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Accumulation of psychological problems in UK cities; A quantile regression approach

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ABSTRACT

The rich get richer and the poor face poverty in cities. Inspired by this economic accumulation, we study if domains of psychological well-being also accumulate across six psychological dimensions in cities. According to accumulation theory, we expect the most pronounced urban-rural disparities in the extremes of a total well-being distribution. We test this using quantile regression on a sample of 39,368 UK residents aged 40 to 70. Using a continuous and objective measure of urbanicity, we examined urban-rural differences through non-linear statistical models. We find evidence for UK urban residents accumulating psychological problems meaning the psychologically worst off face additional disadvantages in cities. We also observe a smaller general shift in total satisfaction meaning everyone is expected to do worse in cities. Lastly, we observe optimal distances between highly urban and rural areas for the central quantiles, 10% to 90%. In contrast, the unhappiest and happiest 10% show a healthy monotonic association with increasing distance from city centers.

0. Introduction

Ensuring that urban living is conducive to physical and mental health is of paramount importance, as the majority of the global population — totaling more than 5 billion people — resides in cities, a number that will continue to grow in the coming decades (Helliwell et al., 2021; UN-Habitat, 2016; United Nations et al., 2019; van der Wal et al., 2021).Urban inequality is a central challenge to this aim. Across income, productivity, social networks, and health, urban dynamics create vast differences between people (Mora et al., 2021; Kelly, 2000; Wilson, 1987). Directly, inequality leaves large parts of urban populations impoverished, and indirectly, it harms society at large by eroding social cohesion, stability, and overall well-being (Jung & Sunde, 2014; Kelly, 2000; Morrison, 2021b; Pickett & Wilkinson, 2015).

Accumulation has been proposed as a mechanism driving the urban inequality (Arvidsson et al., 2023; Gomez-Lievano et al., 2017). By accumulation we refer to feedback loops of problems causing further problems (negative accumulation) or success causing further success (positive accumulation). Cities drive negative accumulation, for instance when high living costs trap manual laborers and service workers in areas of segregation, long commutes, and high crime rates (Sassen, 2004; Wilson, 1987). On the other hand, cities are cauldrons mixing a diversity of ethnic, racial, gender, and sexual minorities into subcultures. Not only people, but also ideas, technologies, expertise, and knowledge mix and synergize (Gomez-Lievano et al., 2017). These synergies make cities central drivers of the past century's great acceleration of material growth (Arvidsson et al., 2023; Lorenz-Spreen et al., 2019). However, individuals have to display prior success or early talent in order to access these opportunities for synergy (Arvidsson et al., 2023; Morrison, 2024). This creates positive accumulation where a minority of already socioeconomically advantaged accumulate further advantages in cities (Arvidsson et al., 2023).

It is unknown whether similar accumulation dynamics and the consequent inequality holds for psychological well-being in cities. The present article aims to address this question. We conceptualize inequality in terms of six psychological domains: happiness, meaning in life, friendship satisfaction, family satisfaction, job satisfaction, and economic satisfaction. Negative (positive) accumulation occurs when an individual accumulates problems across these domains. Several psychological theories support the idea of psychological accumulation by arguing for causal reinforcement or spill-over effects between psychological domains. The broaden-and-build theory of emotions states that positive emotions broaden our action and thought. Thus, when one life domain triggers positive emotions, we are likely to take beneficial actions in other domains (Fredrickson, 2001). For instance,

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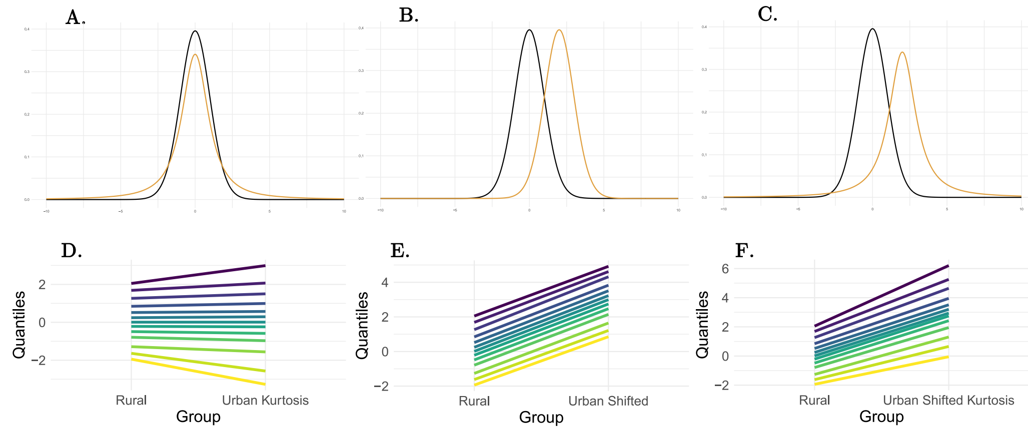

Fig. 1. Three types of urban-rural differences. Each figure in the top panel shows a form of change between two groups. The black distribution is a normal distribution, while the yellow distributions show heavier tails (left-most), shifted mean (middle), and heavier tails with shifted mean (right-most). The bottom panel shows the resulting quantile regressions for the three types of change where we assume the rural group to be represented by the black normal distribution in all three plots.(See the web version of this article for colored figures.)

financial prosperity can ease family life, while financial hardship often strains family dynamics. The idea that psychological problems cause further problems is the basis of the network theory of psychopathology (Borsboom & Cramer, 2013; Bringmann, 2024). We theorize that both healthy and unhealthy feedback loops between psychological domains might be amplified in cities by the increased pace of life and abundance of opportunities for success and failure (Bettencourt et al., 2007).

We test for accumulation by distinguishing three forms of change in a total satisfaction distribution. This distribution is obtained by computing a total satisfaction score comprising the six aforementioned psychological domains for 39,368 UK participants aged 40 to 69. The urban accumulation theory predicts that we should see the largest urban-rural differences in the tails of the distribution. Alternatively, urban-rural differences might be characterized by a general shift in the distribution, a combination of heavier tails and a general shift, or no difference. In Fig. 1 we illustrate the three forms of change. **A.** shows a normal distribution (black) and a distribution with heavy tails (red) consistent with positive and negative accumulation. Alternatively, and contrary to the accumulation theory, urban-rural differences might be better characterized by a general shift in the distribution (Fig. 1 **B.**), or a combination of both heavier tails and overall shift (Fig. 1 **C.**). Following (Mora et al., 2021) and (Morrison, 2021a), we use quantile regression to disentangle these three forms of change. The bottom panel of Fig. 1 shows how quantiles (2.5%, 5%, 10%, …, 90%, 95%, 97%) are expected to change for two groups for each of the three types of change. A central challenge in urban psychology is to define and compare urban and rural areas. We use the method of (Finnemann et al., 2021), who propose a continuous and objective measure of urbanicity. It defines urbanicity of an individual as the distance to the nearest city center. This distance is normalized based on the size of the nearest city to account for the differences between e.g. living 10 km from London and Leeds. The former is still urban area while the latter is countryside. This measure avoids the difficult task of drawing city boundaries and can detect sub- and peri-urban effects with non-linear statistical modeling (see part *A.* to **D.** of Fig. 2 for further explanation).

We analyze London and the rest of the UK in two separate analyses. London potentially differs from other cities by its “global” status (Sassen, 2004). Digitization over the past century made information about space and mobility accessible, leading to increased concentration of international finance, headquarters of international firms, and international migration concentrating in places like New York, Tokyo, and London (Murray, 2022; Sassen, 2004). The consequent increase in living prices, population density, extensive commuting times, and so forth might also lead to distinct psychological dynamics separating London from the rest of the UK (Sassen, 2004).

A couple of studies have investigated urban-rural differences in well-being using quantile regression (Burger et al., 2022; Morrison, 2021b; Nguyen et al., 2007). Most relevant, Morrison (2021b) compares well-being distributions of capital versus non-capital areas in Austria, Slovenia, and Czechia. In Czechia and Austria, they find evidence consistent with positive accumulation in capitals but not negative accumulation. In Slovenia, the reverse pattern of negative accumulation, but not positive, is found. A central limitation of this study is the reliance on a dichotomy of capital and non-capital, which is possibly confounded by effects specific to sub- or peri-urban areas. In contrast, we use a continuous measure of urbanicity that detects such effects. We also study a wider range of quantiles and compare urban versus rural areas rather than capital versus non-capital.

1. Methods

For our study, we use data from the UK Biobank, a large-scale ongoing data project. The study protocol and rationale are extensively described elsewhere.[1] Ethical approval for the Biobank was granted by the North West Multi-centre Research Ethics Committee.[2] Ethical approval for our study was obtained from the Ethics Review Board at the Faculty of Behavioral and Social Science, University of Amsterdam.[3]

The UK Biobank initially invited legally registered individuals aged 40 to 69 in the UK, living within 40 km of one of 22 assessment centers. The main data collection period ran from 2006 to 2010 and totaled approximately 500,000 participants. For our analysis, we used a subset of 39,368 participants who had no missing data in the geographic variables or the six psychological variables that compose our total satisfaction variable. The substantial reduction in participant numbers is due to some questions being introduced at later stages of the data collection. The sample was further split into a London sample of 14,363 participants and a remaining UK sample of 25,005 participants. We preprocessed, analyzed, and visualized our data using R (R. Core Team, 2020). All code is available in our online repository (https://osf.io/hpj4d/). Details of each step in our methodology are described in the following sections.

1 https://www.ukbiobank.ac.uk/media/gnkeyh2q/study-rationale.pdf

2 https://www.ukbiobank.ac.uk/learn-more-about-uk-biobank/about-us/ethics

3 available here https://osf.io/hpj4d/.

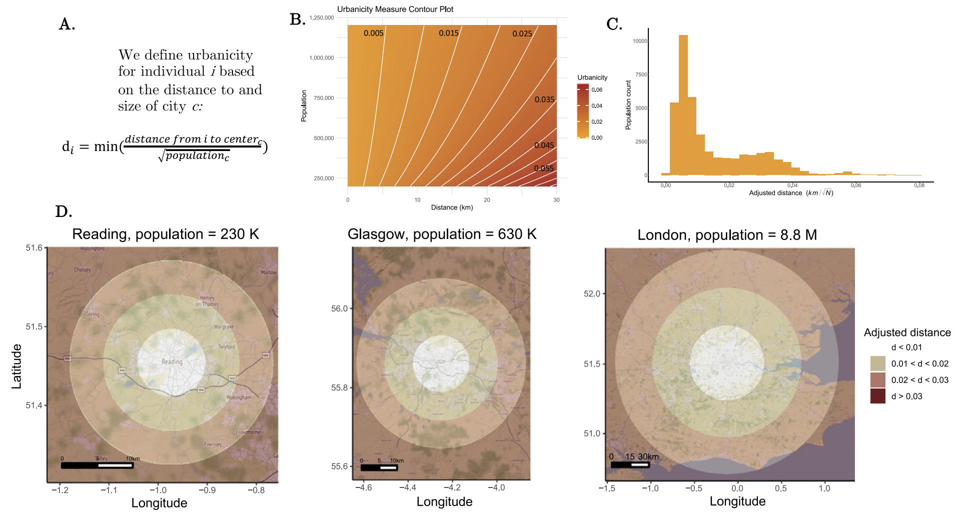

Fig. 2. Methods plot: **A.** Equation used to compute our independent variable, adjusted distance to nearest city. **B.** Contour plot illustrating how urbanicity depends on both the distance from and the size of cities. **C.** Empirical histogram of adjusted distance. **D.** Adjusted distances shown for three cities of varying sizes.

1.1. Dependent variable

Our dependent variable is a total satisfaction score comprised of six psychological domains: happiness, meaning in life, friendship satisfaction, family satisfaction, economic satisfaction, and job satisfaction. We chose these variables as they reflect important psychological domains of well-being, social satisfaction, and economic satisfaction. To ensure each domain contributes equally we chose two variables for each. Each of the variables was answered on a 6-step ordinal scale. We transform all six psychological dimensions so that extremely dissatisfied is scored as −1, neutral as 0, and extremely satisfied as 1. The total satisfaction score is then obtained by computing the sum score of the six variables for each participant. It ranges from −6 to 6 and a sum score of ±6 indicates a person has answered extremely satisfied (dissatisfied) across the six dimensions

1.2. Independent variable

The study's independent variable is the city size adjusted shortest distance to a city center (introduced in Finnemann et al. (2024)). It is computed based on participants' home location as well as official city centers and city population data obtained from the National Geospatial-Intelligence Agency. Both city center and population data are available at (https://osf.io/hpj4d/). To derive the urbanicity score we used the equation of Fig. 2 **A.**. For each participant i, we computed the distance to each city center c and divided the outcome by the square root of the city's population. Using the square root of the population as a proxy for city size is justified in (Prieto-Curiel et al., 2023). Because we normalize by city size, the urbanicity of a participant depends both on the distance from a city center and the size of the city. For instance, $d = 0.1$ reflects radii of 4 km, 7 km, and 10 km from cities of 200k, 500k, and 1M populations. While $d = 0.3$ reflects radii of 12, 21, and 30 km for the same city sizes. Thus, for all cities the city center is the most urban point and as we move away from the center our metric predicts increased rurality. How fast rurality increases is determined by $\sqrt{population_c}$ of city c. In Fig. 2, the contour plot shows how different distances are assumed to be equally urban depending on the size of the distance. We also illustrate the distances of $d = 0.01$, $d = 0.02$, and $d = 0.03$ for three cities of different sizes.

For each participant, we retain the smallest adjusted distance as the measure of urbanicity. By retaining the smallest value, participants are assigned to the nearest city. Therefore, if a participant resides 55 km from London, in the direction of Reading, they would be assigned to Reading if $d_{Reading}/pop_{Reading} < d_{London}/pop_{London}$. The adjusted distances, d_i, serve as our independent variable for all analyses.

1.3. Statistical analysis

As mentioned in the introduction, we employ quantile regression to disentangle three forms of change illustrated in Fig. 1. We denote the q_p quantile as the point where p% of the data points fall below this value. For instance, if the value of the median (50% quantile) increases from one to two in rural areas, this reflects that 50% of the sample scores one or less in urban areas while 50% score two or less in rural areas. In general, higher quantile values are healthier because more individuals score healthier across the six psychological domains. For our main analysis, we examined the 2.5%, 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, 95%, and 97.5% quantiles. We modeled the q_p quantile as follows:

$$q_p = \beta_{0p} + \beta_{1p} d + \beta_{2p} d^2 + \beta_{3p} d^3 + \beta_{4p} a + \beta_{5p} s$$

This model incorporates linear (d), quadratic (d^2), and cubic terms (d^3) for the adjusted distance variable. Including these non-linear terms is motivated by previous research indicating that depression and well-being reach optimal levels at intermediate distances between highly urban and highly rural areas (Breslau et al., 2014; Finnemann et al., 2024). In Fig. 3, we illustrate the functional forms associated with linear, cubic, and quadratic terms. By investigating the significance of the different terms we gain insight into the functional relationship between total satisfaction and adjusted distances to the city. The linear trend is associated with a straight line, while the quadratic term allows the functional form to change direction once and form either a u-shape with a local minimum or an inverse u-shape with a local optimum. If the parameter value is positive we expect a u-shape while we expect an inverse u-shape for negative coefficients. By also including the cubic term we allow a more flexible functional form that can change direction twice. We included sex s and age a as covariates to avoid our results being confounded by their association with urbanicity (Morrison, 2021a).

The model was estimated using the *Quantreg* R package with the default Barrodale and Roberts algorithm for l_1-penalized regression. The penalized regression shrinks estimates towards 0 in order to limit over-fitting and is the default estimation for quantile regression (Koenker, 2024). Inflated Type I errors are a potential concern in quantile regression due to the analysis of multiple quantiles. While LASSO helps mitigate this issue by reducing over-fitting, we also focus on interpreting results that are consistent across several quantiles to enhance the robustness and reliability of our findings.

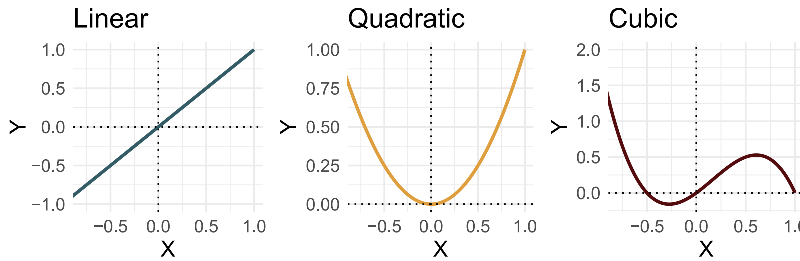

Fig. 3. Three functional relationships. Our statistical model includes linear (d), quadratic (d^2), and cubic terms (d^3), allowing us to model and detect potential non-linear relationships between total satisfaction and adjusted distance to city centers.

The UK Biobank data exhibits a healthy volunteer bias (Fry et al., 2017), with participants being less diverse, older, healthier, and wealthier than the general population. To address this, we followed Alten et al. (2022), who developed participant weights using UK census micro-data. All models were estimated using participant weights.

We visualized our results using a combination of histograms and quantile regression plots. The histograms display the distribution of the total satisfaction scores with quantile lines superimposed to illustrate the density and spread of the data. Quantile regression results are visualized using plots that show the estimated coefficients and their 95% confidence intervals for different quantiles, allowing us to observe the effects of urbanicity across the distribution. Additionally, predicted values for specific quantiles (2.5%, 50%, and 97.5%) are plotted as functions of the adjusted distance to city centers with 95% confidence bands. All visualizations were created using the R packages *ggplot2* and *jtools* (Long, 2022; Wickham, 2016).

Due to London's distinct global profile, we treat it in a separate analysis. We split our sample after we have computed the nearest city center for all participants. Those with London as their nearest center are treated in one analysis, while the remaining UK population is treated in a separate one.

1.4. Robustness analysis

Our analysis involves a series of methodological choices that might influence the results. To examine this, we have conducted several robustness checks. First, we tested the robustness of our results to different city size thresholds. We repeated the analysis, including city centers of cities with populations of at least 50,000, 100,000, 150,000, and 200,000 inhabitants, to assess the consistency of our findings across various urban scales. Second, we evaluated the impact of omitting participant weights. Since the UK Biobank data exhibits a healthy volunteer bias, participant weights were used to correct for this bias. We re-ran the analysis without these weights to investigate the extent to which the weights shape our results. Third, we assessed the robustness of our results to the inclusion of covariates. Specifically, we omitted controls for sex and age in some models to determine the sensitivity of our results to these demographic factors. Lastly, we studied the effect of London on our results by rerunning our analysis while excluding all participants with London assigned as their nearest city.

2. Results

A total satisfaction score was computed for 39,368 participants without missing data. The mean age across the entire sample is 53 and the sex distribution is 22,498 female and 16,870 male. The sample was predominantly white with 37,398 white, 664 Asian or Asian British, 566 Black or Black British, 126 Chinese, 305 mixed, and 309 indicating another ethnic identity. 6242 (15.9%) participants reported they attended religious events weekly. For the main analysis, we included city centers of all cities with more than 200k inhabitants (see Supplementary Figure S3 in the supplementary materials for cases where we include smaller cities).

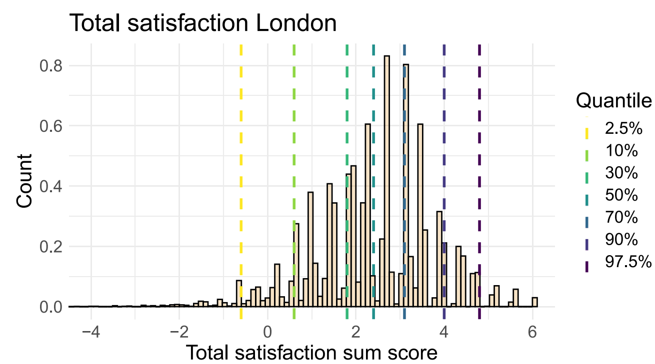

Fig. 4. Histogram of total satisfaction scores for London. Scores of ± 6 indicate the participant was extremely (un)satisfied across happiness, meaning in life, family satisfaction, friendship satisfaction, job satisfaction, and financial satisfaction. The plot is overlaid with 2.5%, 10%, 30%, 50%, 70%, 90%, and 97.5% quantiles.

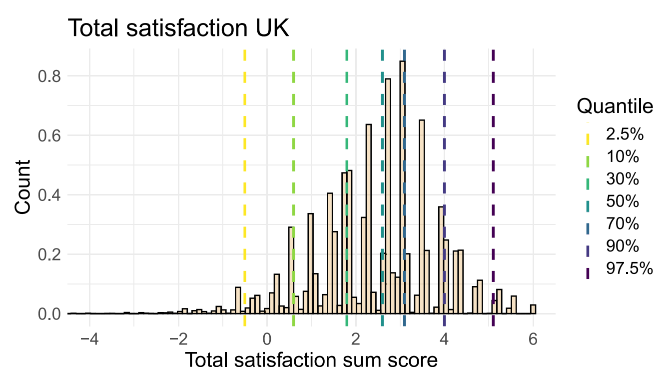

Fig. 5. Histogram of total satisfaction scores for the UK excluding London. Scores of ± 6 indicate the participant was extremely (un)satisfied across happiness, meaning in life, family satisfaction, friendship satisfaction, job satisfaction, and financial satisfaction. The plot is overlaid with 2.5%, 10%, 30%, 50%, 70%, 90%, and 97.5% quantiles.

In Figs. 4 and 5 we report histograms of total satisfaction scores for London and the rest of the UK with 7 quantiles overlaid. Overall, we observe similar distributions characterized by a negative skew and a median around 2.4, suggesting most participants do well in terms of total satisfaction.

2.1. Quantile regression results: the UK without London

For ease of interpretation, we first present the full non-linear association between urbanicity and total satisfaction for three illustrative quantiles. In Fig. 6, the predicted 2.5% (lower bound), 50% (median), and 97.5% (upper bound) quantiles are plotted against adjusted

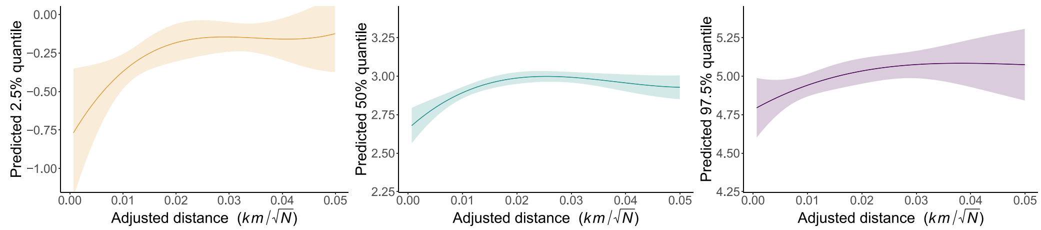

Fig. 6. The UK without London: predicted 2.5%, 50%, and 97.5% total-satisfaction quantiles as a function of adjusted distance.

distance. All three curves reach their minimum near city centers, indicating that the lowest total satisfaction values occur near city centers. The 2.5% quantile shows the largest urban–rural gradient, rising from approximately −0.75 to −0.25. The median curve shows a less strong association with urbanicity but has a peak around 0.025, suggesting an optimal distance in the hinterlands of cities. The 97.5% quantile exhibits a modest but continuous increase with distance.

We can classify the results into three distinct profiles: (1) The lowest quantiles (2.5%–5%) exhibit the strongest positive linear associations and both non-significant quadratic and cubic associations. (2) The middle quantiles (10%–70%) feature significant linear, quadratic, and cubic terms. (3) The highest quantiles (80%–97.5%) display the smallest associations with only a few significant associations. The three urban gradients discussed earlier in Fig. 6 illustrate one representative quantile from each category (2.5%, 50% and 97.5%).

To verify that these patterns are not specific to the chosen quantiles, we now investigate the entire distribution through 13 quantiles ranging from 2.5% to 97.5%. Fig. 7 displays the linear (Distance), quadratic (Distance^2) and cubic (Distance^3) coefficients (with 95% CIs) for the 13 quantiles. Line colors transition from bright yellow (2.5%) reflecting the psychologically worst-off to deep purple (97.5%) representing the best off.

All linear terms are positive, with the steepest slopes in the lowest quantiles (2.5%–5%), indicating the strongest urban-rural differences for the psychologically worst-off. Turning to the quadratic coefficients (Distance^2), we see significant negative quadratic coefficients appear in the middle quantiles (10%–70%); these suggest peaks at intermediate distances consistent with the middle plot of Fig. 6. Cubic effects (Distance^3) are significant for quantiles 10%–70%, introducing subtle asymmetries in these mid-range curves.

We can classify the results into three distinct profiles: (1) The lowest quantiles (2.5%–5%) exhibit the strongest positive linear associations and non-significant quadratic nor cubic associations. (2) The middle quantiles (10%–70%) feature significant linear, quadratic, and cubic terms. (3) The highest quantiles (80%–97.5%) display the smallest associations with only a few significant associations.

The three urban gradients discussed earlier from Fig. 6 illustrate one representative quantile from each category (2.5%, 50%, and 97.5%).

To see how the entire total-satisfaction distribution changes with distance, we plot all 13 quantiles. To better compare them, we subtract the total-satisfaction at city centers for each quantile. Fig. 8 shows the 13 quantiles equalized at city centers. It reveals the largest urban-rural differences in the 2.5% quantile, which is consistent with parameter estimates of Fig. 7. For the 10% to 70% quantiles, we observe substantial differences between city centers and their peak at intermediate distances between highly urban and rural areas. These peaks are consistent with the significant quadratic coefficients for these quantiles. We see the smallest differences for the top quantiles, with the smallest differences for the 95% quantile, as expected from the coefficients.

2.2. Quantile regression results: London

Lastly, we study the 14,363 participants who have London assigned as their nearest city. In this analysis, we examine the quantiles at various distances to Trafalgar Square ranging up to 30 km. The coefficients and 95% confidence bands are shown in Fig. 9. We see significant linear effects of distance on the 2.5% to 60% quantile with stronger associations for lower quantiles. There are neither significant quadratic nor cubic effects. This suggests that the lower half and especially the bottom 10% of the total satisfaction distribution moves in a healthy direction for individuals living further from Trafalgar Square but within 30 km of it.

2.3. Robustness results

The supplementary material shows the results of the robustness analyses. We find that our results are robust to including city centers of cities with more than 50,000, 100,000, and 150,000 inhabitants as well as omitting participant weights. Our results are also robust to omitting sex as covariate.

When we do not control for age, we see substantial changes to our results. In general, the patterns become less systematic but we still see substantial urban-rural differences in most quantiles except for the 70% and 80% quantiles. Some notable differences from the main results are a weaker association between urbanicity and the 2.5% quantile and stronger associations between urbanicity and the top quantiles (90%, 95%, and 97.5%). This latter result is consistent with the higher rural prevalence of elderly and elderly scoring higher on total satisfaction.

3. Discussion

Inspired by urban accumulative inequality, we employed a novel methodology combining a continuous measure of urbanicity with non-linear statistical modeling to test if urban-rural differences in total satisfaction are driven by changes in the tails, an overall shift, or a combination of the two. We find evidence for a combination of the two. The largest differences are observed in the bottom quantiles indicating that psychological problems accumulate in urban areas. We do not find evidence for urban positive accumulation as the top quantiles decline suggesting the psychologically best off do better outside cities. Lastly, we find evidence for an overall shift in the distribution as all quantiles have their minimum in cities suggesting that everyone is expected to do worse in cities. This urban penalty is least pronounced for the best off and most pronounced for the worst off, suggesting increased psychological inequality in cities. Interestingly, this pattern is the direct opposite of how income distributions change with urbanization — the entire distribution increases, but the effect is much stronger in the top quantiles (Mora et al., 2021).

These findings are largely consistent with the existing literature. Studies of mean differences in happiness robustly find urban residents to score worse in Western Europe, North America, Australia, and New Zealand (Brereton et al., 2008; Burger et al., 2020; D'Acci, 2021; Dunlop et al., 2016; Fassio et al., 2013; Finnemann et al., 2024; Gerdtham & Johannesson, 2001; Glaeser et al., 2016; González et al., 2011; Lenzi & Perucca, 2019; Morrison, 2021b; Sørensen, 2021). There are few quantile based results we can compare our findings against. One exception is Morrison (2021b), who studies the tails of well-being distributions by comparing capital and non-capital areas in Slovenia, Czechia, and Austria. They find the largest urban-rural differences in

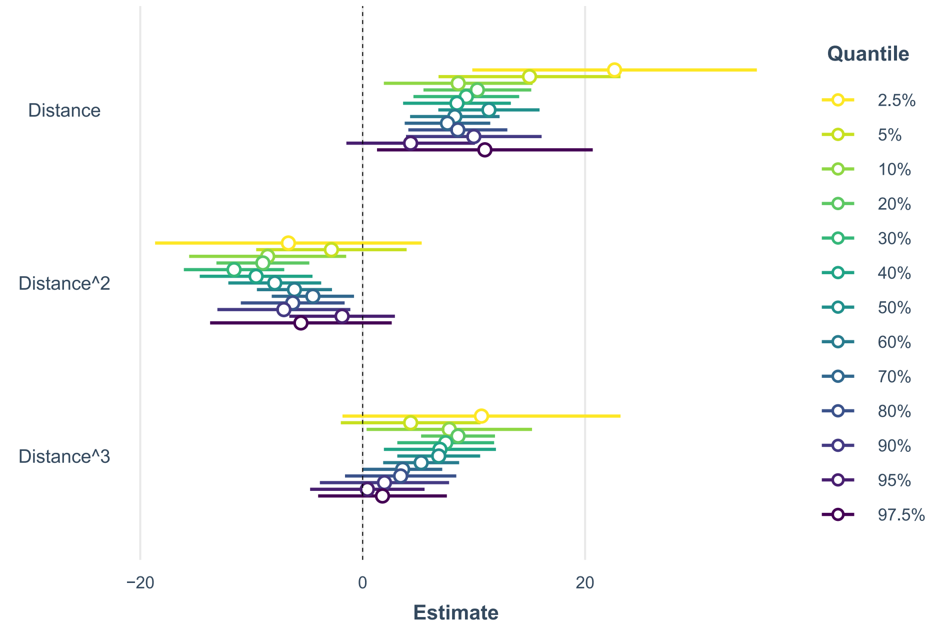

Fig. 7. The UK without London: estimated linear (Distance), quadratic (Distance^2) and cubic (Distance^3) coefficients for 13 total-satisfaction quantiles, with 95% confidence intervals.

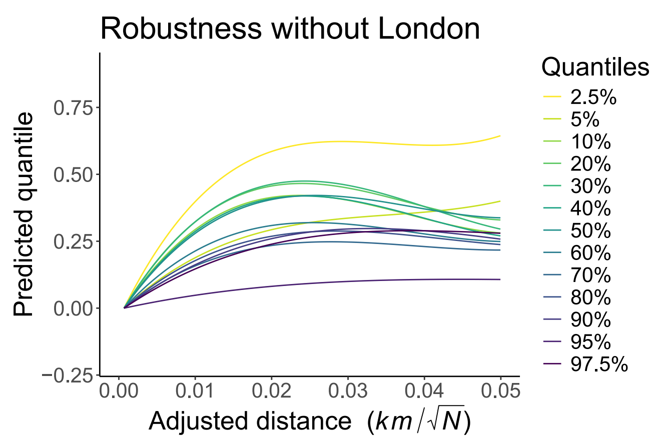

Fig. 8. The UK without London: 13 predicted quantiles as a function of adjusted distance with their minimum value subtracted (value at city centers) for better comparisons.

the unhealthy tail, similar to us, in Slovenia but not Hungary and Czechia.

We can understand the strongest urban penalty for the worst-off by combining a range of perspectives on urban struggles from happiness economics (Burger, 2021; Hoogerbrugge & Burger, 2022), regional science (Morrison, 2024), and sociology (Sassen, 2004; Wilson, 1987). The converging explanation is that minorities and non-tertiary educated individuals accumulate additional disadvantages in cities. Cities are sought for by governments, companies, and high-skilled workers for economic growth. Over the past years this has oriented the labor market in cities towards specialized jobs in research, finance, and technology (Sassen, 2004; Wilson, 1987). This creates a feedback loop where career and economically driven individuals are increasingly locating in cities, further amplifying cities' economic attraction. At the same time, cities are home to community seeking racial, sexual, gender, and ethnic minorities. These communities are typically employed in manual and service jobs which are increasingly inadequate to sustain city life. Theorists argue this leads to a breakdown of the community structures with consequent crime, segregation, and poverty (Sassen, 2004; Wilson, 1987). This explanation is aligned with recent empirical evidence showing that tertiary education, and thus access to specialized jobs, is central for the well-being of city migrants (Burger, 2021; Hoogerbrugge & Burger, 2022).

Consistent with this narrative, UK cities concentrate ethnic, religious, sexual, and gender minority populations. In 2011, 40% of London residents belonged to a non-White ethnic group, the highest share nationwide, while the White share exceeded 95% in many rural districts (Office for National Statistics, 2012). London also recorded the country's lowest proportion of Christians (48%) and the highest share following a religion other than Christianity (25%), whereas Christian affiliation remained the majority response in largely rural regions such as the North East (68%) and North West (67%) (Office for National Statistics, 2013). The same urban concentration applies to sexual minorities: Census 2021 shows London with the largest LGBT+ population (4.3%), compared with under 2% in most rural regions (Office for National Statistics, 2023). Cohort evidence indicates that higher own-group ethnic density can buffer common mental disorders (Das-Munshi et al., 2010), yet the protective effect is offset when minorities encounter discrimination and structural racism—still pervasive in London, according to the 2024 Marmot review (Institute of Health Equity, 2024). These problems are likely exacerbated by limited and mislocated mental-health funds in the UK during the 2000s, where only 10.8% of total NHS programme expenditure was directed to specialist mental-health services—a level the Department of Health labeled "persistently below need" (Department of Health, 2011). Because allocations were tied to historic capitation rather than current morbidity, high-prevalence inner-city areas did not receive proportionately larger budgets resulting in the longest waiting times across the country (Audit Commission, 2010).

Although our results show a disproportionate urban penalty for the worst off, we also see a general, albeit smaller, decline across the entire distribution. We hypothesize this due to the plethora of general urban stressors documented in the literature, such as increasing living and housing costs (Burger, 2021), traffic congestion (Chang et al., 2017), housing instability, extended commuting (Bettencourt, 2013; Chatterjee et al., 2020), crime rates (Baranyi et al., 2021; Lund et al., 2018), lack of green/blue spaces, and noise (Bratman et al., 2019; European Environment Agency, 2020; Gascon et al., 2015; Gidlöf-Gunnarsson & Öhrström, 2007; Houlden et al., 2018; Markevych et al., 2017; Mucci

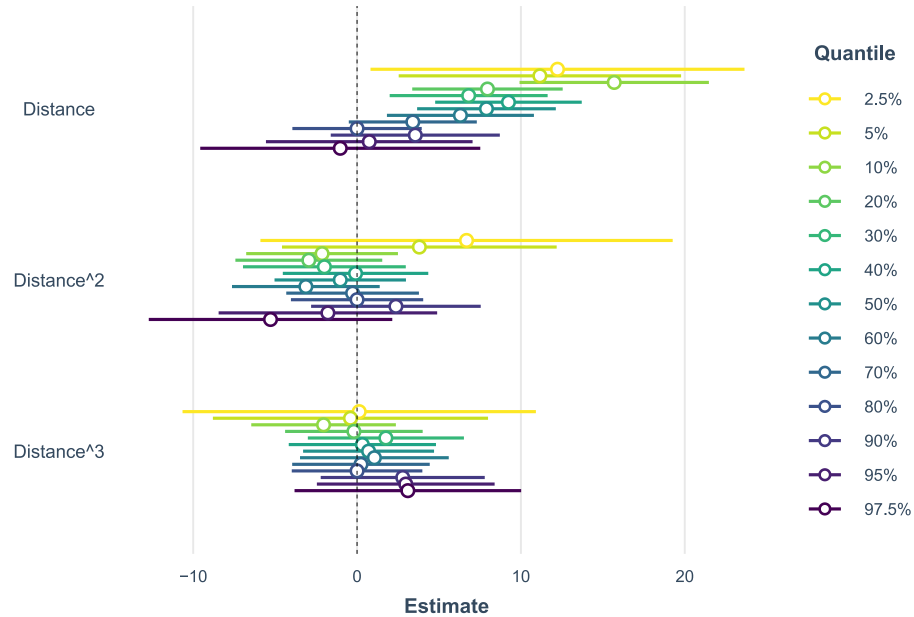

Fig. 9. London: estimated coefficients for 13 quantiles with 95% confidence intervals. Distance show the linear effect of the adjusted distances on the quantiles. "$Distance^2$" and "$Distance^3$" show the quadratic and cubic estimates respectively.

et al., 2020). Specifically, in the UK, economic pressures intensified during the late 2000s: tight Green-Belt planning constraints added an estimated 20%–40% premium to southern house prices (Hilber & Vermeulen, 2016), and CPI inflation peaked at 5.2% in September 2008, eroding real wages (Office for National Statistics, 2015). In London, private rents were already absorbing close to one-half of median earnings by the end of the decade (Office for National Statistics, 2021).

On the surface, our results suggest that individuals might benefit from moving out of cities. This conclusion is complicated by selection effects whereby the observed differences are shaped by systematic migration of psychologically resilient and vulnerable individuals rather than places themselves enhancing or harming well-being. Specifically, the urban-rural differences are likely exacerbated by many happy families migrating to sub- and peri-urban areas, while singles, minorities, and other psychologically vulnerable groups increasingly stay in cities (Burger, 2021; Hoogerbrugge & Burger, 2022). We encourage future research to examine selection versus place effects through longitudinal designs tracking the well-being of migrating families and minorities.

We also observe a pattern that separates the extreme quantiles (2.5%, 5%, 95%, 97.5%) from the central ones (10% to 70%). The central quantiles display non-linear associations with urbanicity with optimal values at intermediate distances between highly urban and rural areas. The optimal distance is approximately $d = \frac{0.025\,\text{km}}{\sqrt{N}}$, which for a city with 200,000 inhabitants, such as Leeds, corresponds to around 11 km from the city center, while for a city of 1 million inhabitants, this distance is around 25 km. For the extreme quantiles, we do not observe optimal intermediate distances; instead, their peaks occur at the maximum distance we investigated.

Our robustness results show that we can include cities down to 50,000 inhabitants, omit participant weights, and omit sex as a covariate without substantial changes to our results. Our results show that it is important for our results that we control for age. When age is omitted as a control variable, we find a much less systematic pattern, although we still observe all quantiles having their minimum score in cities.

An important limitation is the age range of participants from 39 to 70 years old, as determined by the U.K. Biobank cohort. The exclusion of younger generations is an unfortunate limitation given the increasing concern for the well-being of younger adults and new families facing the question of urban versus rural living (Sohn, 2022). The existing literature on urban-rural well-being differences among younger adults indicates that education plays a critical role. Specifically, young adults tend to report higher well-being in rural areas *unless* they move to cities for higher education (Burger, 2021; Hoogerbrugge & Burger, 2022; Morrison, 2024).

Another limitation is the healthy volunteer bias inherent in the U.K. Biobank (Fry et al., 2017). The participants tend to be less diverse, socioeconomically advantaged, and healthier compared to the general populations. We acknowledge this limitation and encourage replication of our study in more diverse samples to validate our findings. Nevertheless, we have taken steps to mitigate this bias by applying participant weights as proposed by previous research, which has been shown to reduce this bias by up to 78% (Alten et al., 2022). This method fits a machine learning model using census data to create weights. In the Supplementary Figure S6 we report results without the participant weights and see little changes. Still, we acknowledge there is a systematic problem of our data being largely based on a easy to access population while we are particularly interested in the hard to access population of individuals with accumulated problems which are unlikely to participate in data collection projects. Therefore, we encourage future projects studying hard to access populations in cities to validate our findings further.

A third limitation concerns the scope of our outcome variable, total satisfaction, which, while comprehensive, lacks validation and does not explicitly account for important dimensions such as mental and physical health. Mental and physical health are critical components of overall well-being, and their exclusion may limit our understanding of the full impact of urban living on individual satisfaction. Future research should consider incorporating these dimensions to provide a more holistic view of well-being in urban contexts.

Additionally, our sample is limited to the UK; therefore, broader generalizations become difficult. Our research aligns with the existing literature on the urban happiness penalty shown in Western Europe, North America, Australia, and New Zealand. However, our more fine grained analysis of quantiles using a continuous measure of urbanicity has, to our knowledge, not been done before. Morrison (2021b) find heterogeneous associations between quantiles and capital versus capital living across Czechia, Slovenia, and Austria. This heterogeneity suggests complex dynamics between urban well-being and national differences. Further replication research across countries and exploration of mediating factors is needed to better understand who cities pose a risk for.

Finally, the measure of urbanicity employed in our study, while effective for our purposes, is based on simplifying assumptions that may not fully capture the complexity of urban environments. Our measure relies on a strong monocentric city model, which is applicable to European and U.K. cities with historical centers, but less appropriate for more sprawled cities such as American ones. We also acknowledge that there is great heterogeneity within cities of wealthy and poor neighborhoods which our method does not detect. However, our aim is to understand geographic differences on the larger scale of urban versus rural areas.

Precisely because of this spatial diversity, urbanicity is better treated as a continuum than as a binary category. Our distance-based measure offers one such gradient; the most widely used alternative is population density. Earlier work with the same cohort shows that the two metrics concur at the extremes—dense city centers and remote rural areas—but diverge in the middle (Finnemann et al., 2024). Future studies that combine both metrics may reveal which environmental factors drive these contrasting mid-range patterns.

Despite its simplifying assumptions, a key strength of our distance-based measure is that it treats urbanicity as a gradient rather than as dichotomous. The most widely used gradient-based alternative is population density. Earlier work with the same cohort shows that the two metrics concur at the extremes—dense city centers and remote rural areas—but diverge in the middle (Finnemann et al., 2024). Integrating both metrics in future research may clarify which factors drive these different patterns.

A potential issue with quantile regression is its sensitivity to the choice of quantiles. To address this, we analyzed a broad range of 13 quantiles, spanning from 2.5% to 97.5%. Our confidence in the findings is strengthened by the consistency of the results across these quantiles. Future research could further validate our results by employing distributional methods, such as modeling empirical distributions with truncated skewed normal distributions. However, this approach is challenging due to its sensitivity to violations of underlying assumptions.

This study's strengths are that we study a large sample of 39,368 individuals using a continuous and objective measure of urbanicity that allows us to detect trends in both city centers, around cities, and far from cities. Another strength is that our results are highly robust to including cities down to 50,000 inhabitants, omitting the control for sex, and omitting the participant weights.

In summary, our findings contribute to the established body of literature documenting the psychological disadvantages associated with urban living. Our study extends this by demonstrating that the most disadvantaged individuals bear a disproportionately greater burden of psychological distress in cities. This aligns with the idea that cities exacerbate the accumulation of psychological problems, leading to increased psychological inequality. This subgroup of highly disadvantaged individuals represents a critical risk group for future research and targeted mental health interventions. Although these effects are most pronounced in the disadvantaged, a smaller but notable urban penalty appears to affect the broader population. This highlights cities as critical environments for investigating the causes and impacts of psychological stressors, and for designing targeted interventions to alleviate the psychological challenges.

CRediT authorship contribution statement

Adam Finnemann: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **René Freichel:** Writing – review & editing. **Han van der Maas:** Writing – review & editing, Supervision, Funding acquisition. **Denny Borsboom:** Writing – review & editing, Supervision, Funding acquisition. **Reinout Wiers:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT-4 in order to assist with text refinement and improving readability. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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Declaration of competing interest

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

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The UK Biobank is accessed under the project ID 102526.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.cities.2025.106630.

Data availability

All code and city data are publicly available at https://osf.io/hpj4d/.

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