Good-life cities.
Identifying the local conditions driving subjective well-being in European cities

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Abstract

This paper analyses subjective well-being differences across European cities. It contributes to the geography of well-being literature by distinguishing individual and city-level determinants of life satisfaction in a cross-country setting and providing additional insights to the literature that tackled the urban-well-being paradox i.e., the observed lower subjective well-being in urban settings compared to rural areas, higher socio-economic and net migration trends in cities. The empirical analysis relies on the 2019 EU Quality of Life in European Cities' survey, covering nearly 60,000 individuals across 83 European cities. Such data is combined with city level indicators on a set of socio-economic, demographic, and environmental characteristics of the cities, obtained from a variety of sources. Results show that, after having controlled for individual characteristics, cities with average higher life satisfaction have better air quality, higher shares of foreign-born population, better recreational amenities, and less heatwaves. Importantly, we observe significantly higher life satisfaction in cities able to attract higher shares of internal migrants from other regions. At the same time, happier cities have far more expensive housing, while there are not necessarily richer. The latter results are consistent with the spatial equilibrium framework. Finally, smaller city size may also be associated with higher life satisfaction, but results are less stable.

Keywords: cities, well-being, Europe, amenities
JEL codes: R10, R58, I31

Introduction

Since the last couple of decades, both scholars and policy makers have increasingly looked at well-being indicators to measure progress of societies. The release of the 2009 report of the Commission on the Measurement of Economic Performance and Social Progress (Stiglitz et al., 2009) further triggered the adoption of a more nuanced, people-based, and outcome-oriented perspective (OECD, 2011; 2014). One of the key novelties brought about by these developments was the increasing use – in policy discourse, media, and academic studies – of subjective well-being metrics to assess progress, at least to complement other objective outcomes. The most popular and comprehensive measures of subjective well-being are people's self-appreciation of their own lives, either taken as a whole (i.e., life satisfaction) or in selected spheres (i.e., satisfaction with one's job, health conditions, or with public services provided locally, among others).

The empirical evidence produced during the last decade has advanced considerably to understand the drivers of subjective well-being, supporting policy makers when designing public policy. Several individual characteristics, such as people's income, job, health conditions, and marital status, among others, are factors that, according to the existing studies, matter for people's well-being (Becchetti and Pelloni, 2013). More recently, a strand of literature labelled "geography of happiness" (see Ballas and Thanis, 2022 for a recent and succinct review) has been focusing on spatial differences in subjective well-being and on how contextual characteristics can affect such differences. This literature, which benefited from the rapidly-increased availability of georeferenced survey data, builds on the idea that such place-based features experienced by people in their everyday lives are important and can be incorporated in the design of policy. A recent large academic and policy debate on the geography of discontent (McCann, 2020; Dijkstra et al., 2020) has further highlighted how relevant is nowadays to understand the nature, drivers, and implications of well-being differences across places.

A large part of the "geography of happiness" literature focused on urban-rural differences in subjective well-being, most often measured in terms of life satisfaction. In this respect, recent studies revealed the existence of an "urban well-being paradox", although only in developed countries (Burger et al., 2021; Tassinari et al., 2023). According to such a paradox, people living in urban areas report lower levels of life satisfaction, on average, despite being found to have generally higher living standards in many dimensions of life compared to their rural counterparts. The most recent literature has identified several factors that may lay behind the urban well-being paradox. These include differences in social capital and access to nature (Sørensen, 2021), higher unmet expectations in urban areas (Hanell, 2022), higher exposure to interpersonal inequalities in urban areas, and different groups (i.e., *élite* people) benefiting more than others from urban advantages (Lenzi and Perucca, 2023). Carsen and Leknes (2022) provide another possible explanation through differences in mobility between citizens – even in a context of continuing urbanisation and urban concentration in developed countries (Moreno-Monroy et al., 2021). More specifically, mobile people tend to be happier in cities and drive migration patterns, although they are a minority of population and thus cannot compensate the lower well-being levels observed in urban settings.

This paper assesses the individual and contextual factors behind differences in life satisfaction across European cities. It does so by exploiting EU-released survey data on the Quality of Life in the European Cities combined with cross-sectional differences in physical, environmental, and socio-economic conditions at the city scale. While descriptive in nature, this study sheds some further light on the reasons behind the urban well-being paradox and overcomes some of the limitations of the geography of happiness literature, as highlighted below.

First, this study complements most of the existing studies in the "geography of happiness" literature in terms of its spatial scale and scope. The large part of that literature focuses either on the urban-rural spatial dichotomy (Morrison and Weckroth, 2018; Okulicz-Kozaryn, 2017; Sørensen, 2014, 2021; among others) or on the neighbourhood characteristics, thus adopting an intra-city perspective (Mouratidis, 2019, 2020; Wang et al., 2019; Ala-Mantila et al., 2019). As highlighted by Weckroth et al. (2022), the concept of urbanity remains too vague to understand *where* the sources of benefits and costs of different types of location are. Aggregating all types of locations in either "urban" or "rural" ones does not allow specific places – other than perhaps density of population – to be identified and thus investigated in its key characteristics. In this study, on the other hand, we treat each individual city within the European sample considered as a separate unit, comparable in many aspects that are important for people's life.

The concept of urbanity has been traditionally very heterogeneous, subject to a multitude of definitions across countries and often measured in terms of subjective perception rather than in terms of objective and comparable features (Dijkstra et al., 2021). On the other hand, the definition of cities is much less controversial, and this study uses the one recommended by the United Nations for international statistical comparisons.[1] This allows us to overcome another typical limitation of the geography of happiness literature, namely the imprecise or inconsistent geographical units available to carry out the study. To the authors' knowledge, there are no studies in this strand of literature focusing on subjective well-being differences across cities in a large cross-country setting.

Related to the point above, our analysis benefits from a high-quality measurement of life satisfaction at the city scale, limiting potential biases deriving from the choice of inappropriate units of analysis. Differently from most international surveys, the Quality of Life in European Cities survey was designed to be representative at the scale of cities. In addition, both the survey data on individual's quality of life and the city-level statistics used to capture the contextual features experienced by individuals refer to the same consistent city definition.

We carried out an empirical analysis structured in two steps, following the framework proposed by Combes et al. (2011). In a first step, we use micro-data on life satisfaction to estimate the specific city well-being scores which account for the observable individual aspects affecting the dependent variable. In a second step, we explore the factors associated with the estimated city well-being scores, looking at measures of socio-economic, demographic, amenities, and environmental conditions at the city scale. Results suggest that, in line with previous studies, being male, poorly educated, jobless, middle-aged, and with low income is associated with lower life satisfaction. After having controlled for all those factors, cities with higher life satisfaction that remains unexplained by those individual characteristics tend to have better air quality, higher shares of migrants, better recreational amenities, as well as shorter and/or less frequent extreme weather events (i.e., heatwaves). In addition, the capacity of cities to attract more internal migrants from other regions (relative to the city population) is associated with average higher levels of life satisfaction. At the same time, city-level life satisfaction premia come at a price. Housing prices in cities with higher life satisfaction are significantly higher than other cities with observed lower subjective well-being. This holds notwithstanding the mostly non-significant association between income per capita and life satisfaction, consistently with the spatial equilibrium framework.

The remainder of the paper is organised as follows. Section 2 provides a short background on the spatial dimension of subjective well-being and advances some potential explanations about the benefits and costs of cities in terms of life satisfaction. Section 3 provides details on the data and the methodology used in the study, while section 4 presents the results. Finally, Section 5 provides some conclusive remarks and suggests possible avenue for further research.

[1] https://unstats.un.org/unsd/statcom/51st-session/documents/2020-37-FinalReport-E.pdf (Last access 22/07/2023)

Cities and well-being: a background

The relationship between urban living and well-being has puzzled many scholars due to an observed disconnect between objective material conditions and subjective well-being observed in most developed countries. The economic advantages of cities have been widely demonstrated, notably in terms of increasing workers' and firms' productivity, boosting innovation, and rising incomes (Glaeser, 2008). When it comes to embracing a wider quality of life perspective, cities rank high in terms of several other outcomes (i.e., larger service provision, better access to modern technology and cultural amenities), but they are exposed to higher crime and air pollution (OECD, 2020). What has attracted attention in recent times is the observed lower life satisfaction in urban locations compared to rural ones in developed countries, despite urban areas keep attracting population from the latter (i.e., urban well-being paradox).

We consider four different explanations for such a paradox, which are subsequently explored empirically. The first and most simple one is that less happy people locate in cities (self-selection). In turn, this might depend on cultural aspects (Senik, 2014), prevalence of extrinsic or personally focused values (Morrison and Wekroth, 2018), urban malaise (Okulicz-Kozaryn and Mazelis, 2018; Wirth, 1938), or other idiosyncratic sources of unhappiness in urban living. Using micro-data to control for individual characteristics and their association with life satisfaction allows to at least partially control for self-selection of different groups of individuals across space, a necessary step before looking at contextual characteristics to understand spatial differences in life satisfaction. In the case of most of the available survey data, basic socio-demographic and education characteristics are easily accounted for, while others, more cultural and value-oriented, are more difficult to be measured. Overall, assessing spatial differences in life satisfaction only after having controlled for how different individuals locate across space should at least in part correct for self-selection.

Second, high population density, which typically characterises urban living, can be a direct source of specific negative externalities, such as air and noise pollution, crime, or longer commutes. This applies even more in large cities, which typically have the highest densities. Connected to these aspects are also extreme weather events. The intensity of heatwaves, for example, are mediated by density, as urban-islands effects (i.e., gaps in temperatures between built-up surfaces and its surroundings) tend to characterise most cities in developed countries and it has been found to increase with city size (OECD, 2022). According to this view, negative agglomeration externalities might more than offset other benefits of agglomeration, resulting in a lower overall subjective well-being among city dwellers. If this is the case, part of the "unhappiness" of cities could be captured by congestion, environmental quality, crime, and presence/absence of amenities, among others. All aspects that are relevant at the city-scale.

A third explanation, partially linked to the previous one, is related to the heterogeneity of city population combined with different willingness to migrate by the various population segments. This is based on the idea that the observed low average life satisfaction in large cities is linked to differences between education groups (see Morrison, 2020). Highly educated people can easily cluster in high-quality neighbourhoods, allowing them to enjoy the benefits of living in cities, while other less educated groups locate in more disadvantaged areas, which are more exposed to negative agglomeration externalities. According to this view, a relatively small share of highly educated and very mobile people drives the rural-urban migration and the observed continuous growth of cities. Larger shares of incumbent city residents are less satisfied although they have more constraints to change location. As a result, the average life satisfaction in cities can be lower than that observed elsewhere, even in cities which are growing (see Carlsen and Leknes, 2022, for an empirical analysis on this). This view is also consistent with the arguments originally made by Fischer (1972) who explained the urban malaise in large cities by the migration to "idealised communities". In the framework of our study, the city-level life satisfaction differentials can be explored against the composition of the city population by education and migration background.

Finally, another interpretation of the urban well-being paradox is connected to the spatial equilibrium theory (Rosen, 1979; Roback, 1982) and the way it is framed in the mainstream urban economics (Glaeser, 2008). The idea of spatial equilibrium requires that, in equilibrium, individuals are indifferent about locations. This implies that positive outcomes in one location, such as high wages, access to city centres, and high-quality education, must be compensated by other negative attributes, like housing prices or congestion. Reconciling the spatial equilibrium framework with the observed lower life satisfaction levels in urban areas would require treating life satisfaction as an argument of the individuals' utility function – thus as a type of amenity – rather than as a proxy of utility (Glaeser et al., 2016; Chauvin et al., 2017). This way, life satisfaction is treated as a "good" that can be traded to compensate for higher wages, better education, or other urban amenities. On the other hand, the concept of utility would rather capture the breadth of choices for individuals. From an empirical point of view, such an assumption would be consistent with a negative relationship between life satisfaction and real income. Therefore, we should observe higher rents in cities with higher life satisfaction, implying that, in the long run, more happiness should compensate for lower real income. All the arguments made above are explored jointly in a cross-country framework at the scale of cities.

Data and method

This paper combines microdata on individuals' life satisfaction from the EU survey on Quality of Life in European Cities carried out in 2019 with city-level statistics from a variety of sources (Eurostat, OECD, etc.) capturing socio-economic, environmental, and demographic conditions in European cities, as well as characteristics of the built environment. Cities are defined consistently across all European countries according to the EU-OECD definition of cities (Dijkstra et al., 2019). This scale is the one for which the EU survey is designed to be statistically representative and, similarly, city-level statistics are modelled at a consistent scale.

Measuring individual life satisfaction: the survey on well-being in cities

Every three years since 2004, the European Commission has monitored the quality of life in a number of European cities through a dedicated survey. The survey asks for some key personal characteristics and focuses on perceived quality of life and satisfaction with a set of set of city characteristics such as job opportunities, public transport, quality of public administration, and perceived safety and inclusiveness. For the 2019 edition, 700 full interviews were conducted for each of the 83 cities surveyed between July and September 2019, for a total of 58,100 full interviews. See Table A1 in the appendix for the full list of cities.

Measuring city-level features

The statistical indicators used in this study to capture the contextual characteristics at the city scale come from a variety of sources. Some of them are the results of authors' elaborations based on other statistics and available data. Table 1 summarises the data sources along with summary statistics for the city-level statistics used in the analysis. Most of those statistics come from the OECD Statistical Portal, which provides a rich set of indicators at the scale consistent with the one adopted in this study and used for stratifying the samples in the subjective well-being survey used for the first step.

We divide the indicators into four groups. The first consists of basic information about the population and the area of the cities, aimed at accounting for population density. A second group captures conditions about the quality of the environment, extreme weather, and amenities. More specifically, air quality is measured through the population-weighted average exposure to fine particulate matter that is less than 2.5 microns in diameter (PM2.5). The concentration of PM2.5 in the air is an important dimension of air quality. Monitoring such particles is particularly relevant across cities, as

PM2.5 are generally the results of the combustion of liquid and solid fuels for vehicles, industrial, and housing energy production. Another indicator to capture the quality of the environment is the share of green areas over the total surface of a city. While this is just a measure of quantity and not of quality of nature, it can still be relevant at in consistently defined urban environment with high-density of population, such as the cities considered in this study. The city context in terms of extreme weather is instead measured in terms of the average number of days per year of strong heat stress or worse (Universal Thermal Comfort Index, UTCI, > 32°C). The UTCI considers air temperature, wind, radiation, and humidity and enables to assess the impact of atmospheric conditions on the human body. The Recreation Potential Indicator (RPI) (Kompil et al., 2015) aims to map the capacity of ecosystems to provide nature-based outdoor recreation opportunities that can be enjoyed on a daily basis, i.e. primarily by people living in the area of interest. Its components, presented in Table A2 in Appendix, include the suitability of land to support recreational activities, the blue-green infrastructure in urban areas, the presence of natural areas, the presence and quality of water bodies and coastal areas and the accessibility to recreational services.
A third group of indicators captures the social environment and the heterogeneity of the population. First, the share of working-age population with tertiary education is used to capture the average level of education in the city, which was found to be a driver of subjective well-being in a recent study (Weckroth et al., 2022). In addition, the share of foreign-born population captures the degree of diversity of the city population, as well as the capacity of a city to attract people from other countries. In this extent, Ivlevs and Veliziotis (2017), for example, demonstrate that migrants play an important (heterogeneous) role on subjective well-being. This indicator can be further disaggregated between foreign-born in another EU country or outside of the EU. Besides the stock of foreign-born migrants, internal migration flows are captured by the indicator *netmob*, which measures the number of net migrants (yearly average over 2015-19) from other NUTS-3 regions in the same country to the NUTS-3 region where the city is located, relative to the regional population.

A fourth group concerns the economic environment and prosperity level in the city. Given the challenges in getting direct measures of household income at the city scale, we used as proxy the Gross Domestic Product per capita. Richer cities are expected to be more attractive than other by offering more opportunities in terms of jobs as well as higher material standards of leaving. Therefore, we expect a positive association between economic prosperity and city-level life satisfaction. At the same time, living in happier cities is expected to be more expensive than living elsewhere, consistently with the general idea of spatial equilibrium (Rosen, 1979; Roback, 1982). In this respect, we used the Eurostat's novel Mapadomo database to capture average house price levels in the NUTS-3 region where the city is located. We expect a positive correlation between life satisfaction and house prices, indicating lower real income in happier cities compared to less happy ones for the same nominal wages.

Table 1. Descriptive statistics for the city-level statistics

Variable	Obs.	Description	Year of ref.	Mean	Std. dev.	Min.	Max.	Source
pop	78	Total resident population (log).	2019	13.414	1.151	11.219	16.431	OECD (2023a)
area	72	Total surface area, km2 (log).	2019	5.922	0.981	3.838	8.048	OECD (2023a)
pm25 pollution	78	Pop-weighted average exposure to PM2.5.	2019	13.126	4.737	4.200	26.2	OECD (2023a)
heatwaves	78	Days per year of strong heat stress or worse (UTCI > 32°C).	2018	25.423	32.946	0.000	158	OECD (2022)
RPI	59	Composite indicator (see Table A2).	2010	10.82	1.042	7.855	13.073	Kompil et al. (2015)
green areas	59	Share of green areas over total surface.	2020	42.488	20.696	5.790	95.69	OECD (2023)
share tertiary edu.	61	Share of working age population with tertiary education.	2019	36.075	12.08	12.500	60.6	Authors' elab. on Eurostat (2023)
share foreigners	52	Share of foreign-born Population.	2019	0.172	0.101	0.017	0.466	OECD (2023b)
netmob	65	Internal migration across NUTS3 regions.		0.02	0.409	-1.234	1.028	OECD (2023a)
GDP p.c.	62	Gross Domestic Product, EURO (log).	2019	24.152	1.052	21.199	25.99	Authors' elab. on ARDECO
ppm2	51	Average (transaction) price per m2 of useful floor area in the region, EUR, annual average (log).	2019	7.606	0.585	5.812	8.945	Authors' elaboration on Eurostat (2021)

Methods

The research question is set in a two-stage linear model as in Combes et al. (2008) and Obaco et al. (2023), which allows distinguishing between self -selection of individuals with different characteristics across cities. More specifically, in a first step, individuals' life satisfaction is modelled against a set of observable characteristics of the individuals which might affect their subjective well-being as well as against a variable controlling for the location (i.e., city). In formal terms, we estimate the following equation:

$$y_{ic} = \alpha + \beta_c + \varphi \mathbf{X}_{ic} + \varepsilon_{ic} \,, \qquad (1)$$

where y_{ic} is the life satisfaction score of the i-th individual living in the c-th city. β_c is a coefficient associated to each city where each respondent is located (a sort of city fixed effect). $\mathbf{X}_{ic}$ is a vector of characteristics of the individual, including their socio-economic and demographic characteristics that might drive individuals' life satisfaction. ε_{ic} is a vector of standard errors that are clustered at the city-level. Given that life satisfaction score is an ordinal variable with for possible outcomes (not at all satisfied, somewhat not satisfied, somewhat satisfied, totally satisfied), we tested three different specifications. We first dichotomized the dependent variable and we applied a Linear Probability Model (LPM) and a logit. Then, we used an ordered logit maintaining the variable in its original form.

In a second step, the residual levels of subjective well-being associated to each city are regressed on the observable city-level characteristics, as indicated below:

$$\hat{\beta}_c = \mathbf{U}_c + \varepsilon_{2c}, \qquad (2)$$

where $\hat{\beta}_c$ is the coefficient estimated in equation (1) and represent levels of city-life satisfaction cleaned from sorting/composition of individuals with different characteristics. $\boldsymbol{U_c}$ is a set of city-level characteristics which might be conducive to further life satisfaction once individual characteristics have been considered.

For a further robustness check, to address the hierarchical structure of the dataset, we also run our estimates considering together individual and contextual variables. In this case, by modelling both individuals and their contexts simultaneously, we assume that there is a general pattern that holds across groups of a population belonging to the same city. To address the hierarchical structure of the dataset, we rely on two alternative approaches. The first consists in the introduction of a random intercepts at city level to explicitly model for variation that we do not model (Hox, 1995). The second is to cluster standard errors at the city (Bryan and Jenkins, 2016; Graham and Felton, 2006).[2]

Results and discussion

Modelling individuals' life satisfaction

The results of the first step are in Table 1. Age has a negative impact on individuals' wellbeing, i.e. the elderly they are, the less they are satisfied with their life. On the other hand, sex is not statistically significant. Interestingly, those that lived in another city for at least 1 year are less satisfied of their life compared to those that did not. Those living in a household with daughters less than 25 are more satisfied with their life than singles. However, this result holds only for LPM and logit model. Education plays a positive role on wellbeing. In particular, the coefficient of tertiary education is bigger in size than the coefficient on secondary education. Compared to those working full-time, individuals working part-time or unemployed experience worst quality of life. Instead, retired persons do not have significantly different wellbeing than full-time workers. Finally, the variable denoting difficult economic conditions, as expected, is negative and significant.

Table 2: Regression results on first step

	LPM	Logit	Ologit
Intercept	0.7508 ***	1.2840 ***	
	(0.0152)	(0.1053)	
Age: 25-39	-0.0142 *	-0.1010 *	-0.2429 ***
	(0.0057)	(0.0490)	(0.0322)
Age: 40-54	-0.0433 ***	-0.3419 ***	-0.4208 ***
	(0.0057)	(0.0476)	(0.0319)
Age: 55 and over	-0.0484 ***	-0.3773 ***	-0.4037 ***
	(0.0065)	(0.0537)	(0.0364)
Sex: Female	0.0069 *	0.0570 *	0.0193
	(0.0030)	(0.0251)	(0.0167)
Lived in another city	-0.0049	-0.0379	-0.0364 *
	(0.0030)	(0.0254)	(0.0169)

[2] This approach is only suitable for LPM because, as pointed out by Greene (2012, 692-693) because in nonlinear models, if errors do not satisfy the standard assumptions of the model, then this might lead to biased parameter estimates. On the other hand, in linear regression models point estimates are unbiased even if errors are heteroskedastic.

Household comp.: Other	0.0005 (0.0057)	0.0087 (0.0468)	-0.0215 (0.0320)
Household comp.: Household with children with less than 25	0.0126 ** (0.0039)	0.1031 ** (0.0327)	0.0272 (0.0216)
Household comp.: Household with children more than 25	-0.0001 (0.0050)	0.0029 (0.0406)	-0.0403 (0.0277)
Education: Secondary	0.0331 *** (0.0050)	0.2303 *** (0.0387)	0.1161 *** (0.0280)
Education: Tertiary	0.0492 *** (0.0051)	0.3685 *** (0.0401)	0.2622 *** (0.0286)
Working Status: Part-time Empl.	-0.0207 *** (0.0051)	-0.1756 *** (0.0422)	-0.1127 *** (0.0285)
Working Status: Unemployed	-0.0726 *** (0.0067)	-0.5009 *** (0.0490)	-0.3487 *** (0.0376)
Working Status: Retired	0.0002 (0.0055)	-0.0219 (0.0446)	0.0485 (0.0305)
Working Status: Other	-0.0202 *** (0.0056)	-0.1615 *** (0.0464)	-0.0876 ** (0.0316)
Difficult to pay a bill	-0.0981 *** (0.0034)	-0.7296 *** (0.0265)	-0.5684 *** (0.0190)
Not at all satisfied | Not very satisfied			-3.1533 *** (0.0894)
Not very satisfied | Fairly satisfied			-1.6207 *** (0.0875)
Fairly satisfied | Very satisfied			0.8678 *** (0.0873)
Observations	55626	55626	55424
City FE	yes	yes	yes
R^2 / R^2 adjusted	0.063 / 0.062		

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. For LPM models errors are clustered at city level. For Logit and Ologit models asymptotic standard errors are used (see Green, 2012, pp. 692-693). A variable combining the design weight and the post-stratification weight has been used as weighting variable for each of the estimations reported in the Table. Reference category for age is 18-24, for Household composition is single family, and foe working status is full- time employment.

Figure 1. City-level life satisfaction differentials (Ologit model)

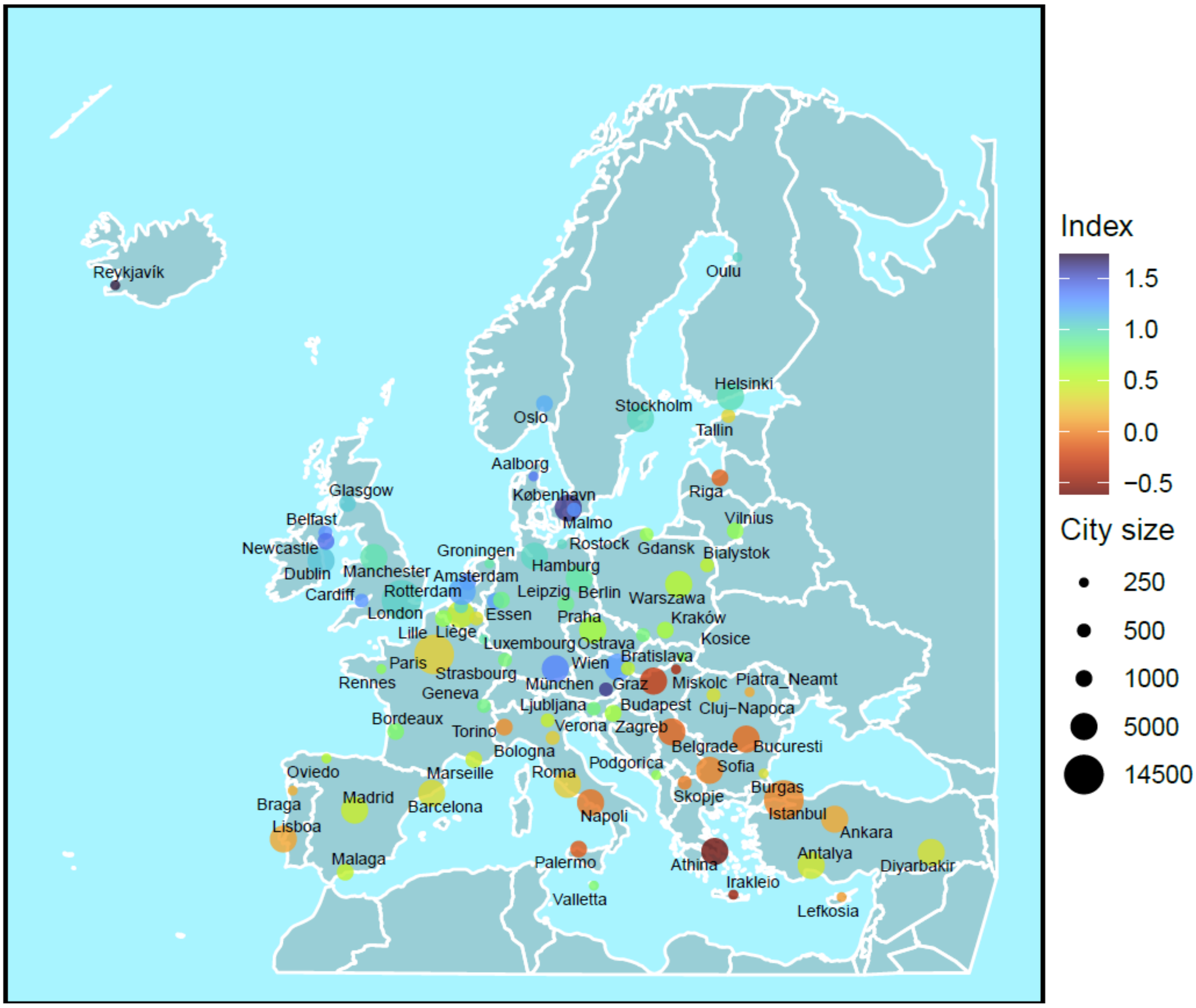


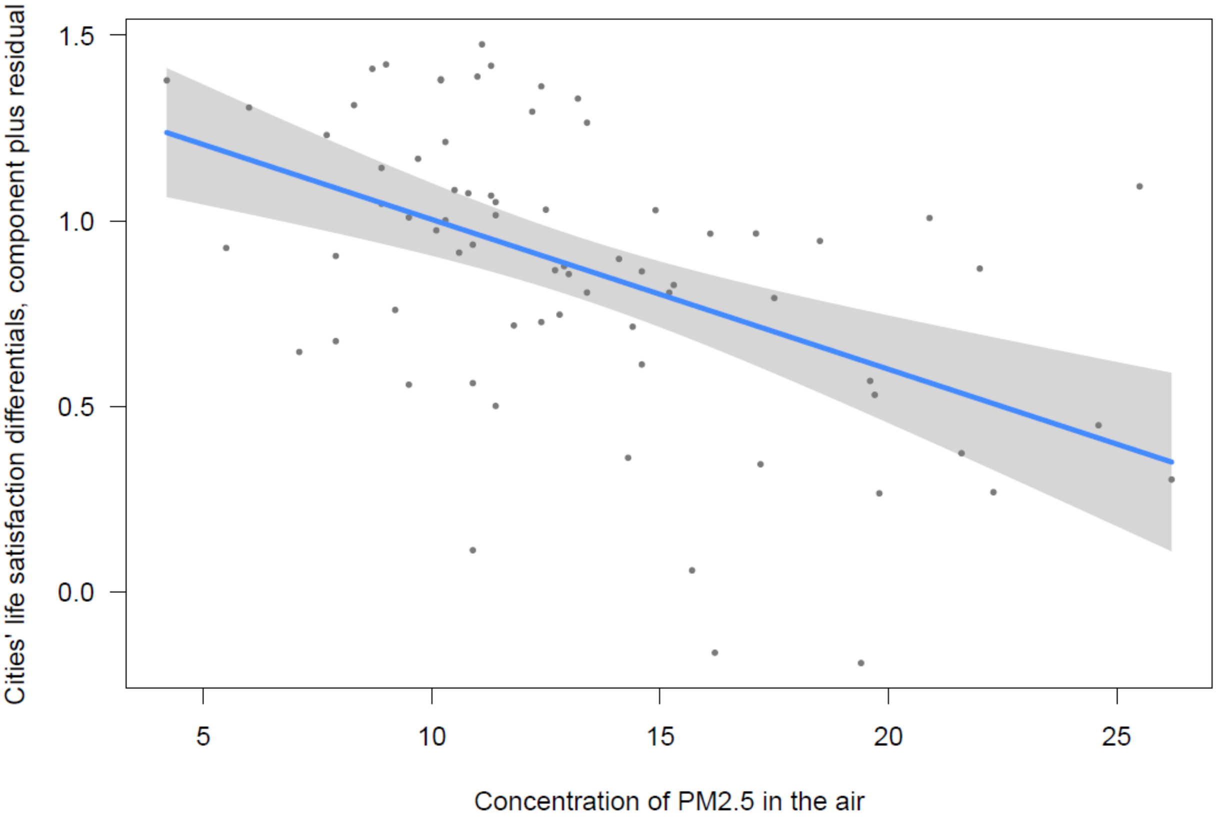
Figure 1 shows the city-level life satisfaction differentials controlling for individual characteristics referred to the ologit model (model (3) in Table 2). We observe that worst performing cities are located in southern Europe and in Balkan countries. On the other hand, the best performing cities are in the continental and northern Europe. It is interesting to observe that life satisfaction in Polish cities is relatively high compared to other eastern countries. As visually shown in Figure A1, the correlation of city-level life satisfaction before and after controlling for individual characteristics is particularly high and equal to 0.87 and 0.96 for the ologit and logit model, respectively, and to 0.98 for the LPM. However, looking at the Figure, we can highlight some relevant aspects. In particular, Greek and Turkish cities, which are at the bottom of the ranking, perform comparatively less well after controlling for individual characteristics. The same happens for a group of cities scoring particularly well, i.e. Copenhagen, Graz Rekykjavik and Rotterdam. On the other hand, a set of cities whose average level of life satisfaction is close to the average improve after controlling for individual characteristics. These are mainly located in Poland, Spain, and in some other countries. Unfortunately, it is not possible to identify an empirical regularity.

Contextual characteristics and life satisfaction

After having identified the cities' life satisfaction differentials in the section above, we explore how such differentials relate to the contextual characteristics at the scale of cities. Due to the cross-sectional nature of the analysis and the obvious limitations in the available information at the city scale, we cannot claim any causality in the results showed in the following paragraphs. That said, our analysis provides a comprehensive perspective on the role of contextual characteristics on life satisfaction differentials. Results allows shedding lights on several important aspects that tend to be associated to higher reported life satisfaction once accounted for the heterogeneity of the city population and factors that play out at the individual level.

To address the limitations in the degrees of freedom for the pooled regression at the city-scale, we present results by focusing each time on a set of city-level characteristics separately, based on the assumptions made in Section 2. The detailed results of the regression analysis are summarized in Tables 3-5. This approach makes us consider four groups of factors possibly affecting life satisfaction. First, diseconomies of agglomeration are accounted for by focusing on total population, surface, and air pollution. The latter are assumed to be strongly associated to concentrations of people in space, but also on the type of economic activities and vehicle traffic characterizing each city. Among the factors considered, we observe that total population and population density are not associated to differences in life satisfaction in our sample of European cities. On the other hand, results show that cities characterized by worse air quality have lower life satisfaction levels than cities with better air quality. Such a results is represented in Figure 2 (partial residual plot), which shows the association between air quality and life satisfaction differentials once the other city-level characteristics related to diseconomies of agglomeration (i.e., log of population and area) are considered.

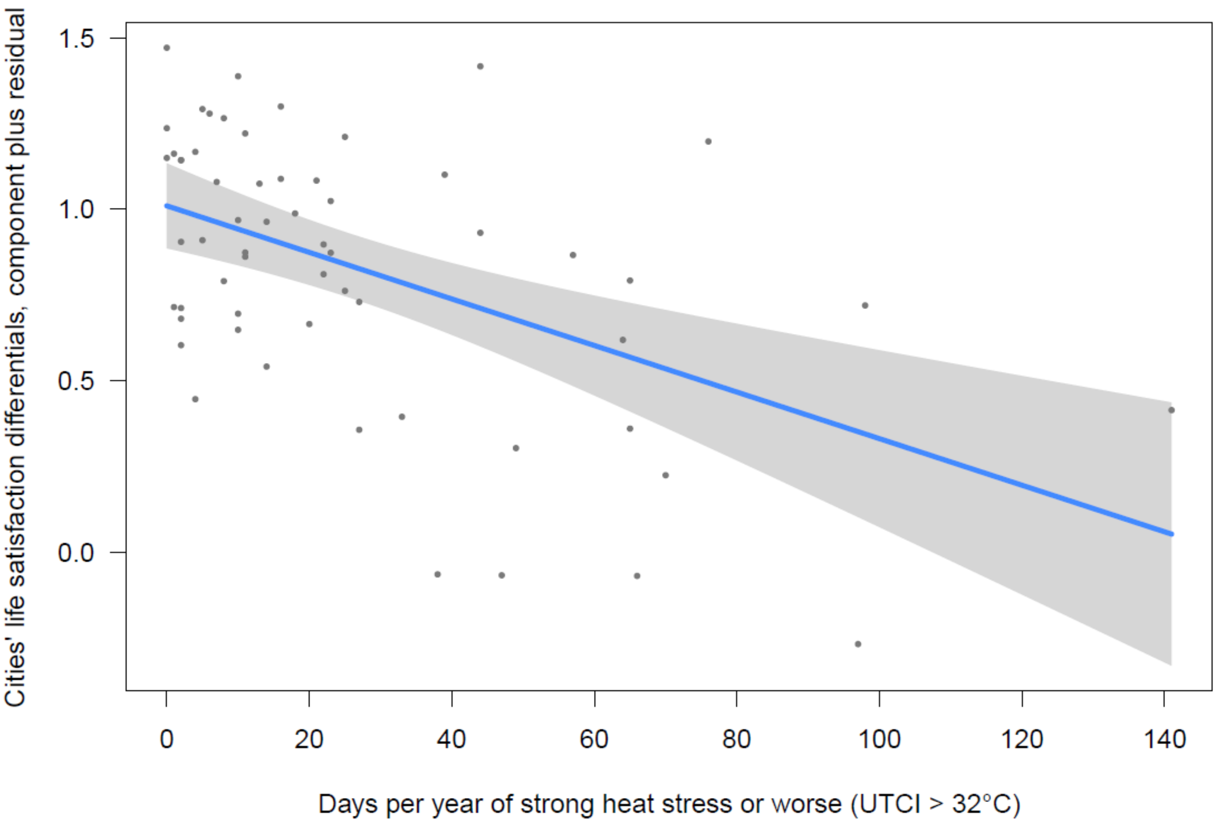
Figure 2. Air pollution (concentration of PM 2.5) and life satisfaction, partial residual plot



Notes: the plot is based on column (1) of Table 3. Shaded area represents 95 per cent confidence interval.

A second group of characteristics focuses on cities' conditions in terms of environmental quality, extreme weather, and presence of amenities. For most cities in our sample, we were able to quantify the share of green areas within each city as well as the extent to which cities are affected by heatwaves. The latter feature was measured in terms of the number of days per year of strong heat stress (see the Data section for details). In addition to these features, a composite indicator capturing the recreational amenities in each city was included. Among those factors, the presence and intensity of heatwaves are clearly associated to lower life satisfaction in cities (Fig. 3). This confirms previous analysis on German households by Osberghaus and Kühling (2016), who assessed the impact of storms, heavy rains, floods, and heatwaves on life satisfaction. They found a direct and negative effect only in the case of heatwaves. Another study focusing on Australia, while reporting no association between heatwaves and current subjective well-being, found results on expectations for future well-being (Zander et al., 2019). As for the other amenities that were included in the analysis, the composite indicator on the presence of amenities is significantly associated with higher life satisfaction, confirming that amenities are conducive to higher well-being in cities. Finally, we found no association between the share of green areas and life satisfaction across the cities in our sample.

Figure 3. Days per year of heat stress (heatwaves) and life satisfaction, partial residual plot



Notes: the plot is based on column (2) of Table 3. Shaded area represents 95 per cent confidence interval.

A third group of contextual factors was introduced to account for the social-cultural composition of the city population. Recent research in the context of Finland showed that the share of educated population in a city is strongly associated to life satisfaction (Weckroth et al., 2022). This result would suggest that being surrounded by a social environment characterized by highly educated people can be conducive to higher life satisfaction, thus it would be a source of positive externalities. However, our results do not support such a statement, as the coefficient related to the share of population with tertiary education is never statistically different from zero.

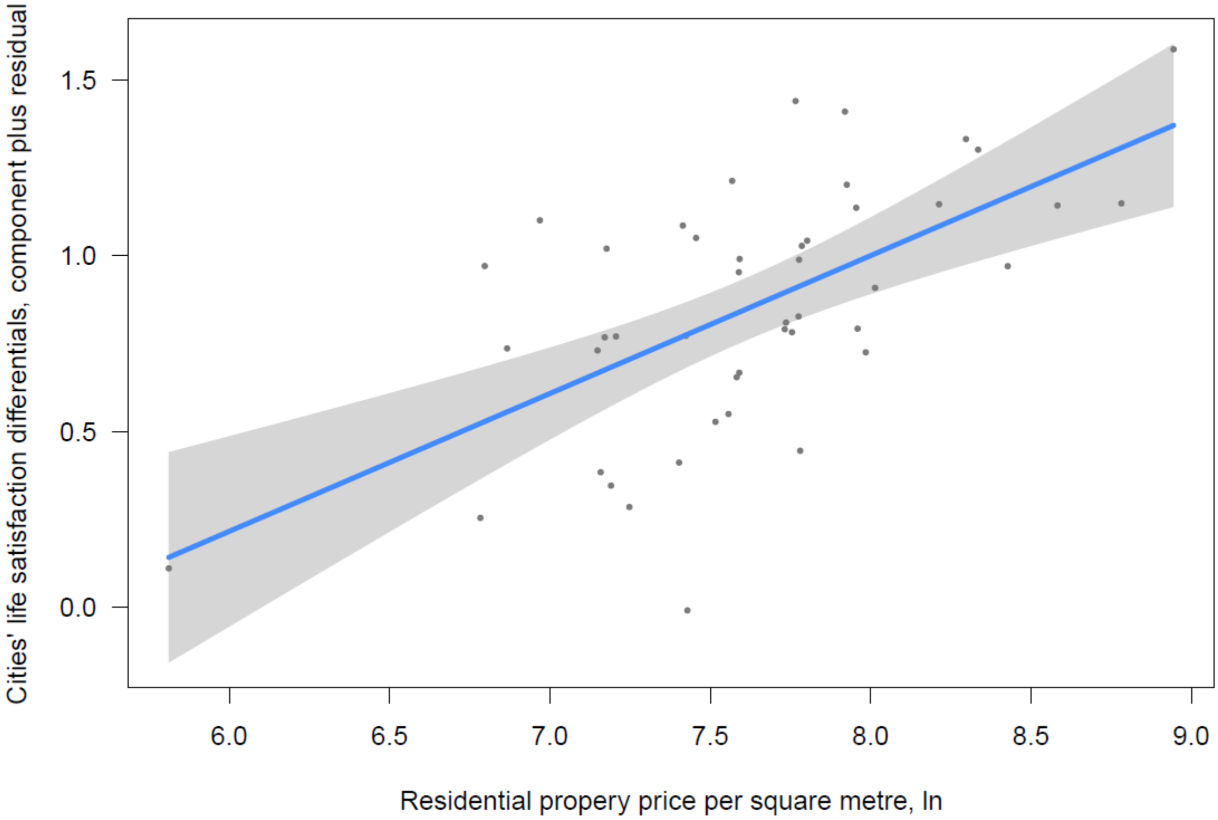
Another aspect included in the analysis is related to the cultural diversity of the urban environment. The socio-economic consequences of cultural diversity, considered in terms of the heterogeneity in the country of birth or ethnicity, has been assessed in many domains, with both positive and negative results. For example, positive impacts have been found on productivity and wages (Ottaviano and Peri, 2005) while negative results have been shown through reduction in social capital and trust (Letki, 2008; Sturgis et al., 2011). In this context, however, very little is known on the role that cultural diversity plays on subjective well-being, except a study on British districts. Such a study reported a negative relationship between cultural diversity and life satisfaction for white British people and a non-significant relationship for other groups (Longhi, 2014). Contrary, in those findings we observe slightly higher life satisfaction in cities with higher shares of foreign-born individuals. If the share of foreign-born population is further disaggregated in those born in the EU or outside of the EU, results are stronger when considering people born within the European Union.[3]

A fourth group of factors concerns the economic prosperity in the city as well as the demand for the city as captured by the housing price levels and by net internal migration flows. As argued in Section

[3] Results available upon request.

2, if the spatial equilibrium framework holds, we should observe no correlation between life satisfaction and income per capita. On the other hand, if life satisfaction captures a compound amenity of the city, then we should find higher rents in happier cities. Overall, our results seem to be consistent with the spatial equilibrium framework, as the life satisfaction differentials are almost always uncorrelated with GDP per capita, while they are strongly and positively correlated with house price levels. In other words, living in cities with average higher life satisfaction is significantly more expensive compared to other less happy cities. This holds also when accounting for the rate of internal migration to the city during the last five years. Consistently with expectations, cities attracting higher shares of internal migrants tend to have higher levels of life satisfaction.
Finally, in Table A3-A5 in Appendix we performed robustness checks by means of multilevel models and in Table A6 we estimated an LPM with both individual and contextual variables and clustered standard errors. Results confirm our main estimates.

Figure 4. Residential property price per square metre and life satisfaction, partial residual plot



Notes: the plot is based on column (4) of Table 3. Shaded area represents 95 per cent confidence interval.

Table 3. Regression results on city-level life satisfaction differentials (Logit)

	(1)	(2)	(3)	(4)	(5)
Intercept	2.2119 ***	0.1000	0.6575 *	-2.4303 *	-0.0135
	(0.5545)	(0.4951)	(0.2887)	(1.1648)	(2.7055)
log pop	-0.0375				-0.0487
	(0.0554)				(0.1923)
log area	-0.0532				-0.2691
	(0.0469)				(0.2908)
pm25 pollution	-0.0404 ***				-0.0075
	(0.0100)				(0.0183)
heatwaves		-0.0068 **			-0.0012
		(0.0022)			(0.0078)
log RPI_{2010}		0.0840			0.0282
		(0.0451)			(0.1118)
share green $areas_{2010}$		-0.0003			0.0001
		(0.0018)			(0.0038)
share tertiary edu.			0.0018		-0.0018
			(0.0068)		(0.0095)
share foreigners			0.9400		-1.0111
			(0.5630)		(1.3356)
log GDP p.c.				0.0249	-0.1655
				(0.0932)	(0.2119)
log ppm2				0.3923 ***	0.6436 ***
				(0.0631)	(0.1568)
netmob				0.3252 ***	0.0860
				(0.0861)	(0.1790)
Observations	72	59	48	46	31
R^2 / R^2 adjusted	0.308 / 0.277	0.313 / 0.276	0.059 / 0.018	0.444 / 0.404	0.624 / 0.406

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Heteroskedastic robust standard errors in parentheses.

Table 4. Regression results on city-level life satisfaction differentials (LPM)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.3244 ***	0.0450	0.1006 *	-0.3111	-0.0263
	(0.0794)	(0.0736)	(0.0423)	(0.1547)	(0.3145)
log pop	-0.0064				-0.0001
	(0.0078)				(0.0225)
log area	-0.0055				-0.0344
	(0.0056)				(0.0328)
pm25 pollution	-0.0054 ***				-0.0013
	(0.0014)				(0.0027)
heatwaves		-0.0010 *			-0.0004
		(0.0004)			(0.0010)

log RPI_{2010}		0.0100 (0.0065)			-0.0017 (0.0157)
share green $areas_{2010}$		0.0000 (0.0002)			0.0001 (0.0005)
share tertiary edu.			0.0003 (0.0010)		-0.0001 (0.0013)
share foreigners			0.1414 (0.0750)		-0.1366 (0.1570)
log GDP p.c.				0.0043 (0.0119)	-0.0168 (0.0235)
log ppm2				0.0519 *** (0.0092)	0.0793 *** (0.0203)
netmob				0.0431 ** (0.0122)	0.0152 (0.0210)
Observations	72	59	48	46	31
R^2 / R^2 adjusted	0.306 / 0.275	0.311 / 0.273	0.067 / 0.026	0.468 / 0.430	0.643 / 0.436

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedastic robust standard errors in parentheses.

Table 5. Regression results on city-level life satisfaction differentials (Ologit)

	(1)	(2)	(3)	(4)	(5)
Intercept	2.2767 ** (0.6715)	-0.2498 (0.6478)	0.3380 (0.3273)	-5.5297 *** (1.2970)	-3.1109 (3.4553)
log pop	-0.0949 (0.0672)				-0.2381 (0.1783)
log area	0.0441 (0.0617)				0.0231 (0.2611)
pm25 pollution	-0.0469 *** (0.0105)				0.0158 (0.0212)
heatwaves		-0.0086 *** (0.0025)			-0.0050 (0.0057)
log RPI_{2010}		0.0965 (0.0590)			0.1515 (0.1122)
share green $areas_{2010}$		-0.0007 (0.0024)			0.0003 (0.0039)
share tertiary edu.			0.0008 (0.0075)		-0.0063 (0.0099)
share foreigners			1.6870 * (0.7973)		0.4937 (1.5034)
log GDP p.c.				0.2106 (0.1170)	0.0677 (0.2523)

log ppm2				0.5016 *** (0.0967)	0.5753 * (0.2345)
netmob				0.2826 * (0.1232)	0.2196 (0.2635)
Observations	72	59	48	46	31
R^2 / R^2 adjusted	0.261 / 0.229	0.351 / 0.315	0.120 / 0.081	0.491 / 0.454	0.693 / 0.515

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Heteroskedastic robust standard errors in parentheses.

Concluding remarks

This study has used a recently released survey data designed for a large set of European cities to analyse the individual and contextual drivers of life satisfaction, with most of the focus put on the latter. The analysis first looks at the individual features explaining differences in life satisfaction to construct a measure of life satisfaction differentials at the city scale. Such analysis places several cities in North and Centre of Europe (e.g., Reykjavík, Amsterdam, Strasbourg, Munich) as those providing their citizens with the highest life satisfaction. Subsequently, we focus on four groups of contextual factors that are potentially associated with higher life satisfaction levels, namely diseconomies of agglomerations, environmental quality and extreme weather, social environment, and economic prosperity. We show that cities with average higher life satisfaction have better air quality, higher shares of foreign-born population, better recreational amenities, and less heatwaves. Population density and size are not significantly related to life satisfaction differentials across the cities considered. Regarding the economic prosperity domain, we obtain results consistent with the spatial equilibrium framework. More specifically, differences in life satisfaction is not associated with differences in income, but instead they are strongly associated with price differences (i.e., as captured in terms of housing). Consistently, cities attracting more internal migrants from other cities and regions of the same countries have clearly higher scores in terms of life satisfaction. The way we can interpret these latter findings is that life satisfaction is a feature of cities that, in the long run, is compensated by other lower outcomes in other domains, notably in terms of higher prices.

We believe that our cross-city approach provides a complementary perspective to the literature on spatial differences in well-being, including the apparently loosely related strand of literature focusing on the urban well-being paradox. This is because to understand why cities often fare worse than rural areas despite the many observed advantages of cities, it is important to look more closely at the features that are specific to cities and that affect life satisfaction. In other words, some of the drivers of the urban-rural gap in life satisfaction can also be seen (and perhaps more usefully) from the perspective of city. One thing that is lost with the "urban-rural" approach is that urban and rural are "amorphous" and "ubiquitous" spaces, they do not allow the identification of specific places, but reflect an average of what happens at different population densities.

Looking at the same problems through the lens of specific cities allows us to verify whether some of the factors that may underlie the differences between urban and rural areas are also verified by comparing units that have two "superior" characteristics: a) they are more homogeneous and comparable units with respect to all other unobserved features; b) identify well-defined locations, rather than averages of variegated locations having similar densities. For example, we can assume that one of the factors underlying urban-rural gaps in life satisfaction is air quality. If this is true, then we should also find the same relationship between cities, which are however much more easily definable entities and in which we can also more easily intervene as a policy maker. Identifying the drivers of well-being at the city scale can help overcome the challenges that our contemporary cities are facing in terms of ensuring good lives to their citizens. In the long run, this could affect the intensity and the nature of the above-mentioned paradox.

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Appendix

Table A1: Sample composition by EU and non-EU countries

European Union	
Austria	Graz, Vienna
Belgium	Antwerp, Brussels (Greater), Liège
Bulgaria	Burgas, Sofia
Croatia	Zagreb
Cyprus	Nicosia
Czechia	Ostrava, Prague
Denmark	Aalborg, Copenhagen (Greater)
Estonia	Tallinn
Finland	Helsinki (Greater), Oulu
France	Bordeaux, Lille, Marseille, Rennes, Strasbourg, Paris (Greater)
Germany	Berlin, Dortmund, Essen, Hamburg, Leipzig, Munich, Rostock
Greece	Athens, Heraklion
Hungary	Budapest, Miskolc
Ireland	Dublin
Italy	Bologna, Naples (Greater), Palermo, Roma, Turin, Verona
Latvia	Ríga
Lithuania	Vilnius
Luxembourg	Luxembourg
Malta	Valletta (Greater)
Netherlands	Amsterdam (Greater), Groningen, Rotterdam (Greater)
Poland	Białystok, Cracow, Gdańsk, Warsaw
Portugal	Braga, Lisbon
Romania	Bucarest, Cluj, Napoca, Piatra, Neamț
Slovakia	Bratislava, Košice
Slovenia	Ljubljana
Spain	Barcelona (Greater), Madrid, Málaga, Oviedo
Sweden	Malmö, Stockholm (Greater)
Other Countries	
Albania	Tirana
Iceland	Reykjavík
Republic of North Macedonia	Skopje
Montenegro	Podgorica
Norway	Oslo
Serbia (RS)	Belgrade
Switzerland	Geneva, Zurich
Turkey	Ankara, Istanbul, Anatalya, Diyabakir
The United Kingdom	Belfast, Cardiff, Glasgow, London (Greater), Manchester (Greater), Tyneside conurbation (Greater)

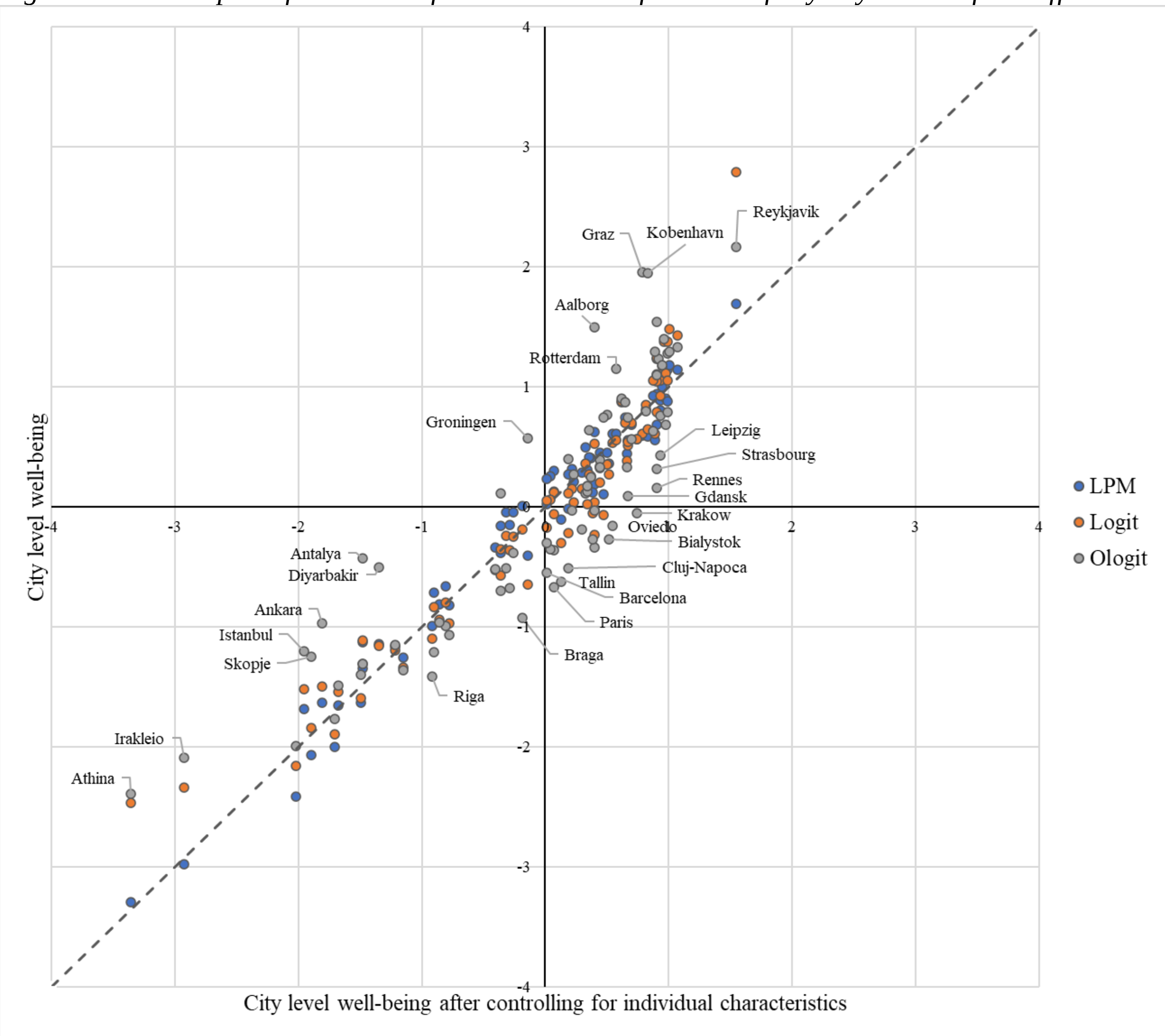
Table A2: Components and inputs for recreation potential model.

Component	Inputs	Expected effects on recreation potential
Suitability of Land to support recreational activities	Land use	Land use types capacity to support recreational activities
Urban	Green Urban Areas	Blue-green infrastructures play a key role in supporting nature based recreational activities in Functional Urban Areas
	Natural riparian areas	
	Bathing water quality	
	Semi-natural vegetation (grassland and woody vegetation)	
Natural Features influencing the potential provision NATURE	Natural protected areas	The presence of protected areas increase the availability of recreation opportunities and the quality of the sites

	Semi-natural vegetation (woody vegetation and grassland)	Increase of vegetation heterogeneity in agricultural areas
Water	Geomorphology of coast Marine protected areas Bathing water quality Blue flags Lakes Natural riparian areas	The presence of water provides different opportunities for recreation. Four key aspects were considered: the distance from inland coast and sea coast; geomorphology of the sea coast; bathing water quality, and presence of natural riparian areas
Proximity	Road network	The road network and built up areas allow the computation of a proximity index, the types of roads considered depend on the scale of the assessment, When focusing at a local scale, i.e. metropolitan, only pedestrian and local roads are used.
	Built-up areas	

Source: Kompil et al. (2015)

Figure A1: Scatterplot of the share of inhabitants satisfied with life by city and the fixed effects



Notes: city level well-being is normalized.

Table A3: logit multilevel model

	(1)	(2)	(3)	(4)	(5)

Intercept	3.1769 ***	1.1613 *	1.7778 ***	-0.9948	1.2404
	(0.5801)	(0.5039)	(0.2622)	(0.9735)	(1.8463)
Age: 25-39	-0.0741	-0.1438 *	0.0120	-0.0803	0.0719
	(0.0608)	(0.0683)	(0.0769)	(0.0759)	(0.0911)
Age: 40-54	-0.2978 ***	-0.4002 ***	-0.3106 ***	-0.3482 ***	-0.2948 ***
	(0.0590)	(0.0660)	(0.0743)	(0.0729)	(0.0876)
Age: 55 and over	-0.3417 ***	-0.4350 ***	-0.2783 ***	-0.3517 ***	-0.2081 *
	(0.0662)	(0.0727)	(0.0829)	(0.0809)	(0.0977)
Sex: Female	0.0937 **	0.0966 **	0.0407	0.0788 *	0.0532
	(0.0309)	(0.0329)	(0.0379)	(0.0372)	(0.0458)
Lived in another city	-0.0382	-0.0399	-0.0522	-0.0205	-0.0576
	(0.0311)	(0.0330)	(0.0384)	(0.0373)	(0.0462)
Household comp.: Other	-0.0012	0.0162	0.0685	0.0493	0.1551
	(0.0574)	(0.0619)	(0.0702)	(0.0703)	(0.0853)
Household comp.: Household with children with less than 25	0.0926 *	0.1378 **	0.2165 ***	0.1185 *	0.2516 ***
	(0.0403)	(0.0432)	(0.0501)	(0.0488)	(0.0600)
Household comp.: Household with children more than 25	-0.0063	0.0402	0.0994	0.0509	0.0919
	(0.0502)	(0.0527)	(0.0637)	(0.0594)	(0.0754)
Education: Secondary	0.2883 ***	0.2750 ***	0.2596 ***	0.2816 ***	0.3326 ***
	(0.0466)	(0.0500)	(0.0588)	(0.0561)	(0.0686)
Education: Tertiary	0.3861 ***	0.3945 ***	0.3947 ***	0.3944 ***	0.5008 ***
	(0.0484)	(0.0523)	(0.0614)	(0.0587)	(0.0715)
Working Status: Part-time Empl.	-0.2057 ***	-0.2028 ***	-0.2446 ***	-0.2737 ***	-0.2604 ***
	(0.0515)	(0.0551)	(0.0632)	(0.0606)	(0.0752)
Working Status: Unemployed	-0.4905 ***	-0.5245 ***	-0.4430 ***	-0.4213 ***	-0.3124 **
	(0.0630)	(0.0676)	(0.0804)	(0.0784)	(0.0996)
Working Status: Retired	-0.0656	-0.0574	-0.0397	-0.0479	-0.0297
	(0.0544)	(0.0568)	(0.0663)	(0.0643)	(0.0795)
Working Status: Other	-0.1605 **	-0.2113 ***	-0.1805 *	-0.2248 **	-0.2506 **
	(0.0575)	(0.0620)	(0.0718)	(0.0697)	(0.0849)
Difficult to pay a bill	-0.7583 ***	-0.7465 ***	-0.7232 ***	-0.7285 ***	-0.7101 ***
	(0.0327)	(0.0342)	(0.0402)	(0.0389)	(0.0479)
log pop	-0.0131				-0.1143
	(0.0552)				(0.1457)
log area	-0.0666				-0.2566
	(0.0572)				(0.1651)
pm25 pollution	-0.0385 ***				-0.0050
	(0.0093)				(0.0152)
heatwaves		-0.0059 ***			-0.0012
		(0.0017)			(0.0043)

log RPI_{2010}		0.1100 * (0.0479)			0.0595 (0.0737)
share green $areas_{2010}$		-0.0013 (0.0025)			-0.0010 (0.0026)
share tertiary edu.			0.0032 (0.0062)		-0.0029 (0.0057)
share foreigners			1.0506 (0.6206)		-0.9373 (0.9064)
log GDP p.c.				-0.0328 (0.0874)	-0.1786 (0.1308)
log ppm2				0.4502 *** (0.0907)	0.6957 *** (0.1764)
netmob				0.2637 * (0.1251)	0.0936 (0.1643)
Random Effects					
σ^2	3.29	3.29	3.29	3.29	3.29
τ_{00}	0.09 $_{\text{city\_code}}$	0.10 $_{\text{city\_code}}$	0.13 $_{\text{city\_code}}$	0.07 $_{\text{city\_code}}$	0.04 $_{\text{city\_code}}$
ICC	0.03	0.03	0.04	0.02	0.01
N	58 $_{\text{city\_code}}$	50 $_{\text{city\_code}}$	40 $_{\text{city\_code}}$	40 $_{\text{city\_code}}$	28 $_{\text{city\_code}}$
Observations	38875	33530	26876	26816	18796

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. A variable combining the design weight and the post-stratification weight has been used as weighting variable for each of the estimations reported in the Table. Reference category for age is 18-24, for Household composition is single family, and foe working status is full- time employment.

Table A4: linear multilevel model

	(1)	(2)	(3)	(4)	(5)
Intercept	1.0265 *** (0.0768)	0.7595 *** (0.0716)	0.8308 *** (0.0358)	0.4597 *** (0.1288)	0.7254 * (0.3050)
Age: 25-39	-0.0107 (0.0068)	-0.0178 * (0.0076)	-0.0008 (0.0081)	-0.0106 (0.0083)	0.0046 (0.0095)
Age: 40-54	-0.0357 *** (0.0067)	-0.0469 *** (0.0075)	-0.0350 *** (0.0080)	-0.0404 *** (0.0082)	-0.0334 *** (0.0094)
Age: 55 and over	-0.0415 *** (0.0076)	-0.0518 *** (0.0084)	-0.0321 *** (0.0091)	-0.0415 *** (0.0092)	-0.0247 * (0.0106)
Sex: Female	0.0112 ** (0.0035)	0.0113 ** (0.0038)	0.0044 (0.0041)	0.0088 * (0.0042)	0.0055 (0.0049)
Lived in another city	-0.0056 (0.0035)	-0.0053 (0.0038)	-0.0068 (0.0042)	-0.0023 (0.0042)	-0.0062 (0.0049)
Household comp.: Other	-0.0017 (0.0068)	0.0025 (0.0073)	0.0078 (0.0078)	0.0060 (0.0081)	0.0179 (0.0093)
Household comp.: Household with children with less than 25	0.0109 * (0.0045)	0.0161 ** (0.0050)	0.0234 *** (0.0053)	0.0142 ** (0.0055)	0.0275 *** (0.0063)

Household comp.: Household with children more than 25	0.0000 (0.0059)	0.0058 (0.0063)	0.0118 (0.0070)	0.0066 (0.0069)	0.0104 (0.0082)
Education: Secondary	0.0403 *** (0.0058)	0.0388 *** (0.0063)	0.0338 *** (0.0070)	0.0387 *** (0.0070)	0.0436 *** (0.0081)
Education: Tertiary	0.0511 *** (0.0060)	0.0520 *** (0.0065)	0.0479 *** (0.0072)	0.0512 *** (0.0072)	0.0611 *** (0.0083)
Working Status: Part-time Empl.	-0.0240 *** (0.0060)	-0.0238 *** (0.0065)	-0.0273 *** (0.0070)	-0.0316 *** (0.0071)	-0.0287 *** (0.0083)
Working Status: Unemployed	-0.0662 *** (0.0082)	-0.0719 *** (0.0089)	-0.0563 *** (0.0098)	-0.0532 *** (0.0098)	-0.0362 ** (0.0115)
Working Status: Retired	-0.0046 (0.0064)	-0.0042 (0.0068)	-0.0027 (0.0074)	-0.0017 (0.0075)	-0.0002 (0.0088)
Working Status: Other	-0.0192 ** (0.0067)	-0.0238 ** (0.0073)	-0.0183 * (0.0079)	-0.0244 ** (0.0080)	-0.0257 ** (0.0093)
Difficult to pay a bill	-0.0993 *** (0.0040)	-0.0990 *** (0.0043)	-0.0909 *** (0.0048)	-0.0942 *** (0.0048)	-0.0869 *** (0.0056)
log pop	-0.0026 (0.0073)				-0.0085 (0.0237)
log area	-0.0081 (0.0075)				-0.0325 (0.0268)
pm25 pollution	-0.0051 *** (0.0012)				-0.0009 (0.0025)
heatwaves		-0.0008 ** (0.0002)			-0.0004 (0.0007)
log RPI_{2010}		0.0135 * (0.0068)			0.0020 (0.0121)
share green $areas_{2010}$		-0.0001 (0.0004)			0.0000 (0.0004)
share tertiary edu.			0.0006 (0.0009)		-0.0001 (0.0009)
share foreigners			0.1401 (0.0863)		-0.1223 (0.1466)
log GDP p.c.				-0.0027 (0.0116)	-0.0187 (0.0215)
log ppm2				0.0582 *** (0.0121)	0.0849 ** (0.0282)
netmob				0.0374 * (0.0165)	0.0175 (0.0263)
Random Effects					
σ^2	0.12	0.12	0.11	0.11	0.11
τ_{00}	0.00 city_code	0.00 city_code	0.00 city_code	0.00 city_code	0.00 city_code

ICC	0.01	0.02	0.02	0.01	0.01
N	58 $_{city\_code}$	50 $_{city\_code}$	40 $_{city\_code}$	40 $_{city\_code}$	28 $_{city\_code}$
Observations	38875	33530	26876	26816	18796

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. A variable combining the design weight and the post-stratification weight has been used as weighting variable for each of the estimations reported in the Table. Reference category for age is 18-24, for Household composition is single family, and foe working status is full- time employment.

Table A5: ologit multilevel model

	(1)	(2)	(3)	(4)	(5)
Not at all satisfied | Not very satisfied	-5.0312 *** (0.7471)	-2.8282 *** (0.6022)	-3.6279 *** (0.2987)	1.9826 (1.2501)	-0.4533 (1.8056)
Not very satisfied| Fairly satisfied	-3.5200 *** (0.7467)	-1.2047 * (0.6016)	-1.9739 *** (0.2971)	3.6136 ** (1.2498)	1.2017 (1.8052)
Fairly satisfied | Very satisfied	-0.9999 (0.7464)	1.4125 * (0.6016)	0.5785 (0.2968)	6.2015 *** (1.2503)	3.7986 * (1.8054)
Age: 25-39	-0.2021 *** (0.0390)	-0.2783 *** (0.0434)	-0.1897 *** (0.0478)	-0.1985 *** (0.0481)	-0.1961 *** (0.0568)
Age: 40-54	-0.3986 *** (0.0385)	-0.4950 *** (0.0428)	-0.4384 *** (0.0473)	-0.4170 *** (0.0472)	-0.4415 *** (0.0563)
Age: 55 and over	-0.3953 *** (0.0437)	-0.5044 *** (0.0480)	-0.4067 *** (0.0535)	-0.4255 *** (0.0532)	-0.4297 *** (0.0634)
Sex: Female	0.0316 (0.0200)	0.0293 (0.0216)	0.0095 (0.0241)	0.0108 (0.0242)	0.0136 (0.0289)
Lived in another city	-0.0339 (0.0201)	-0.0378 (0.0218)	-0.0370 (0.0244)	-0.0391 (0.0243)	-0.0479 (0.0292)
Household comp.: Other	0.0021 (0.0386)	0.0235 (0.0418)	0.0377 (0.0459)	0.0436 (0.0468)	0.0940 (0.0551)
Household comp.: Household with children with less than 25	0.0315 (0.0258)	0.0516 (0.0281)	0.0699 * (0.0313)	0.0459 (0.0315)	0.0731 (0.0375)
Household comp.: Household with children more than 25	-0.0091 (0.0332)	-0.0002 (0.0356)	0.0425 (0.0409)	0.0168 (0.0394)	-0.0008 (0.0486)
Education: Secondary	0.1510 *** (0.0332)	0.1447 *** (0.0361)	0.1350 *** (0.0409)	0.1500 *** (0.0401)	0.1775 *** (0.0484)
Education: Tertiary	0.2827 *** (0.0341)	0.2830 *** (0.0372)	0.2791 *** (0.0421)	0.2785 *** (0.0413)	0.3333 *** (0.0496)
Working Status: Part-time Empl.	-0.1346 *** (0.0340)	-0.1337 *** (0.0369)	-0.1559 *** (0.0412)	-0.1760 *** (0.0410)	-0.1895 *** (0.0490)
Working Status: Unemployed	-0.3087 *** (0.0467)	-0.3485 *** (0.0509)	-0.2280 *** (0.0577)	-0.2652 *** (0.0569)	-0.1770 ** (0.0685)
Working Status: Retired	0.0296 (0.0362)	0.0340 (0.0388)	0.0462 (0.0435)	0.0254 (0.0431)	0.0456 (0.0521)

	(1)	(2)	(3)	(4)	(5)
Working Status: Other	-0.1017 **	-0.1795 ***	-0.1686 ***	-0.1527 ***	-0.2036 ***
	(0.0379)	(0.0413)	(0.0461)	(0.0461)	(0.0553)
Difficult to pay a bill	-0.5550 ***	-0.5650 ***	-0.5339 ***	-0.5144 ***	-0.5138 ***
	(0.0230)	(0.0246)	(0.0281)	(0.0279)	(0.0335)
log pop	-0.0624				-0.3198 *
	(0.0706)				(0.1593)
log area	0.0176				0.0522
	(0.0698)				(0.1915)
pm25 pollution	-0.0419 ***				0.0219
	(0.0114)				(0.0176)
heatwaves		-0.0082 ***			-0.0057
		(0.0020)			(0.0050)
log RPI_{2010}		0.1336 *			0.1815 *
		(0.0576)			(0.0873)
share green $areas_{2010}$		-0.0026			-0.0011
		(0.0029)			(0.0030)
share tertiary edu.			0.0006		-0.0075
			(0.0074)		(0.0066)
share foreigners			1.8676 *		0.6486
			(0.7342)		(1.0180)
log GDP p.c.				0.1585	0.0398
				(0.1112)	(0.1345)
log ppm2				0.5440 ***	0.6558 **
				(0.1148)	(0.2021)
netmob				0.2067	0.2531
				(0.1568)	(0.1889)
Random Effects					
σ^2	3.29	3.29	3.29	3.29	3.29
τ_{00}	0.15 city_code	0.15 city_code	0.20 city_code	0.13 city_code	0.07 city_code
ICC	0.04	0.04	0.06	0.04	0.02
N	58 city_code	50 city_code	40 city_code	40 city_code	28 city_code
Observations	38740	33450	26810	26746	18743

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. A variable combining the design weight and the post-stratification weight has been used as weighting variable for each of the estimations reported in the Table. Reference category for age is 18-24, for Household composition is single family, and foe working status is full- time employment.

Table A6: LPM with clustered standard errors at city level

	(1)	(2)	(3)	(4)	(5)
Age: 25-39	1.0213 ***	0.7654 ***	0.8403 ***	0.4715 **	0.7238 ***
	(0.0781)	(0.0607)	(0.0362)	(0.1450)	(0.1949)
Age: 40-54	-0.0106	-0.0201	-0.0030	-0.0111	0.0056
	(0.0114)	(0.0140)	(0.0141)	(0.0145)	(0.0171)

Age: 55 and over	-0.0365 ** (0.0116)	-0.0495 *** (0.0144)	-0.0382 * (0.0156)	-0.0417 ** (0.0150)	-0.0325 (0.0191)
Sex: Female	-0.0434 *** (0.0121)	-0.0557 *** (0.0163)	-0.0363 * (0.0170)	-0.0425 ** (0.0159)	-0.0238 (0.0182)
Lived in another city	0.0108 ** (0.0041)	0.0106 * (0.0045)	0.0036 (0.0051)	0.0086 (0.0046)	0.0052 (0.0059)
Household comp.: Other	-0.0043 (0.0050)	0.0002 (0.0051)	0.0004 (0.0056)	0.0007 (0.0054)	-0.0059 (0.0063)
Household comp.: Household with children with less than 25	-0.0056 (0.0093)	-0.0012 (0.0095)	0.0029 (0.0094)	0.0039 (0.0106)	0.0156 (0.0115)
Household comp.: Household with children more than 25	0.0095 (0.0061)	0.0151 * (0.0065)	0.0220 *** (0.0065)	0.0142 (0.0074)	0.0280 *** (0.0081)
Education: Secondary	-0.0012 (0.0069)	0.0065 (0.0077)	0.0122 (0.0070)	0.0053 (0.0081)	0.0105 (0.0086)
Education: Tertiary	0.0416 *** (0.0082)	0.0358 *** (0.0083)	0.0309 ** (0.0106)	0.0393 *** (0.0106)	0.0455 *** (0.0104)
Working Status: Part-time Empl.	0.0514 *** (0.0100)	0.0503 *** (0.0098)	0.0433 *** (0.0132)	0.0505 *** (0.0127)	0.0613 *** (0.0134)
Working Status: Unemployed	-0.0242 ** (0.0085)	-0.0220 ** (0.0081)	-0.0247 * (0.0099)	-0.0324 *** (0.0098)	-0.0284 * (0.0128)
Working Status: Retired	-0.0675 *** (0.0110)	-0.0712 *** (0.0132)	-0.0569 *** (0.0158)	-0.0535 *** (0.0133)	-0.0343 * (0.0137)
Working Status: Other	-0.0049 (0.0075)	-0.0048 (0.0085)	-0.0044 (0.0095)	-0.0038 (0.0076)	0.0001 (0.0101)
Difficult to pay a bill	-0.0195 ** (0.0070)	-0.0241 ** (0.0080)	-0.0203 * (0.0091)	-0.0243 ** (0.0083)	-0.0255 * (0.0109)
log pop	-0.1084 *** (0.0080)	-0.1084 *** (0.0098)	-0.1077 *** (0.0144)	-0.0998 *** (0.0095)	-0.0896 *** (0.0111)
log area	-0.0021 (0.0078)				-0.0082 (0.0159)
pm25 pollution	-0.0078 (0.0050)				-0.0329 (0.0189)
heatwaves	-0.0049 *** (0.0014)				-0.0009 (0.0014)
log RPI_{2010}		-0.0007 ** (0.0002)			-0.0004 (0.0007)
share green $areas_{2010}$		0.0134 * (0.0058)			0.0020 (0.0085)
share tertiary edu.		-0.0001 (0.0002)			-0.0000 (0.0003)

share foreigners			0.0006 (0.0010)		-0.0001 (0.0008)
log GDP p.c.			0.1316 (0.0682)		-0.1234 (0.0998)
log ppm2				-0.0033 (0.0129)	-0.0188 (0.0138)
netmob				0.0578 *** (0.0086)	0.0849 *** (0.0145)
Observations	38740	33450	26810	26746	18743
R^2 / R^2 adjusted	0.038 / 0.038	0.038 / 0.038	0.030 / 0.030	0.035 / 0.035	0.038 / 0.037

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses. A variable combining the design weight and the post-stratification weight has been used as weighting variable for each of the estimations reported in the Table. Reference category for age is 18-24, for Household composition is single family, and foe working status is full-time employment.