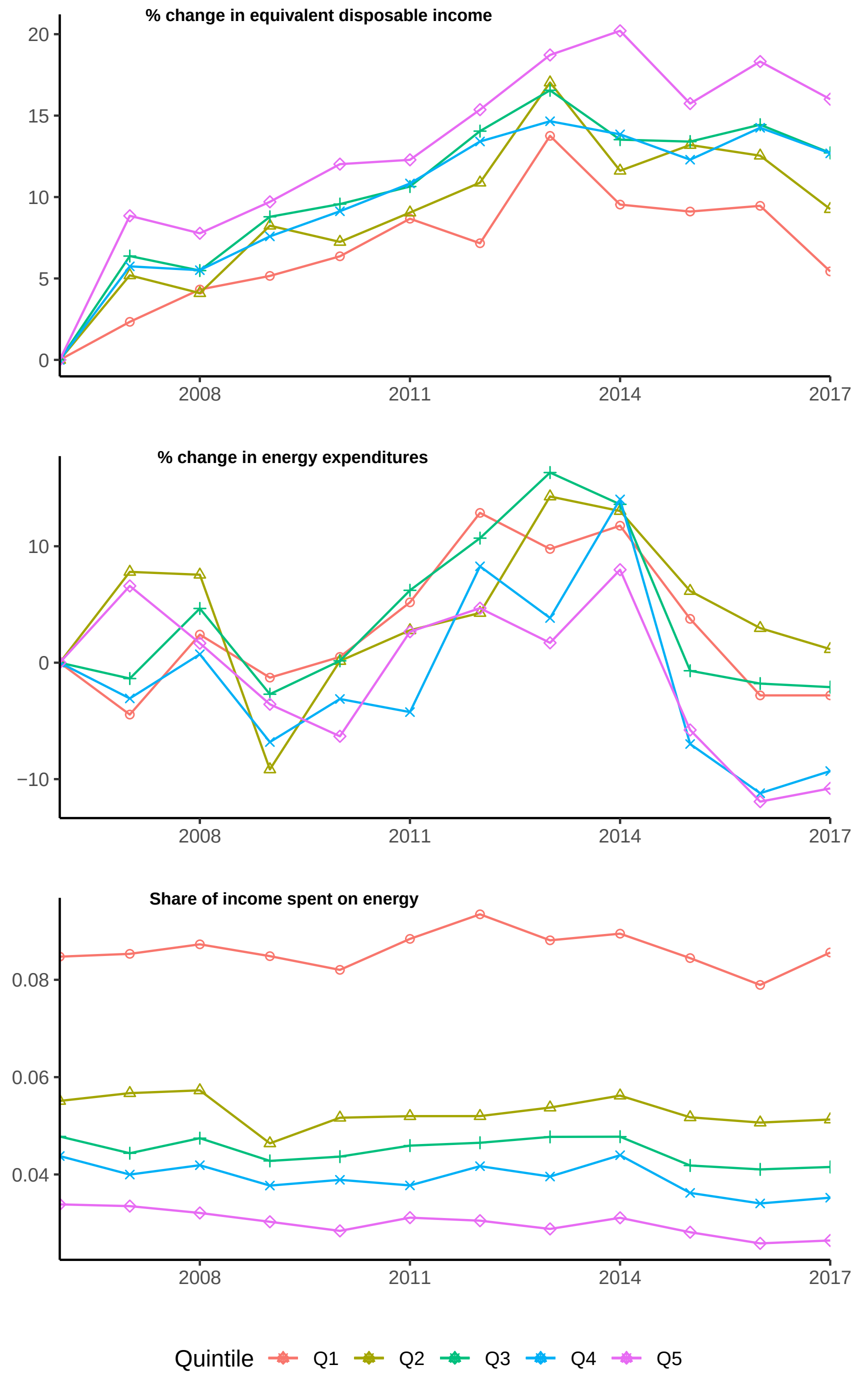
Source: Own illustration based on data from the Swiss Household Budget Survey provided by the Federal Statistics Office.

We also consider a different approach by looking at the fraction of energy expenditures in overall expenditures instead of income (see also Glaeser et al. (2022)). The results are depicted in Figure A1 in the Appendix. This alternative is important to consider since reported income can be substantially below overall household expenditure in the lowest quintile of the household income distribution. This likely reflects the omission of some transfer program receipts in the measure of income or some transitory income fluctuations that may render current income below permanent income. Such transitory income fluctuations may also play a role at the highest income levels, where reported income may overstate permanent income, for instance if a household realizes substantial capital gains in a particular year. Hence, scaling outlays on energy expenditures by total expenditure, rather than total income, may provide additional insights about the relative burdens compared to scaling by income.

We further illustrate the developments of income shares spent on energy in Figure 2. As the figure reveals, all income quintiles experienced an increase in disposable income until 2017. This increase was more pronounced for higher quintiles. Expenditures on energy remained roughly constant for the lowest three quintiles and decreased for the two top quintiles. This can probably also be attributed to increased investments in the energy efficiency of household appliances and self-generation of energy, such as the installation of solar panels among the richest households. The bottom panel depicts the evolution of the share of income spent on energy. As the graph shows, the shares were mostly constant during the observed time frame and higher income groups spent significantly less on energy than the lower income counterparts.

We scrutinize the possible reasons behind these divergences. Hence, we decompose these by car ownership, retirement status or by the linguistic region the household is living in. A further decomposition of these characteristics by income quintile is presented in Figure A2 in the Appendix.

Figure 2: Development of average income, average energy expenditures, and share of income spent on energy by quintile

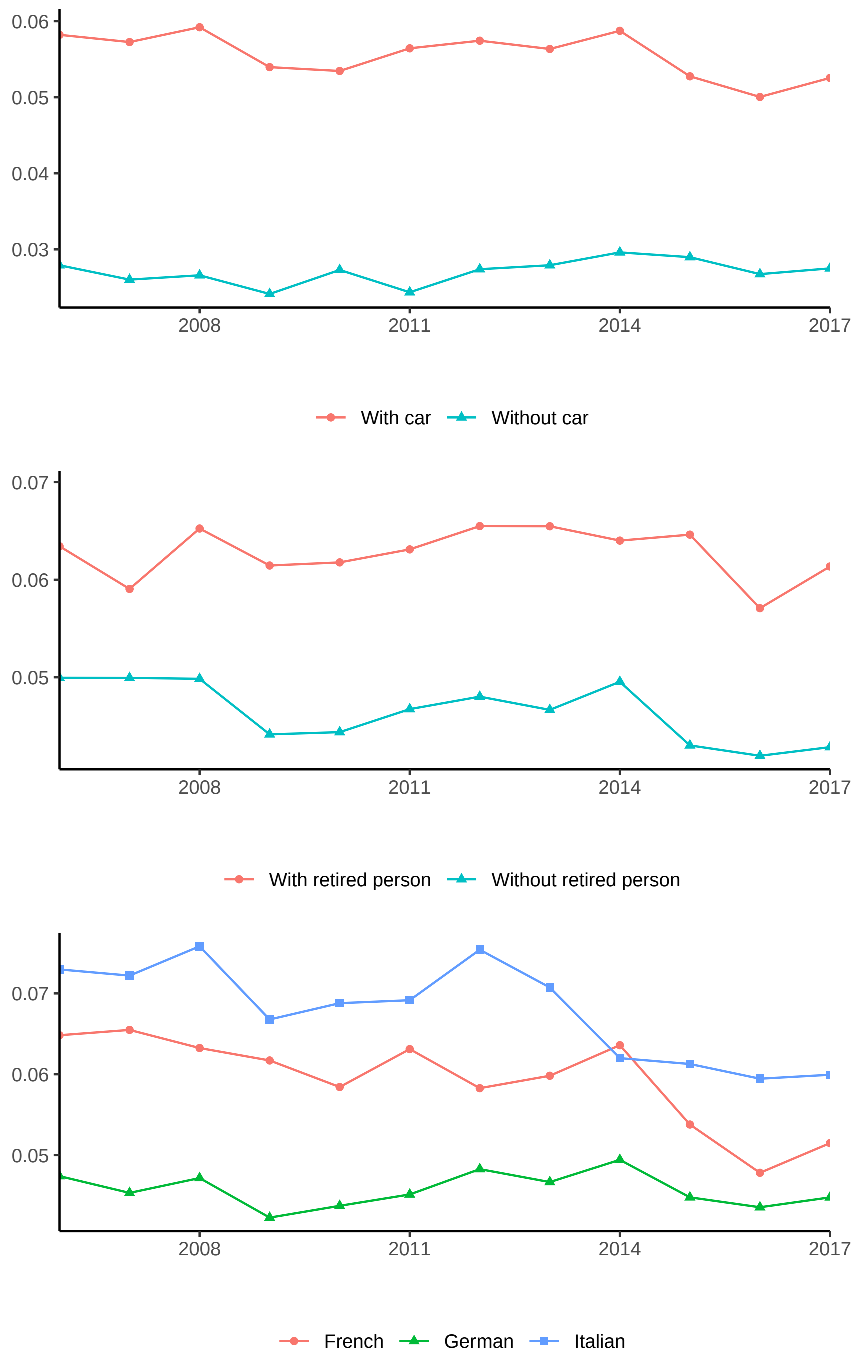


Source: Own illustration based on data from the Swiss Household Budget Survey provided by the Federal Statistics Office. Numbers of income and energy expenditures are equalised.

Figure 3 reveals that energy expenditures as a share of income are around 3 percentage points higher for households owning a car compared to those without. This is the case since expenditures on fuels represent a large fraction of total energy expenditure as also depicted in Figure 1. Furthermore, retired households also spend a larger share of income on energy, compared to non-retired ones, mainly due to the considerably lower disposable income. Monthly disposable income amounts to on average 3,474 CHF for retired households and to 5,013 CHF for non-retired ones in 2017. Differences also emerge between linguistic regions with the highest shares for Ticino and the lowest for the German speaking households. There are two possible explanations for these findings. First, population weighted average electricity prices are higher in the Italian and French speaking regions, compared to German speaking regions (see Figure A3 in the Appenix).[11] Second, average disposable equalised incomes are higher in German speaking regions (see Figure A4 in the Appendix).

[11] In Switzerland, electricity markets are not liberalized for households yet. This implies that households cannot choose their electricity supplier and we can therefore attribute the different energy utilities to the corresponding municipalities in each language region. Data on residential electricity prices for each Swiss municipality since 2009 is retrieved from the Federal Electricity Commission (*https://www.strompreis.elcom.admin.ch/*)

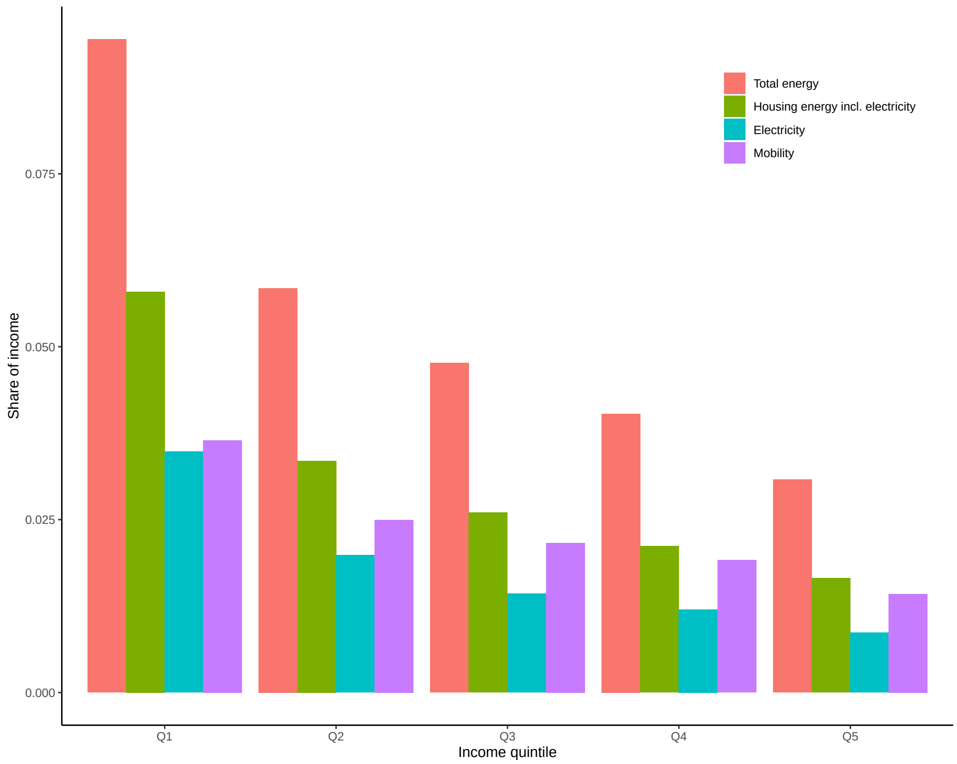
Figure 3: Share of income spent on energy for different household compositions



Source: Own illustration based on data from the Federal Statistics Office (FSO).

In Figure 4 we present projections of the announced energy price increases on energy expenditures. According to our projections the share of income spent on energy increases by more than 10% for all income quintiles. From 0.086 to 0.094 for the lowest income quintile and from 0.026 to 0.031 for the highest income quintile. This means that households in the lowest income quintile with monthly disposable income of up to 2,666 CHF, spend nearly 1 in ten CHF on energy, or on average around 253 CHF per month.

Figure 4: Projected share of income spent on energy for different income quintiles in 2023



Source: Own illustration based on data from the Swiss Household Budget Survey provided by the Federal Statistics Office.

Since electricity price increases display a large variation among municipalities, we perform a sensitivity analysis simulating a situation in which every household is subject to the highest price increase recorded among all utilities and municipalities in 2023. Under this assumption, the share of income spent on energy increases by 1.6 percentage points to 11% for the lowest income quintile.[12] For the highest income households the share would increase to 3.8% instead of 3.1%.

[12] In the base case we use weighted average electricity prices in the linguistic regions.

3.3 Energy Poverty

The above analysis reveals that households allocate significant portions of their incomes to energy expenditures. In this subsection, we delve deeper into the topic of energy poverty in Switzerland compared to European Union countries. We employ two expenditure-based criteria for identifying energy poverty. The first criterion defines a household as energy poor if its energy expenditure exceeds twice the national median (referred to as 2M), following the methodology of the Energy Poverty Observatory. The second criterion, known as the Ten-Percent-Rule (TPR), identifies households as energy poor if their energy expenditure represents more than 10% of their income.(Churchill et al. (2020)).[13]

In Table 2, we observe that energy poverty levels have remained relatively stable over time, with a slight decrease noted between 2006 and 2017 when considering the Ten-Percent-Rule (TPR) criterion. The 2M measure displays almost no change, which is plausible given that median values tend to change gradually, reflecting shifts near the maximum observed levels. Consequently, in 2017, nearly 17% of surveyed households had energy expenditures exceeding twice the national median. Projections for 2023 suggest a potential increase in energy poverty levels, although these levels are still comparable to those of past years. According to the TPR, around 8% of surveyed households in 2017 spent more than 10% of their income on energy.

Within the wider European context, Switzerland experiences considerably lower levels of energy poverty when applying the Ten-Percent-Rule (TPR). However, when using the 2M criterion, most countries exhibit lower levels of energy poverty compared to Switzerland. This discrepancy can be explained by the fact that in other countries, a larger proportion of households have high energy expenses, leading to a higher national median and consequently smaller discrepancies between individual household expenses and the national median.

[13] We report figures that also consider mobility related fuel expenses under overall household energy expenses. If we exclude this category from the computation of energy expenses only 2.7% of surveyed households in Switzerland can be labeled as energy poor. Similarly low numbers are obtained for Luxembourg or Malta.

Table 2: Energy poverty in Switzerland

Year	TPR	2M
2006	0.116	0.173
2007	0.100	0.174
2008	0.106	0.175
2009	0.083	0.185
2010	0.094	0.177
2011	0.102	0.186
2012	0.105	0.175
2013	0.100	0.175
2014	0.100	0.161
2015	0.085	0.173
2016	0.074	0.165
2017	0.079	0.168
2023	0.106	0.179

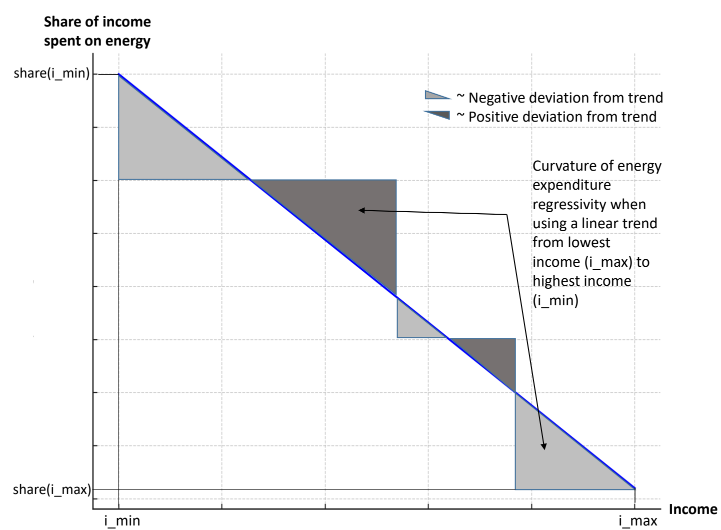
3.4 Regressivity of energy expenditures - the degree of convexity

The regressivity of energy expenditures can be assessed in several ways. First, it can be measured by the difference in the share of income spent on energy between the lowest and highest income households. A larger difference indicates a more regressive impact of energy expenditures. Second, an often overlooked aspect is the rate at which this share decreases across the income distribution, from the lowest to the highest incomes. If the share decreases disproportionately, the degree of regressivity is higher compared to a system where the share decreases linearly. This concept is similar to the analysis of tax progressivity, where a progressive tax system has average tax rates that increase with income, while a regressive system has rates that decrease with income. Additionally, if the rate at which the average tax rate increases (or decreases) itself increases (or decreases), the tax structure becomes even more progressive (or regressive).

We compute a novel measure to capture the degree of convexity in energy expenditures by assessing the rate at which average energy expenditure shares decrease as income increases. The following graphs illustrate this concept. Figure 6 shows the shares of income spent on energy, ordered from lowest to highest income groups in Switzerland for the year 2017. After grouping the observations into bins of 500, we calculate the average share of income spent on energy for each bin. The red dashed line represents a hypothetical distribution where these shares decrease linearly from the lowest to the highest income. However, the observed shares deviate from this linear distribution. A curve below the red line for lower income groups indicates that the shares decrease at a diminishing rate as income rises.

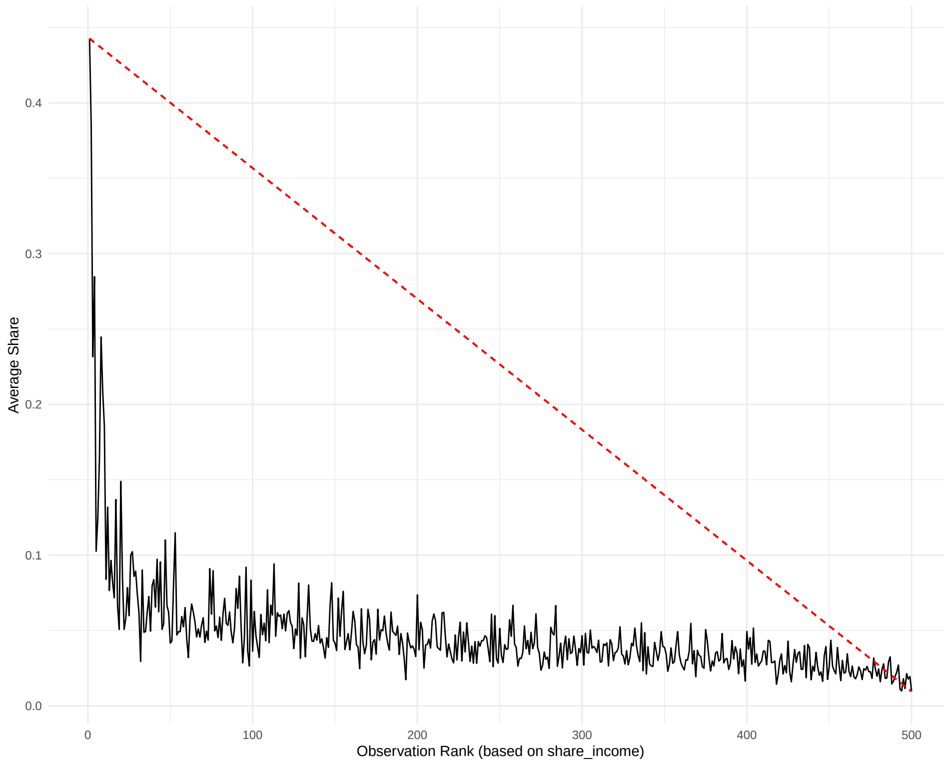
The measure of energy expenditure regressivity is calculated as follows. First, we determine the individual deviation of the observed shares from the hypothetical linear shares. Negative values indicate a higher degree of regressivity. We then sum these deviations and normalize by the number of groups over which we averaged the shares. This provides the average deviation of observed shares of income spent on energy from a "proportional" regressivity across income groups. Table 3 presents the corresponding values for different years. The values are negative for all years, indicating that the shares abruptly decrease from low to high incomes. Only three out of the 19 European Union countries (see Table A7 in the Appendix) feature higher values for the degree of convexity in absolute terms, suggesting that Switzerland belongs to the group of countries with the highest degrees of regressivity.

Figure 5: Curvature of energy expenditures



Notes: Blue line assumes energy expenditure shares decrease linearly with income. *Source:* Own illustration.

Figure 6: Degree of convexity of energy expenditure shares in Switzerland



Source: Own illustration based on data from SHBS.

Table 3: Graphical representation of the regressivity of energy expenditures in Switzerland

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2023
Index	-0.080	-0.225	-0.080	-0.103	-0.124	-0.262	-0.215	-0.097	-0.165	-0.144	-0.156	-0.179	-0.199

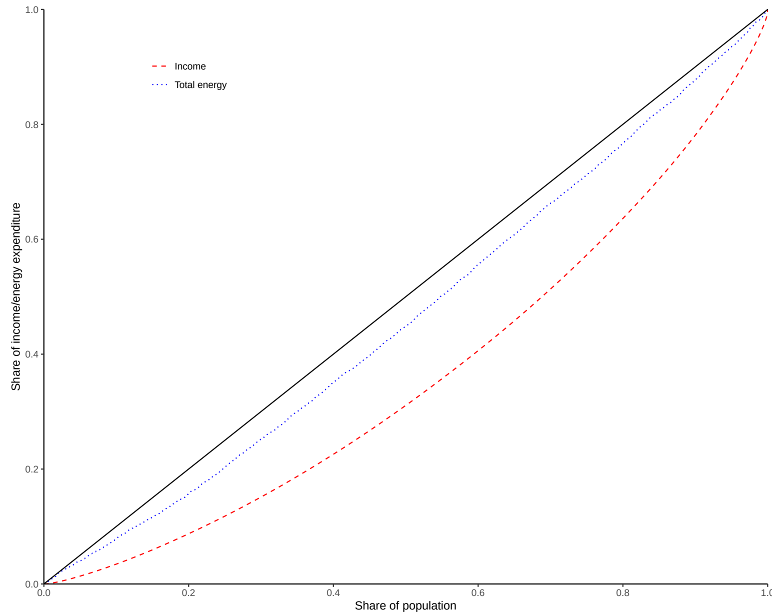
3.5 Regressivity of energy expenditures - Concentration and Kakwani index

While these descriptive statistics provide a snapshot of the disparity in energy expenditure shares among households, a more nuanced examination of inequality and especially the regressivity of energy expenditures requires additional indices. To delve deeper into this topic, we turn to concentration curves (energy Lorenz curves) and energy Kakwani indices. In a scenario of complete equality in energy consumption across households, the energy Lorenz curve would align as a diagonal from (0,0) to (1,1). The energy concentration index for each country $j = 1, ..., J$ and year t (C_{jt}), is defined as

$$C_{jt} = \frac{2}{n \cdot \mu_{jt}} \sum_{i=1}^{n} exp_{ijt} R_{ijt} - 1 \tag{2}$$

where exp_{ijt} denotes the specific type of energy expenditure (i.e. electricity, heating, mobility) in the respective country j and year t, $\mu_{jt} = \frac{1}{n} \sum_{i=1}^{n} exp_{ijt}$ mean energy expenditures in the respective country and R_{ijt} the relative rank of the i-th household in the income distribution of the respective economy. C_{jt} ranges between -1 and 1 and is defined as twice the area between the concentration curve and the diagonal. The further the concentration curve lies from the diagonal, the greater the degree of inequality in energy expenditures across the income distribution. When the diagonal and the concentration curve overlap $C_{jt} = 0$. It is negative (positive) when the concentration curve lies above (below) the diagonal. If it is positive, it means that energy consumption expenditures are concentrated more among high-income households. The concentration index is actually a Gini coefficient applied to energy expenditures. Hence, it is a measure of *relative* inequality, meaning that a doubling of everyone's energy expenditures leaves the index unchanged. The following figure displays the income Lorenz curve and the concentration curve for overall household energy expenditures for Switzerland and the year 2017. On the y-axis households are ordered by income while on the x-axis we see the cumulative expenditure or income up to the corresponding income percentile. Figure 7 illustrates that total energy expenditures are less concentrated than income in Switzerland.

Figure 7: Lorenz Curve and Concentration Curve for Energy Expenditures in Switzerland 2017



Source: Own illustration based on data from SHBS.

To facilitate a numerical comparison instead of relying on energy expenditure concentration curves, we employ Kakwani indices. Developed by Kakwani (1977) as a measure of tax progression, the Kakwani index is originally defined as the difference between the concentration index of tax payments and the Gini income coefficient (G_{jt}). This index is informative about the degree of regressivity of energy expenditures. Hence, the Kakwani index for energy expenditures in country j and year t is defined as:

$$K_{jt} = C_{jt} - G_{jt} \tag{3}$$

and equals the area between the Lorenz and the energy expenditure concentration curve. G_{jt}, the Gini index, is defined as:

$$G_{jt} = \frac{\sum_{i=1}^{n} \sum_{l=1}^{n} |x_{ijt} - x_l|}{2n\bar{x}_{jt}} \tag{4}$$

where n is the number of households in the population in country j and year t, x_{ij} is the disposable income of the ith household, and $\bar{x}_{jt}$ is the mean income. In general, $-2 <= K_j <= 1$. If the concentration curve of energy expenditures lies above the income Lorenz curve (as in Figure 7 above), $K_j < 0$ which means that the cumulative share of energy expenditure exceeds the cumulative share of income and thus implies regressive energy expenditures. The opposite is true for positive values of K_{jt}.

The dataset enables us to distinguish between various categories of energy expenditures. The mobility category encompasses spending on gasoline and diesel, while there is a separate category for electricity expenditures. The household energy category includes spending on gas, district heating, and electricity. Our analysis consistently reveals the regressive nature of energy expenditures. The numbers in Table 4 show that the degree of regressivity stayed constant over the 2006-2017 period. The table underscores that the most pronounced regressivity occurs with respect to housing-related energy expenditures, encompassing expenditures on electricity and heating. Once again, this may simply reflect the fact that a large share of the population does not own a car and the share of low-income households without a car exceeds the share of high-income households owning a car. Within the broader European context (see Table 9), Switzerland appears to have slightly higher absolute values of the Kakwani index, thus suggesting a slightly more pronounced regressivity.

Table A2 and Table A6 in the Appendix present the results for the 7 different administrative regions and the three distinct linguistic regions. The numbers reveal only small discrepancies between the administrative regions, language of the households and energy categories. However, while in Zurich the degree of regressivity increased from -0.12 to -0.25 between 2006 and 2017, it marginally decreased in Ticino. In terms of mobility related expenses Zurich features the lowest energy expenditure concentration at the end of the sample period. This may occur since in urban regions like Zurich, many households do not own a car. This is also reflected in the data since the share of households without a car is the highest in Zurich with 27%, whereas it is below 19% in all other regions. Furthermore, the inequality

Table 4: Gini index, Concentration and Kakwani indices for different energy categories for Switzerland

Year	Gini	CI ET	CI EH	CI EL	CI FU	KI ET	KI EH	KI EL	KI FU
2006	0.26	0.07	0.04	0.01	0.15	-0.19	-0.22	-0.25	-0.11
2007	0.27	0.08	0.05	0.02	0.16	-0.19	-0.22	-0.25	-0.11
2008	0.27	0.06	0.02	0.01	0.15	-0.20	-0.25	-0.25	-0.12
2009	0.27	0.08	0.04	0.02	0.16	-0.19	-0.23	-0.25	-0.11
2010	0.27	0.08	0.04	0.03	0.14	-0.19	-0.23	-0.24	-0.13
2011	0.27	0.07	0.05	0.02	0.14	-0.20	-0.22	-0.24	-0.13
2012	0.27	0.08	0.04	0.04	0.14	-0.19	-0.23	-0.23	-0.13
2013	0.27	0.07	0.03	0.02	0.13	-0.20	-0.24	-0.25	-0.13
2014	0.28	0.08	0.06	0.05	0.13	-0.20	-0.22	-0.23	-0.15
2015	0.27	0.07	0.03	0.02	0.12	-0.20	-0.24	-0.25	-0.15
2016	0.27	0.06	0.03	0.01	0.12	-0.21	-0.25	-0.27	-0.15
2017	0.28	0.07	0.04	0.03	0.11	-0.20	-0.23	-0.25	-0.16
2023	0.28	0.08	0.06	0.03	0.12	-0.20	-0.22	-0.24	-0.16

Note: CI = Concentration Index, KI = Kakwani Index, ET = Total energy, EH = Household energy, EL = electricity, FU = fuel

in electricity consumption expenditures is relatively constant over time in all regions. The dis-aggregation by linguistic region listed in Table A2 reveals that the degree of regressivity of total household energy expenditures does not vary much across linguistic regions .

If we turn to the impact of recent energy price increases, the projected Kakwani coefficients presented in Table 4 for 2023 show that overall energy expenditures regressivity stays constant at a value of -0.20. With respect to the concentration of energy expenditures predicted for 2023, we only project a small increase for housing energy expenditures (including heating and electricity) and fuel expenditures. This can be especially attributed to the sharp increase in gas prices which rise by more than 80% compared to 2017, whereas electricity prices increase by around 30% . However, the increase in electricity prices substantially differs between municipalities. For instance, municipalities where the local energy utility produces its own electricity or had concluded long-term contracts with electricity producers that were not subject to renewal at the peak of the energy crises face lower price increases. With respect to gasoline and diesel prices, the projected increase amounted to 20% and

33% respectively compared to 2017. We also find rather homogeneous effects across administrative and linguistic regions. The highest increase in the concentration index related to housing and total energy expenditures is recorded in Lake Geneva region. French and Italian speaking regions experience slightly higher increases in total energy expenditure inequality.

Nevertheless, we should acknowledge the limitations of the data when interpreting the findings. For example, the data sample does not include any heating oil expenditures. These are captured by the "flat-rate ancillary costs" category. Unfortunately, it is not possible to extract detailed heating source information using these utility expenses. Heat pumps, district heating and gas expenses for certain households are only included in the lump-sum utility costs. Thus, for 57.4% of all households that do not report distinct gas or district heating expenses, we assume they heat with electricity. [14]

3.6 Regressivity of energy expenditures - Socio-demograhic factors contribution to energy expenditure concentration

In a next step we delve deeper into understanding the magnitude of the contribution of distinct socio-demographic factors to energy expenditure inequality. Thus, we decompose the energy concentration index into potential determinants to assess the relative contribution of each of these various covariates in explaining energy expenditure inequality. This analysis is important, insofar as different policy instruments to counteract energy expenditure inequality may be appropriate instead of for instance just lump-sum transfers to low income households, if the results reveal that different factors may have opposite effects on the distribution of energy expenditures among households. Following Wagstaff, van Doorslaer and Watanabe

[14] As a plausibility check we compare the share of households by heating source in the SHBS survey with official numbers published by the Statistical Office of Switzerland in the building statistics. According to the latter, 20% of households use a heat pump or electricity heating, while 24.9% and 8% heat with gas and district heating respectively. In the SHBS data sample, the latter shares amount to 15.8% and 20.8% respectively. Thus, our calculations probably underestimate the impact, since in the data sample households with renewable energy heating systems are overrepresented whereas households relying on fossil energy sources are underrepresented. For instance, while gas and oil heating represent 65% of heating systems in Switzerland they feature only a share of 16% in our sample. Since energy price increases for fossil fuels clearly exceed those for renewable energy, the actual impact of recent price increases is probably underestimated.

(2003) and Huang (2022) we regress our variable of interest exp_{ijt} on a number of controls:

$$exp_{ijt} = \alpha + \sum_k \beta_{kjt} x_{kijt} + \epsilon_{ijt} \tag{5}$$

β_{kjt} thereby represent the respective coefficients and ϵ_{ijt} the error term. We use the following control variables: equivalent income, number of income earners, household size, and dummy indicators accounting for socio-economic status and household type. [15] Hence, the concentration index C_{jt} can be expressed as:

$$C_{jt} = \sum_k \frac{\beta_{kjt}\bar{x}_{kjt}}{\mu_{jt}} C_{kjt} + \frac{GC_{\epsilon jt}}{\mu_{jt}} \tag{6}$$

$$GC_{\epsilon jt} = \frac{2}{n} \sum_{i=1}^{n} \epsilon_{ijt} R_{ijt} \tag{7}$$

μ_{jt} thereby represent average energy expenditures in country j in year t, $\bar{x}_{kjt}$ the mean of the variable considered and C_{kjt} the concentration index of the respective variable in country j and year t. $GC_{\epsilon jt}$ is a generalized concentration index for the residual. Hence, the energy concentration index can be decomposed into a deterministic component $\sum_k \frac{\beta_{kjt}\bar{x}_{kjt}}{\mu_{jt}} C_{kjt}$ defined as the weighted sum of the concentration indices of the regressors and a residual component representing the inequality in energy expenditures that cannot be explained by systematic variations in the regressors. The weight of the respective concentration indices C_{kjt} is given by the elasticity of energy expenditures with respect to the respective regressor $\frac{\beta_{kjt}\bar{x}_{kjt}}{\mu_{jt}}$.

Table 5 displays the outcomes of the decomposition analysis for Switzerland and the year 2017. According to equation (7), the impact of each element on the disparity in energy

[15] The indicator variables for the different household type categories (1-6) capture the composition of the household, such as one-, two- or three-person household with or without children. The indicator variables for socio-economic status (1-6) represent manual worker and non manual workers in the private and public sector respectively, as well as self-employed or unemployed individuals. Additionally, we use indicator variables of the age of the household head (above 65, between 64 and 24 and below 24), the number of income earners (0-4, where 4 indicates households with more than three income earners), and the household size (1-7, where 7 stands for all households with more than 6 household members).

expenses is ascertained by multiplying the concentration index with the elasticity of the respective determinant. The concentration index for each determinant (i.e income, household size, etc.) illustrates how the determinant is distributed among different income groups, thereby indicating the level of inequality. All coefficients should be interpreted with the reference category being the indicator variable with the lowest numerical value, except for equivalent income, which is a numeric variable measured at the level scale. The largest values for the elasticities in absolute terms are recorded for equivalent income, the age of the household head and different household types. In Table 6 we also present the fraction of inequality in energy expenditures explained by different components. Thus, in Switzerland in 2017, equivalent income explains 52.7% of the energy expenditure concentration index. The household type and the number of income earners explain 17.4% and 23.9% respectively. In contrast, covariates such as household size or the age of the household head even feature a negative contribution and thus lead to a more equal distribution of energy expenditures along the income distribution. These latter findings may be attributed to the fact that, for instance, bigger households may feature relatively higher energy consumption but at the same time may also be more prevalent among the poorer households.

Table 5: Coefficients, elasticity and the corresponding concentration indices for Switzerland in 2017

Variable	**Coefficient**	**SE**	**Elasticity**	**CI**
Äquivalenzeinkommen	0.008**	0.001	0.137	0.277
Age HH head 2	64.695**	9.231	0.148	0.088
Age HH head 3	69.020**	13.791	0.068	-0.26
HH size 3	83.768**	21.374	0.036	0.106
HH size 4	65.190**	23.335	0.033	-0.038
HH size 5	133.019**	26.618	0.020	-0.125
HH size 6	140.344**	39.811	0.004	-0.257
HH size 7	192.251**	87.976	0.001	-0.321
HH type 2	17.127**	18.520	0.003	-0.254
HH type 3	113.446**	8.256	0.147	0.076
HH type 4	70.764**	23.284	0.068	0.017
HH type 9	93.276**	20.667	0.013	0.073
1 income earner	27.145**	11.347	0.038	0.027
2 income earner	38.359**	13.449	0.044	0.265
3 income earner	111.102**	21.048	0.015	0.187
4 income earner	151.935**	37.740	0.004	0.250
5 income earner	293.080**	67.554	0.002	0.324

Notes: 1% significance level (**), 5% significance level (**). The dummy variables "socio-economic status" and "HH type" indicate the socio-economic and demographic composition of the household. The following categories apply: one adult (1), two adults (2), more than two adults (3), one adult with children (4), two adults with children (5), more than two adults with children (6). The reference category for all indicators is represented by the lowest value of the indicator. For example households with no income earner is the reference category. The variable household size 1 does not appear in the table as it is multicollinear to HH type 1 and hence household size 2 is the reference category.

Table 6: Contribution of different socio-demographic variables to explaining the concentration index

Variable	**Contribution**	**Percent**
Concentration index	0.072	100
Equivalent income	0.038	52.7
Age HH head	-0.005	-6.7
HH size	-0.001	-2.0
HH type	0.013	17.4
# income earner	0.017	23.9
Residual	0.011	14.6

3.7 Comparison to European Union Countries

In this subsection, we present the results of projected price increases for 2023 and their implications for the regressivity of energy expenditures across various European Union countries, allowing for comparison with Switzerland. The following table shows the minimum and maximum values of energy expenditures as a share of equivalized disposable household income for 2020 and 2023, stratified by the lowest and highest income quintiles.

Table 7: Highest and lowest shares of income spent on household energy expenditures for income quintiles 1 and 5 in 2020 and 2023

Year	**Income quintile**	**Max**	**Min**
2020	1	Croatia (30.1%)	Luxembourg (7.5%)
2020	5	Bulgaria (12.4%)	Luxembourg (2.8%)
2023	1	Greece (34.4%)	Luxembourg (8.3%)
2023	5	Greece (14.8%)	Luxembourg (3.9%)

Notes: The thresholds for calculating the quintiles in 2020 are 29,581, 38,996, 48,525, 64,856 for Luxembourg, 2,287, 2,949, 3,906, 5,267 for Bulgaria and 3,639, 5,301, 6,999, 9,554 for Croatia.

Among the poorest households in the 18 analyzed European countries [16], Croatian house-

[16] Austria, Belgium, Bulgaria, Croatia, Republic of Cyprus, Denmark, Estonia, France, Germany, Greece, Hungary, Ireland, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Slovakia, and Slovenia

holds stand out with the largest share of energy expenditures, nearly four times higher than that of the poorest Luxembourg households. Additionally, all countries except Malta show an average share of income spent on energy exceeding 10% for the lowest income quintile, both in 2020 and in the 2023 projections. This suggests that, based on expenditure-based measures of energy poverty, households in these countries can be classified as energy poor. In contrast, in Switzerland in 2017, even the poorest households spent less than 10% of their income on energy, on average. In 2023, only under the most extreme scenario—where all households, regardless of location, face the highest projected increase in electricity prices—does the share of income spent on energy for the lowest income quintile rise to 11%, qualifying these households as energy poor. Conversely, for the richest households, Bulgaria records the highest expenditure share, more than four times greater than that of the richest households in Luxembourg. Thus, Croatian low income households, with an equivalised monthly household income $<= 3,639$ Euro allocate one out of every three Euros of their disposable income towards energy-related expenditures. The most pronounced difference in expenditure shares between the highest and lowest income quintiles is observed in Croatia in 2020, with a substantial 19 percentage points difference, while Luxembourg exhibits the smallest difference at 4.7 percentage points. We also provide an overview of the average share of income spent on energy by income quintile for different energy sources (total energy, household energy, electricity and fuel) for each country in the Appendix.

Thus, within the broader European context, Switzerland exhibits the lowest proportions of income allocated to energy expenditure across all income quintiles.[17] Furthermore, with a 6 percentage point difference in energy expenditure shares between the first and the fifth income quintiles, Switzerland is also at the lower end among the analysed countries. With respect to the projections for 2023, Switzerland experiences a relatively modest impact compared to other countries. In particular, the 1.6 and 0.7 percentage point increases in the energy expenditure share for the lowest and highest income quintiles respectively are consid-

[17] Once again we should note that the numbers for Switzerland refer to the year 2017 whereas the latest survey data for European Union countries pertains to 2020.

erably lower compared to the 8.7 and 5.7 percentage points increases observed for instance in Greece. By and large, Switzerland falls within the midrange of projected changes in the proportions of income allocated to energy expenditure in our projections for 2023.

We now turn to the measures that capture the degree of convexity and regressivity of energy expenditure shares. Table 8 presents the results for the convexity of energy expenditure shares. Notably, for nearly all years and countries, the values are negative, indicating an abrupt decrease in energy expenditure shares as income increases. However, only Greece, Luxembourg and Netherlands feature in 2020 higher absolute values than the value of -0.179 we compute for Switzerland in 2017. This suggests that in the majority of the analysed 19 European Union countries the rate at which energy expenditure shares decline witch income is less pronounced and hence the degree of regressivity lower.

Table 9 shows the distribution of concentration indices of energy expenditures in various European Union states in the year 2020. With a value of 0.072 of the concentration index in 2017, Switzerland features a considerably lower concentration of total household energy expenditures compared to the European Union counterparts where the mean and median values for the analysed 19 European Union countries amount to around 0.13-0.14 in 2015 and 2020 respectively. This holds true across all considered energy categories. However, in terms of the degree of regressivity of total household energy expenditures as mirrored in the Kakwani index, Switzerland features with a value of -0.2 in 2017 slightly more regressive household energy expenditures compared to the EU counterparts where the mean and median Kakwani indices amounts to -0.15 and -0.16 in 2015 and 2020.

While all countries feature regressive household energy expenditures, significant variations in the degree of regressivity exist. Luxembourg features the most regressive total household energy expenditures, with a value of the Kakwani index of -0.26, slightly lower than that of Switzerland. In contrast, Bulgaria exhibits a substantially lower degree of regressivity at -0.07 (see **??**). Thus, it is essential to highlight that focusing solely on the fraction of income spent on energy is not a definitive indicator of the degree of regressivity.

Table 8: Degree of convexity of energy expenditure shares in EU countries

country	2010	2015	2020	2023
BE	-0.179	-0.120	-0.083	-0.108
BG	-0.098	-0.108	0.002	0.003
CY	-0.125	-0.023	-0.023	-0.019
CZ	-0.103	0.062		
DE	-0.076	-0.062	-0.122	-0.124
DK	-0.126	-0.061	-0.025	-0.026
EE	-0.136	-0.188	-0.044	-0.046
EL	-0.179	-0.229	-0.232	-0.147
ES	-0.098	-0.073	-0.057	-0.080
FI	-0.081	-0.114		
FR	-0.125	-0.143	-0.143	-0.046
HR	-0.099	0.008	0.053	0.181
HU	-0.080	-0.179	-0.162	-0.189
IE	-0.201	-0.165		
LT	-0.117	-0.094	-0.044	-0.050
LV	-0.099	-0.075	-0.101	-0.074
MT	-0.111	-0.131	-0.131	-0.125
PL	-0.098	-0.043		
PT	-0.074	-0.147		
RO	0.003	-0.001		
SE	0.038	0.037		
SI	-0.183	-0.110	-0.127	-0.112
SK	0.108	-0.061	-0.113	-0.105
UK	-0.094			
LU		-0.131	-0.202	-0.068
NL		-0.217	-0.210	-0.202
AT			-0.058	-0.067

Note: The numbers represent the sum of the differences between the actual energy expenditure shares and linearly decreasing expenditure shares from the lowest to the highest incomes.

The countries with the highest or lowest shares in this regard differ from those with the lowest or highest degrees of regressivity, adding complexity to the overall picture.

Switzerland's less concentrated energy expenditure in comparison to the majority of the reference countries may indicate enhanced energy accessibility. However, this circumstance naturally engenders heightened regressivity, as lower-income households also exhibit relatively elevated energy consumption levels.

Table 9: Summary statistics concentration indices EU countries

CI Total	2010	2015	2020	2023
Min	0.09	0.04	0.02	0.06
Mean	0.15	0.14	0.13	0.16
Median	0.17	0.14	0.13	0.14
Max	0.24	0.23	0.22	0.25
CI Household	2010	2015	2020	2023
Min	0.04	0.02	0.01	0.06
Mean	0.10	0.09	0.08	0.12
Median	0.10	0.09	0.07	0.12
Max	0.17	0.16	0.15	0.20
CI Electricity	2010	2015	2020	2023
Min	0.03	-0.00	0.00	0.02
Mean	0.09	0.08	0.08	0.10
Median	0.09	0.08	0.09	0.10
Max	0.15	0.16	0.16	0.18
CI Fuel	2010	2015	2020	2023
Min	0.11	0.07	0.04	0.08
Mean	0.26	0.23	0.21	0.23
Median	0.28	0.21	0.20	0.21
Max	0.52	0.50	0.44	0.45

Notes: The data does not contain all countries in all sample periods. Therefore, the distribution does not contain a constant sample size.

Table 10: Summary statistics Kakwani indices EU states

Kakwani Total	2010	2015	2020	2023
Min	-0.24	-0.24	-0.20	-0.18
Mean	-0.14	-0.14	-0.15	-0.13
Median	-0.15	-0.15	-0.16	-0.13
Max	-0.03	-0.06	-0.07	-0.01
Kakwani Household	2010	2015	2020	2023
Min	-0.28	-0.28	-0.23	-0.22
Mean	-0.20	-0.19	-0.20	-0.16
Median	-0.20	-0.19	-0.20	-0.17
Max	-0.10	-0.10	-0.17	-0.06
Kakwani Electricity	2010	2015	2020	2023
Min	-0.29	-0.29	-0.24	-0.21
Mean	-0.21	-0.20	-0.20	-0.18
Median	-0.22	-0.21	-0.20	-0.19
Max	-0.12	-0.10	-0.16	-0.11
Kakwani Fuel	2010	2015	2020	2023
Min	-0.24	-0.21	-0.19	-0.18
Mean	-0.04	-0.05	-0.06	-0.06
Median	-0.04	-0.06	-0.07	-0.06
Max	0.21	0.20	0.15	0.16

Table 11: Summary statistics Gini indices for EU states in 2020

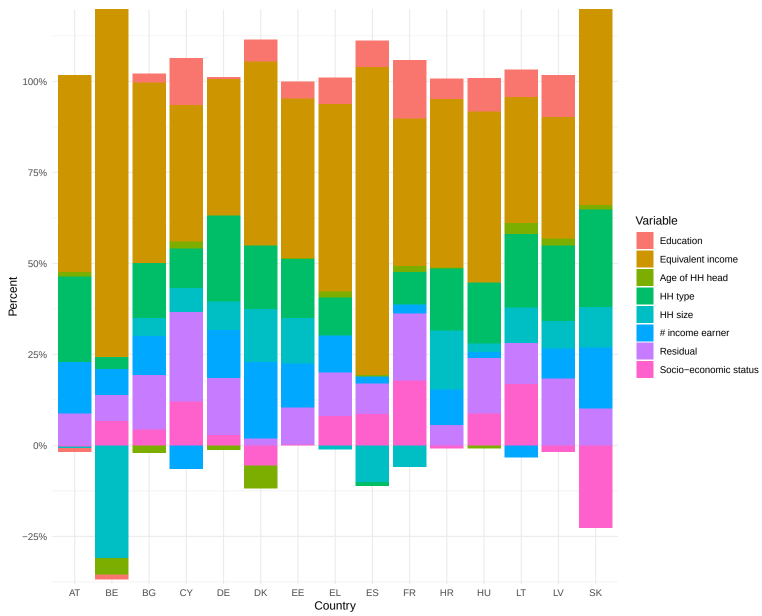
Gini	2010	2015	2020	2023
Min	0.22	0.22	0.22	0.22
Mean	0.29	0.29	0.28	0.28
Median	0.29	0.28	0.28	0.28
Max	0.36	0.37	0.35	0.34

Figure 8 illustrates the relative contributions of different socio-economic variables to explaining the concentration index for various European Union states in 2020. Equivalent income stands out as the main contributor to the concentration index, albeit its contribution varies to a large extent between countries. Hence, in Latvia the contribution amounts to only 33% whereas it is even as high as 113% in Belgium. As depicted in the graph, in some countries, a number of socio-demographic factors even feature a negative contribution to the concentration index. This is especially the case for household size (in particular in Belgium and Spain) and socio-economic status (in Slovakia and Denmark). Accordingly, these variables counteract the positive effect of the other variables and hence cushion the effect on the inequality of household energy expenditures. This feature can for instance be explained in the following way. A larger household size implies also a higher energy consumption but at the same time bigger households are more prevalent at the lower end of the income distribution. Hence, this implies that the energy Lorenz curve moves upwards toward the diagonal and thus energy expenditures are more equally distributed across income.

According to the results presented in Table 4, Switzerland aligns closely with the considered European Union countries. With 52.7% contribution, disposable income emerges as the predominant factor elucidating the concentration index. [18]

[18] We have to note however that the SHBS data does not provide information on education and socio-economic status.

Figure 8: Relative contribution of different socio-demographic variables to explaining the concentration index for various European Union states in 2020



Source: Own illustration based on data from Eurostat.

Notes: Same sample as in ??.

4 Conclusion

This paper analyses the allocation of the household energy expenditure burden along the income distribution in Switzerland in comparison to a number of European Union economies. Furthermore, we gauge the influence of the recent price spikes on the burden of household energy expenditures along the income distribution both for Switzerland overall as well as for different administrative and linguistic regions. We analyse cross-sectional survey data from Switzerland and 19 European countries for the years 2006-2017 (Switzerland) and 2010, 2015, and 2020 (EU), unveiling regressive energy expenditures across all countries and years analyzed. The degree of regressivity experiences a slight decrease between 2010 and 2020 in 8 out of 13 European Union countries but stayed constant in Switzerland. Switzerland stands out in terms of quite low shares of income spent on energy. In 2017, the poorest and richest households in the survey spent 8.6% and 2.6% of their equivalent disposable income on household energy expenditures. These numbers do not vary much between administrative regions, with slightly higher shares for the French and Italian speaking regions in Switzerland. Furthermore, the difference of 6 percentage points between the burden for the poorest and richest households in the survey is among the smallest compared to the analysed EU countries where the difference can even reach 19 percentage points (Croatia). The effect of recent price spikes is projected to be rather small in Switzerland in comparison to some EU countries. Thus, even assuming the highest price increases for electricity recorded among municipalities in 2023, our projections only imply an increase in the burden for the lowest and highest income quintile to 11% or 3.8% respectively. The corresponding values are much higher for the 19 EU countries where, for instance in Greece we project shares of 34.4% and 14.8% for the lowest and highest income quintile respectively.

In terms of energy poverty measured by the TPR (Ten Percent Rule), Switzerland and Luxembourg have the smallest proportion of households with energy expenditures exceeding 10% of their income. However, when applying the 2M criterion (twice the median), 17% of households in Switzerland report energy expenditures that are more than double the national median, a rate higher than in most analyzed EU countries. This discrepancy is explained by the fact that many surveyed households in these countries report high energy expenditures, which raises the national median and consequently results in a smaller proportion of households surpassing the twice-median threshold.

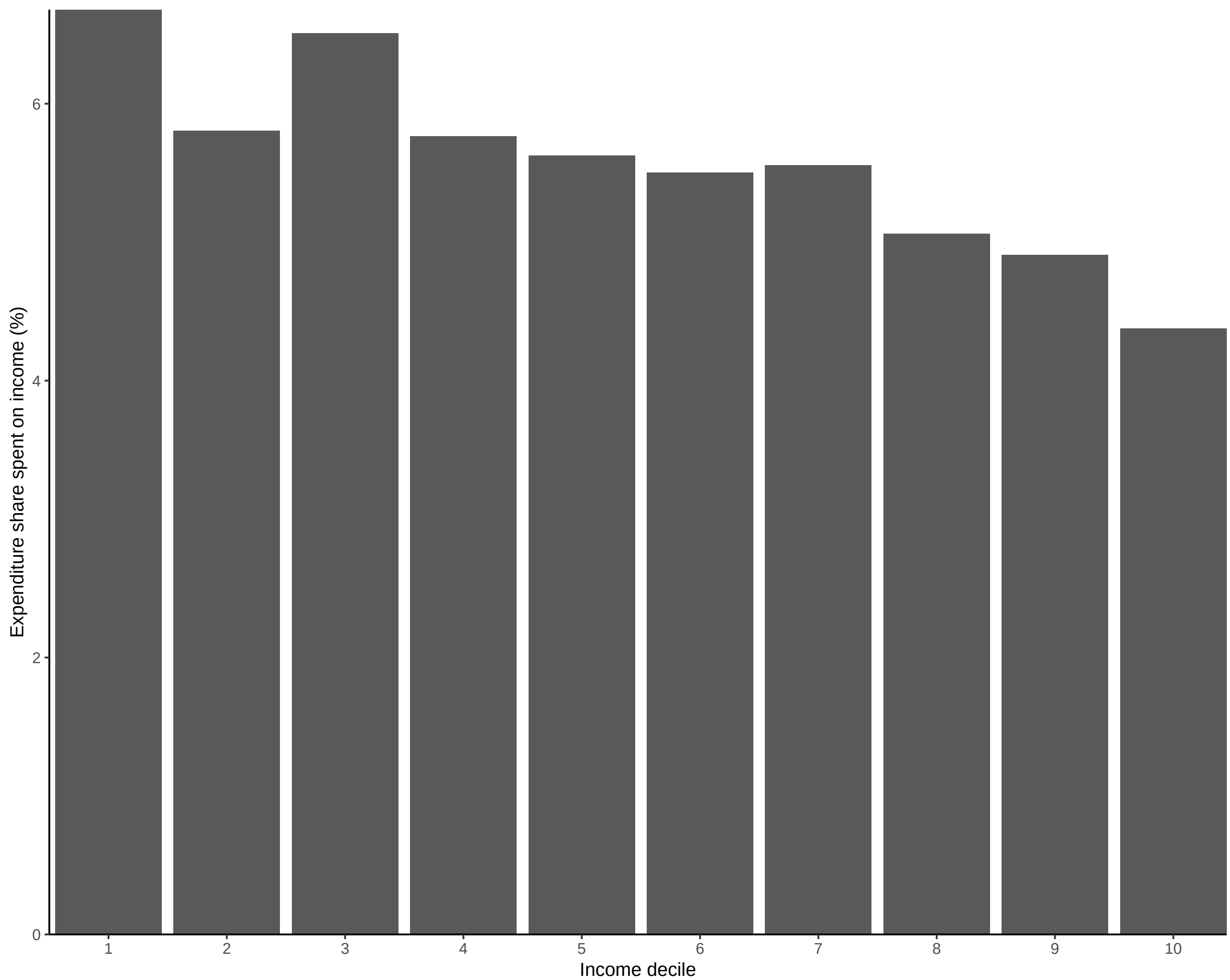
Furthermore, we document a considerable variation in the degree of regressivity among the studied countries, with Luxembourg, Spain, and Switzerland exhibiting the most pronounced regressivity (-0.20 in 2020 and 2017 respectively in Spain and Switzerland, -0.26 in Luxembourg in 2020) and Bulgaria displaying the least degree of regressivity (-0.07 in 2020). A crucial aspect emphasized in our analysis is that assessing inequality in the distribution of the energy expenditure burden among households requires a more nuanced approach than solely focusing on the fraction of income spent on energy. As illustrated, the countries with the lowest or highest share of equivalent disposable income spent on energy differ from those with the lowest or highest degree of regressivity, underscoring the importance of a comprehensive examination of these dynamics.

Furthermore, while we observe a significant impact of price spikes on various energy poverty measures, the effect on the degree of regressivity is minimal. This outcome, however, depends heavily on the assumptions made regarding energy price elasticities across different income levels.

Finally, we examine the contribution of various socio-demographic variables to the overall concentration index of energy expenditures. Equivalent income emerges as the main contributor to explaining the concentration of overall household energy expenditures, however its contribution varies to a large extent. In Switzerland equivalent income alone explains more than 50% of the overall energy expenditure concentration index, but only 33% in Latvia or even 85% in Spain. However, we also find that variables such as household size or age of the household head may even feature a negative contribution to the concentration of energy expenditures, thus counteracting the effect of the other variables and yielding more equally distributed energy expenditures along the income distribution. Understanding the contribution of these drivers is important in view of potential appropriate policy instruments that can be employed to address the potential adverse effects of higher energy prices.

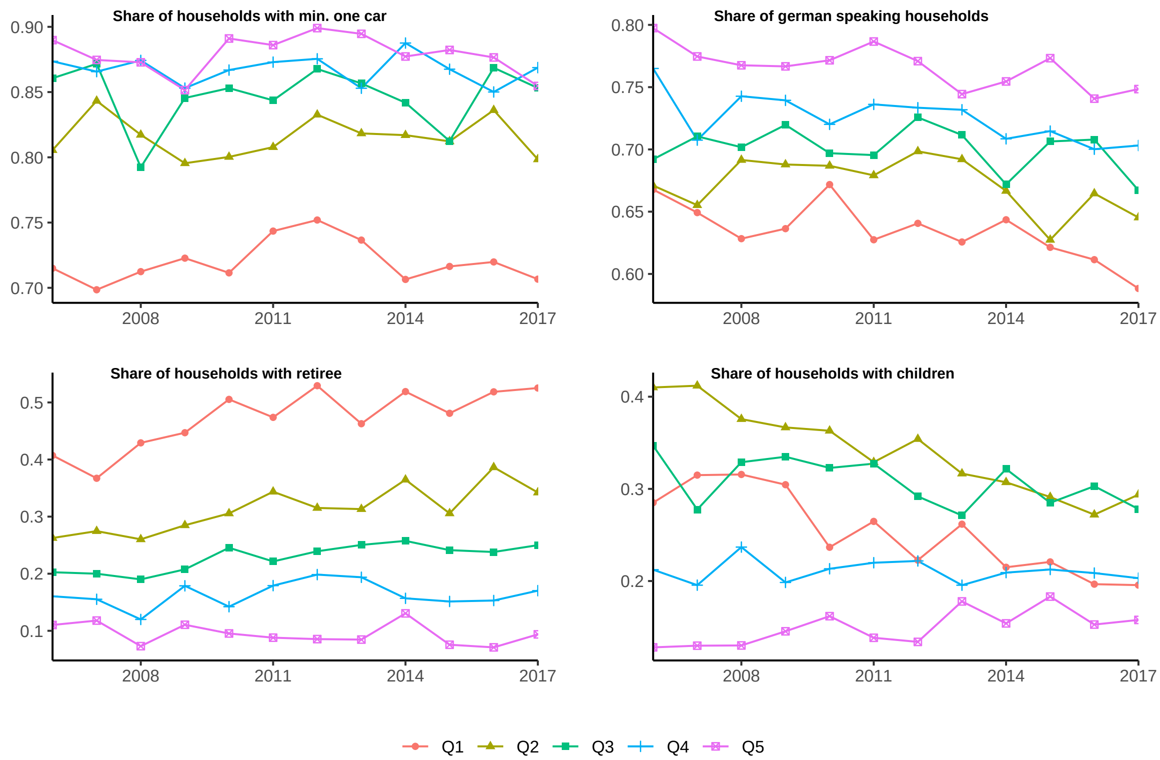
Appendix

Figure A1: Share of expenditures spent on energy by income decile



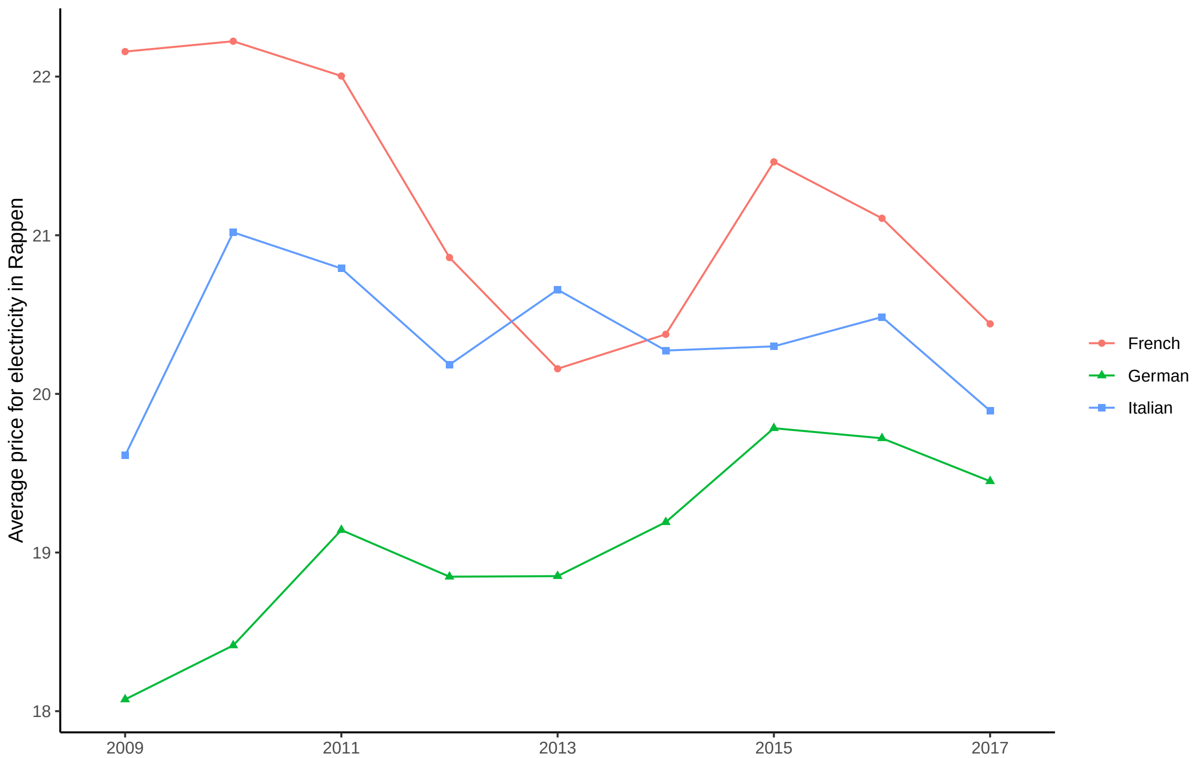
Source: Own illustration based on data from the Swiss Household Budget Survey provided by the Federal Statistics Office.

Figure A2: Decomposition of socio-demographic characteristics by income quintile



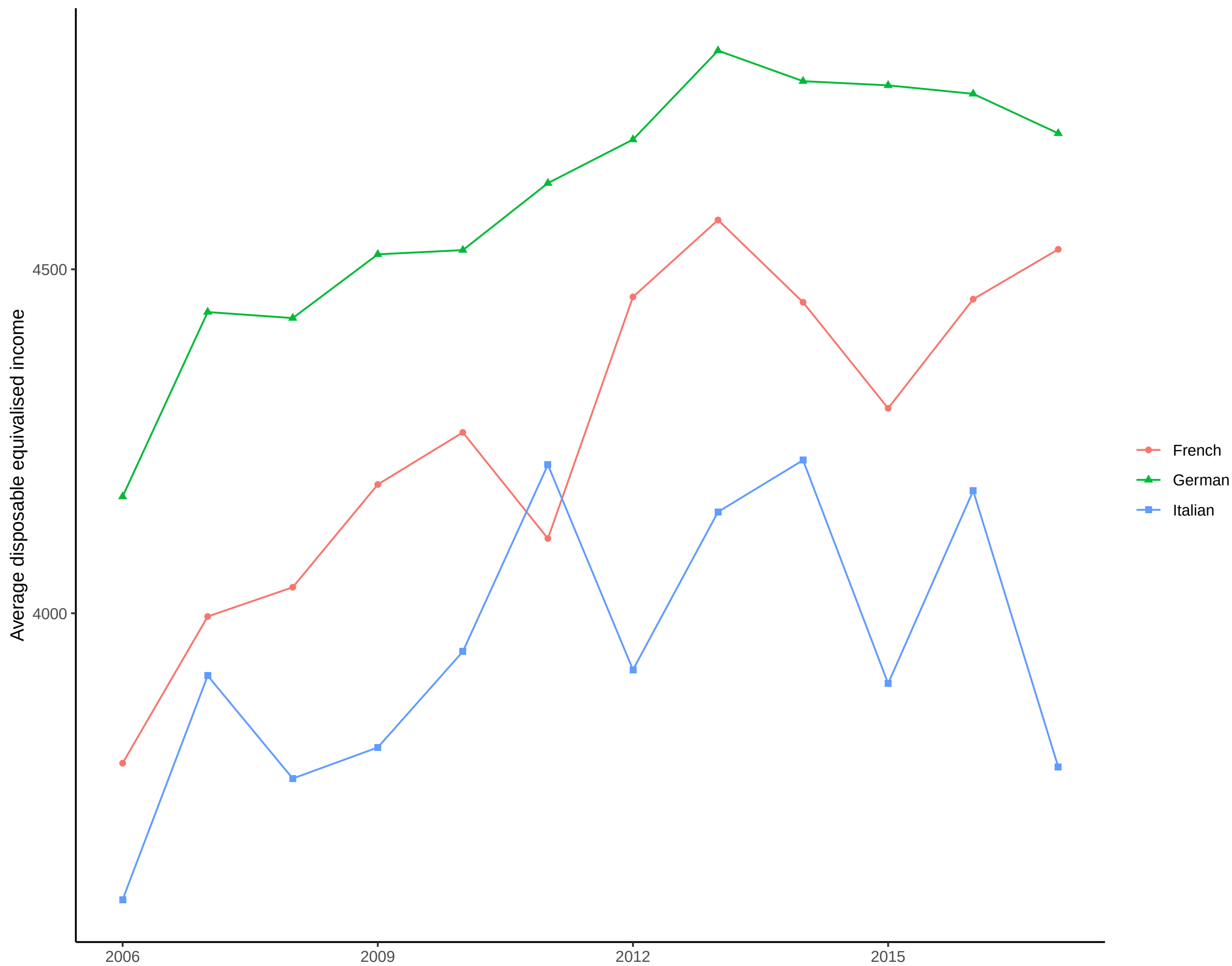
Source: Own illustration based on data from the Swiss Household Budget Survey provided by the Federal Statistics Office.

Figure A3: Development of electricity prices by linguistic region



Source: Own illustration based on data from the Federal Statistics Office.

Figure A4: Development of the average disposable equalised income by linguistic region



Source: Own illustration based on data from the Swiss Household Budget Survey provided by the Federal Statistics Office.

Table A1: Energy price elasticities (η) for different source of energy

Energy	η	η	η	η	η	**Split**	**Reference**
Gas	-0.24				-0.14	income (45% / 55%)	Auffhammer and Rubin (2018)
Fuel	-0.63	-0.47	-0.37	-0.29	-0.21	expenditure quintiles	Wadud et al. (2009)
RDH*	-0.607		-0.598		-0.232	income quarters (1/4,2/4,1/4)	Trotta et al. (2022)
Electricity	-0.166	-0.103	-0.074	-0.063	-0.081	income quintiles	Feger et al. (2022)

***Residential district heating**

Table A2: Gini and Concentration indices for different energy sources in Switzerland and by linguistic regions (LR) (2006 - 2023)

LR	Year	Gini	CI ET	CI EH	CI EL	CI FU	KI ET	KI EH	KI EL	KI FU
German	2006	0.26	0.09	0.06	0.02	0.16	-0.17	-0.20	-0.24	-0.10
German	2007	0.27	0.09	0.05	0.02	0.17	-0.18	-0.22	-0.25	-0.10
German	2008	0.27	0.06	0.00	-0.01	0.16	-0.20	-0.26	-0.27	-0.10
German	2009	0.26	0.07	0.04	0.02	0.15	-0.19	-0.22	-0.24	-0.11
German	2010	0.27	0.08	0.03	0.03	0.16	-0.19	-0.24	-0.24	-0.11
German	2011	0.26	0.08	0.06	0.04	0.13	-0.19	-0.20	-0.23	-0.13
German	2012	0.27	0.08	0.03	0.04	0.15	-0.19	-0.23	-0.23	-0.11
German	2013	0.26	0.08	0.04	0.02	0.14	-0.18	-0.22	-0.24	-0.12
German	2014	0.28	0.08	0.05	0.04	0.13	-0.20	-0.23	-0.24	-0.15
German	2015	0.27	0.07	0.03	0.02	0.12	-0.20	-0.24	-0.25	-0.14
German	2016	0.27	0.06	0.02	-0.00	0.14	-0.21	-0.25	-0.27	-0.13
German	2017	0.27	0.07	0.04	0.04	0.11	-0.20	-0.23	-0.23	-0.16
German	2023	0.27	0.07	0.05	0.04	0.11	-0.20	-0.22	-0.23	-0.16
French	2006	0.25	0.08	0.02	0.02	0.18	-0.17	-0.23	-0.24	-0.07
French	2007	0.26	0.10	0.09	0.04	0.17	-0.16	-0.17	-0.22	-0.09
French	2008	0.27	0.09	0.06	0.07	0.16	-0.18	-0.21	-0.20	-0.10
French	2009	0.27	0.10	0.07	0.04	0.18	-0.17	-0.20	-0.24	-0.10
French	2010	0.27	0.09	0.08	0.04	0.10	-0.18	-0.18	-0.22	-0.17
French	2011	0.25	0.08	0.05	0.01	0.16	-0.18	-0.21	-0.25	-0.10
French	2012	0.27	0.09	0.05	0.04	0.15	-0.18	-0.22	-0.23	-0.13
French	2013	0.29	0.07	0.02	0.03	0.13	-0.23	-0.27	-0.27	-0.16
French	2014	0.27	0.10	0.06	0.07	0.15	-0.18	-0.21	-0.20	-0.12
French	2015	0.26	0.08	0.04	0.05	0.10	-0.18	-0.22	-0.21	-0.16
French	2016	0.27	0.08	0.07	0.04	0.09	-0.19	-0.20	-0.23	-0.18
French	2017	0.29	0.10	0.07	0.05	0.13	-0.19	-0.22	-0.24	-0.16
French	2023	0.29	0.11	0.10	0.06	0.14	-0.18	-0.19	-0.23	-0.16
Italian	2006	0.25	0.06	0.02	-0.01	0.15	-0.19	-0.22	-0.26	-0.10
Italian	2007	0.28	0.08	0.04	0.02	0.13	-0.20	-0.24	-0.26	-0.15
Italian	2008	0.26	0.10	0.09	0.07	0.14	-0.16	-0.18	-0.20	-0.12
Italian	2009	0.27	0.11	0.04	0.02	0.25	-0.15	-0.22	-0.25	-0.02
Italian	2010	0.25	0.11	0.04	0.05	0.17	-0.15	-0.21	-0.20	-0.09
Italian	2011	0.30	0.13	0.09	0.07	0.23	-0.17	-0.20	-0.22	-0.07
Italian	2012	0.29	0.11	0.10	0.10	0.10	-0.18	-0.19	-0.19	-0.19
Italian	2013	0.25	0.09	0.05	0.03	0.15	-0.16	-0.20	-0.22	-0.10
Italian	2014	0.28	0.12	0.11	0.06	0.16	-0.16	-0.17	-0.22	-0.12
Italian	2015	0.26	0.10	0.07	-0.02	0.19	-0.16	-0.19	-0.29	-0.07
Italian	2016	0.30	0.07	0.04	0.01	0.11	-0.23	-0.26	-0.29	-0.19
Italian	2017	0.26	0.10	0.07	-0.01	0.15	-0.16	-0.19	-0.27	-0.11
Italian	2023	0.26	0.11	0.09	-0.00	0.15	-0.15	-0.17	-0.26	-0.11

Note: CI = Concentration Index, KI = Kakwani Index, ET = Total energy, EH = Household energy, EL = electricity, FU = fuel

Figure A2 depicts the share of households owning at least one car, share of German speaking households, share of retiree households and share of households with at least one child for each income quintile. The prevalence of retiree households among the lowest incomes reflects a mechanical effect since quintiles are computed as a function of disposable income. Therefore, some households that display a large fraction of their income spent on energy must not considered as energy poor if they also own wealth. Car owners are most likely represented among the richest households since almost 90 per cent of households in the fifth income quintile own a car, whereas the share of car owners is twenty percentage points lower for the poorest households. This also affects energy inequality for fuels, since those ones that do not own a car are less affected by fuel prices. Hence, total energy expenditure inequality as illustrated in Figure 2 may conceal the fact that energy expenditures that everyone incurs (like electricity or heating) could be even more unequally distributed. Fuel expenditures which are more concentrated at the top of the income distribution will make up for lower relative housing energy expenditures. Families with children are overrepresented in the lower middle class, whereas they represent less than 20 per cent of households in the highest quintile. Whereas only 60 per cent of lowest income households are German speaking, they represent about 80 per cent of the richest households.

Table A3: Share of income spent on energy by country, year and income quintile

Country	Year	Quintile	Total energy	Household	Electricity	Fuel	Share of expenditure
AT	2020	1	0.12	0.08	0.04	0.04	0.09
AT	2023	1	0.14	0.10	0.05	0.04	0.10
AT	2020	2	0.09	0.05	0.02	0.03	0.08
AT	2023	2	0.10	0.07	0.03	0.04	0.10
AT	2020	3	0.07	0.04	0.02	0.03	0.08
AT	2023	3	0.09	0.06	0.03	0.03	0.10
AT	2020	4	0.06	0.03	0.02	0.02	0.08
AT	2023	4	0.07	0.05	0.02	0.03	0.10
AT	2020	5	0.04	0.02	0.01	0.02	0.07
AT	2023	5	0.06	0.03	0.02	0.02	0.09
BE	2010	1	0.15	0.12	0.04	0.04	0.11
BE	2015	1	0.13	0.10	0.04	0.04	0.11
BE	2020	1	0.10	0.08	0.04	0.03	0.08
BE	2023	1	0.14	0.11	0.06	0.03	0.11
BE	2010	2	0.12	0.08	0.03	0.04	0.10
BE	2015	2	0.11	0.07	0.03	0.04	0.11
BE	2020	2	0.08	0.06	0.03	0.03	0.08
BE	2023	2	0.12	0.09	0.05	0.03	0.11
BE	2010	3	0.10	0.07	0.02	0.04	0.10
BE	2015	3	0.09	0.06	0.03	0.03	0.09
BE	2020	3	0.07	0.05	0.02	0.02	0.07

BE	2023	3	0.10	0.08	0.04	0.02	0.11
BE	2010	4	0.09	0.05	0.02	0.03	0.09
BE	2015	4	0.08	0.05	0.02	0.03	0.09
BE	2020	4	0.06	0.04	0.02	0.02	0.07
BE	2023	4	0.09	0.07	0.03	0.02	0.11
BE	2010	5	0.06	0.04	0.01	0.02	0.08
BE	2015	5	0.06	0.04	0.02	0.02	0.08
BE	2020	5	0.04	0.03	0.01	0.02	0.07
BE	2023	5	0.07	0.05	0.02	0.02	0.10
BG	2010	1	0.17	0.16	0.12	0.02	0.11
BG	2015	1	0.20	0.18	0.12	0.01	0.14
BG	2020	1	0.20	0.19	0.12	0.01	0.14
BG	2023	1	0.22	0.21	0.12	0.01	0.15
BG	2010	2	0.17	0.15	0.10	0.02	0.13
BG	2015	2	0.18	0.16	0.10	0.02	0.15
BG	2020	2	0.19	0.17	0.10	0.02	0.15
BG	2023	2	0.21	0.18	0.10	0.02	0.16
BG	2010	3	0.16	0.13	0.08	0.02	0.13
BG	2015	3	0.17	0.14	0.08	0.03	0.15
BG	2020	3	0.18	0.14	0.08	0.04	0.15
BG	2023	3	0.20	0.16	0.08	0.04	0.17
BG	2010	4	0.15	0.12	0.07	0.03	0.14
BG	2015	4	0.16	0.12	0.07	0.04	0.15
BG	2020	4	0.15	0.10	0.06	0.05	0.14
BG	2023	4	0.18	0.12	0.07	0.06	0.16
BG	2010	5	0.13	0.09	0.06	0.04	0.13
BG	2015	5	0.13	0.08	0.05	0.05	0.14
BG	2020	5	0.12	0.07	0.04	0.05	0.13
BG	2023	5	0.15	0.08	0.05	0.06	0.15
CY	2010	1	0.13	0.07	0.05	0.06	0.08
CY	2015	1	0.19	0.08	0.06	0.11	0.11
CY	2020	1	0.19	0.08	0.06	0.11	0.11
CY	2023	1	0.23	0.12	0.09	0.11	0.14
CY	2010	2	0.11	0.06	0.04	0.05	0.08
CY	2015	2	0.15	0.06	0.04	0.09	0.11
CY	2020	2	0.15	0.06	0.04	0.09	0.11
CY	2023	2	0.19	0.09	0.07	0.09	0.14
CY	2010	3	0.10	0.05	0.03	0.05	0.08
CY	2015	3	0.13	0.05	0.04	0.08	0.12
CY	2020	3	0.13	0.05	0.04	0.08	0.12
CY	2023	3	0.18	0.08	0.06	0.09	0.15

CY	2010	4	0.09	0.04	0.03	0.04	0.08
CY	2015	4	0.11	0.04	0.03	0.07	0.11
CY	2020	4	0.11	0.04	0.03	0.07	0.11
CY	2023	4	0.14	0.07	0.05	0.08	0.14
CY	2010	5	0.06	0.03	0.02	0.03	0.07
CY	2015	5	0.08	0.03	0.02	0.05	0.09
CY	2020	5	0.08	0.03	0.02	0.05	0.09
CY	2023	5	0.10	0.05	0.03	0.05	0.12
CZ	2010	1	0.18	0.16	0.07	0.02	0.21
CZ	2015	1	0.18	0.15	0.06	0.03	0.20
CZ	2010	2	0.15	0.12	0.05	0.04	0.19
CZ	2015	2	0.15	0.11	0.05	0.04	0.19
CZ	2010	3	0.14	0.10	0.04	0.04	0.18
CZ	2015	3	0.13	0.09	0.04	0.04	0.18
CZ	2010	4	0.12	0.08	0.04	0.04	0.17
CZ	2015	4	0.12	0.08	0.03	0.04	0.17
CZ	2010	5	0.10	0.07	0.03	0.03	0.16
CZ	2015	5	0.10	0.06	0.03	0.04	0.16
DE	2010	1	0.14	0.10	0.04	0.04	0.11
DE	2015	1	0.14	0.10	0.00	0.04	0.11
DE	2020	1	0.13	0.10	0.05	0.03	0.11
DE	2023	1	0.18	0.14	0.07	0.04	0.15
DE	2010	2	0.12	0.07	0.03	0.05	0.11
DE	2015	2	0.12	0.08	0.00	0.04	0.11
DE	2020	2	0.10	0.07	0.03	0.04	0.10
DE	2023	2	0.14	0.10	0.05	0.04	0.14
DE	2010	3	0.10	0.06	0.02	0.04	0.11
DE	2015	3	0.10	0.06	0.00	0.04	0.11
DE	2020	3	0.09	0.05	0.02	0.04	0.09
DE	2023	3	0.13	0.08	0.04	0.04	0.13
DE	2010	4	0.09	0.05	0.02	0.04	0.10
DE	2015	4	0.09	0.05	0.00	0.04	0.10
DE	2020	4	0.08	0.04	0.02	0.03	0.09
DE	2023	4	0.11	0.07	0.03	0.04	0.13
DE	2010	5	0.06	0.03	0.01	0.03	0.08
DE	2015	5	0.07	0.04	0.00	0.03	0.09
DE	2020	5	0.06	0.03	0.01	0.03	0.08
DE	2023	5	0.08	0.05	0.02	0.03	0.11
DK	2010	1	0.15	0.13	0.04	0.03	0.12
DK	2015	1	0.13	0.11	0.04	0.02	0.12
DK	2020	1	0.13	0.11	0.03	0.02	0.11

DK	2023	1	0.15	0.14	0.06	0.02	0.14
DK	2010	2	0.11	0.08	0.03	0.03	0.11
DK	2015	2	0.10	0.07	0.03	0.03	0.12
DK	2020	2	0.08	0.06	0.02	0.02	0.10
DK	2023	2	0.11	0.10	0.05	0.02	0.14
DK	2010	3	0.09	0.06	0.02	0.03	0.11
DK	2015	3	0.08	0.06	0.02	0.02	0.11
DK	2020	3	0.06	0.05	0.02	0.02	0.09
DK	2023	3	0.10	0.08	0.05	0.02	0.14
DK	2010	4	0.08	0.05	0.02	0.03	0.11
DK	2015	4	0.07	0.05	0.02	0.02	0.11
DK	2020	4	0.05	0.04	0.01	0.01	0.08
DK	2023	4	0.08	0.07	0.04	0.02	0.13
DK	2010	5	0.06	0.04	0.02	0.02	0.10
DK	2015	5	0.06	0.04	0.01	0.02	0.10
DK	2020	5	0.04	0.03	0.01	0.01	0.07
DK	2023	5	0.07	0.05	0.03	0.01	0.12
EE	2010	1	0.22	0.17	0.08	0.05	0.16
EE	2015	1	0.20	0.16	0.06	0.04	0.18
EE	2020	1	0.16	0.12	0.05	0.04	0.14
EE	2023	1	0.18	0.14	0.08	0.04	0.16
EE	2010	2	0.15	0.12	0.04	0.03	0.16
EE	2015	2	0.16	0.12	0.05	0.04	0.18
EE	2020	2	0.12	0.08	0.04	0.04	0.13
EE	2023	2	0.14	0.10	0.06	0.04	0.16
EE	2010	3	0.13	0.09	0.04	0.04	0.15
EE	2015	3	0.13	0.09	0.04	0.05	0.16
EE	2020	3	0.09	0.06	0.03	0.04	0.12
EE	2023	3	0.12	0.08	0.05	0.04	0.15
EE	2010	4	0.12	0.08	0.04	0.05	0.16
EE	2015	4	0.11	0.07	0.03	0.04	0.15
EE	2020	4	0.08	0.04	0.02	0.03	0.11
EE	2023	4	0.10	0.06	0.04	0.04	0.14
EE	2010	5	0.10	0.06	0.03	0.04	0.14
EE	2015	5	0.08	0.05	0.02	0.04	0.13
EE	2020	5	0.06	0.03	0.02	0.03	0.11
EE	2023	5	0.07	0.04	0.03	0.03	0.13
EL	2010	1	0.17	0.12	0.04	0.05	0.09
EL	2015	1	0.27	0.19	0.11	0.08	0.11
EL	2020	1	0.26	0.21	0.12	0.05	0.12
EL	2023	1	0.34	0.29	0.21	0.05	0.18

EL	2010	2	0.11	0.08	0.03	0.03	0.09
EL	2015	2	0.17	0.12	0.06	0.05	0.12
EL	2020	2	0.16	0.12	0.06	0.04	0.13
EL	2023	2	0.26	0.22	0.16	0.04	0.21
EL	2010	3	0.10	0.06	0.02	0.04	0.09
EL	2015	3	0.15	0.10	0.04	0.05	0.12
EL	2020	3	0.13	0.09	0.05	0.04	0.12
EL	2023	3	0.23	0.18	0.13	0.05	0.21
EL	2010	4	0.09	0.04	0.02	0.04	0.09
EL	2015	4	0.13	0.07	0.03	0.06	0.12
EL	2020	4	0.11	0.07	0.04	0.04	0.12
EL	2023	4	0.19	0.15	0.11	0.05	0.21
EL	2010	5	0.07	0.03	0.01	0.04	0.08
EL	2015	5	0.10	0.05	0.02	0.05	0.11
EL	2020	5	0.09	0.05	0.03	0.04	0.11
EL	2023	5	0.15	0.11	0.08	0.04	0.18
ES	2010	1	0.18	0.10	0.07	0.08	0.09
ES	2015	1	0.19	0.11	0.08	0.08	0.09
ES	2020	1	0.14	0.09	0.06	0.05	0.09
ES	2023	1	0.20	0.15	0.12	0.06	0.13
ES	2010	2	0.13	0.07	0.05	0.06	0.09
ES	2015	2	0.13	0.08	0.05	0.05	0.09
ES	2020	2	0.11	0.07	0.04	0.04	0.09
ES	2023	2	0.17	0.12	0.09	0.05	0.13
ES	2010	3	0.12	0.05	0.04	0.06	0.09
ES	2015	3	0.12	0.06	0.04	0.06	0.09
ES	2020	3	0.09	0.05	0.03	0.04	0.08
ES	2023	3	0.15	0.11	0.07	0.04	0.14
ES	2010	4	0.10	0.04	0.03	0.05	0.08
ES	2015	4	0.10	0.05	0.03	0.05	0.09
ES	2020	4	0.07	0.04	0.03	0.03	0.08
ES	2023	4	0.13	0.09	0.06	0.04	0.14
ES	2010	5	0.07	0.03	0.02	0.04	0.07
ES	2015	5	0.07	0.04	0.02	0.04	0.08
ES	2020	5	0.05	0.03	0.02	0.02	0.07
ES	2023	5	0.09	0.07	0.04	0.03	0.12
FI	2010	1	0.10	0.06	0.04	0.04	0.08
FI	2015	1	0.09	0.05	0.04	0.03	0.06
FI	2010	2	0.09	0.05	0.03	0.04	0.09
FI	2015	2	0.07	0.04	0.03	0.03	0.07
FI	2010	3	0.08	0.04	0.03	0.04	0.09

FI	2015	3	0.07	0.04	0.03	0.03	0.08
FI	2010	4	0.08	0.04	0.02	0.04	0.09
FI	2015	4	0.06	0.03	0.02	0.03	0.07
FI	2010	5	0.07	0.03	0.02	0.03	0.09
FI	2015	5	0.05	0.03	0.02	0.02	0.07
FR	2010	1	0.15	0.09	0.06	0.06	0.07
FR	2015	1	0.14	0.09	0.06	0.05	0.08
FR	2020	1	0.14	0.09	0.06	0.05	0.08
FR	2023	1	0.16	0.11	0.07	0.05	0.10
FR	2010	2	0.11	0.05	0.03	0.05	0.09
FR	2015	2	0.09	0.05	0.04	0.04	0.09
FR	2020	2	0.09	0.05	0.04	0.04	0.09
FR	2023	2	0.12	0.07	0.05	0.05	0.12
FR	2010	3	0.09	0.04	0.03	0.05	0.10
FR	2015	3	0.08	0.05	0.03	0.04	0.09
FR	2020	3	0.08	0.05	0.03	0.04	0.09
FR	2023	3	0.11	0.06	0.04	0.05	0.12
FR	2010	4	0.08	0.04	0.02	0.04	0.09
FR	2015	4	0.07	0.04	0.02	0.03	0.09
FR	2020	4	0.07	0.04	0.02	0.03	0.09
FR	2023	4	0.09	0.05	0.03	0.04	0.11
FR	2010	5	0.06	0.03	0.02	0.03	0.08
FR	2015	5	0.05	0.03	0.02	0.02	0.07
FR	2020	5	0.05	0.03	0.02	0.02	0.07
FR	2023	5	0.06	0.04	0.02	0.03	0.10
HR	2010	1	0.26	0.21	0.11	0.04	0.13
HR	2015	1	0.31	0.25	0.12	0.06	0.15
HR	2020	1	0.30	0.26	0.11	0.05	0.14
HR	2023	1	0.34	0.29	0.11	0.05	0.16
HR	2010	2	0.18	0.13	0.06	0.05	0.13
HR	2015	2	0.21	0.16	0.07	0.06	0.15
HR	2020	2	0.22	0.16	0.07	0.06	0.15
HR	2023	2	0.25	0.19	0.07	0.07	0.17
HR	2010	3	0.16	0.11	0.05	0.05	0.13
HR	2015	3	0.19	0.12	0.06	0.06	0.15
HR	2020	3	0.18	0.11	0.05	0.07	0.15
HR	2023	3	0.22	0.15	0.05	0.08	0.18
HR	2010	4	0.15	0.08	0.04	0.06	0.14
HR	2015	4	0.16	0.09	0.04	0.06	0.14
HR	2020	4	0.16	0.09	0.04	0.07	0.14
HR	2023	4	0.20	0.12	0.04	0.08	0.18

HR	2010	5	0.11	0.06	0.03	0.05	0.13
HR	2015	5	0.13	0.07	0.03	0.06	0.14
HR	2020	5	0.11	0.06	0.03	0.06	0.13
HR	2023	5	0.14	0.08	0.03	0.06	0.16
HU	2010	1	0.28	0.26	0.10	0.02	0.19
HU	2015	1	0.23	0.20	0.07	0.03	0.16
HU	2020	1	0.20	0.17	0.06	0.03	0.09
HU	2023	1	0.15	0.12	0.05	0.03	0.07
HU	2010	2	0.23	0.20	0.07	0.02	0.19
HU	2015	2	0.20	0.17	0.05	0.03	0.16
HU	2020	2	0.17	0.14	0.04	0.04	0.10
HU	2023	2	0.11	0.08	0.04	0.03	0.07
HU	2010	3	0.20	0.17	0.06	0.03	0.18
HU	2015	3	0.18	0.14	0.05	0.04	0.16
HU	2020	3	0.15	0.11	0.04	0.04	0.10
HU	2023	3	0.14	0.10	0.03	0.04	0.09
HU	2010	4	0.17	0.14	0.05	0.03	0.17
HU	2015	4	0.17	0.12	0.04	0.05	0.16
HU	2020	4	0.14	0.09	0.03	0.05	0.11
HU	2023	4	0.14	0.09	0.02	0.05	0.11
HU	2010	5	0.13	0.10	0.03	0.03	0.15
HU	2015	5	0.14	0.09	0.03	0.06	0.16
HU	2020	5	0.11	0.06	0.02	0.05	0.10
HU	2023	5	0.11	0.07	0.02	0.05	0.11
IE	2010	1	0.17	0.10	0.05	0.07	0.11
IE	2015	1	0.17	0.11	0.05	0.05	0.11
IE	2010	2	0.11	0.06	0.03	0.05	0.11
IE	2015	2	0.11	0.07	0.03	0.05	0.11
IE	2010	3	0.09	0.05	0.02	0.05	0.11
IE	2015	3	0.10	0.05	0.02	0.05	0.11
IE	2010	4	0.08	0.03	0.02	0.04	0.10
IE	2015	4	0.08	0.04	0.02	0.04	0.09
IE	2010	5	0.05	0.02	0.01	0.03	0.09
IE	2015	5	0.06	0.03	0.01	0.03	0.09
LT	2010	1	0.20	0.14	0.05	0.05	0.11
LT	2015	1	0.25	0.20	0.06	0.05	0.12
LT	2020	1	0.22	0.20	0.06	0.03	0.13
LT	2023	1	0.22	0.19	0.08	0.03	0.13
LT	2010	2	0.16	0.12	0.03	0.04	0.12
LT	2015	2	0.20	0.15	0.04	0.05	0.13
LT	2020	2	0.17	0.14	0.04	0.03	0.13

LT	2023	2	0.17	0.14	0.06	0.03	0.13
LT	2010	3	0.15	0.10	0.03	0.05	0.13
LT	2015	3	0.19	0.13	0.03	0.06	0.14
LT	2020	3	0.14	0.11	0.04	0.03	0.13
LT	2023	3	0.15	0.12	0.05	0.03	0.14
LT	2010	4	0.13	0.07	0.02	0.06	0.13
LT	2015	4	0.17	0.10	0.03	0.07	0.14
LT	2020	4	0.13	0.09	0.03	0.04	0.14
LT	2023	4	0.14	0.10	0.04	0.04	0.15
LT	2010	5	0.11	0.05	0.02	0.05	0.13
LT	2015	5	0.14	0.08	0.02	0.06	0.14
LT	2020	5	0.08	0.05	0.02	0.02	0.11
LT	2023	5	0.09	0.06	0.03	0.02	0.13
LU	2015	1	0.09	0.06	0.03	0.03	0.08
LU	2020	1	0.08	0.05	0.02	0.03	0.07
LU	2023	1	0.08	0.05	0.02	0.03	0.07
LU	2015	2	0.07	0.04	0.02	0.03	0.07
LU	2020	2	0.06	0.03	0.01	0.02	0.06
LU	2023	2	0.06	0.04	0.02	0.03	0.07
LU	2015	3	0.06	0.04	0.01	0.02	0.06
LU	2020	3	0.05	0.03	0.01	0.02	0.05
LU	2023	3	0.07	0.04	0.01	0.03	0.07
LU	2015	4	0.05	0.03	0.01	0.02	0.06
LU	2020	4	0.04	0.02	0.01	0.02	0.04
LU	2023	4	0.05	0.03	0.01	0.02	0.06
LU	2015	5	0.04	0.02	0.01	0.01	0.05
LU	2020	5	0.03	0.02	0.01	0.01	0.04
LU	2023	5	0.04	0.02	0.01	0.01	0.06
LV	2010	1	0.31	0.26	0.08	0.05	0.16
LV	2015	1	0.24	0.21	0.07	0.03	0.17
LV	2020	1	0.25	0.23	0.07	0.02	0.15
LV	2023	1	0.29	0.28	0.12	0.02	0.17
LV	2010	2	0.23	0.18	0.05	0.04	0.17
LV	2015	2	0.19	0.16	0.05	0.03	0.16
LV	2020	2	0.18	0.15	0.04	0.03	0.14
LV	2023	2	0.22	0.18	0.08	0.03	0.17
LV	2010	3	0.19	0.15	0.04	0.05	0.16
LV	2015	3	0.18	0.13	0.04	0.05	0.16
LV	2020	3	0.16	0.11	0.04	0.04	0.13
LV	2023	3	0.20	0.15	0.08	0.05	0.17
LV	2010	4	0.17	0.12	0.03	0.06	0.16

LV	2015	4	0.17	0.10	0.04	0.07	0.16
LV	2020	4	0.14	0.09	0.03	0.05	0.13
LV	2023	4	0.18	0.12	0.06	0.06	0.17
LV	2010	5	0.13	0.08	0.02	0.06	0.14
LV	2015	5	0.13	0.07	0.03	0.06	0.14
LV	2020	5	0.10	0.06	0.02	0.04	0.12
LV	2023	5	0.14	0.09	0.04	0.05	0.15
MT	2010	1	0.14	0.06	0.05	0.08	0.09
MT	2015	1	0.13	0.06	0.04	0.07	0.09
MT	2020	1	0.13	0.06	0.04	0.07	0.09
MT	2023	1	0.12	0.06	0.04	0.06	0.09
MT	2010	2	0.09	0.04	0.03	0.05	0.08
MT	2015	2	0.08	0.04	0.03	0.05	0.09
MT	2020	2	0.08	0.04	0.03	0.05	0.09
MT	2023	2	0.08	0.04	0.03	0.04	0.09
MT	2010	3	0.08	0.03	0.03	0.05	0.09
MT	2015	3	0.08	0.03	0.02	0.05	0.09
MT	2020	3	0.08	0.03	0.02	0.05	0.09
MT	2023	3	0.07	0.03	0.02	0.04	0.09
MT	2010	4	0.07	0.02	0.02	0.05	0.09
MT	2015	4	0.07	0.02	0.02	0.04	0.09
MT	2020	4	0.07	0.02	0.02	0.04	0.09
MT	2023	4	0.06	0.02	0.02	0.04	0.09
MT	2010	5	0.06	0.02	0.02	0.04	0.09
MT	2015	5	0.05	0.01	0.01	0.03	0.08
MT	2020	5	0.05	0.01	0.01	0.03	0.08
MT	2023	5	0.05	0.02	0.01	0.03	0.08
NL	2015	1	0.13	0.09	0.03	0.04	0.09
NL	2020	1	0.11	0.08	0.02	0.03	0.07
NL	2023	1	0.15	0.11	0.03	0.03	0.10
NL	2015	2	0.09	0.05	0.02	0.04	0.09
NL	2020	2	0.07	0.04	0.01	0.03	0.07
NL	2023	2	0.10	0.07	0.02	0.03	0.10
NL	2015	3	0.08	0.04	0.02	0.04	0.09
NL	2020	3	0.06	0.04	0.01	0.03	0.07
NL	2023	3	0.10	0.07	0.02	0.03	0.11
NL	2015	4	0.07	0.04	0.01	0.04	0.09
NL	2020	4	0.05	0.03	0.01	0.02	0.07
NL	2023	4	0.09	0.06	0.02	0.03	0.11
NL	2015	5	0.06	0.03	0.01	0.03	0.08
NL	2020	5	0.04	0.02	0.01	0.02	0.06

NL	2023	5	0.07	0.05	0.01	0.02	0.10
PL	2010	1	0.21	0.17	0.07	0.04	0.13
PL	2015	1	0.19	0.15	0.07	0.04	0.13
PL	2010	2	0.19	0.15	0.05	0.04	0.16
PL	2015	2	0.17	0.13	0.05	0.03	0.15
PL	2010	3	0.17	0.13	0.04	0.04	0.16
PL	2015	3	0.16	0.12	0.04	0.04	0.16
PL	2010	4	0.16	0.11	0.04	0.04	0.16
PL	2015	4	0.14	0.10	0.03	0.04	0.15
PL	2010	5	0.12	0.08	0.02	0.04	0.15
PL	2015	5	0.11	0.07	0.02	0.04	0.14
PT	2010	1	0.23	0.15	0.08	0.07	0.12
PT	2015	1	0.27	0.18	0.11	0.08	0.13
PT	2010	2	0.17	0.10	0.05	0.06	0.13
PT	2015	2	0.18	0.11	0.06	0.07	0.14
PT	2010	3	0.16	0.08	0.04	0.07	0.14
PT	2015	3	0.16	0.08	0.05	0.07	0.14
PT	2010	4	0.14	0.06	0.03	0.08	0.14
PT	2015	4	0.14	0.07	0.04	0.07	0.14
PT	2010	5	0.10	0.04	0.02	0.06	0.12
PT	2015	5	0.09	0.04	0.03	0.05	0.11
RO	2010	1	0.18	0.18	0.08	0.01	0.10
RO	2015	1	0.20	0.19	0.10	0.01	0.11
RO	2010	2	0.18	0.17	0.07	0.01	0.12
RO	2015	2	0.19	0.18	0.08	0.01	0.13
RO	2010	3	0.17	0.16	0.05	0.02	0.13
RO	2015	3	0.17	0.15	0.06	0.02	0.13
RO	2010	4	0.16	0.13	0.05	0.02	0.13
RO	2015	4	0.16	0.13	0.05	0.03	0.14
RO	2010	5	0.14	0.10	0.03	0.04	0.13
RO	2015	5	0.13	0.09	0.04	0.04	0.14
SE	2010	1	0.11	0.06	0.00	0.05	0.09
SE	2015	1	0.10	0.05	0.04	0.05	0.08
SE	2010	2	0.09	0.05	0.00	0.04	0.10
SE	2015	2	0.09	0.04	0.03	0.05	0.09
SE	2010	3	0.08	0.04	0.00	0.04	0.10
SE	2015	3	0.08	0.04	0.03	0.05	0.10
SE	2010	4	0.07	0.03	0.00	0.04	0.09
SE	2015	4	0.08	0.03	0.02	0.05	0.11
SE	2010	5	0.06	0.03	0.00	0.03	0.09
SE	2015	5	0.06	0.02	0.02	0.03	0.09

SI	2010	1		0.24	0.19	0.09	0.05	0.13
SI	2015	1		0.27	0.18	0.08	0.09	0.16
SI	2020	1		0.22	0.14	0.07	0.08	0.14
SI	2023	1		0.23	0.16	0.08	0.08	0.15
SI	2010	2		0.16	0.11	0.04	0.05	0.12
SI	2015	2		0.19	0.11	0.04	0.08	0.17
SI	2020	2		0.16	0.09	0.04	0.07	0.15
SI	2023	2		0.17	0.10	0.05	0.07	0.16
SI	2010	3		0.14	0.09	0.03	0.05	0.12
SI	2015	3		0.15	0.08	0.03	0.07	0.17
SI	2020	3		0.14	0.07	0.03	0.07	0.15
SI	2023	3		0.15	0.08	0.04	0.07	0.16
SI	2010	4		0.12	0.07	0.03	0.05	0.11
SI	2015	4		0.14	0.07	0.03	0.07	0.17
SI	2020	4		0.12	0.06	0.03	0.06	0.15
SI	2023	4		0.13	0.07	0.03	0.07	0.16
SI	2010	5		0.09	0.05	0.02	0.04	0.11
SI	2015	5		0.11	0.05	0.02	0.06	0.17
SI	2020	5		0.10	0.04	0.02	0.06	0.14
SI	2023	5		0.11	0.05	0.02	0.06	0.16
SK	2010	1		0.24	0.21	0.09	0.02	0.20
SK	2015	1		0.23	0.21	0.08	0.02	0.19
SK	2020	1		0.20	0.18	0.07	0.02	0.18
SK	2023	1		0.21	0.19	0.06	0.02	0.19
SK	2010	2		0.20	0.18	0.06	0.02	0.20
SK	2015	2		0.19	0.17	0.05	0.02	0.19
SK	2020	2		0.16	0.14	0.05	0.02	0.17
SK	2023	2		0.17	0.15	0.05	0.02	0.18
SK	2010	3		0.18	0.15	0.05	0.03	0.19
SK	2015	3		0.16	0.13	0.04	0.03	0.18
SK	2020	3		0.14	0.11	0.04	0.03	0.16
SK	2023	3		0.15	0.12	0.04	0.03	0.18
SK	2010	4		0.16	0.12	0.04	0.04	0.18
SK	2015	4		0.13	0.10	0.03	0.03	0.16
SK	2020	4		0.11	0.08	0.03	0.03	0.15
SK	2023	4		0.12	0.09	0.03	0.03	0.17
SK	2010	5		0.13	0.09	0.03	0.04	0.17
SK	2015	5		0.10	0.07	0.02	0.03	0.14
SK	2020	5		0.09	0.06	0.02	0.03	0.13
SK	2023	5		0.10	0.07	0.02	0.03	0.15
UK	2010	1		0.16	0.10	0.05	0.05	0.11

UK	2010	2	0.11	0.06	0.03	0.04	0.12
UK	2010	3	0.09	0.05	0.02	0.04	0.13
UK	2010	4	0.08	0.04	0.02	0.04	0.13
UK	2010	5	0.06	0.03	0.01	0.03	0.11

Source: Own calculatiosn based on data from the European Household Budget Survey provided by Eurostat and price elasticity estimates for energy of various recent studies. The table shows the share of the respective expenditures (total energy expenditures, household energy expenditures, electricity expenditures, fuel expenditures) as a share of income by country, year and income quintile in the columns 4 to 7 and as a share of overall household expenditure in the column 8.

Table A4: Energy price developments by country

Country	Income'20	Income'22	Gasoline'20	Diesel'20	Oil'20	Gasoline'23	Diesel'23	Oil'23	Gas'23	Gas'20	Elec'23	Elec'20	Heat'20	Heat'23	Hydro'20	2Hydro'23	Solid'20	Solid'23	Fuel'20	Fuel'23
Austria	108.59	116.95	1.24	1.20	0.69	1.69	1.84	1.39	0.08	0.02	0.21	0.14	96.50	120.50	121.30	143.10	127.30	161.00	1.22	1.77
Belgium	109.37	120.90	1.46	1.47	0.53	1.83	1.85	1.06	0.06	0.02	0.38	0.18	96.50	120.50	121.30	143.10	127.30	161.00	1.47	1.83
Bulgaria	113.93	118.43	1.06	1.05	0.92	1.40	1.57	1.38	0.12	0.02	0.10	0.08	96.50	120.50	121.30	143.10	127.30	161.00	1.06	1.47
Croatia	113.93	118.43	1.37	1.32	0.57	1.53	1.73	1.12	0.08	0.03	0.12	0.10	96.50	120.50	121.30	143.10	127.30	161.00	1.35	1.64
Cyprus	113.93	118.43	1.23	1.27	0.78	1.48	1.69	1.23	0.08	0.02	0.26	0.13	96.50	120.50	121.30	143.10	127.30	161.00	1.24	1.53
Czechia	129.22	146.32	1.22	1.21	0.63	1.67	1.68	1.21	0.08	0.02	0.36	0.13	96.50	120.50	121.30	143.10	127.30	161.00	1.21	1.68
Denmark	111.59	117.54	1.65	1.39	1.35	2.12	1.94	2.00	0.13	0.02	0.36	0.09	96.50	120.50	121.30	143.10	127.30	161.00	1.57	2.07
Estonia	128.09	150.54	1.43	1.25	0.82	1.87	1.87	1.38	0.13	0.02	0.21	0.09	96.50	120.50	121.30	143.10	127.30	161.00	1.36	1.87
Finland	106.00	111.35	1.61	1.43	0.91	2.08	2.21	1.70	0.08	0.02	0.19	0.12	96.50	120.50	121.30	143.10	127.30	161.00	1.56	2.11
France	111.3	114.56	1.55	1.44	0.87	2.02	2.00	1.44	0.07	0.03	0.17	0.13	96.50	120.50	121.30	143.10	127.30	161.00	1.48	2.01
Germany	112.07	111.96	1.47	1.27	0.60	1.94	1.94	1.27	0.05	0.02	0.23	0.14	96.50	120.50	121.30	143.10	127.30	161.00	1.40	1.94
Greece	113.93	118.43	1.68	1.40	1.02	2.03	1.90	1.32	0.15	0.02	0.46	0.13	96.50	120.50	121.30	143.10	127.30	161.00	1.65	2.02
Hungary	160.76	203.38	1.16	1.20	1.20	1.73	1.84	1.84	0.14	0.02	0.09	0.08	96.50	120.50	121.30	143.10	127.30	161.00	1.18	1.76
Ireland	111.70	119.80	1.47	1.37	0.63	1.72	1.82	1.18	0.08	0.03	0.38	0.21	96.50	120.50	121.30	143.10	127.30	161.00	1.41	1.78
Italy	103.88	106.72	1.63	1.50	1.30	1.98	2.00	1.73	0.11	0.02	0.32	0.14	96.50	120.50	121.30	143.10	127.30	161.00	1.57	1.99
Latvia	147.69	164.75	1.30	1.19	0.67	1.75	1.81	1.35	0.14	0.02	0.24	0.10	96.50	120.50	121.30	143.10	127.30	161.00	1.23	1.79
Lithuania	197.80	246.78	1.25	1.14	0.50	1.62	1.77	1.12	0.12	0.02	0.20	0.10	96.50	120.50	121.30	143.10	127.30	161.00	1.17	1.73
Luxembourg	99.29	107.07	1.23	1.11	0.50	1.66	1.71	1.09	0.11	0.03	0.17	0.15	96.50	120.50	121.30	143.10	127.30	161.00	1.16	1.69
Malta	113.93	118.43	1.56	1.42	1.14	1.44	1.29	1.08	0.08	0.02	0.12	0.12	96.50	120.50	121.30	143.10	127.30	161.00	1.50	1.37
Netherlands	112.66	118.63	1.78	1.41	1.12	1.96	1.86	2.04	0.06	0.02	0.32	0.14	96.50	120.50	121.30	143.10	127.30	161.00	1.73	1.94
Poland	133.35	163.56	1.14	1.15	0.71	1.52	1.72	1.40	0.10	0.03	0.10	0.09	96.50	120.50	121.30	143.10	127.30	161.00	1.14	1.61
Portugal	118.73	133.92	1.59	1.42	1.19	1.81	1.70	1.71	0.10	0.02	0.20	0.11	96.50	120.50	121.30	143.10	127.30	161.00	1.48	1.74
Romania	113.93	118.43	1.09	1.10	0.91	1.42	1.62	1.51	0.15	0.03	0.27	0.10	96.50	120.50	121.30	143.10	127.30	161.00	1.09	1.51
Slovakia	123.36	144.35	1.35	1.22	0.96	1.66	1.71	0.96	0.08	0.03	0.13	0.11	96.50	120.50	121.30	143.10	127.30	161.00	1.29	1.68
Slovenia	120.22	136.34	1.21	1.21	0.95	1.42	1.63	1.23	0.08	0.03	0.15	0.11	96.50	120.50	121.30	143.10	127.30	161.00	1.21	1.53
Spain	106.47	108.30	1.34	1.22	0.65	1.75	1.77	1.21	0.10	0.02	0.30	0.12	96.50	120.50	121.30	143.10	127.30	161.00	1.27	1.76
Sweden	110.50	116.97	1.54	1.57	1.07	1.90	2.26	1.48	0.14	0.03	0.25	0.12	96.50	120.50	121.30	143.10	127.30	161.00	1.55	2.04

Table A5: Energy poverty in European Union countries

country	TPR_2010	TPR_2015	TPR_2020	TPR_2023	2M_2010	2M_2015	2M_2020	2M_2023
BE	0.405	0.381	0.216	0.412	0.120	0.095	0.139	0.113
BG	0.669	0.796	0.760	0.819	0.121	0.081	0.094	0.099
CY	0.362	0.565	0.565	0.735	0.114	0.121	0.121	0.110
CZ	0.687	0.675			0.056	0.065		
DE	0.387	0.415	0.317	0.554	0.110	0.110	0.100	0.100
DK	0.362	0.300	0.204	0.376	0.154	0.159	0.184	0.145
EE	0.552	0.550	0.370	0.475	0.191	0.166	0.194	0.170
EL	0.419	0.657	0.620	0.909	0.134	0.133	0.132	0.099
ES	0.470	0.469	0.322	0.608	0.171	0.173	0.185	0.143
FI	0.317	0.224			0.165	0.176		
FR	0.337	0.287	0.287	0.388	0.216	0.209	0.209	0.199
HR	0.750	0.807	0.801	0.869	0.106	0.101	0.116	0.105
HU	0.881	0.832	0.694	0.562	0.073	0.082	0.096	0.121
IE	0.361	0.386			0.151	0.143		
LT	0.569	0.736	0.571	0.600	0.175	0.134	0.173	0.165
LV	0.751	0.732	0.666	0.808	0.153	0.133	0.139	0.129
MT	0.317	0.258	0.258	0.250	0.149	0.152	0.152	0.152
PL	0.651	0.624			0.161	0.145		
PT	0.597	0.679			0.181	0.141		
RO	0.627	0.663			0.173	0.153		
SE	0.286	0.289			0.129	0.170		
SI	0.622	0.769	0.686	0.737	0.125	0.101	0.093	0.093
SK	0.818	0.754	0.635	0.668	0.077	0.079	0.095	0.110
UK	0.355				0.152			
LU		0.135	0.082	0.139		0.118	0.137	0.136
NL		0.277	0.144	0.370		0.086	0.097	0.069
AT			0.228	0.342			0.150	0.151

Table A6: Gini and Concentration indices for different energy sources in Switzerland and by administrative regions (AR) (2006 - 2023)

AR	Year	Gini	CI ET	CI EH	CI EL	CI FU	KI ET	KI EH	KI EL	KI FU
Genferseeregion	2006	0.26	0.08	0.03	0.02	0.15	-0.18	-0.23	-0.23	-0.10
Genferseeregion	2007	0.27	0.10	0.10	0.05	0.17	-0.17	-0.17	-0.22	-0.10
Genferseeregion	2008	0.27	0.09	0.07	0.06	0.15	-0.18	-0.20	-0.21	-0.11
Genferseeregion	2009	0.28	0.13	0.09	0.06	0.21	-0.15	-0.19	-0.22	-0.07
Genferseeregion	2010	0.27	0.08	0.07	0.03	0.07	-0.19	-0.20	-0.24	-0.20
Genferseeregion	2011	0.25	0.07	0.05	0.02	0.16	-0.17	-0.20	-0.23	-0.09
Genferseeregion	2012	0.27	0.10	0.06	0.07	0.16	-0.17	-0.22	-0.20	-0.11
Genferseeregion	2013	0.29	0.06	0.00	0.01	0.15	-0.23	-0.28	-0.28	-0.13
Genferseeregion	2014	0.28	0.09	0.05	0.09	0.15	-0.19	-0.23	-0.20	-0.13
Genferseeregion	2015	0.27	0.10	0.07	0.07	0.11	-0.17	-0.20	-0.19	-0.16
Genferseeregion	2016	0.28	0.07	0.06	0.06	0.09	-0.21	-0.22	-0.22	-0.19
Genferseeregion	2017	0.30	0.10	0.08	0.07	0.11	-0.20	-0.22	-0.22	-0.19
Genferseeregion	2023	0.30	0.12	0.11	0.08	0.12	-0.18	-0.19	-0.22	-0.18
Espace_Mittelland	2006	0.24	0.09	0.07	0.04	0.16	-0.15	-0.18	-0.21	-0.08
Espace_Mittelland	2007	0.26	0.13	0.09	0.05	0.19	-0.13	-0.17	-0.21	-0.06
Espace_Mittelland	2008	0.26	0.07	0.03	0.04	0.15	-0.19	-0.23	-0.23	-0.11
Espace_Mittelland	2009	0.24	0.05	0.02	-0.01	0.12	-0.19	-0.22	-0.25	-0.11
Espace_Mittelland	2010	0.24	0.09	0.05	0.06	0.16	-0.15	-0.19	-0.19	-0.09
Espace_Mittelland	2011	0.25	0.07	0.07	0.03	0.12	-0.18	-0.18	-0.22	-0.13
Espace_Mittelland	2012	0.26	0.07	0.05	0.06	0.14	-0.18	-0.21	-0.20	-0.12
Espace_Mittelland	2013	0.26	0.08	0.05	0.06	0.11	-0.18	-0.21	-0.20	-0.15
Espace_Mittelland	2014	0.25	0.07	0.05	0.05	0.14	-0.18	-0.21	-0.21	-0.12
Espace_Mittelland	2015	0.24	0.06	0.03	0.03	0.09	-0.19	-0.22	-0.22	-0.16
Espace_Mittelland	2016	0.24	0.08	0.03	0.00	0.18	-0.16	-0.21	-0.24	-0.06
Espace_Mittelland	2017	0.25	0.08	0.05	0.02	0.16	-0.17	-0.21	-0.23	-0.09
Espace_Mittelland	2023	0.25	0.08	0.06	0.02	0.16	-0.17	-0.19	-0.23	-0.09
Nordwestschweiz	2006	0.27	0.09	0.05	0.01	0.14	-0.18	-0.21	-0.26	-0.13
Nordwestschweiz	2007	0.27	0.10	0.02	0.02	0.18	-0.17	-0.26	-0.25	-0.09
Nordwestschweiz	2008	0.28	0.08	0.05	0.01	0.17	-0.20	-0.24	-0.27	-0.11
Nordwestschweiz	2009	0.25	0.10	0.08	0.04	0.15	-0.15	-0.16	-0.21	-0.09
Nordwestschweiz	2010	0.28	0.08	0.02	0.06	0.18	-0.20	-0.26	-0.22	-0.10
Nordwestschweiz	2011	0.26	0.07	0.07	0.05	0.10	-0.19	-0.19	-0.21	-0.17
Nordwestschweiz	2012	0.25	0.08	0.07	0.06	0.11	-0.17	-0.19	-0.20	-0.14
Nordwestschweiz	2013	0.25	0.07	0.03	0.02	0.12	-0.18	-0.22	-0.22	-0.13
Nordwestschweiz	2014	0.27	0.11	0.09	0.04	0.14	-0.17	-0.18	-0.24	-0.14
Nordwestschweiz	2015	0.27	0.09	0.06	0.06	0.17	-0.18	-0.21	-0.21	-0.10
Nordwestschweiz	2016	0.28	0.05	0.02	0.00	0.11	-0.22	-0.25	-0.27	-0.17

Table A6: Gini and Concentration indices for different energy sources in Switzerland and by administrative regions (AR) (2006 - 2023)

AR	Year	Gini	CI ET	CI EH	CI EL	CI FU	KI ET	KI EH	KI EL	KI FU
Nordwestschweiz	2017	0.25	0.10	0.07	0.06	0.16	-0.15	-0.18	-0.19	-0.09
Nordwestschweiz	2023	0.25	0.11	0.09	0.06	0.16	-0.14	-0.16	-0.18	-0.09
Zürich	2006	0.27	0.15	0.13	0.06	0.18	-0.12	-0.14	-0.20	-0.08
Zürich	2007	0.27	0.11	0.10	0.05	0.15	-0.16	-0.17	-0.22	-0.12
Zürich	2008	0.26	0.10	0.03	0.02	0.19	-0.16	-0.23	-0.24	-0.07
Zürich	2009	0.28	0.10	0.07	0.04	0.13	-0.18	-0.21	-0.24	-0.16
Zürich	2010	0.28	0.11	0.08	0.05	0.15	-0.16	-0.20	-0.22	-0.13
Zürich	2011	0.28	0.10	0.07	0.03	0.16	-0.17	-0.21	-0.24	-0.11
Zürich	2012	0.27	0.10	0.05	0.02	0.17	-0.17	-0.22	-0.25	-0.11
Zürich	2013	0.26	0.13	0.09	0.08	0.18	-0.13	-0.17	-0.19	-0.09
Zürich	2014	0.28	0.09	0.08	0.08	0.10	-0.19	-0.20	-0.20	-0.18
Zürich	2015	0.30	0.07	0.01	0.04	0.16	-0.23	-0.29	-0.26	-0.14
Zürich	2016	0.26	0.08	0.06	0.05	0.12	-0.18	-0.20	-0.21	-0.14
Zürich	2017	0.28	0.03	0.00	0.05	0.07	-0.25	-0.28	-0.23	-0.20
Zürich	2023	0.28	0.04	0.01	0.05	0.07	-0.24	-0.26	-0.23	-0.20
Ostschweiz	2006	0.24	0.07	0.04	0.02	0.18	-0.17	-0.21	-0.22	-0.06
Ostschweiz	2007	0.26	0.05	0.02	0.01	0.16	-0.21	-0.24	-0.26	-0.11
Ostschweiz	2008	0.25	0.06	-0.03	-0.03	0.18	-0.19	-0.28	-0.27	-0.07
Ostschweiz	2009	0.27	0.03	0.03	0.03	0.10	-0.23	-0.24	-0.24	-0.16
Ostschweiz	2010	0.26	0.09	0.04	0.02	0.19	-0.17	-0.23	-0.25	-0.07
Ostschweiz	2011	0.25	0.07	0.08	0.02	0.10	-0.18	-0.17	-0.23	-0.15
Ostschweiz	2012	0.27	0.05	-0.03	-0.02	0.16	-0.22	-0.30	-0.29	-0.12
Ostschweiz	2013	0.26	0.09	0.05	0.01	0.16	-0.17	-0.21	-0.25	-0.10
Ostschweiz	2014	0.29	0.10	0.06	0.07	0.12	-0.19	-0.23	-0.22	-0.17
Ostschweiz	2015	0.25	0.08	0.04	0.00	0.14	-0.17	-0.21	-0.24	-0.10
Ostschweiz	2016	0.26	0.11	0.07	0.04	0.17	-0.15	-0.19	-0.22	-0.09
Ostschweiz	2017	0.28	0.10	0.07	0.08	0.14	-0.18	-0.21	-0.20	-0.14
Ostschweiz	2023	0.28	0.10	0.08	0.08	0.15	-0.17	-0.20	-0.19	-0.13
Zentralschweiz	2006	0.27	0.07	0.01	-0.02	0.17	-0.19	-0.26	-0.29	-0.10
Zentralschweiz	2007	0.26	0.08	0.01	0.01	0.20	-0.19	-0.25	-0.25	-0.07
Zentralschweiz	2008	0.25	0.04	-0.01	0.01	0.14	-0.21	-0.26	-0.25	-0.12
Zentralschweiz	2009	0.26	0.12	0.03	0.05	0.26	-0.15	-0.23	-0.21	-0.00
Zentralschweiz	2010	0.27	0.07	0.02	0.03	0.17	-0.20	-0.25	-0.24	-0.10
Zentralschweiz	2011	0.26	0.14	0.08	0.08	0.22	-0.12	-0.18	-0.17	-0.04
Zentralschweiz	2012	0.26	0.11	0.09	0.07	0.18	-0.15	-0.18	-0.20	-0.08
Zentralschweiz	2013	0.27	0.05	-0.01	-0.04	0.12	-0.22	-0.27	-0.31	-0.14
Zentralschweiz	2014	0.29	0.08	0.03	0.02	0.18	-0.21	-0.26	-0.27	-0.11

Table A6: Gini and Concentration indices for different energy sources in Switzerland and by administrative regions (AR) (2006 - 2023)

AR	Year	Gini	CI ET	CI EH	CI EL	CI FU	KI ET	KI EH	KI EL	KI FU
Zentralschweiz	2015	0.26	0.07	0.04	-0.01	0.09	-0.19	-0.23	-0.27	-0.17
Zentralschweiz	2016	0.29	0.06	-0.01	-0.02	0.13	-0.24	-0.30	-0.32	-0.17
Zentralschweiz	2017	0.27	0.08	0.05	0.05	0.08	-0.19	-0.22	-0.22	-0.19
Zentralschweiz	2023	0.27	0.09	0.06	0.06	0.08	-0.19	-0.21	-0.22	-0.19
Tessin	2006	0.25	0.06	0.02	-0.01	0.15	-0.19	-0.23	-0.26	-0.10
Tessin	2007	0.28	0.08	0.04	0.02	0.13	-0.20	-0.24	-0.26	-0.15
Tessin	2008	0.27	0.10	0.09	0.07	0.14	-0.16	-0.17	-0.19	-0.13
Tessin	2009	0.27	0.11	0.05	0.02	0.24	-0.15	-0.22	-0.24	-0.02
Tessin	2010	0.25	0.11	0.04	0.05	0.17	-0.15	-0.21	-0.20	-0.09
Tessin	2011	0.30	0.13	0.09	0.07	0.22	-0.17	-0.21	-0.22	-0.08
Tessin	2012	0.29	0.11	0.11	0.11	0.11	-0.18	-0.18	-0.18	-0.19
Tessin	2013	0.25	0.08	0.04	0.03	0.15	-0.16	-0.21	-0.22	-0.09
Tessin	2014	0.28	0.11	0.11	0.05	0.16	-0.17	-0.18	-0.23	-0.12
Tessin	2015	0.26	0.10	0.08	-0.02	0.19	-0.16	-0.19	-0.29	-0.07
Tessin	2016	0.30	0.07	0.04	0.01	0.10	-0.24	-0.26	-0.29	-0.20
Tessin	2017	0.26	0.10	0.07	-0.01	0.15	-0.16	-0.19	-0.27	-0.11
Tessin	2023	0.26	0.11	0.09	-0.00	0.15	-0.15	-0.17	-0.26	-0.11

Note: CI = Concentration Index, KI = Kakwani Index, ET = Total energy, EH = Household energy, EL = electricity, FU = fuel

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Perception vs. Reality: The Air Pollution Perception Gap and Socioeconomic Status*

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Abstract

This paper analyzes the gap between objectively measured and subjectively perceived air pollution in Switzerland, with a focus on socioeconomic differences. Using $PM_{2.5}$ data from Copernicus Atmosphere Monitoring Service (CAMS) and Atmospheric Composition Analysis Group (ACAG), combined with administrative data (STATPOP) and survey data (EU-SILC), we examine to what extent perception reflects actual exposure. While air pollution levels have declined, WHO thresholds are still exceeded in many areas. We find only weak socioeconomic gradients in measured exposure, but perception varies systematically: lower-income individuals and renters and financially constrained respondents report higher perceived pollution. To place Switzerland in context, we compare its exposure and perception levels to those in other European countries. Switzerland ranks mid-field in measured pollution but reports among the lowest perceived pollution levels, suggesting a relatively large perception gap. Due to limited spatial precision in matching exposure and perception data in Switzerland, we complement our analysis with a UK case study. There, fine-grained data confirm the perception gap and show that public pollution alerts significantly increase perceived exposure. Our findings highlight the role of information in shaping environmental perception. Policy tools such as localized alerts may help reduce perception gaps and support more equitable risk awareness.

Keywords: air pollution, perception, environmental justice, air pollution information

JEL Codes: Q52, Q53

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1 Introduction

Air pollution represents a pressing global issue, posing severe risks to public health and imposing substantial economic burdens. Worldwide, numerous cities frequently experience air pollution levels surpassing the thresholds established by the World Health Organization (WHO). This contributes to more than 4 million preventable deaths globally each year, including over 200,000 within Europe.(Fuller et al. (2022); European Environment Agency (2024)) Although Switzerland is not generally perceived as struggling with air pollution, a study commissioned by the Swiss Federal Office for the Environment (BAFU) (Castro et al., 2023) estimates that approximately 2,300 premature deaths occur annually in Switzerland as a result of air pollution.

These effects are however, not evenly distributed - socially and economically disadvantaged population groups bear a disproportionate share of the health and economic impacts of air pollution, as they are often exposed to higher levels of pollutants due to systemic inequalities in urban planning, housing quality, and occupational hazards (Hajat et al. (2015)). This environmental inequality is a crucial concern for policymakers and researchers alike, given its implications for public health equity and social justice.

Despite increasing awareness of air pollution's adverse effects, a significant gap persists between the objectively measured levels of air pollution and the public's subjective perception of it. Prior studies (e.g., Kim & Kwan (2021); Song & Kwan (2023)) highlight this divergence on the macro level, with perceptions often influenced by cultural, psychological, and contextual factors, such as neighborhood effects or information asymmetries. Such misalignment between measured and perceived risks have practical implications: individuals who underestimate their exposure may fail to take protective actions, while those with exaggerated perceptions may face undue anxiety or misdirected resources. Greenstone et al. (2022) show that increasing the *reported* particulate matter concentration in China due to improved monitoring increases online searches for face masks, which are strong predictors of purchases. This suggests that, due to the lack of information, people were unable to optimally protect themselves from air pollution based on their preferences. In this context, accurate information can be viewed as a classic public good with the private market likely to provide suboptimally low levels. Hence, the consequences of negative environmental externalities worsen and opportunities of adaption remain unused (Greenstone, 2024).

Based on household data from the Swiss Federal Statistical Office's Statistics on Population and Households (STATPOP) and pollution data from Copernicus Atmosphere Monitoring Service (CAMS) and Atmospheric Composition Analysis Group (ACAG), this paper analyzes the air pollution situation in Switzerland, including regional disparities, in relation to both national limit values and those set by the WHO, and situates the findings within the current scientific literature. In contrast to much of the international literature (e.g., Hajat et al. (2015); Colmer et al. (2020)), we find no clear evidence of a systematic negative socioeconomic gradient in measured exposure for Switzerland. Differences by income are small, but we find a positive correlation between being foreign-born or living in urban areas and measured air pollution. To identify potential gaps between perceived and measured air pollution, we also examine public perceptions of air pollution in Switzerland. We leverage data from the European Union Statistics on Income and Living Conditions (EU-SILC), which also includes information for Switzerland, to analyze how perceptions of air pollution vary with socio-economic characteristics. Our findings suggest that in Switzerland a clearer socioeconomic pattern is observed for *perceived* air pollution compared to measured pollution: the probability to report to feel subject to air pollution and grime is higher among individuals with lower incomes, tenants, and those facing financial hardship. In contrast, we find no negative correlation between income and measured air pollution when using STATPOP data merged with CAMS or or ACAG data- However, we have to acknowledge that we base our analysis of the corellation between socio-economic variables and perceived vs measured air pollution on completely different datasets.

Moreover, the EU-SILC dataset allows us to explore how perception patterns vary across countries and over time, thereby allowing a comparison between Switzerland and other European countries. Switzerland ranks mid-field in actual $PM_{2.5}$ levels but reports among the lowest perceived pollution. This suggests that the Swiss population may underestimate its relative exposure—especially compared to countries with cleaner air but higher perceived pollution. The combined use of EU-SILC data with modeled pollution estimates from CAMS and ACAG allows us to assess the perception gap—that is, the discrepancy between perceived and measured air pollution—across countries and over time. The data further allow us to compare the relationship between socio-economic status (SES) and perceived air pollution with existing evidence on the relationship between SES and measured pollution, across a broader European context.

In a final step, we demonstrate how combining fine-grained air pollution measurements with micro-level survey data enables a more rigorous analysis of air pollution perception gaps in developed countries. Drawing on background pollution data from the UK Department for Environment, Food & Rural Affairs (Defra), and socio-economic and perception data from the Understanding Society survey, we gain valuable insights about the discrepancies between measured and perceived air pollution. This excursus also examines the effect of air pollution alerts on public awareness, and thus their potential to reduce perception gaps. The UK case offers important lessons for other countries in designing mitigation strategies and policy interventions that foster socially beneficial behaviors and promote public health at scale.

The remainder of this paper is structured as follows: Section 2 reviews the related literature, Section 3 provides an overview of the data, Section 4 explains the methods, Section 5 provides and discusses the results, Section 6 illustrates the impact of the London air pollution alert system on air pollution perception in a major industrialized country, Section 7 discusses policy implications and concludes.

2 Literature

The growing body of literature on air pollution exposure and socioeconomic disparities consistently demonstrates that communities with lower socioeconomic status (SES) are generally exposed to higher concentrations of harmful air pollutants. Studies such as Pratt et al. (2015), Evans & Kantrowitz (2002), and Hajat et al. (2013) provide evidence of this trend in various contexts. In a global review based on ambient air pollution criteria, Hajat et al. (2015) illustrate that communities with lower SES in regions such as North America, Asia, Africa, and other parts of the world are subject to higher concentrations of criteria air pollutants. However, research outside the western hemisphere remains limited. In contrast, in the Chinese context, Wang et al. (2022) observe that groups of higher socio-economic status are more likely to experience higher ambient levels of nitrogen dioxide (NO_2) and $\mathrm{PM}_{2.5}$. This finding is attributed to the stage of industrialization, where economic development correlates with both SES and air pollution. In Europe, research findings are mixed (Hajat et al., 2015). For example, Samoli et al. (2019) identify a significant relationship between NO_2 levels and factors such as population density, the proportion of residents born outside the European Union (EU28), crime rates, and unemployment.

Research focusing on ethnicity instead of SES yields similar results. For instance, Perlin et al. (2001) report that a significantly higher proportion of African-American children under the age of five live in low-income households located near industrial sources of air pollution compared to white children. More recent studies confirm that areas with lower SES and higher proportions of minority populations tend to have greater exposure to air pollution (Pratt et al. (2015), Gray et al. (2013), Banzhaf (2012), Hsiang et al. (2019), Colmer et al. (2020), Currie et al. (2023)). Apart from the study by Huss et al. (2010), which uses data from 2000 to 2005, research on the Swiss context remains scarce. This study investigates the mortality risk associated with aircraft noise while controlling for air pollution, using data from the Swiss National Cohort and background air pollution concentrations at individuals' places of residence. A dispersion model for PM10, developed by the Federal Office for the Environment in 2000 to calculate background pollution, allows for fine-grained grids (200x200m), enabling more precise matching compared to our data. However, their results are based solely on descriptive statistics and are not part of the main research questions. The descriptive statistics show a positive correlation between PM10 exposure and being unemployed, being a foreign national, and having tertiary education. No consistent patterns were observed with respect to age or gender.

The analysis of the associations between various socioeconomic and demographic variables and air pollution exposure essentially depends on how "affected by air pollution" is operationalized. Although survey data based on self-reported exposure may seem less reliable than objective local air pollution measurements, significant methodological challenges exist with the use of purely objective data. For instance, Kim & Kwan (2021) find evidence of a neighborhood averaging problem (Kwan, 2018) in assessing individual exposures to ozone. Song & Kwan (2023) similarly note discrepancies in real-time air pollution data in Hong Kong due to individual mobility patterns, which complicate the assignment of precise exposure levels (Graff Zivin & Neidell, 2013). Self-reported exposure, particularly for highly mobile individuals, may therefore provide a more accurate measure in certain cases. Chiarini et al. (2020) argue that "subjective indicators are an important component of integrated analyses of environmental quality, as they allow for the consideration of the social dimension of urban sustainability, which interacts with its environmental and economic dimensions." Thus, according to Chiarini et al. (2021) the ranking of countries may substantially differ if objectives versus subjective air quality measures are employed.

The literature also highlights the benefits of improving public access to pollution information. Barwick et al. (2024) find that China's real-time air quality monitoring program significantly increased public awareness, leading to behavioral changes such as reduced outdoor exposure and increased protective spending. These changes collectively contributed to reduced air pollution-related mortality. Such findings highlight the potential of targeted information dissemination to reduce the perception gap, which have also been observed in the same context by Greenstone et al. (2022) and in studies in related fields of research such as weather forecasting (Burlig et al. (2024), Shrader et al. (2023)).

This study contributes to the existing literature by examining how objective exposure and perceived air pollution vary with different socio-economic characteristics, and by exploring the role of interventions — such as air pollution alerts — that increase environmental awareness and reduce the gap between measured and perceived pollution levels. While previous studies focus on countries where air pollution may be an even bigger problem, we add to the growing literature with new evidence from Switzerland and other western industrialized countries. By investigating these aspects, this research aims to provide actionable insights for policymakers seeking to address air pollution, its perception, and its unequal burden on vulnerable populations.

3 Data

This analysis draws on several datasets. First, we use the European Union Statistics on Income and Living Conditions (EU-SILC), a cross-sectional survey that provides annual information on socio-economic and demographic characteristics (SES)—including age, household structure, employment status, income[1], and education—for Switzerland and 31 other European countries. The survey is harmonized and the sampling employs a representative method to gather data on income, poverty, social exclusion, and living conditions. In addition to SES indicators, the survey includes the following question, which we use as a proxy for perceived air pollution: "*In the area where you live, do you have pollution, grime, or other environmental problems caused, among others, by traffic or industry?*" This question serves as our primary outcome variable and is intended to capture whether respondents perceive pollution as a problem, thereby measuring self-reported exposure to environmental issues. Although the wording is relatively broad, it has been widely used in the literature as

[1] We calculate equivalized income to facilitate comparisons across households of different sizes. For details on the calculation, see the description of income in Table A1 in the Appendix.

a subjective indicator of air pollution, particularly when combined with objective measures such as $PM_{2.5}$ concentrations (see, e.g., Eurostat (2024)). The explicit reference to traffic and industry indicates a focus on outdoor pollution, which aligns with the type of air pollution we aim to compare perceived pollution against. If anything, the broad formulation of the question is likely to overestimate air pollution perception, as it may also capture other environmental nuisances. The annual data set has been available since 2004 and 2005 for most countries, whereas countries such as Croatia and Serbia are included only from 2010 and from 2013, respectively. The most recent year for which we have data is 2022. The number of observations per country and year varies, ranging from 2,267 (Denmark in 2011) to 22,276 (Greece in 2018). In Switzerland, the data we employ for the regressions contains includes the years from 2007 to 2020, with the number of observations ranging from 6,471 (2007) to 8,061 (2020). The regression data includes only time periods up to 2020, as, despite having information on air pollution perception for 2021 and 2022, the data does not contain information on all socio-economic status (SES) variables for these years. The lowest geographical resolution available in the dataset corresponds to the NUTS-2 level, which prevents an accurate spatial matching with localized particulate matter concentrations. Seven countries do not even provide the information on the NUTS-2 location.

Second, we utilize air pollution data from the Copernicus Atmosphere Monitoring Service (CAMS), provided by the European Commission. The dataset offers half-hourly measurements of fine particulate matter ($PM_{2.5}$) on a $0.1^{\circ} \times 0.1^{\circ}$ latitude-longitude grid (approximately 10 km $\times$ 10 km) for the period 2013 to 2022. The CAMS regional air quality product is based on an ensemble of eleven state-of-the-art numerical air quality models developed by European research institutions. This study focuses on $PM_{2.5}$ concentrations, as $PM_{2.5}$ is the most widely used proxy for human exposure to ambient air pollution (Liu et al. (2022)) and has been consistently linked to serious health risks (Feng et al., 2016). We rely on annual average $PM_{2.5}$ levels to match the temporal resolution of the STATPOP data and to reflect long-term exposure, which the literature identifies as more relevant for adverse health outcomes than short-term peaks (Yitshak-Sade et al., 2018). The World Health Organization (WHO) recommends that the annual mean concentration of $PM_{2.5}$ should not exceed 5g/m$^{\mathbf{3}}$ World Health Organization (2021).[2]

Third, we use air pollution data from the Atmospheric Composition Analysis Group (ACAG) at Washington University. The dataset provides annual average concentrations of fine particulate matter ($PM_{2.5}$) at a high spatial resolution of $0.01^\circ \times 0.01^\circ$ latitude-longitude (approximately 1 km $\times$ 1 km), covering the entire globe, including Switzerland and Europe. The $PM_{2.5}$ estimates combine satellite-based aerosol optical depth (AOD) data (e.g., MODIS, MISR), outputs from the GEOS-Chem chemical transport model, and ground-based monitoring data using statistical models to produce high-resolution surface-level concentrations.We use the ACAG data specifically for the Swiss context, where we have access to detailed socioeconomic data at the municipal level. The fine spatial resolution of the ACAG dataset allows for a more precise matching of pollution exposure with local demographic and socioeconomic characteristics. For the rest of Europe, where such granular population data are not available, the coarser-resolution CAMS dataset is sufficient for our purposes.

Forth, we use data from STATPOP, the official population and household statistics provided by the Swiss Federal Statistical Office (FSO). STATPOP offers annual counts of the permanent resident population in Switzerland at the municipal level, including demographic characteristics such as age distribution, nationality, and household structure. To capture socioeconomic conditions more comprehensively, we complement STATPOP with income data derived from social insurance records and additional socioeconomic indicators from the Swiss Structural Survey (”Strukturerhebung”). This enriched dataset allows us to match municipal-level air pollution data with detailed socioeconomic profiles and to analyze the relationship between $PM_{2.5}$ exposure and socioeconomic status (SES) within Switzerland.

Fifth, we incorporate population distribution data from the WorldPop project, which

[2]This guideline is more stringent than the 2005 WHO recommendation, which set the annual limit at 10g/m$^{\mathbf{3}}$.

provides high-resolution estimates of total population per grid cell at a spatial resolution of 30 arc seconds (approximately 1 km at the equator). This dataset enables the calculation of population-weighted average $PM_{2.5}$ concentrations across different geographic units. By applying these weights, we can more accurately compare perceived air pollution with aggregated objective pollution measures over time in European countries other than Switzerland.

Sixth, for the analysis of the perception gap and the effects of the London air pollution alert we draw on the Understanding Society (US) dataset, which provides comparable information on SES and air pollution perceptions as EU-SILC. Understanding Society is the UK Household Longitudinal Study, started in 2009 and interviewed around 40,000 households. Understanding society contains detailed information on variables such as income, employment, education, and health. Central to this study is a question on how respondents experience environmental influences in their neighborhood, which serves as an analogue to the pollution variable from the EU-SILC. US includes geocoded information, allowing for spatial analysis. For the present analysis we use data ayquired under a special license agreement that provides information at the finer-grained "lower layer super output area" (LSOA) level[3], which is sufficient for spatial merging with air pollution data while simplifying the application process. Additionally, the dataset records the survey response date, which is relevant to the analysis in the final subchapter of this paper.

Seventh, we use air pollution data from the UK Department for Environment, Food & Rural Affairs (DEFRA), which provides high-resolution ground-based and modelled air quality measurements across the United Kingdom. The dataset includes daily mean concentrations of particulate matter ($PM_{2.5}$), either collected from a network of automatic monitoring stations under the Automatic Urban and Rural Network (AURN), or derived from DEFRA's Pollution Climate Mapping (PCM) model. The modelled data are available on a fine spatial grid with a resolution of approximately 1 km $\times$ 1 km, enabling detailed spatial analysis and

[3]A Lower-layer Super Output Area (LSOA) is a small geographic unit used for statistical analysis in England and Wales. LSOAs were introduced by the ONS (Office for National Statistics) for the Census and are designed to contain a consistent population size, typically around 1,000-3,000 residents or 400-1,200 households. (Definition by Oxford Consultants for Social Inclusion)

merging with other high-resolution datasets. All data are quality-assured and publicly available via the UK-AIR platform. The information on the annual average $PM_{2.5}$ concentration is available over the whole sample period of the US data.

Table 1 presents summary statistics of the survey variables used in this analysis for Switzerland and EU countries, respectively. A detailed description of the variables can be found in Table A1 in the Appendix. On average, 10% (14%) of respondents in Switzerland (EU) report that they feel affected by air pollution. The values for the variables income, education, tenant, suburban, and foreigner are significantly higher in Switzerland compared to the values for the EU. The values for the remaining variables are similar for the Swiss and EU sample. Table 2 provides a summary of the variables from the STATPOP and ACAG datasets used for the Swiss analysis, while Table 3 summarizes the variables from the Understanding Society dataset used in the UK analysis. We have to note that while the data for Switzerland in Table 1 refers to the years 2007-2020, the data reported in Table 2 uses data for 2013-2022. We can see that mean income is significantly higher in Table 2 compared to Table 1. This may be due to the fact that the FSO data only includes households with labor income [4], whereas the SILC data also covers households with other, potentially lower, income sources (such as social transfers). Accounting for these households as well, may lower the average income within the SILC data. The absence of households without labor income (primarily retired households) could also explain the lower average age and the higher average number of children observed in the FSO data. The difference in urbanization and suburbanization rates may stem from differing definitions of these categories, especially since their combined shares are quite similar across both datasets. The discrepancy in the education variable could also be at least partially explained by the exclusion of persons without income in the FSO data (students, retired people). The analysis with UK data uses information from 2011-2022.

[4] Although households without labor income are included in the raw dataset, they are excluded from the analysis as the logarithmic transformation of income requires strictly positive values.

Table 1: Summary statistics for selected variables in Switzerland and Europe (SILC)

	N	Mean	SD	Min	Max
Switzerland					
Pollution	101,550	0.10	0.30	0	1
Income (in 1,000 Euro)	101,550	44.67	32.18	0	1,431
Education	101,550	0.48	0.50	0	1
Tenant	101,550	0.52	0.50	0	1
HH size	101,550	2.33	1.27	1	11
Age	101,550	53.65	16.00	16	81
No financial cushion	101,550	0.16	0.37	0	1
Children	101,550	0.23	0.42	0	1
Urban	101,550	0.37	0.48	0	1
Suburban	101,550	0.45	0.50	0	1
Rate rich	101,550	0.05	0.12	0	1
Foreigner	101,550	0.15	0.35	0	1
Europe					
Pollution	3,665,328	0.14	0.34	0	1
Income (in 1,000 Euro)	3,665,328	17.50	19.17	0	9,266
Education	3,665,328	0.33	0.47	0	1
Tenant	3,665,328	0.19	0.39	0	1
HH size	3,665,328	2.50	1.36	1	28
Age	3,665,328	53.11	16.73	13	81
No financial cushion	3,665,328	0.36	0.48	0	1
Children	3,665,328	0.25	0.43	0	1
Urban	3,277,441	0.38	0.49	0	1
Suburban	3,277,441	0.26	0.44	0	1
Rate rich	3,665,328	0.03	0.09	0	1
Foreigner	3,581,235	0.05	0.22	0	1

Table 2: Summary statistics for selected variables in Switzerland (STATPOP - income > 0)

	N	Mean	SD	Min	Max
PM2.5 (CAMS)	$2,315,779$	10.05	2.32	3.57	21.20
PM2.5 (ACAG)	$2,297,766$	9.95	2.06	3.69	17.89
Income (in 1,000 CHF)	$2,315,779$	74.72	84.54	0.001	$29,474.82$
Education	$2,315,779$	0.35	0.48	0	1
Work	$2,315,779$	0.73	0.45	0	1
Foreigner	$2,315,779$	0.36	0.48	0	1
HH size	$2,315,779$	2.96	1.43	1	97
Children	$2,315,779$	0.36	0.48	0	1
Age	$2,315,779$	43.15	15.43	15	106
Urban	$2,308,559$	0.63	0.48	0	1
Suburban	$2,308,559$	0.21	0.41	0	1

Table 3: Summary statistics for selected variables in UK (Understanding Society)

	N	Mean	SD	Min	Max
Perceived pollution	$847,453$	0.14	0.35	0	1
Income (in 1'000)	$847,453$	14.85	20.42	0	$8,617$
Work	$847,453$	0.64	0.48	0	1
Education	$847,453$	0.29	0.46	0	1
Foreigner	$847,453$	0.05	0.22	0	1
Tenant	$847,453$	0.18	0.38	0	1
HH size	$847,453$	2.63	1.43	1	27
Age	$847,453$	51.07	16.41	15	81
Urban	$847,453$	0.39	0.49	0	1
Suburban	$847,453$	0.23	0.42	0	1
No financial cushion	$847,453$	0.63	0.48	0	1
Rate rich	$847,453$	0.03	0.23	0	1
Children	$847,453$	0.28	0.45	0	1

4 Methods

We apply a range of methods to examine the relationship between socioeconomic status and both perceived as well as measured air pollution. This includes descriptive tools as well as various regression models, which are briefly summarized in the following section.

The core models are logistic regressions where the dependent variable is a binary indicator of whether an individual reports feeling affected by air pollution. For this analysis, we use data from the EU-SILC survey, which provides information on self-reported exposure to air pollution along with detailed socioeconomic characteristics.

Our baseline specification is a logistic regression of the form:

$$\Pr(\text{PercPollution}_i = 1) = \frac{1}{1 + \exp\left(-\left(\sum_{j=1}^{J} \beta_j \, \text{SES}_{ij} + \gamma_{\text{t}}\right)\right)}.$$

(1)

Here, Pollution_i is a binary variable equal to 1 if individual i reports being affected by air pollution. The term SES_{ij} is a vector which includes control variables j such as income, education, employment status, and age, with β_j representing the respective coefficients. Additionally, γ_{t} controls for time trends, capturing unobserved factors that vary across time.

In our excursus, in which we are able to match UK survey data with local air pollution concentrations, we expand the regression specification to:

$$\Pr(\text{PercPollution}_{it} = 1) = \frac{1}{1 + \exp\left(-\left(\sum_{j=1}^{J} \beta_j \, \text{SES}_{itj} + \sigma \, \text{PM25}_{at} + \alpha_{\text{a}} + \gamma_{\text{t}}\right)\right)}.$$

PM25_{at} is the annual mean exposure to $\text{PM}_{2.5}$ at the individual's residential location in year t. The model includes LSOA-level fixed effects (α_{a}) and year fixed effects (γ_{t}) to account for unobserved spatial and temporal heterogeneity. Standard errors are clustered at the LSOA level (`LSOA11CD`). This part of the analysis uses UK survey data with geographic identifiers and pollution records.

To examine the impact of public information on pollution perception, we extend the model by including a binary indicator for whether an official air pollution alert was active in the month before the survey:

$$\Pr(\text{PercPollution}_{it} = 1) = \frac{1}{1 + \exp\left(-\left(\sum_{j=1}^{J} \beta_j \, \text{SES}_{ijt} + \theta \, \text{alert}_{at} + \sigma \, \text{PM25}_{at} + \alpha_{\text{a}} + \gamma_{\text{t}}\right)\right)}. \tag{3}$$

The variable alert_{at} indicates whether a pollution alert was issued in the respondent's area at the time of the interview. This model assesses whether public alerts influence individuals' perception independently of actual pollution levels.

In addition to perception-based outcomes, we estimate a linear regression model where actual $PM_{2.5}$ exposure is used as the dependent variable:

$$\text{PM25}_i = \sum_{j=1}^{J} \beta_j \, \text{SES}_{ij} + \gamma_{\text{t}} + \varepsilon_i. \tag{4}$$

This model allows us to examine the extent to which socio-economic factors are correlated with differential exposure to air pollution in Switzerland. γ_{t} controls for a time trend. The error term ε_i captures unobserved individual-level variation. For this analysis, we use Swiss STATPOP data, which includes high-resolution information on residential location and population characteristics.

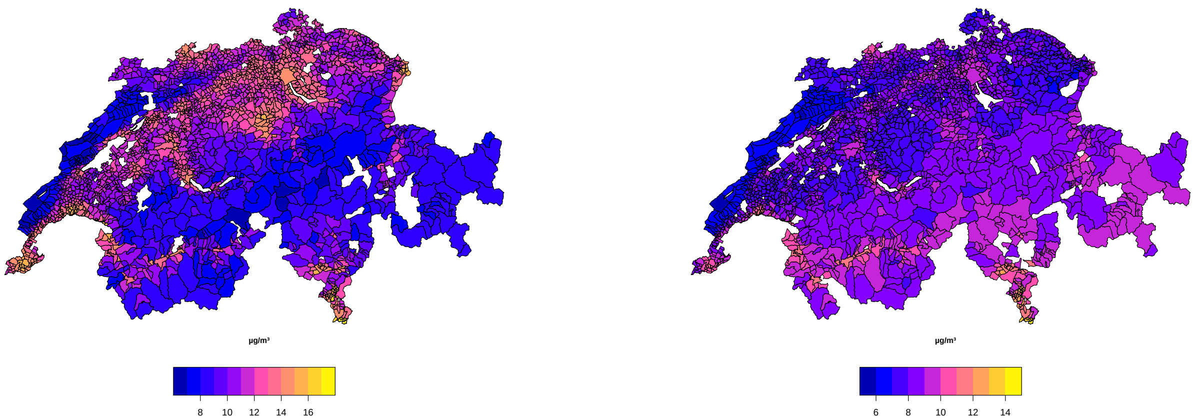
5 Results

5.1 Air pollution exposure in Switzerland

This section examines exposure to air pollution in Switzerland and analyzes the relationship between socioeconomic status and $PM_{2.5}$. The results are discussed in light of the existing literature, allowing for a comparison of our findings with the broader research landscape.

Figure 1 show the spatial distribution of $PM_{2.5}$ exposure based on ACAG data. The maps reveal that air pollution concentrations are particularly high in urban areas and Alpine valleys. In contrast, rural areas appear to be largely unaffected—at least when looking at annual municipal averages. This pattern confirms the well-documented association in the literature between urbanity and elevated levels of air pollution. Looking at absolute values, we observe that in 2013, average $PM_{2.5}$ exposure significantly exceeded the former WHO guideline of 10 μg/m^3 in many municipalities. On average, the $PM_{2.5}$ concentration was 12.6μg/m^3. By 2022, the situation appears to have improved, but numerous municipalities still report values above the 10 μg/m^3 threshold. The average $PM_{2.5}$ concentration was 9.1μg/m^3. In the meantime, the WHO has lowered its recommended guideline to 5 μg/m^3–a target that continues to be exceeded in many areas.

Figure 1: Spatial distribution of the average measured air pollution in CH for 2013 and 2022.



2013 2022

Source: Own illustration based on data from ACAG and FSO.

The reduction in $PM_{2.5}$ exposure is also visible in Figure 2, which shows the annual averages based on CAMS and ACAG data, weighted by population using the *Strukturerhebung*. The two series closely correlate over the observed time period and yield very similar levels for 2022. In both cases, the values lie slightly below the former WHO guideline but remain well above the current recommendation.

Figure 2: Development of the average measured air pollution in CH 2013-2022

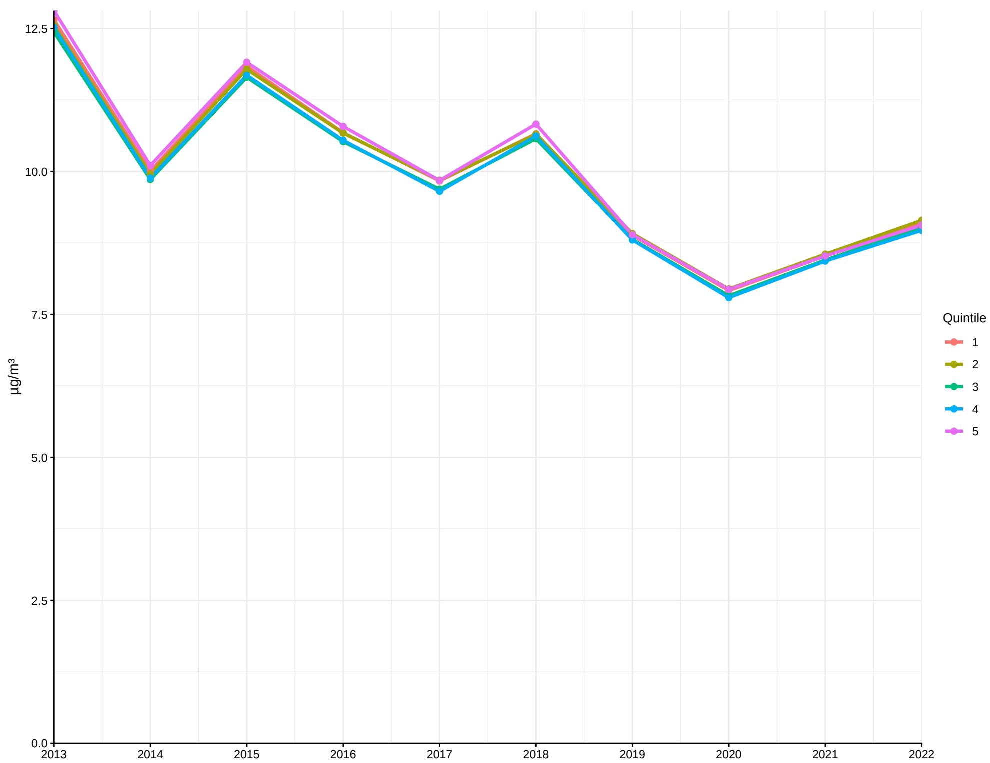
Source: Own illustration based on data from CAMS and the Federal Statistical Office (FSO).

This pattern is also evident in Figure 3, which plots annual average $PM_{2.5}$ exposure by income quintile. No substantial differences between income groups can be observed. The results remain consistent even when excluding observations with non-positive income values prior to defining income quintiles (see Figure A1 in the Appendix).[5] In this case as well, the average $PM_{2.5}$ exposure levels across quintiles largely overlap. One possible explanation is that the data linkage was performed at a relatively aggregated level, potentially masking variation in exposure by income. Even though the matching was carried out at the finest

[5]For the regression analysis we only keep observations with non-zero income.

spatial resolution available, it is still possible that the exposure assignment is not sufficiently precise. This may be due to within-grid variation in $PM_{2.5}$ concentrations, which can lead to measurement error in the estimated exposure values. Future research would benefit from access to more granular data, provided such data become available.

Figure 3: Development of the average measured air pollution by income quintile in CH 2013-2022



Source: Own illustration based on data from CAMS and Federal Statistical Office (FSO).

Building on this initial descriptive evidence on the relationship between SES and $PM_{2.5}$ concentrations, we now turn to more sophisticated approaches. In the next step, we regress measured $PM_{2.5}$ exposure on different socioeconomic characteristics. The results are reported in Table 4. We conduct this analysis using both the ACAG and CAMS data sources. We estimate each specification on a restricted sample that includes only individuals with positive income. Unsurprisingly, urban and suburban areas experience higher levels of air pollution. $PM_{2.5}$ concentration is positively correlated with income, although the magnitude of the coefficient is economically negligible. $PM_{2.5}$ levels are also positively correlated with being a foreign-born individual and higher educational attainment, whereas it is negatively correlated with having children and being employed. The positive correlation between measured $PM_{2.5}$ and income or education stands in contrast to findings in the existing literature. However, we need to emphasize that the data linkage may be insufficiently precise, and these results should not be interpreted as evidence of causal relationships.

Table 4: Measured Pollution and Socioeconomic Characteristics

	Dependent variable:	
	ACAG	CAMS
	(1)	(2)
Log income	0.003^{***}	0.049^{***}
	(0.001)	(0.001)
Work	-0.088^{***}	-0.114^{***}
	(0.002)	(0.003)
Education	0.109^{***}	0.150^{***}
	(0.002)	(0.002)
Foreigner	0.179^{***}	0.215^{***}
	(0.002)	(0.002)
HH size	0.002^{**}	-0.009^{***}
	(0.001)	(0.001)
Urban	1.791^{***}	0.948^{***}
	(0.002)	(0.003)
Suburban	0.513^{***}	0.395^{***}
	(0.003)	(0.004)
Age	0.0003^{***}	0.001^{***}
	(0.0001)	(0.0001)
Children	-0.033^{***}	0.020^{***}
	(0.002)	(0.003)
Observations	2,297,766	2,308,559
Year FE	Yes	Yes

Note: Normal standart errors. Data: 2013-2022, Observations with positive income. *p<0.1; **p<0.05; ***p<0.01

5.2 Air pollution perception in Switzerland

After examining measured pollution, we now shift our focus to perceived pollution. The comparison between the two measures is not perfect, as the underlying datasets substantially differ and the surveyed households are not the same across samples. The data on perceived air pollution stem from the EU-SILC survey. Since these survey data are only available at the NUTS-2 level, it is unfortunately not possible to make precise statements about the

Table 5: Measured Pollution and Socioeconomic Characteristics

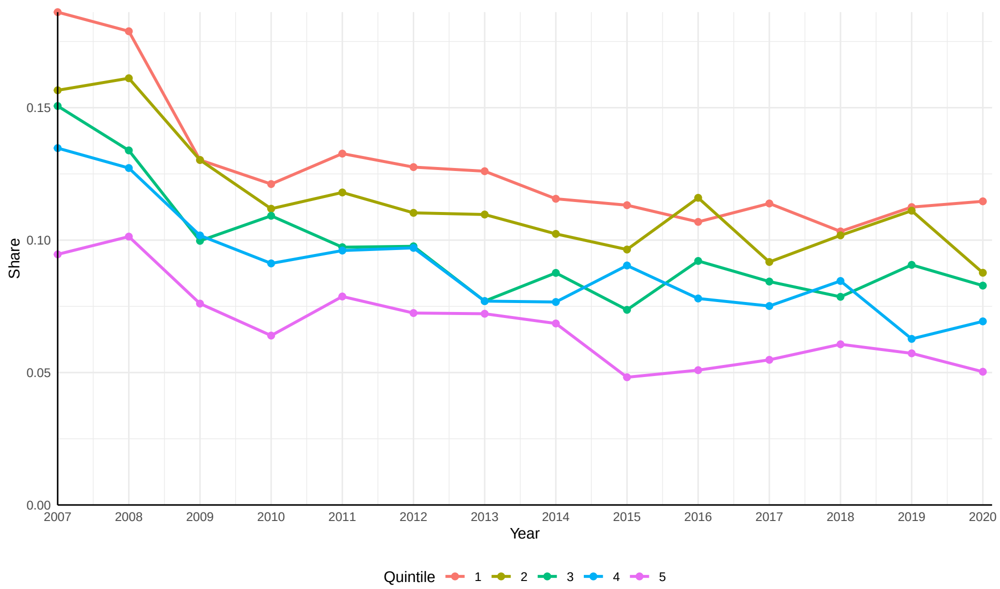
	Dependent variable:	
	ACAG	CAMS
	(1)	(2)
Log income	0.001*	−0.000
	(0.001)	(0.001)
Work	−0.002*	0.002
	(0.001)	(0.001)
Education	−0.003***	−0.010***
	(0.001)	(0.003)
Foreigner	−0.002*	0.000
	(0.001)	(0.002)
HH size	−0.002***	−0.002***
	(0.000)	(0.001)
Age	0.000*	−0.000*
	(0.000)	(0.000)
Children	0.001	0.001
	(0.001)	(0.001)
Observations	2,297,766	2,308,559
Year FE	Yes	Yes
Area FE	Yes	Yes

Clustered standard errors on municipality level. *Data: 2013-2022, Observations with positive income.* *p<0.1; **p<0.05; ***p<0.01

actual pollution exposure of households in the SILC data. As a result, a direct comparison of perceived and objectively measured air pollution at the individual or household level is not possible. We address this limitation with the excursus on the air pollution gap in the UK.

The distribution of perceived air pollution between income groups is illustrated in Figure 4. Figure 4 reveals several key findings: First, the share of survey households reporting that they feel affected by air pollution has been decreasing over time. As we have seen in section 5.1, air quality in Switzerland objectively improved in recent years and this is also perceived by households. Second, lower income quintiles consistently report a higher share of affected households. Third, the gap between income quintiles remains more or less stable throughout the observation period. In 2020, the difference between the share of respondents who report to feel affected by pollution and grime in the lowest and highest income quintile amounts to approximately 7 percentage points. This gap may be interpreted in two ways: either lower-income households are indeed more affected by air pollution, or they are more likely to report feeling affected. It is conceptually difficult to provide a convincing explanation for why lower-income individuals would systematically overreport their exposure to air pollution. Thus, in contrast to the descriptive evidence on measured air pollution and income, where no substantial discrepancies were found between income quintiles, this does not hold for subjective appraisals where discrepancies exist.

Figure 4: Development of the share of the population feeling affected by air pollution in Switzerland by income quintile



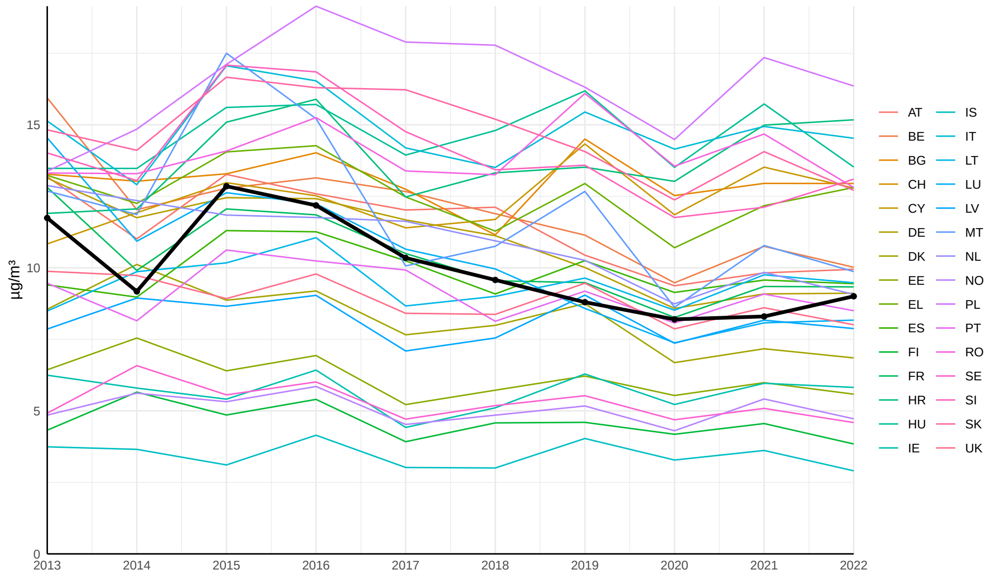
Source: Own illustration based on data from Eurostat.

In the following we present the results of logistic regressions on the correlation between socioeconomic characteristics and the probability to feel subject to pollution and grime. Column 2 in Table 6 presents the resulting coefficients for Switzerland. These results should once again be interpreted as correlations and do not imply any causal relationships. Households living in urban or suburban areas of Switzerland report feeling more affected by air pollution. This aligns with findings in the literature and with our analysis of $PM_{2.5}$ exposure in Section 5.1. It suggests that these households are not only de facto more exposed but are also aware of their higher exposure to air pollution. Income is negatively associated with perceived air pollution. Foreign-born individuals, tenants, individuals who report difficulties in paying their bills, and households with older household heads are more likely to report feeling affected by air pollution. In contrast to the findings from the literature, we find both in the case of measured as well as perceived pollution a positive correlation with education status. This may be because in Switzerland may be more concentrated in larger, more polluted cities. To sum up, we find both similarities as well as discrepancies between the effects of socioeconomic characteristics on measured vs perceived pollution, but we need to emphasize that the analyses are based on completely different datasets.

5.3 Air pollution in Europe

Comparing $PM_{2.5}$ concentrations in Switzerland (marked black in Figure 5) to those in other European countries shows that Switzerland ranks around the middle in terms of air pollution exposure. Figure 5 illustrates that this position has remained relatively stable over the period from 2012 to 2022. The main purpose of this figure is to situate Switzerland within the broader European context, rather than to highlight specific countries. Nonetheless, it is clearly visible that the lower end of the distribution is consistently formed by Scandinavian countries, with Iceland and Finland showing the lowest $PM_{2.5}$ levels, followed by Norway and Sweden. Poland, on the other hand, reports the highest values throughout most of the period. Other countries such as Italy and Hungary also tend to be among those with the highest pollution levels. The range in 2022 is indeed substantial: the $PM_{2.5}$ concentration in Iceland was 2.90 $\mu g/m^3$, a level that is considered harmless even by the latest WHO guidelines. In contrast, Poland recorded a value of 16.36 $\mu g/m^3$, which significantly exceeds even the former WHO recommendations. Switzerland has a $PM_{2.5}$ concentration of 9.01 $\mu g/m^3$, ranking 12th lowest among the 30 European countries for which we have data.

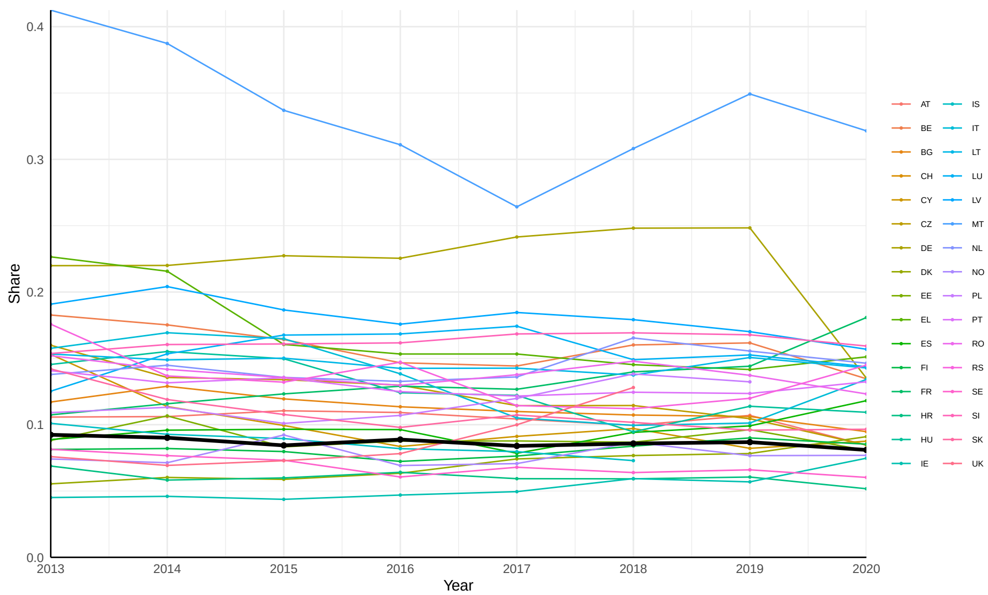
Figure 5: Average $PM_{2.5}$ exposure in Switzerland compared to European countries in 2013-2022



Source: Own illustration based on data from CAMS.

Focusing on perceived air pollution reveals certain deviations from the previous figure. Figure 6 shows that during the time period from 2013 to 2020, the share of respondents subject to perceived air pollution mostly stayed almost constant (in Switzerland, Ireland) or even declined (in Germany or Latvia). Figure 6 also illustrates that the share of respondents who report to feel subject to pollution in Switzerland is consistently among the lowest in Europe. In some years, countries such as Ireland, Croatia, and the Scandinavian nations report lower levels of perceived pollution. Malta consistently ranks at the top, while Germany also shows persistently high values. In 2020, the share of survey respondents reporting being affected by air pollution ranges from 5.2% to 32.1%. In Switzerland, this share is 8.1%, the sixth lowest in the sample. This suggests that Switzerland tends to overestimate its air quality relative to its actual $PM_{2.5}$ concentration when compared to other countries. A similar pattern is observed in countries like Croatia. Conversely, countries such as Malta and Germany appear to underestimate their relative position. The Scandinavian countries seem to have an accurate perception of their standing, as they report the lowest levels of both exposure and perception. Chiarini et al. (2021) categorizes countries into over- and underestimators, as well as those with both low exposure and low perception. The countries discussed fall into the same categories in our analysis.

Figure 6: Development of the share of the population feeling affected by air pollution in Switzerland compared to European countries in 2013-2022



Source: Own illustration based on data from Eurostat.

The correlations between socio-economic status (SES) variables and reporting to be subject to air pollution and grime are largely consistent between Switzerland and other European countries. As shown in Table 6, the main determinants of our dependent variable of interest—urbanity, income, tenant status and education—exhibit the same sign and similar statistical significance in both column (1) and column (2). The coefficients for urban and suburban residence are larger in the aggregate European sample than in Switzerland, which may be attributed to the presence of significantly larger metropolitan areas in other European countries compared to Swiss urban centers. The regression for the EU aggregate further reveals positive and significant associations between perceived air pollution and household size, while having children is negatively associated with perception. While in Switzerland there seems to be a positive correlation between reporting to be subject to pollution and grime and being of foreign nationality, this does not apply to the overall EU sample or individual countries.

To provide a more differentiated view, we contrast the Swiss results with findings from individual countries. While the sign and significance of many coefficients vary across countries, urbanity and suburbanity consistently exhibit positive associations with perceived air pollution. Also, the lack of financial security tends to correlate positively with perceived exposure. This aligns with the existing literature on air pollution exposure, which suggests that individuals with lower incomes are typically more exposed to air pollution. This is even more remarkable, as these individuals may lack the time, resources, or capacity to accurately perceive or assess their environmental conditions.

Table 6: Logit regression results in the EU and by country

	Dependent variable:									
	Pollution									
	EU	CH	DE	IT	PL	BG	ES	RO	SE	NO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log income	−0.129***	−0.252***	−0.044***	0.005	0.099***	−0.242***	−0.014	0.099***	0.169***	−0.034
	(0.002)	(0.021)	(0.014)	(0.009)	(0.013)	(0.019)	(0.013)	(0.016)	(0.028)	(0.027)
Education	0.046***	0.042*	0.024*	0.120***	−0.080***	−0.081***	0.097***	−0.072***	0.190***	−0.047*
	(0.004)	(0.024)	(0.015)	(0.014)	(0.021)	(0.026)	(0.018)	(0.026)	(0.026)	(0.026)
Foreigner	−0.011	0.070**	−0.162***	−0.250***	−0.123	−0.033	−0.188***	0.032	−0.298***	0.002
	(0.007)	(0.030)	(0.047)	(0.028)	(0.163)	(0.147)	(0.037)	(0.355)	(0.064)	(0.062)
Tenant	0.165***	0.230***	0.168***	0.118***	0.220***	−0.002	0.067***	0.200***	0.454***	−0.011
	(0.004)	(0.026)	(0.016)	(0.015)	(0.029)	(0.056)	(0.023)	(0.063)	(0.028)	(0.039)
HH size	0.032***	−0.013	−0.028***	0.061***	0.008	0.161***	−0.003	0.010	−0.138***	−0.109***
	(0.002)	(0.013)	(0.009)	(0.006)	(0.006)	(0.009)	(0.008)	(0.009)	(0.015)	(0.015)
Urban	0.940***	0.567***	0.916***	1.577***	0.928***	1.274***	1.082***	1.039***	0.862***	0.334***
	(0.004)	(0.034)	(0.023)	(0.018)	(0.017)	(0.026)	(0.021)	(0.021)	(0.030)	(0.029)
Suburban	0.446***	0.175***	0.330***	0.744***	0.522***	0.436***	0.537***	0.570***	0.240***	0.109***
	(0.005)	(0.034)	(0.023)	(0.019)	(0.020)	(0.035)	(0.026)	(0.029)	(0.035)	(0.034)
Age	−0.001***	0.009***	−0.011***	0.003***	−0.0002	−0.010***	−0.004***	−0.003***	−0.002**	−0.001*
	(0.0001)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rate rich	0.263***	−0.142	0.097	0.381***	1.078***	−0.106	0.055	−0.015	−0.141	−0.162
	(0.019)	(0.096)	(0.083)	(0.051)	(0.134)	(0.173)	(0.075)	(0.400)	(0.154)	(0.139)
Children	−0.074***	−0.054	−0.018	−0.097***	0.033	−0.092***	0.072***	0.153***	0.212***	0.048
	(0.005)	(0.038)	(0.024)	(0.017)	(0.021)	(0.033)	(0.021)	(0.029)	(0.042)	(0.042)
No financial cushion	0.223***	0.492***	0.246***	0.233***	0.360***	0.218***	0.373***	0.271***	0.252***	0.497***
	(0.004)	(0.028)	(0.017)	(0.013)	(0.016)	(0.027)	(0.018)	(0.019)	(0.034)	(0.032)
Observations	3,275,172	101,550	130,707	270,868	208,754	83,087	192,863	103,868	102,993	98,431

Note: normal standart errors in brackets *p<0.1; **p<0.05; ***p<0.01

5.4 Air pollution perception gap - The case of UK

As discussed in Sections 5.1 and 5.2, the comparison between air pollution exposure and perception—and their correlation with socioeconomic status (SES) variables—is limited due to inconsistencies in the underlying datasets. Moreover, the spatial resolution of the available data may not be sufficiently granular to support robust conclusions. To address these limitations, we now turn to the United Kingdom, where it is possible to combine individual-level

Table 7: Logit regression results in the EU and by country

	Dependent variable:									
	Pollution									
	EU	CH	DE	IT	PL	BG	ES	RO	SE	NO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log income	-0.129^{***}	-0.253^{***}	-0.044^{***}	0.005	0.099^{***}	-0.242^{***}	-0.014	0.099^{***}	0.169^{***}	-0.034
	(0.002)	(0.021)	(0.014)	(0.009)	(0.013)	(0.019)	(0.013)	(0.016)	(0.028)	(0.027)
Education	0.046^{***}	0.043^{*}	0.024^{*}	0.120^{***}	-0.080^{***}	-0.081^{***}	0.097^{***}	-0.072^{***}	0.190^{***}	-0.047^{*}
	(0.004)	(0.024)	(0.015)	(0.014)	(0.021)	(0.026)	(0.018)	(0.026)	(0.026)	(0.026)
Foreigner	-0.010	0.072^{**}	-0.162^{***}	-0.250^{***}	-0.123	-0.033	-0.188^{***}	0.032	-0.298^{***}	0.002
	(0.007)	(0.030)	(0.047)	(0.028)	(0.163)	(0.147)	(0.037)	(0.355)	(0.064)	(0.062)
Tenant	0.165^{***}	0.231^{***}	0.168^{***}	0.118^{***}	0.220^{***}	-0.002	0.067^{***}	0.200^{***}	0.454^{***}	-0.011
	(0.004)	(0.026)	(0.016)	(0.015)	(0.029)	(0.056)	(0.023)	(0.063)	(0.028)	(0.039)
HH size	0.032^{***}	-0.013	-0.028^{***}	0.061^{***}	0.008	0.161^{***}	-0.003	0.010	-0.138^{***}	-0.109^{***}
	(0.002)	(0.013)	(0.009)	(0.006)	(0.006)	(0.009)	(0.008)	(0.009)	(0.015)	(0.015)
Urban	0.941^{***}	0.566^{***}	0.916^{***}	1.577^{***}	0.928^{***}	1.274^{***}	1.082^{***}	1.039^{***}	0.862^{***}	0.334^{***}
	(0.004)	(0.034)	(0.023)	(0.018)	(0.017)	(0.026)	(0.021)	(0.021)	(0.030)	(0.029)
Suburban	0.447^{***}	0.174^{***}	0.330^{***}	0.744^{***}	0.522^{***}	0.436^{***}	0.537^{***}	0.570^{***}	0.240^{***}	0.109^{***}
	(0.005)	(0.034)	(0.023)	(0.019)	(0.020)	(0.035)	(0.026)	(0.029)	(0.035)	(0.034)
Age	-0.001^{***}	0.009^{***}	-0.011^{***}	0.003^{***}	-0.0002	-0.010^{***}	-0.004^{***}	-0.003^{***}	-0.002^{**}	-0.001^{*}
	(0.0001)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rate rich	0.258^{***}	-0.144	0.097	0.381^{***}	1.078^{***}	-0.106	0.055	-0.015	-0.141	-0.162
	(0.019)	(0.096)	(0.083)	(0.051)	(0.134)	(0.173)	(0.075)	(0.400)	(0.154)	(0.139)
Children	-0.075^{***}	-0.055	-0.018	-0.097^{***}	0.033	-0.092^{***}	0.072^{***}	0.153^{***}	0.212^{***}	0.048
	(0.005)	(0.038)	(0.024)	(0.017)	(0.021)	(0.033)	(0.021)	(0.029)	(0.042)	(0.042)
No financial cushion	0.223^{***}	0.491^{***}	0.246^{***}	0.233^{***}	0.360^{***}	0.218^{***}	0.373^{***}	0.271^{***}	0.252^{***}	0.497^{***}
	(0.004)	(0.028)	(0.017)	(0.013)	(0.016)	(0.027)	(0.018)	(0.019)	(0.034)	(0.032)
Observations	3,282,145	101,692	130,707	270,868	208,754	83,087	192,863	103,868	102,993	98,431

Note: normal standard errors in brackets *p<0.1; **p<0.05; ***p<0.01

survey data with high-resolution air pollution measurements. This allows for a more precise examination of the relationship between actual exposure and perceived pollution, as well as how SES factors shape perceptions when controlling for measured exposure. In addition, we assess the impact of targeted information campaigns about poor air quality on public perception, exploring whether such interventions can help reduce the perception–exposure gap. This case study from another Western European country provides valuable insights into the divergence between air pollution exposure and perception—and how this gap might be narrowed through improved data integration and policy interventions.

Table 8 presents the results of logit (columns 1 and 2) and linear probability model (LPM; columns 3 to 6) regressions across various specifications. Columns 1, 3, and 5 exclude the $PM_{2.5}$ variable and estimate the associations between socioeconomic status (SES) variables and responding to be subject to air pollution. In contrast, columns 2, 4, and 6 include $PM_{2.5}$ to control for measured air pollution exposure, thereby isolating the role of SES in shaping perception. Specifications in columns 5 and 6 further incorporate area-specific fixed effects, accounting for time-invariant differences across Lower Layer Super Output Areas (LSOAs).

First, we compare the coefficient signs from column 1 with those from Switzerland and the EU in Table 6. The results show consistent patterns across contexts: the correlations between reporting to be subject to air pollution and education, tenancy status, and urban residence are similar in the UK, Swiss, and broader European settings. Individuals living in urban areas are both more exposed to and more likely to perceive exposure to air pollution, and the same tends to hold for tenants. More educated individuals tend to feel more affected. [6] This may reflect heightened awareness among the more educated. Notably, education is the only variable that retains both the sign and statistical significance across all model specifications.

As in Switzerland, the probability to report to be subject to air pollution is higher for individuals with a migrant background. Income shows a significant negative coefficient, as in Switzerland. Interestingly, the other indicator of economic well-being—the affluence rate—displays the opposite signs. In the UK, more affluent individuals appear to feel more affected by air pollution, which may again relate to greater environmental awareness. The positive coefficient for no financial cushion is comparable to Switzerland. This suggests that those with less financial security have a higher probability to report that they feel subject to air pollution.

Second, we examine the correlations while controlling for $PM_{2.5}$. Columns 2 and 4 use the same specifications as columns 1 and 3, respectively, but include matched air pollution exposure as a control variable. The matching was possible due to information on the LSOA in which the household resides and the 1x1 km grid of background pollution data from DEFRA. The inclusion of $PM_{2.5}$ measures as a control changes the interpretation of the SES coefficients to reflect associations conditional on $PM_{2.5}$ exposure. We observe that including $PM_{2.5}$ reduces the size of all significant coefficients. Conditional on $PM_{2.5}$, the variables education, urban residence, affluence rate, and financial cushion are positively correlated with the perception of air pollution, whereas having children and the age of the

[6] Recent literature finds that they are generally less exposed to air pollution (see e.g., Hajat et al. (2015) or Branis & Linhartova (2012)). According to Table 4, in the Swiss context this does not hold as higher educated people seem to live in more exposed areas. This might be explained by the fact that more educated people tend to live in bigger cities like Zurich which, within all urban areas, have a higher demand for educated people and where air pollution is higher. But, as explained earlier, the matching we were able to do was spatially not precise enough to draw general conclusions.

household head are negatively associated. This suggests that better-educated and more affluent individuals, as well as households living in urban areas, are indeed more aware of the actual air pollution issues. Looking at column 6, we see that in the linear probability model (LPM) with area fixed effects, only education and the wealth-related variables retain their sign and statistical significance. Interestingly, when controlling for de facto pollution, the probability to report to be subject to pollution is now negatively correlated with being a tenant or having a migrant background.

Lastly, we observe that the coefficients for are positive in both the Logit and LPM specifications without area fixed effects. This suggests that, on average, people tend to perceive increases in $PM_{2.5}$ levels. However, once area fixed effects are included, the sign of the $PM_{2.5}$ coefficient changes, casting doubt on the previous interpretation. This indicates that there may be a perception gap: people are not fully aware of the actual air quality in their environment.

such a perception gap can be addressed by a number of policies, one alternative being an air pollution alert. London's air pollution alert system was introduced in 2018 and is based on forecasts from three independent institutions: airText, Defra (Department for Environment, Food Rural Affairs), and Imperial College London. Each group produces its own air quality forecast, which are then combined into a single metric – the Daily Air Quality Index (DAQI). Based on the DAQI, each day is classified into one of four air pollution levels: low, moderate, high, or very high. If the forecast indicates a high or very high pollution level, an air pollution alert is automatically triggered. These alerts are communicated to the public via social media, digital displays at Underground stations, bus stops, river piers, and electronic signs along major roads. Between 2018 and 2022, a total of 15 high pollution alerts were issued through this system. Conditional on background pollution levels, the occurrence of an alert in the month prior to the survey can be treated as quasi-random. This enables identification of the causal effect of air pollution alerts on perception by comparing individuals exposed to recent alerts with those who were not, holding pollution constant.

Looking at Figure 7, we observe that ahigher share of individuals living in urban areas report to feel affected by air pollution. We therefore restrict our sample to the 62,930 observations located in urban areas. Within this group, the share of households reporting to be affected by air pollution is noticeably higher among those for whom an air pollution alert occurred in the month preceding the survey. This difference becomes smaller when we extend the reference period for identifying alerts to two or three months prior to the interview. Since the alert system is only active in London, it is important to control for London residency in the analysis. As shown in Figure 7, the share of individuals reporting to feel affected by air pollution is higher in London than in other urban areas. While it is possible that individuals outside of London are also indirectly affected—either through actual pollution spillovers or media coverage—this would likely bias our estimates downwards, leading to an underestimation of the true effect of the alert.

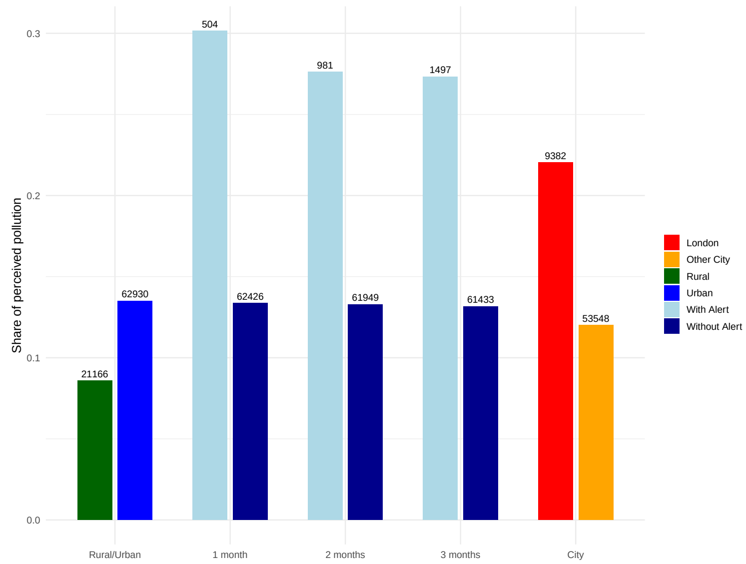
Table 8: Regression results based on Logit (1 & 2) and Linear Probability Model regressions (3 - 6)

Dependent Variable:	Perceived pollution					
	(1)	(2)	(3)	(4)	(5)	(6)
PM2.5		0.176***		0.018***		-0.004**
		(0.008)		(0.0008)		(0.002)
Log income	-0.078***	-0.106***	-0.009***	-0.012***	-0.007**	-0.007**
	(0.022)	(0.021)	(0.003)	(0.003)	(0.003)	(0.003)
Employed	0.006	0.001	0.0008	0.0002	0.005	0.005
	(0.032)	(0.031)	(0.003)	(0.003)	(0.004)	(0.004)
Education	0.182***	0.158***	0.020***	0.018***	0.014***	0.014***
	(0.029)	(0.029)	(0.003)	(0.003)	(0.004)	(0.004)
Migrant background	0.222***	-0.051	0.027***	-0.002	-0.015**	-0.015**
	(0.037)	(0.038)	(0.005)	(0.005)	(0.007)	(0.007)
Tenant	0.083***	0.006	0.009***	0.002	-0.011**	-0.011**
	(0.032)	(0.032)	(0.003)	(0.003)	(0.005)	(0.005)
Household size	-0.058	-0.064	-0.006	-0.006	0.001	0.001
	(0.042)	(0.042)	(0.005)	(0.004)	(0.005)	(0.005)
Urban area	0.444***	0.152***	0.042***	0.011***	0.020	0.020
	(0.039)	(0.041)	(0.003)	(0.004)	(0.023)	(0.023)
Affluence rate	0.430***	0.333***	0.046***	0.035***	0.033**	0.033**
	(0.104)	(0.104)	(0.012)	(0.012)	(0.013)	(0.013)
Age	-0.005***	-0.005***	-0.0006***	-0.0005***	-0.0002	-0.0002
	(0.0010)	(0.0010)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Children in HH	-0.149***	-0.144***	-0.017***	-0.016***	-0.008	-0.008
	(0.038)	(0.038)	(0.004)	(0.004)	(0.005)	(0.005)
No financial cushion	0.534***	0.510***	0.072***	0.068***	0.058***	0.058***
	(0.045)	(0.046)	(0.007)	(0.007)	(0.008)	(0.008)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
LSOA11 FE					Yes	Yes
Observations	84,096	84,096	84,096	84,096	84,096	84,096

Clustered (LSOA11CD) standard errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 7: Share of the population feeling affected by air pollution in the UK by specific group



Note: Comparisons 2, 3, 4, and 5 refer exclusively to the urban population. Numbers above the bar represent the number of households for the respective group. *Source:* Own illustration based on data from Eurostat.

Table 9 presents the effect of air pollution alerts on the probability to report to be subject to air pollution, estimated using logit regressions. The effect is positive and robust across specifications. While adding controls—such as $PM_{2.5}$ concentrations, a London dummy, and socioeconomic status (SES) variables—reduces the magnitude of the coefficient, it remains statistically significant. The results are consistent when using a linear probability model (LPM), which additionally allows for the inclusion of area fixed effects (see Table A2).

Importantly, the marginal effects from the main logit specification (shown in Table 10) closely match those from the LPM, reinforcing the robustness of our findings. Specifically, experiencing an alert in the month prior to the survey increases the probability of reporting to feel affected by air pollution by approximately 4 percentage points. Table A3 and Table A4 in the Appendix demonstrate that the effect remains statistically significant—though somewhat smaller—when considering alerts occurring within the last two or three months before the survey.

Table 9: Logit regression results of air pollution alert

Dependent Variable:	Perceived pollution			
	(1)	(2)	(3)	(4)
Alert last months	0.841***	0.427***	0.302***	0.306***
	(0.108)	(0.108)	(0.108)	(0.109)
PM2.5		0.179***	0.148***	0.146***
		(0.008)	(0.010)	(0.010)
London			0.236***	0.236***
			(0.049)	(0.051)
Income				-0.005
				(0.012)
Work				-0.025
				(0.034)
Education				0.127***
				(0.032)
Foreign				-0.104**
				(0.042)
Tenant				0.011
				(0.035)
Household size				-0.018
				(0.046)
Affluence rate				0.291**
				(0.127)
Age				-0.005***
				(0.001)
Children				-0.142***
				(0.042)
No financial cushion				0.552***
				(0.049)
Year FE	Yes	Yes	Yes	Yes
Observations	62,930	62,930	62,930	62,930

Clustered (LSOA11CD) standard errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Marginal effects of air pollution alert

Dependent Variable:	*Perceived Pollution*			
	(1)	(2)	(3)	(4)
Alert last month	0.129	0.056	0.038	0.039

6 Conclusion

This paper examines the relationship between objectively measured and subjectively perceived air pollution in Switzerland, with a focus on how this relationship varies across socioeconomic groups. Using high-resolution $PM_{2.5}$ data (from CAMS and ACAG) and combining them with socioeconomic indicators from Swiss administrative data (STATPOP) and drawing on subjective air pollution perception data from EU-SILC, we investigate the extent and determinants of what we term the air pollution perception gap.

Our findings show that, while average $PM_{2.5}$ exposure in Switzerland has declined over the past decade, many municipalities—particularly in urban regions and Alpine valleys—still exceed both the previous and the newly updated WHO guideline values. In contrast to much of the international literature, we find no strong evidence of a systematic negative SES gradient in *measured* exposure. Exposure differences by income are minor; however, there is a positive correlation between measured pollution and being foreign-born or living in urban areas.

In contrast, perceived air pollution shows a clearer socioeconomic pattern. Lower-income individuals and tenants are more likely to report being affected by pollution, while also those with financial difficulties tend to report higher perceived exposure—possibly. These findings indicate that the perception gap is not randomly distributed but linked to specific social and economic characteristics.

To place the Swiss results in a broader context, we compare the survey results to those of other European countries using harmonized data. Switzerland ranks mid-field in terms of actual $PM_{2.5}$ levels but reports among the lowest share of respondents who report to be subject to air pollution. This suggests that the Swiss population tends to underestimate its relative exposure, especially when compared to countries with objectively better air quality but higher shares of respondents who report to be subject to pollution and grime. These patterns are consistent across years and point to a persistent perception–exposure mismatch in Switzerland.

Given data limitations in Switzerland—most notably the limited spatial precision with which perception and exposure data can be matched— we complement our analysis with a case study from the UK. Using the Understanding Society panel and geocoded air pollution data, we are able to directly compare measured and perceived exposure at a much finer spatial scale. The UK evidence confirms the existence of a perception gap and demonstrates that public air pollution alerts significantly increase the likelihood of individuals reporting being affected by pollution, even after controlling for $PM_{2.5}$ levels. This suggests that information interventions can meaningfully influence environmental perception.

The results have important implications for Swiss environmental policy. A key finding is that public perception of air pollution does not fully reflect actual exposure. This gap can reduce the effectiveness of protective behavior and limit public support for stricter environmental measures. As the UK case illustrates, targeted communication tools such as air quality alerts can raise awareness and narrow the perception gap.

Swiss authorities could consider implementing similar alert systems or expanding access to localized and timely air quality information. These interventions may be particularly valuable in high-exposure urban areas and for groups with lower environmental awareness.

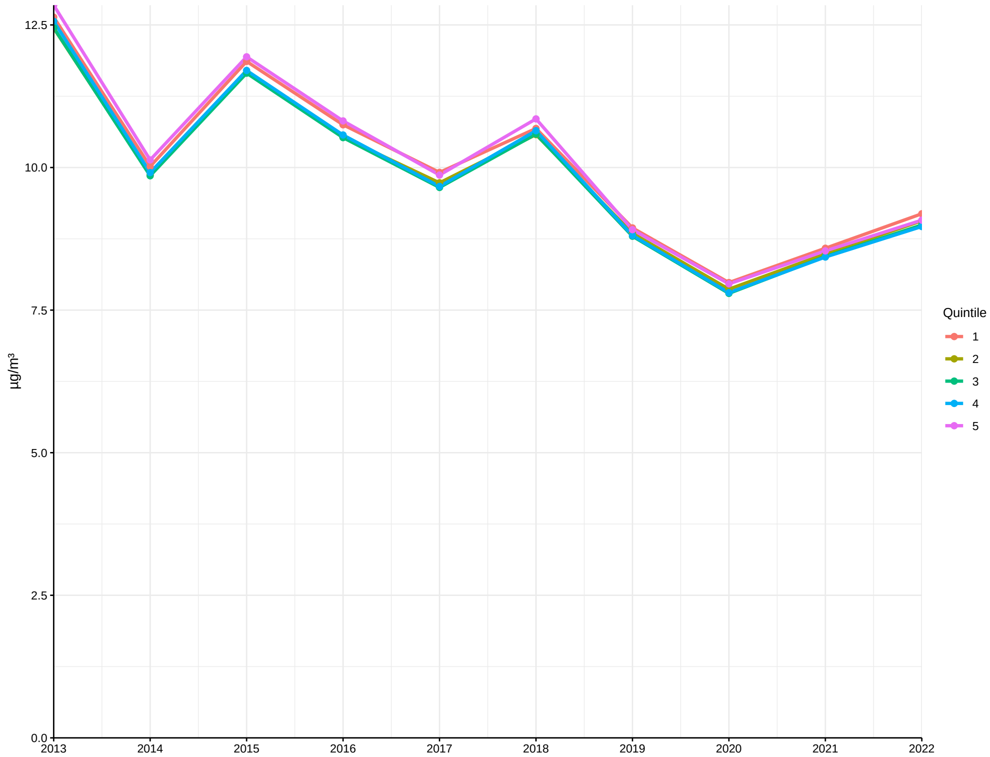
For future research, a central challenge remains the integration of fine-grained exposure data with individual-level perception and mobility information in the Swiss context. Further work is also needed to better understand the cognitive and informational drivers of the perception gap and how these interact with socioeconomic factors. Experimental or longitudinal designs could help to identify causal mechanisms and evaluate the effectiveness of policy interventions aimed at improving environmental awareness and equity.

Appendix

Table A1: Descriptions of the variables in the EU-SILC data set

Variable	Description	Codes
Pollution	Pollution problems	=1 if the household states that it has pollution, grime or other environmental problems in the local area; =0 otherwise
Income	Equivalized income is obtained by dividing the disposable income by the number of equivalent adults in the household. The OECD scale assigns a weight of 1 for the first adult, 0.5 for each additional household member aged 14 and above, and 0.3 for each additional household member under 14.	in 1000 Euros
Work	Work status of household reference person	=1 for employed or self-employed; =0 otherwise
Education	Education level of household reference person	=1 if tertiary education; 0 otherwise
Foreigner	Citizenship	=1 for being foreigner; =0 otherwise
HH size	Household size	numeric
Age	Age of the household head	numeric
Tenant	Tenure status	=1 for being tenant; =0 otherwise
Urban	Degree of urbanization	=1 if densely populated areas (cities/large urban areas); =0 otherwise
Suburban	Degree of urbanization	=1 if intermediate density areas (towns and suburbs/small urban areas); =0 otherwise
No financial cushion	Ability of being able to cover unexpected expenses	=1 if not being able to cover unexpected expenses; =0 otherwise
Rate rich	Income from real and financial activities	Income from real and financial activities as a share from total household income
Children	Household has children	=1 if at least one child; =0 otherwise

Figure A1: Development of the average measured air pollution by income quintile 2013-2022 (only positive income)



Source: Own illustration based on data from CAMS and FSO.

Table A2: LPM regression results of air pollution alert

Dependent Variable:	Neighborhood pollution				
	(1)	(2)	(3)	(4)	(5)
Alert last months	0.144***	0.094***	0.067***	0.067***	0.048**
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
PM2.5		0.020***	0.015***	0.015***	-0.004**
		(0.0009)	(0.001)	(0.001)	(0.002)
London			0.045***	0.045***	
			(0.007)	(0.007)	
Income				-0.0004	-9.65×10^{-5}
				(0.0006)	(0.0006)
Work				-0.003	0.004
				(0.004)	(0.005)
Education				0.015***	0.014***
				(0.004)	(0.005)
Foreign				-0.013**	-0.021***
				(0.005)	(0.008)
Tenant				0.002	-0.013**
				(0.004)	(0.006)
Household size				-0.002	0.005
				(0.005)	(0.006)
Affluence rate				0.033**	0.044**
				(0.016)	(0.018)
Age				-0.0006***	-0.0002
				(0.0001)	(0.0002)
Children				-0.017***	-0.008
				(0.005)	(0.006)
No financial cushion				0.077***	0.068***
				(0.008)	(0.008)
Year FE	Yes	Yes	Yes	Yes	Yes
LSOA FE					Yes
Observations	62,930	62,930	62,930	62,930	62,930

Clustered (LSOA11CD) standard errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A3: Logit regression results of air pollution alert (2)

Dependent Variable:	Neighborhood pollution			
	(1)	(2)	(3)	(4)
Alert last months	0.727***	0.308***	0.178**	0.172**
	(0.080)	(0.080)	(0.081)	(0.082)
PM2.5		0.178***	0.148***	0.146***
		(0.008)	(0.010)	(0.010)
London			0.234***	0.234***
			(0.050)	(0.052)
Income				-0.005
				(0.012)
Work				-0.025
				(0.034)
Education				0.127***
				(0.032)
Foreign				-0.103**
				(0.042)
Tenant				0.011
				(0.035)
Household size				-0.017
				(0.046)
Affluence rate				0.289**
				(0.127)
Age				-0.005***
				(0.001)
Children				-0.142***
				(0.042)
No financial cushion				0.552***
				(0.049)
Year FE	Yes	Yes	Yes	Yes
Observations	62,930	62,930	62,930	62,930

Clustered (LSOA11CD) standard errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A4: Logit regression results of air pollution alert (3)

Dependent Variable:	Neighborhood pollution			
	(1)	(2)	(3)	(4)
Alert last months	0.739***	0.310***	0.179**	0.172**
	(0.068)	(0.068)	(0.070)	(0.070)
PM2.5		0.176***	0.148***	0.147***
		(0.008)	(0.010)	(0.010)
London			0.221***	0.223***
			(0.051)	(0.053)
Income				-0.005
				(0.012)
Work				-0.026
				(0.034)
Education				0.126***
				(0.032)
Foreign				-0.103**
				(0.042)
Tenant				0.011
				(0.035)
Household size				-0.018
				(0.046)
Affluence rate				0.291**
				(0.127)
Age				-0.005***
				(0.001)
Children				-0.141***
				(0.042)
No financial cushion				0.552***
				(0.049)
Year FE	Yes	Yes	Yes	Yes
Observations	62,930	62,930	62,930	62,930

Clustered (LSOA11CD) standard errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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