Urban Land Use Fragmentation and Human Wellbeing

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Abstract

We study how land use fragmentation affects the life satisfaction of city dwellers. To this end, we calculate fragmentation metrics based on exact geographical coordinates of land use from the European Urban Atlas and of households from the German Socio-Economic Panel. Using OLS and fixed effects specifications, we find little impact on life satisfaction when aggregating over land use types. Looking at particular types, however, we find that it is positively affected by lower average degrees of soil sealing, larger shares of vegetation, and more heterogeneous configurations of medium and low-density urban fabric, especially in areas with higher population density.

Key Words: *Urban Land Use, Urban Land Use Fragmentation, Subjective Wellbeing, Life Satisfaction, Spatial Analysis, SOEP, GIS*

JEL Codes: *C23, Q51, Q57, R20*

1. Introduction

As the speed and scale of urbanisation is expected to increase in the coming years, it is of crucial importance to investigate the effect of urban environments on the quality of life of city dwellers. In 2018, more than half of the world's population (55%) resided in urban areas, and this share is expected to rise to 68% by the middle of the century (UN 2019a). Cities are attractive as they generate positive agglomeration effects such as an effective division of labour, yielding productivity benefits and generating employment opportunities and higher incomes, and they are places where new ideas and technological innovations can thrive. Cities, however, also generate negative external effects such as congestion, noise, and air pollution. By one estimate, in 2016, 90% of city dwellers were breathing unsafe air, resulting in 4.2 million deaths due to air pollution (UN 2019b). Increasing urbanisation and a lack of affordable housing also put pressure on public open spaces such as green spaces, which provide space for social interaction and important ecosystem services (EC 2013). Many of these negative external effects are not traded on markets and some of the positive effects are public goods for which no markets exist. The net effect of urbanisation on the life satisfaction of city dwellers is thus unclear.

Studies investigating agglomeration effects and urban amenities and disamenities have used various approaches for valuation such as stated and revealed preference methods including hedonic pricing.[1] In recent years, the experienced-preference approach, also termed subjective wellbeing approach, has emerged as a widely applied approach for preference elicitation and non-market valuation (Welsch and Ferreira 2014, OECD 2018).[2,3] However, rather few studies explicitly address urban environments or data sets customized to urban environments. One notable exception is MacKerron and Mourato (2009), who look at air quality in London using highly spatially disaggregated data.

In this study, we analyse how urban land use fragmentation affects the life satisfaction of about 15,000 city dwellers in Germany using data from the German Socio-Economic Panel

Study (SOEP) and the European Urban Atlas (EUA 2006). While previous studies have only looked at the relationship between landscape composition (that is, shares of certain land use types, diversity, or evenness indices) and life satisfaction, we explicitly address spatial configuration and fragmentation. In particular, we analyse how landscape composition and configuration, represented by prominent landscape metrics calculated both aggregated across all land use types and individually for selected land use types, affect self-reported life satisfaction.

We find that the level of fragmentation in the residential neighbourhood has surprisingly little impact on their life satisfaction. This holds, in particular, when looking at land use fragmentation at an aggregate level, across all types of land use. When looking at specific land use types, however, a slightly different picture emerges: life satisfaction of residents is higher in areas with lower average soil sealing and larger shares of vegetation, which holds especially in areas that are densely populated. Moreover, life satisfaction of residents tends to be higher in densely populated areas where medium and low-density urban fabric are arranged in a more heterogeneous and fragmented manner.

This paints a diverse picture about the wellbeing impacts of urban growth strategies. Since urban expansion is often closely related to economic growth, the specific expansion patterns merit attention for spatial planning and policy-making. Generally, a consensus has been reached that the development of compact *and* green cities needs to be promoted since urban sprawl, i.e., scattered and unplanned expansion, typically has detrimental economic, social, and ecological impacts (Artmann et al. 2019). The need for the integration of green infrastructure in growing cities is evidenced by findings that further densification leading to higher degrees of soil sealing seems to be detrimental to subjective wellbeing. Especially in already highly densified areas, architectural elements that reduce feelings of density and break up soil sealing, such as small parks and gardens, green spaces, street tree cover, or vertical gardens (Magliocco

2018, Manso and Castro-Gomez 2015), have the potential to alleviate some of the adverse wellbeing impacts of densification.

The remainder of this paper is structured as follows. Section 2 presents an overview of the related literature and this paper's specific contributions. Section 3 provides a description of our data including our landscape fragmentation metrics and their interpretations. Section 4 presents the empirical strategy, and Section 5 our findings. Section 6 concludes and discusses our findings in light of their relevance for recent discussions on urban growth strategies as well as landscape and urban planning and design.

2. Literature Review and Contribution

Few studies have looked at the effects of different types of urban land use on life satisfaction. In an urban context, green space is the most often studied land use type. In general, the observation is that more green space is positively related to life satisfaction, with the majority of city dwellers being undersupplied (Yuan et al. 2018, White et al. 2013, Ambrey and Fleming 2014b, Smyth et al. 2008). Bertram and Rehdanz (2015) and Krekel et al. (2016) both observe a significant, inverted U-shaped effect of the amount of green space on the life satisfaction of people's residential neighbourhood. Some of these studies also look at the effects of other urban land use types: for example, Krekel et al. (2016) consider forests, water bodies, and vacant areas in addition, finding that vacancy has a significantly negative effect on life satisfaction.

The studies on the effect of urban land use mentioned so far, however, only look at the effect of the amount of a certain land use type or the distance to a certain land use type on life satisfaction. Yet, it may also matter for life satisfaction how different land use types are arranged and structured in a certain neighbourhood or city. Some of this is evidenced in the field of landscape ecology, where some studies investigate how landscape structure influences sub-aspects of life satisfaction and visual landscape preferences: for example, Lee et al. (2008)

investigate the relationship between neighbourhood satisfaction and landscape structure represented by different landscape metrics. They show positively significant relationships using pairwise correlations. Likewise, Dramstad et al. (2006) investigate the relationship between visual landscape preferences and landscape structure, also represented by different landscape metrics. They present mixed findings looking at pairwise correlations. Related to this, Palmer (2004) studies the relationship between scenic value and different landscape metrics, finding stronger correlations between shares of certain landscape types and scenic value than between landscape structure and scenic value.

Besides landscape ecology, a stream of literature in psychology going back as early as 1947 (Diamond et al. 1964, Hebb 1947) looks at how our environment affects our brain structure and function, suggesting that more ‘enriched’ environments which are more complex and provide more stimulation facilitate brain plasticity (see Kühn et al. 2017 for a recent paper on urban land use). However, while richness in urban land use may facilitate brain development, several studies in the epidemiological literature suggest that living in denser urban environments is associated with lower mental health and higher incidence of mental health conditions such as schizophrenia (Tost et al. 2015, van Os et al. 2003, 2010).

From these studies, it is therefore not *ex-ante* clear whether a more heterogeneous and fragmented landscape in urban areas brings with it positive or negative wellbeing impacts. It is thus worthwhile to take a closer look at the potential effect of landscape structure or landscape fragmentation on life satisfaction. Particularly in growing cities, it is a debated question how new residential housing and other buildings should be integrated into the existing city structure and whether densification should be preferred over growth along the urban fringes – two very different urban growth strategies (OECD 2014). A similar question applies to urban growth at the regional level, and in particular, whether a more polycentric as opposed to monocentric or centralised as opposed to dispersed urban growth strategy yields stronger wellbeing benefits.

Using repeated cross-section data from the European Social Survey (ESS), Hoogerbrugge et al. (2021) suggest that polycentricism is positively and dispersion negatively associated with life satisfaction, but also that there is an interaction between polycentricism and dispersion (i.e. in more dispersed regions, residents experience more positive effects of polycentric structures than in more centralised regions). To our knowledge, however, there are only two studies that have investigated the link between landscape structure and life satisfaction within cities, at least to some extent.

Brown et al. (2016) use data from the 2001 wave of the OECD Household Survey on Environmental Policy and Individual Change for 33 cities with more than 500,000 inhabitants distributed across five OECD countries and combine it with Corine Land Cover data. Their measure of urban structure – the Shannon's Diversity Index (SDI) – is calculated over all land cover types for a five kilometres radius around a household's post code centroid. They find a strongly negative effect of land cover diversity on residents' life satisfaction for the pooled data. The land cover effects are, however, heterogenous among countries and insignificant for single countries, potentially due to the small sample sizes per country. More recently, Olsen et al. (2019) combine individual responses to the European Urban Audit Perception Surveys (2012 and 2015) with city-level data from the European Urban Atlas for 66 cities in 28 countries. Using multilevel binary logit models, they find evidence that the amount of some land use types is associated with higher life satisfaction (arable land, pastures, and isolated structures) and some with lower (continuous urban fabric, industrial, commercial, public, and military areas). Land use evenness – measured by Shannon's Evenness Index (SEI) – and land use diversity (SDI) have no significant effect on life satisfaction.

We contribute to this literature in several ways: first, we extend the analysis by systematically investigating a wide range of land use fragmentation metrics. So far, either individual land use classes (e.g., the share of green space) or composite metrics (i.e., SEI and

SDI at the landscape level, aggregating over all land use types) have been used. However, indices such as SEI or SDI only represent the relative abundances of different land use types in a landscape and their evenness or diversity but *not* the spatial configuration and fragmentation of a landscape itself (McGarigal 2012).[4] In fact, two landscapes with the same levels of SDI and SEI can have quite different levels of fragmentation (see Section 3.3 for a discussion and an illustration). To our knowledge, we are the first to consider additional landscape metrics which capture not only the composition but also the spatial configuration and fragmentation of landscapes and their effects on the life satisfaction of city dwellers.

Second, we calculate landscape metrics both at the landscape level (i.e., aggregating over all land use types) and at the land use type level. Our selection of fragmentation metrics is borrowed from landscape ecology where metrics have been developed to quantify the structure of a landscape and to study, amongst others, the relationship between landscape structure and the ecological functioning of a landscape (Turner 1989). The same metrics have also been used, e.g., by Lee et al. (2008) and Palmer (2004), to study the relationship between landscape structure and neighbourhood satisfaction and scenic value, respectively.[5]

Third, our study differs from earlier studies by exploiting nationally representative, highly detailed spatial panel data from the SOEP (years 2000 to 2014) that include the exact geographical coordinates of households, merged with highly detailed spatial cross-section data on urban land use from the EUA (year 2006), customized to represent land use fragmentation in compact urban areas around households and reflecting land use in the year 2006. This mirrors more accurately the life realities of people in their neighbourhoods than comparable studies. Brown et al. (2016) use post code data to locate respondents in cities and Corine Land Cover data for calculating landscape fragmentation metrics, which is much coarser than our approach and less suitable for analysing compact urban areas. Olsen et al. (2019) use EUA data but aggregated at the city level. Finally, both studies rely on household cross-section data, whereas the SOEP provides us with household panel data, allowing us to control for time-invariant unobservable characteristics of respondents and of cities throughout our analyses. Importantly, as our land use data are time-invariant and limited to the year 2006, our variables of interest are estimated by respondents who move at least once during the observation period (that is, during the years 2000 to 2014), who are the only group for whom our variables on land use change over time. Looking at such within-individual variation is a deliberate design choice. We discuss issues pertaining to endogenous sorting at greater length in our empirical strategy but note here that about 80% of movers report to move primarily for reasons unrelated to their surroundings (such as job or family reasons). Moreover, regressing the likelihood of moving on our variables of interest, or excluding movers altogether and instead estimating our variables interest by stayers leaves our findings qualitatively unchanged. This suggests that endogenous sorting seems to be a quantitatively rather minor issue, at least when it comes to land use fragmentation. Our estimation sample includes 14,744 individuals living in the 35 major German cities with more than 100,000 inhabitants. Of these 14,744, there are between 3,856 and 2,119 movers (depending on specification) during our 15-years observation period.

3. Data

3.1. Life Satisfaction

We use data on life satisfaction from the SOEP for the period 2000 to 2014. The SOEP is a nationally representative household panel in Germany that has been conducted annually since 1984 and that includes, in its latest wave, longitudinal data on more than 11,000 individuals living in about 30,000 households. Most importantly, the SOEP records – annually since 2000 – the geographical coordinates of households at the street-block level.[6] This allows us to merge data on life satisfaction with data on urban land use based on precise geographical coordinates and to calculate landscape fragmentation metrics for different types of urban land use in a prespecified treatment radius around households.[7] To test for the sensitivity of our results, we calculate landscape fragmentation metrics for two treatment radii: 1,000 (to proxy for local neighbourhood) and 500 metres (to proxy for the more immediate neighbourhood). Following Olsen et al. (2019), we restrict our sample to households living within the administrative boundaries of the cities. In contrast, Brown et al. (2016) consider people living in so-called Functional Urban Areas which includes parts of the hinterlands if they have a functional relationship to the city, e.g. via commuting. The reason for choosing this delineation is that we are particularly interested in what influences life satisfaction in urban areas in which the effects of complexity and density do play a role but the direction of the effect is not clear (Kuehn et al. 2017, Tost et al., 2015, van Os et al. 2010).

Our outcome variable is *life satisfaction*, which is obtained from a single-item eleven-point Likert scale question asking respondents: "How satisfied are you with your life, all things considered?". Answer possibilities range from zero ("completely dissatisfied") to ten ("completely satisfied"). In addition, we obtain data on demographic and human capital characteristics as well as economic conditions at the individual level, household characteristics and housing conditions at the household level, and neighbourhood characteristics at the city level.[8] We routinely include these observables in our regressions to account for differences in time-varying observables between individuals and cities and to control for selection on observables within and between cities.[9]

3.2. Urban Land Use

Our data on urban land use originates from the European Environment Agency's EUA and captures land use in the year 2006. The EUA is a cross-section dataset that records different types of urban land use based on satellite imagery capturing areas greater than a minimum mapping unit of 0.25 hectares for European cities and metropolitan areas with a population of at least 100,000 inhabitants (EEA 2011). Our analysis is restricted to the 35 major German cities and metropolitan areas available in the EUA.[10] A major advantage of the dataset is that it records information based on land use, which is much more precise than information based on land cover. In particular, the sampling process includes a validation stage examining if the classification by satellite imagery is in fact consistent with actual usage (EEA 2011).[11]

The EUA provides one shapefile per city or metropolitan area recording up to 20 types of urban land use, which are categorised into (i) artificial surfaces, (ii) agricultural and semi-natural areas as well as wetlands, (iii) forests, and (iv) water bodies. Artificial surfaces are further disaggregated into (v) urban fabric; (vi) industrial, commercial, public, military, private, and transport units; (vii) mine, dump, and construction sites; and (viii) artificial non-agricultural vegetated areas. Each sub-category then includes the corresponding types of urban land use. For example, urban fabric includes five types of fabric that differ in their average degree of soil sealing, ranging from continuous to discontinuous very-low-density fabric.[12]

Urban fabric is by far the most dominant category of land use in urban settings (about 30% of the landscape covered), and its structure and composition is thus expected to matter for life satisfaction. The category is also interesting in view of recent discussions about urban growth strategies that promote further densification as opposed to growth along the urban fringes. The category urban fabric consists of five types: (i) *continuous urban fabric* (average degree of soil sealing greater than 80%), (ii) *discontinuous dense urban fabric* (sealing between 50% and 80%), (iii) *discontinuous medium-density urban fabric* (sealing between 30% and 50%), (iv) *discontinuous low-density urban fabric* (sealing between 10% and 30%), and (v) *discontinuous very-low-density urban fabric* (sealing less than 10%). Figure 1 illustrates the distribution of the different types of urban fabric exemplarily for the capital city Berlin, the largest and most populated city in Germany.[13]

[Figure 1 about here]

The main criterion for a patch of land to be categorised as urban fabric is (at least partial) residential use.[14] The category covers built-up areas (i.e., residential structures and patterns such as buildings and entry ways) and associated land (i.e., other sealed surfaces such as roads and parking lots). It is important to note that the different types of urban fabric are distinguished only by their average degree of soil sealing and not by their type of building (e.g., single house, apartment building, or high rise), which we routinely control for throughout our regressions. That said, under continuous urban fabric (average degree of soil sealing greater than 80%), buildings, roads, and other sealed surfaces cover most of the area, whereas non-sealed or vegetated surfaces (i.e., gardens, planted areas, and non-planted public areas) are an exception. On the contrary, under discontinuous very-low-density urban fabric (average degree of soil sealing less than 10%), non-sealed or vegetated surfaces are predominant, and sealed surfaces an exception. The other types lie in between these two extremes.

3.3. Landscape Fragmentation Metrics

The landscape fragmentation metrics used in this study capture either the composition of a landscape or the spatial configuration.[15] Those that capture the composition of a landscape refer to "features associated with the variety and abundance of patch types within the landscape, but without considering the spatial character, placement, or location of patches" (McGarigal 2012). Composition metrics include, for example, (i) the total area of a landscape, (ii) the proportion of the area covered by each patch type relative to the total landscape area as well as (iii) the number and (iv) relative abundance of different patch types. Metrics that consider the spatial configuration capture "the spatial character and arrangement, position, or orientation of patches within the […] landscape" (McGarigal 2012). These metrics are influenced by, for example, the size and shape of single patches.[16]

For the purpose of this study, we selected six landscape fragmentation metrics that reflect both landscape composition and spatial configuration. All selected metrics are commonly used in landscape research and have been shown to correlate with ecological aspects such as biodiversity and landscape aesthetics (Uuemaa et al. 2009). Since we do not have a prior as to which type of urban land use matters more for life satisfaction when it comes to land use fragmentation, we first calculate our landscape metrics jointly across all 20 types of land use available in the EUA (so-called overall fragmentation). We then calculate our metrics individually for each type of urban fabric (so-called fabric fragmentation). For both overall and fabric fragmentation, we employ treatment radii of 1,000 (local neighbourhood) and 500 metres (more immediate neighbourhood). There are three exceptions: first, Shannon's Evenness Index (SEI) is calculated only at the aggregate level, i.e., only across all land use types and not for single land use types, as it includes information on the proportional abundance of all types of urban land use and can therefore not reasonably be applied to the patch level. Second, Percentage of Landscape (POL) is calculated only at the patch level as it would be constant if calculated across all land use types (the total area is given by the respective treatment radius). Finally, Mean Patch Size (MPS) is calculated only at the patch level as it is the reciprocal of patch density at the overall level and would therefore add no additional information at this level of analysis. We rescaled this measure by dividing it by 1,000 in order to obtain more meaningful coefficient sizes. Table 1 describes our landscape fragmentation metrics and shows how they are calculated.

[Table 1 about here]

The proportional abundance of each patch type of urban land use within the respective treatment radius (POL) gives a good indication of the composition of the landscape around households. Patch Density (PDe) quantifies the number of patches of a certain patch type at the patch level or the number of patches across all patch types at the aggregate level. The interpretive value of PDe is limited as it conveys no information on the shape of patches. However, it provides information on the heterogeneity of a landscape. Increasing patch density at the aggregate level means that a landscape's grain is becoming finer, indicating greater heterogeneity and fragmentation (Palmer 2004). Edge Density (EDe) measures the length of edge between one patch type and the other patch types relative to the total area within the respective treatment radius at the patch level or the length of total edge relative to the total area at the aggregate level. EDe takes the shape and complexity of patches into account and provides information on visual landscape complexity (Palmer 2004).

The Largest Patch Index (LPI) calculates the percentage of the area within the respective treatment radius that is covered by the largest patch of a certain patch type at the patch level or the largest patch across all patch types at the aggregate level. It is thus a simple measure of how much a landscape is dominated by a certain patch type. MPS is another measure of landscape fragmentation: the larger the MPS within the respective treatment radius, the less fragmented is the landscape considered to be. MPS is derived from the number of patches but does not convey any information about how many patches are present. For these reasons, MPS needs to be interpreted in conjunction with POL and PDe.

Finally, SEI is a measure of how evenly different patch types are represented within a landscape: increasing values of SEI indicate increasing evenness in the distribution of patch areas and thus decreasing dominance of a single patch type within the landscape. The value of SEI is confined to the domain between zero and one, where one indicates totally evenly distributed relative abundances and values close to zero indicate dominance of one patch type.[17] Figure 2 provides a stylised illustration of two different landscapes.

[Figure 2 about here]

Comparing the two stylised landscapes, the metrics referring to the composition of the landscapes are notably equal for both landscapes. POL is the same for each patch type of landscape A and B as all patch types are equally abundant in both landscapes. Consequently, also SEI assumes the same value for both landscapes, which is one due to the equal relative abundance of each patch type in both landscapes. However, the spatial configuration of the patches and patch types varies considerably between both landscapes, which is reflected in the varying values of the configuration metrics PDe, EDe, LPI, and MPS in Table 2, which shows the values of these landscape fragmentation metrics calculated exemplarily for the two landscapes.

[Table 2 about here]

In particular, PDe and EDe are larger for landscape B than for landscape A, reflecting increased spatial heterogeneity and complexity. The values for LPI and MPS, in contrast, are lower for landscape B than A. This reflects less dominance by one patch (type) and stronger fragmentation of landscape B compared to landscape A.

4. Empirical Strategy

4.1. Model

We estimate a linear regression model, separately for each landscape fragmentation metric since some metrics are strongly correlated with each other. Equation 1 shows our baseline model:

$$y_{it} = \beta_0 + X_{it}'\beta_1 + \delta metric_{it,kr} + \eta_{ct} + \gamma_t + \mu_i + \varepsilon_{it} \qquad (1)$$

where y_{it} is life satisfaction of individual i in year t; X_{it} is a vector of controls at the individual, household, and city level to account for differences in time-varying observables across individuals and cities and to control for selection on observables within and between cities; η_{ct}, γ_t, and μ_i are city, year, and individual fixed effects to account for time-invariant unobservables at the city, year, and individual level; and ε_{it} is the idiosyncratic disturbance. Our regressor of interest is $metric_{it,kr}$: it is the respective land use fragmentation metric defined for patch type k within treatment radius r, which is either 1,000 or 500 metres around a household and which varies over time t for individual i if individual i moves (recall that our land use data are time-invariant).[18] In other words, our regressor of interest $metric_{it,kr}$ is estimated by individuals who move at least once during the observation period (that is, during the years 2000 to 2014). This is also the reason why our city fixed effect η_{ct} has a time subscript: from the perspective of an individual who moves, city characteristics do change. $metric_{it,kr}$ is calculated either jointly across all 20 types of urban land use (in case of overall fragmentation) or individually for each type of urban fabric (in case of fabric fragmentation).

Our baseline specification is estimated using OLS after applying a standard within-transformation to eliminate individual fixed effects (the FE within-estimator). We are thus looking at variation within cities *and* individuals. In addition to that, we always estimate comparison models without individual fixed effects (but including city fixed effects) to elicit the relative importance of unobservable individual characteristics. Robust standard errors are routinely clustered at the household level.

Note that we take the mean number of residents per square kilometre, as defined by the Federal Statistical Office's 2011 Microcensus, into account, in order to elicit the relative importance of population density. In an urban context, the effect of urban structure on subjective wellbeing varies strongly depending on whether one lives in densely populated inner-city areas or in less densely populated areas at the urban fringes. We thus routinely control for population density when estimating our models and conduct heterogeneity analyses by splitting our estimation sample using the mean number of residents per square kilometre.[19]

4.2. Possible Limitations

The main limitation of our empirical strategy is that our data on urban land use are time-invariant. We thus implicitly assume that urban land use and fragmentation around households remains constant over time. Although it is quite likely that it does not change substantially, this assumption nevertheless yields three issues – measurement error, endogeneity, and estimation issues – each of which we address below.

4.2.1. Measurement Error

Classical measurement error (resulting in attenuation bias) may occur if land use data are noisily recorded or land use and fragmentation changes over time but this change is uncorrelated with life satisfaction. Both is unobservable to us and may bias our estimates downwards, potentially making them lower bounds to the true estimates.

While there is little we can about the data quality of the EUA (recall, however, that the EUA is subject to various manual checks and considered to be high quality), we look into the second issue – changes in land use and fragmentation over time – in two ways: first, we use a "change layer" between land use in 2006 and land use in 2012 which has recently been published by the EUA to calculate changes in land use over time.[20] We find that these changes are quantitatively rather small, ranging between 0% and 2%, on average.[21] Second, we restrict our model to the year 2006 only, that is, the year in which our land use data are recorded. The results from this restricted model are similar to those from our baseline specification which uses the entire observation period, that is, the years 2000 to 2014.[22] Both exercises suggest that attenuation bias from classical measurement error seems to be a quantitatively rather minor issue. Note that the results also remain similar when restricting our model to symmetric time bins around the year in which our land use data are recorded (i.e., 2005 to 2007, 2004 to 2008, and 2003 to 2009).[23]

4.2.2. Endogeneity

Another limitation of having time-invariant land use data is that, when including individual fixed effects μ_i, the regressor of interest δ is estimated only by individuals who move. Otherwise, there would be no variation in $metric_{it,kr}$ over time, and it would drop out due to multicollinearity.

A common concern in spatial applications is *endogenous sorting*. In our case, this may occur if individuals who are more satisfied with their lives are more likely to select into urban areas with particular types of land use, which, in turn, may make them even more satisfied (or *vice versa*), yielding a correlation between y_{it} and ε_{it}. We find that almost 80% of movers report to move primarily for reasons *un*related to their surroundings (for example, for job or family reasons), suggesting that endogenous sorting may be less of an issue in our case.[24]

Still, moving could be seen as a two-stage process: once individuals move (primarily for reasons unrelated to urban land use in their surroundings), they may – once their move is being realised (say, from one city to another) – also optimise with respect to urban land use in their surroundings. The SOEP has no item that asks respondents about such specific locational decisions. We thus test the sensitivity of our findings to moving behaviour in three ways: first, we regress the likelihood of moving on our land use fragmentation metrics. We do not find that land use fragmentation significantly and systematically predicts moving.[25] Second, we exclude movers altogether, estimating our regressor of interest δ by stayers only (which implies that $metric_{it,kr}$ becomes $metric_{i,kr}$). The results remain qualitatively the same as in our baseline specification. They also remain the same when excluding stayers altogether.[26] Third, we always estimate two sets of models, one with individual fixed effects and one without: in the former, our regressor of interest δ is identified by movers only; in the latter, it is identified by all individuals (both movers and stayers). We find little evidence for systematic differences between both sets of models. Taken together, we cautiously interpret this as suggestive evidence that endogenous sorting may be a quantitatively rather minor issue. Finally, note that movers and stayers are unbalanced in terms of numbers. To further look into this unbalancedness, we match movers and stayers based on all observables at our disposal (one-to-one nearest neighbour matching without replacement) and then include only movers and their statistical clones from the pool of stayers in our estimation. The results from this balanced model largely corroborates the findings from our baseline specification.[27]

Another common concern in spatial applications is *endogenous construction*: happier or unhappier people may "create" changes in land use and fragmentation themselves, which, in turn, may influence their happiness. While we cannot empirically exclude endogenous construction, we have seen that changes in land use between 2006 and 2012 are rather small. Correlating these changes with changes in life satisfaction over the same time period, we find raw correlation coefficients of only -0.026 for our 1000m and -0.015 for our 500m treatment radius, both of which are insignificant and small.

Unfortunately, to the best of our knowledge, there exists no instrument for urban land use fragmentation that satisfies the exclusion restriction (i.e., influencing land use fragmentation without directly affecting life satisfaction). δ should thus be interpreted as an association between the respective urban land use fragmentation metric $metric_{it,kr}$ and life satisfaction y_{it}. Note that we routinely control for a rich set of time-varying observables at the individual, household, and city level as well as time-invariant unobserved heterogeneity at the city and individual level and year fixed effects to minimise endogeneity from reverse causality to the extent possible.

4.2.3. Estimation Issues

Our baseline specification includes individual fixed effects and is estimated using OLS after a standard within-transformation (the FE within-estimator). It should be noted that random effects estimation is, if its assumptions are valid, more efficient than fixed effects estimation. Potentially insignificant estimates may thus be due to inflated standard errors from choosing a less efficient model.

We test whether fixed effects or random effects estimation is more appropriate in our case using a standard Hausman specification test. It yields a χ^2 test statistic of 164.84, leading us to reject the null that differences in estimates between fixed effects (our baseline specification) and random effects estimation are not systematic, suggesting that fixed effects estimation is more appropriate. For completeness, we re-estimate our baseline specification using random effects estimation and the Mundlak "within-between" model (Mundlak, 1978). The results from these alternative estimations largely corroborate the findings from our baseline specification.[28] A final estimation issue comes from the fact that we apply a linear model to a discrete, ordinal dependent variable. This measurement error, however, has been found to be minor in practice (see Ferrer-i-Carbonell and Frijters (2004) for panel as well as Brereton et al. (2008) and Ferreira and Moro (2010) for repeated cross-section data applications).

5. Findings

We now turn to our estimation results. Table 3 presents our findings on overall fragmentation, i.e., calculating our landscape fragmentation metrics across all 20 types of urban land use, for a treatment radius of 1,000 metres around households. We present findings separately for pooled OLS and individual FE models (both include city and year fixed effects), respectively, for all urban areas on average and for urban areas above and below the mean population density.[29]

[Table 3 about here]

We do not find statistically significant effects of either landscape composition or spatial configuration within a treatment radius of 1,000 metres around households on household members' life satisfaction.[30] This finding is different from that in Brown et al. (2016), who do find a statistically significant, *negative* effect of landscape composition (SDI).[31] The authors' study design, however, differs from ours in at least three ways: first, major differences pertain to data and methods. The authors use cross-section data which do not allow them to control for time-invariant unobserved heterogeneity at the individual level by including individual fixed effects. Instead of relying on variation within individuals and, in doing so, taking out some of the selection effects, their variation relies on comparing (potentially quite different) individuals between each other. Moreover, they use data on land *cover* as opposed to *use*, which is prone to measurement error. Finally, they focus on urban areas with more than 500,000 inhabitants, while we focus on urban areas with inhabitants equal to or greater than 100,000.[32]

Second, their study encompasses several countries with potentially quite different patterns of urban land use and hence potentially more variation in respective landscape composition and spatial fragmentation metrics. Interestingly, at the country level, their land cover effect is insignificant as well. This could potentially be due to the small sample sizes per country and would require a more detailed analysis in the future. Third, major differences pertain to the level of spatial aggregation: Brown et al. (2016) use treatment radii of two to ten kilometres around a post code centroid, while we look at treatment radii of 1,000 or 500 metres around households, which is much more precise in terms of geographical location. At this high level of spatial aggregation, we do not find a negative effect of SEI on life satisfaction.

Our findings are more in line with Olsen et al. (2019), who do not find an effect of landscape composition (diversity and evenness) on life satisfaction at the aggregate level either. Regarding landscape composition, they find evidence that the amount of some land use types (arable land, pastures, and isolated structures) is associated with higher life satisfaction and others (continuous urban fabric, industrial, commercial, public and military areas, roads, green urban areas, and herbaceous vegetation) with lower. In contrast, we do not observe a negative relationship between the share of continuous urban fabric and life satisfaction. Even though Olsen et al. (2019) use observations within city boundaries as we do for our analysis, their study is not directly comparable to ours either: again, they rely on cross-section data and calculate landscape metrics at the city level. Moreover, they use data from several European countries but have a lower number of cities per country than we have for Germany.

So far, we did not find statistical evidence in support of urban land use fragmentation playing a significant role for the life satisfaction of city dwellers, at least in case of overall fragmentation across all 20 types of urban land use. Next, we look at fabric fragmentation: Table 4 is constructed analogously to Table 3 but presents landscape fragmentation metrics for the five types of urban fabric, again for a treatment radius of 1,000 metres around households.[33] The five types of urban fabric differ *only* in their average degree of soil sealing, not in the predominant building type or actual land use (remember that, to be classified as urban fabric, there must be at least traces of residential use). Generally, the higher the degree of soil sealing, the lower the degree of non-sealed or vegetated surfaces such as gardens, parks, planted areas, and non-planted public open space, and *vice versa*. A caveat in our analysis of fabric fragmentation is that, in some regressions (for example, for discontinuous very-low-density urban fabric in inner cities where the population is greater than the mean Microcensus level), cell sizes become small.[34]

[Table 4 about here]

When looking at continuous, discontinuous dense, and discontinuous very-low-density urban fabric, we again do not find statistically significant effects of landscape composition and spatial configuration within a treatment radius of 1,000 metres around households on household members' life satisfaction. That is, we do not detect significant effects for urban fabric with average degrees of soil sealing above 50% and below 10%.[35] However, we do detect a pattern of significant effects for discontinuous medium-density urban fabric (MedUF) and low-density urban fabric (LowUF), i.e., urban fabric with an average degree of soil sealing between 10% and 50% (and, in turn, an average degree of non-sealed or vegetated surfaces between 50% and 90%).

We first look at the finding for *Percentage of Landscape* of patch type k (POL_k), which reflects the composition of urban land use within a treatment radius of 1,000 metres. For both MedUF and LowUF, we find statistically significant, positive effects of POL_k on life satisfaction in the OLS model, and in particular, on respondents living in urban areas with above average population density. Thus, respondents who have higher shares of these two types of urban land use in their surroundings report, on average, higher levels of life satisfaction. In case of LowUF, this positive association is also found in the OLS model when all respondents are pooled together. However, there are no statistically significant effects in the more restrictive FE model, in which effects are identified by individuals who move or, in other words, by within-individual variation rather than between-individual comparisons.

Moving on to the landscape fragmentation metrics that reflect spatial configuration, we observe that *Patch Density* (PDe_k) has a statistically significant, positive effect on life satisfaction in urban areas with above average population density. In case of MedUF, this can be observed in both the OLS and the FE model, even though effects in the FE model are only significant at the 10% level. In case of LowUF, this can only be observed in the FE model and the effect is also only significant at the 10% level. Still, this overall positive impact implies that these respondents report, on average, higher life satisfaction if the two urban land use types MedUF and LowUF are structured in a more heterogeneous and fragmented manner in their surroundings. In contrast, we observe one case with a statistically significant, negative effect: in case of MedUF, PDe_k is negatively associated with life satisfaction in the FE model for individuals living in urban areas with below average population density.

The findings for *Edge Density* (EDe_k) are similar to those for PDe_k: we observe a statistically significant, positive effect of EDe_k on life satisfaction in urban areas with above average population density. In case of MedUF, this holds for both the OLS and the FE model, whereas in case of LowUF, this only holds for the OLS model. Similar to the findings for PDe_k, the effect is only significant at the 10% level in the more restrictive FE specification. Similar to increasing PDe_k, increasing EDe_k means that the two urban land use types MedUF and LowUF would be arranged in a more heterogeneous and fragmented manner around households, which seems to be positively associated with life satisfaction.

Looking at the landscape fragmentation metrics *Largest Patch Index* (LPI_k) and *Mean Patch Size* (MPS_k), we only find significant effects for LowUF but not for MedUF: in case of LowUF, LPI_k is positively associated with life satisfaction. In the OLS model, this can be observed for all respondents on average and for those living in urban areas with above average population density. In the more restrictive FE model, a significant effect can only be observed for respondents living in urban areas with below average population density. For MPS_k, we observe strong, significantly positive effects for both the OLS and the FE model, across the board.

At first sight, these findings seem contradictory: increasing LPI_k and MPS_k would imply that the landscape within a 1,000 metres treatment radius around households becomes less fragmented and more dominated by LowUF. In other words, one would expect effects that go into the opposite direction than those for PDe_k and Ede_k. Yet, as we only consider LPI_k and MPS_k at a patch level, increasing values for these landscape metrics for LowUF may also imply that larger areas around households are covered by this type of urban land use. The positive effects of LPI_k and MPS_k may thus plausibly reflect the positive effect of POL_k on life satisfaction. This interpretation is supported by the strong correlation between POL_k and LPI_k (as well as MPS_k). These results would thus underpin that lower degrees of soil sealing and larger shares of vegetation have positive effects on life satisfaction.

In sum, we find evidence that the presence and spatial configuration of discontinuous medium-density urban fabric (MedUF) and low-density urban fabric (LowUF), which both reflect urban areas with a relatively low average degree of soil sealing and hence relatively larger shares of non-sealed and vegetated areas, are particularly important for respondents living in urban areas with above average population density. This group of respondents would benefit both from increasing the share and dominance of these two types of urban land use and from arranging patches in a more heterogeneous and fragmented manner. For the subgroup of respondents living in urban areas with below average population density, results are less clear and not as prominent. Seemingly, this subgroup would also benefit from increasing the dominance of LowUF but would react negatively to increasing heterogeneity and fragmentation in case of MedUF.

6. Discussion

We studied how urban land use fragmentation affects the life satisfaction of about 15,000 city dwellers in Germany. In particular, we analysed how landscape composition and configuration, represented by prominent landscape metrics calculated both at the aggregate landscape level and at the individual patch level, affect self-reported life satisfaction. Previous papers looked at the relationship between landscape composition (that is, shares of certain land use types, diversity, or evenness indices) and life satisfaction, whereas our paper also explicitly takes spatial configuration and fragmentation into account. It further adds to the literature by using a different dataset and methodology, in particular the use of highly detailed, spatial panel data, which allows calculating landscape fragmentation metrics around households with high precision.

We find that urban land use fragmentation has, overall, a surprisingly small impact on life satisfaction, at least at the aggregate level, when calculated across all types of land use and for the average city dweller. Of course, this may be different for different types of city dwellers (for example, there is evidence for differential impacts of green spaces on health, see Mitchell and Popham 2008) and for different measures of wellbeing or mental health. Using our data and methodology, however, we cannot provide conclusive evidence that 'enriched' environments are either advantageous, by providing complexity, novelty, and stimulation, or disadvantageous, by being a stressor, for human wellbeing.

There may be various reasons for a little impact of aggregate urban land use fragmentation on life satisfaction: besides issues pertaining to data and methods, it may well be that people quickly hedonically adapt to changes in urban land use fragmentation in their surroundings, or more likely, that they do not even notice such changes (which are often minor). Another reason may be a difference between evaluative and experiential dimensions of subjective wellbeing: our analysis only looks at life satisfaction, a cognitive evaluative dimension. It may well be that land use fragmentation has a differential impact on day-to-day experiential measures, such as feelings of happiness or sadness. Yet another reason, rooted more in standard economic theory, may be that wellbeing-relevant positive or negative changes in urban land use fragmentation are quickly internalised via real estate prices, implying that no residual wellbeing impact may be detectable.

When looking at particular types of urban land use, however, a different and more nuanced picture emerges. We find evidence that life satisfaction is positively affected by lower average degrees of soil sealing and larger shares of vegetation, especially in areas with above average population density. Moreover, life satisfaction tends to be higher in areas with above average population density when the land use types discontinuous medium-density urban fabric and low-density urban fabric are structured in a more heterogeneous and fragmented manner. Note that, when presenting these findings, we pointed out coefficients with low significance levels and inconsistency of patterns across models to avoid reporting false positives due to multiple hypotheses testing.

We deliberately focused our analysis on the sub-categories of the land use category *urban fabric*, which is the most dominant sub-category (about 30% of the total area covered in our estimation sample) and the most relevant when it comes to recent discussions about urban growth strategies, in particular whether urban growth should come via further densification in inner cities or via growth around the urban fringes. Given our findings on urban fabric, we can add some modest insights to this discussion: first, the finding that life satisfaction is positively affected by lower average degrees of soil sealing and larger shares of vegetation suggests that urban growth should, conditional on feasibility, rather come via growth around the urban fringes. This has clear, negative implications for growth-limiting factors such as green belts around the urban fringes. Second, the fact that life satisfaction tends to be higher in areas with above average population density when the land use types discontinuous medium-density urban fabric and low-density urban fabric are structured in a more heterogeneous and fragmented manner suggests that architectural elements that reduce feelings of density and break up soil sealing may reduce some of the adverse wellbeing impacts of densification. For example, such architectural features could include small parks and gardens, green spaces, street tree cover, or vertical gardens (Magliocco 2018, Manso and Castro-Gomez 2015).

Noting that the main criterion for a patch of land to be categorised as *urban fabric* is (at least partial) residential use, the five types of urban fabric differ in their average degree of soil sealing, not in the predominant building type or actual land use. Generally, the higher the degree of soil sealing, the lower the degree of non-sealed or vegetated surfaces such as gardens, parks, planted areas, and non-planted public areas, and *vice versa*. The sub-categories of urban fabric can thus be expected to capture to a reasonable extent the character of an urban area in the sense of how grey *versus* how green it is. Medium density urban fabric, for example, may be particularly prevalent in areas with single houses or town houses with private gardens while high density urban fabric is prevalent in densely populated inner city areas without much private green. Former studies, which have focused on the role of urban green spaces (Yuan et al. 2018, Krekel et al. 2016, Bertram and Rehdanz 2015, White et al. 2013, Ambrey and Fleming 2014b, Smyth et al. 2008) or on the role of other land use types (Krekel et al. 2016), have mostly ignored the land use categories urban fabric and have thus not been able to investigate the effect of the potentially rich vegetation within areas with residential use.

However, we also need to put into perspective which elements of city structure the landscape metrics used in this paper capture and which elements they do not capture. The landscape metrics used in this paper represent categorical map patterns calculated based on a set of land use types arranged in discrete patches which make up a landscape. The patches per land use type are thus considered to be homogenous and no further aspect of variance within patches can be analysed. Moreover, the scale of analysis of the land use data is predetermined by the land use classification and resolution provided within the EUA. In addition, the metrics calculated are all based on the same information, namely, the sizes, shapes, distributions, and configurations of patches within the landscape. While this is more than previously analysed in the literature, the information content of the metrics is clearly limited by the information entering the calculations. Related, the metrics do, to some extent, represent the same or similar information, as they are calculated based on related input data. Still, we selected only a few landscape metrics to convey distinct and informative key figures characterising the structure and fragmentation of the city areas in which the respondents live.

Moreover, our study is clearly limited in the sense that we cannot say how urban land use fragmentation causally affects life satisfaction. We did our best to come up with the most precise calculations based on exact geographical coordinates of households and shapefiles of urban land use, and we did employ restrictive panel data methods, accounting for time-invariant unobservables at the city, year, and individual level as well as for a wide range of time-varying observables at the individual, household, and city level. Our effects were identified by movers, which was a deliberate choice as the majority of movers self-report to move for reasons primarily unrelated to their surroundings. Yet, moving may be a dynamic process, and there may be unobservables or observables we do not capture and that simultaneously affect both urban land fragmentation and life satisfaction. We thus cannot say that our estimates are causal. A promising area of research in the future is thus to complement good data and methodology with a good causal-design framework to establish causality.

Our results can inform urban planning by shedding light on how urban structure, i.e., fragmentation and densification affect life satisfaction. As Olsen et al. (2019) point out, compact cities which are built more densely than others are considered more sustainable, but it is disputable whether they are also more liveable. Our results show that in areas with high population density, the percentage of landscape covered by discontinuous medium-density and low-density urban fabric shares a positive relationship with life satisfaction: residents living in these areas would thus benefit from increasing the share and dominance of less densely built and more vegetated areas. In addition, these areas should be structured in a more heterogenous way, which also points to a preference for less densification in areas that are already highly populated. Areas with below average population density, however, leave room for further densification without affecting life satisfaction negatively. Seemingly, in these areas, respondents would also benefit from increasing the dominance of discontinuous low-density urban fabric but would react negatively to increasing heterogeneity and fragmentation in case of discontinuous medium-density urban fabric. Structuring these areas more compactly and homogenously would thus tend to benefit residents.

Acknowledgements

We thank the editor and two anonymous referees for very helpful comments and suggestions. Moreover, we thank Neele Larondelle for invaluable help during the early stages of this project.

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Tables

Table 1: Description of Landscape Fragmentation Metrics

Name (Abbreviation)	Formula	Description	Level of analysis	Category of metric	Value domain
Percentage of Landscape (POL)	$POL_k = \frac{\sum_{j=1}^{n_k} a_{kj}}{A}(100)$	Sum of the areas (a_{kj} in m^2) of all patches j of patch type k, divided by total landscape area (A in m^2), multiplied by *100* to convert to *%*	Individual (patch) level only	Composition[a]	$0 < POL_k \leq 100$
Patch Density (PDe)	$PDe_k = \frac{n_k}{A}(10000)$	Number of patches (n) of patch type k, divided by total landscape area (A in m^2), multiplied by *10,000* to convert to *ha*	Aggregate (landscape) and individual (patch) level	Configuration	$0 < PDe_k \leq constrained\ by\ cell\ size$
Edge Density (EDe)	$EDe_k = \frac{\sum_{k=1}^{m_k} e_k}{A}(10000)$	Total length of edge e (in m) involving patch type k, divided by total landscape area (A in m^2), multiplied by *10,000* to convert to *ha*	Aggregate (landscape) and individual (patch) level	Configuration	$0 < EDe_k \leq \infty$
Largest Patch Index (LPI)	$LPI_k = \frac{max_{j=1}^{n_k}(a_{kj})}{A}(100)$	Area of the largest patch of type k (in m^2), divided by total landscape area (in m^2), multiplied by *100* to convert to *%*	Aggregate (landscape) and individual (patch) level	Configuration	$0 < LPI_k \leq 100$
Mean Match Size (MPS)	$MPS_k = \frac{\sum_{j=1}^{n_k} a_{kj}}{n_k}$	Total area covered by patch type k divided by the number of patches of type k, measured in m^2	Individual (patch) level only	Configuration	$0 < MPS_k \leq buffer\ size$
Shannon's Evenness Index (SEI)	$SEI = \frac{-\sum_{k=1}^{m}(P_k * \ln P_k)}{\ln m}$	Minus the sum, across all patch types k, of the proportional abundance (P_k) of each patch type multiplied by the natural logarithm of that proportion, divided by the logarithm of the number of patch types (m)	Aggregate (landscape) level only	Composition	$0 \leq SEI \leq 1$

Note: The subscript "k" denotes the respective patch type of urban land use. If the metrics are calculated at the aggregate level (overall fragmentation), the subscript "k" is dropped for PDe, EDe, LPI, and MPS.

[a] Note that composition metrics are usually calculated for the whole landscape. For POL, this would imply calculating the proportional abundance of each patch type within the landscape. Here, we consider the proportional abundance of selected patch types separately from one another.

Source for formulas, descriptions, and value domains: McGarigal (2015).

Table 2: Calculated Landscape Fragmentation Metrics for Stylised Landscapes in Figure 2

	Landscape A	Landscape B	Level
POL_red	25%	25%	Patch
POL_yellow	25%	25%	Patch
POL_green	25%	25%	Patch
POL_blue	25%	25%	Patch
PDe	4/ha	24/ha	Landscape
PDe_red	1/ha	6/ha	Patch
PDe_yellow	1/ha	12/ha	Patch
PDe_green	1/ha	2/ha	Patch
PDe_blue	1/ha	4/ha	Patch
EDe	200m/ha	830m/ha	Landscape
EDe_red	100m/ha	420m/ha	Patch
EDe_yellow	100m/ha	630m/ha	Patch
EDe_green	100m/ha	190m/ha	Patch
EDe_blue	100m/ha	490m/ha	Patch
LPI	25%	16%	Landscape
LPI_red	25%	6%	Patch
LPI_yellow	25%	6%	Patch
LPI_green	25%	16%	Patch
LPI_blue	25%	11%	Patch
MPS_red	2500 m^2	416.7 m^2	Patch
MPS_yellow	2500 m^2	208.3 m^2	Patch
MPS_green	2500 m^2	1250 m^2	Patch
MPS_blue	2500 m^2	625 m^2	Patch
SEI	1	1	Landscape

Note: We assume a size of 1ha per landscape and 100m^2 for the smallest possible patch.

Table 3: Overall Fragmentation, Treatment Radius of 1,000 Metres

	Life Satisfaction					
	OLS + City Fixed Effects			Individual Fixed Effects		
	Average	**Greater Census**	**Smaller Census**	**Average**	**Greater Census**	**Smaller Census**
Patch Density (PDe)	0.3739 (1.5306)	0.1276 (3.2834)	-0.6026 (1.9305)	0.0007 (0.0016)	-0.0015 (0.0036)	-0.0008 (0.0031)
(Within) R Squared	*0.2691*	*0.2614*	*0.2794*	*0.0859*	*0.0886*	*0.0853*
Edge Density (EDe)	0.0007 (0.0021)	0.0060 (0.0057)	-0.0001 (0.0023)	2.4074 (2.5904)	-2.4889 (6.1062)	-0.0634 (4.1627)
(Within) R Squared	*0.2691*	*0.2615*	*0.2794*	*0.0859*	*0.0886*	*0.0853*
Largest Patch Index (LPI)	0.0005 (0.0009)	0.0008 (0.0017)	-0.0005 (0.0013)	-0.0031 (0.0036)	0.0055 (0.0088)	-0.0039 (0.0048)
(Within) R Squared	*0.2691*	*0.2614*	*0.2794*	*0.0859*	*0.0886*	*0.0853*
Shannon's Evenness Index (SEI)	-0.0065 (0.1875)	0.3422 (0.3669)	-0.1399 (0.2140)	0.1429 (0.2581)	-0.0032 (0.4811)	-0.0560 (0.4586)
(Within) R Squared	*0.2690*	*0.2615*	*0.2794*	*0.0859*	*0.0886*	*0.0853*
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	No	No	No	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57 588	23 332	34 256	57 588	23 332	34 256
Individuals	14 744	6 267	9 392	14 744	6 267	9 392

*Robust standard errors clustered at household level in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Notes: Each estimate comes from a separate regression of Equation 1. The outcome is *life satisfaction* on a 0/10 scale. The treatment radius is 1,000 metres. The census is the mean number of residents per square kilometre (which is about 5,908), as defined by the Federal Statistical Office's 2011 Microcensus. All regressions include city and year fixed effects and a constant. All figures are rounded to four decimal places. See Section 2 for variable definitions and descriptive statistics.
Sources: SOEP, 2000-2014, individuals aged 17 or above; EUA, 2006, 35 major German cities with inhabitants equal to or greater than 100,000; own calculations.

Table 4: Fabric Fragmentation, Treatment Radius of 1,000 Metres

	Life Satisfaction					
	OLS + City Fixed Effects			Individual + City Fixed Effects		
	Average	**Greater Census**	**Smaller Census**	**Average**	**Greater Census**	**Smaller Census**
Panel A: Continuous Urban Fabric						
Percentage of Landscape (POL_k)	0.0978 (0.1060)	0.1049 (0.1581)	-0.0248 (0.1962)	-0.0107 (0.1581)	-0.2332 (0.2873)	-0.0118 (0.4959)
(Within) R Squared	*0.2691*	*0.2614*	*0.2794*	*0.0859*	*0.0886*	*0.0853*
Patch Density (PDe_k)	0.0015 (0.0011)	0.0020 (0.0018)	0.0000 (0.0020)	0.0010 (0.0018)	-0.0010 (0.0036)	0.0021 (0.0050)
(Within) R Squared	*0.2691*	*0.2615*	*0.2794*	*0.0859*	*0.0886*	*0.0853*
Edge Density (EDe_k)	0.0002 (0.0002)	0.0003 (0.0003)	0.0000 (0.0004)	0.0000 (0.0003)	-0.0005 (0.0007)	0.0001 (0.0011)
(Within) R Squared	*0.2691*	*0.2615*	*0.2794*	*0.0859*	*0.0886*	*0.0853*
Largest Patch Index (LPI_k)	0.0013 (0.0207)	0.0023 (0.0333)	-0.0050 (0.0276)	-0.0435 (0.0338)	-0.1245** (0.0594)	0.0029 (0.0621)
(Within) R Squared	*0.2690*	*0.2614*	*0.2794*	*0.0859*	*0.0889*	*0.0853*
Mean Patch Size (MPS_k)	-0.0001 (0.0031)	-0.0013 (0.0056)	-0.0012 (0.0038)	-0.0043 (0.0052)	-0.0144 (0.0099)	0.0005 (0.0090)
(Within) R Squared	*0.2690*	*0.2614*	*0.2794*	*0.0859*	*0.0887*	*0.0853*
Panel B: Discontinuous Dense Urban Fabric						
Percentage of Landscape (POL_k)	-0.0985 (0.1157)	-0.2762 (0.2090)	0.0050 (0.1389)	0.2266 (0.1718)	-0.0209 (0.3788)	0.2461 (0.3188)
(Within) R Squared	*0.2691*	*0.2617*	*0.2794*	*0.0859*	*0.0886*	*0.0853*
Patch Density (PDe_k)	-0.0020 (0.0021)	-0.0042 (0.0037)	-0.0010 (0.0026)	0.0032 (0.0031)	0.0004 (0.0064)	0.0000 (0.0058)
(Within) R Squared	*0.2691*	*0.2616*	*0.2794*	*0.0859*	*0.0886*	*0.0853*
Edge Density (EDe_k)	-0.0002 (0.0003)	-0.0007 (0.0005)	0.0000 (0.0004)	0.0005 (0.0005)	-0.0003 (0.0010)	0.0007 (0.0009)
(Within) R Squared	*0.2691*	*0.2616*	*0.2794*	*0.0859*	*0.0886*	*0.0853*
Largest Patch Index (LPI_k)	0.0003 (0.0122)	-0.0194 (0.0223)	0.0189 (0.0128)	0.0181 (0.0187)	0.0057 (0.0377)	0.0442 (0.0327)

(Within) R Squared	*0.2690*	*0.2615*	*0.2795*	*0.0859*	*0.0886*	*0.0854*
Mean Patch Size (MPS_k)	0.0020 (0.0023)	0.0011 (0.0041)	0.0038 (0.0028)	0.0020 (0.0038)	-0.0023 (0.0076)	0.0064 (0.0068)
(Within) R Squared	*0.2691*	*0.2614*	*0.2795*	*0.0859*	*0.0886*	*0.0853*
Panel C: Discontinuous Medium-Density Urban Fabric						
Percentage of Landscape (POL_k)	0.3809 (0.2521)	1.0943*** (0.3919)	0.2298 (0.3398)	-0.1588 (0.3602)	1.0268 (0.6899)	-0.7153 (0.6563)
(Within) R Squared	*0.2692*	*0.2622*	*0.2794*	*0.0859*	*0.0887*	*0.0853*
Patch Density (PDe_k)	0.0047 (0.0058)	0.0185** (0.0090)	0.0023 (0.0077)	-0.0064 (0.0079)	0.0264* (0.0139)	-0.0264* (0.0146)
(Within) R Squared	*0.2691*	*0.2618*	*0.2794*	*0.0859*	*0.0888*	*0.0855*
Edge Density (EDe_k)	0.0009 (0.0007)	0.0033*** (0.0012)	0.0004 (0.0010)	-0.0006 (0.0011)	0.0038* (0.0021)	-0.0026 (0.0020)
(Within) R Squared	*0.2691*	*0.2621*	*0.2794*	*0.0859*	*0.0887*	*0.0854*
Largest Patch Index (LPI_k)	-0.0021 (0.0130)	0.0037 (0.0214)	-0.0039 (0.0164)	0.0101 (0.0226)	0.0314 (0.0462)	0.0048 (0.0425)
(Within) R Squared	*0.2691*	*0.2614*	*0.2794*	*0.0859*	*0.0886*	*0.0853*
Mean Patch Size (MPS_k)	-0.0006 (0.0012)	-0.0010 (0.0017)	0.0000 (0.0017)	0.0019 (0.0022)	-0.0014 (0.0039)	0.0031 (0.0041)
(Within) R Squared	*0.2691*	*0.2614*	*0.2794*	*0.0859*	*0.0886*	*0.0853*
Panel D: Discontinuous Low-Density Urban Fabric						
Percentage of Landscape (POL_k)	2.0338* (1.0922)	6.0219*** (2.1872)	1.5455 (1.2976)	1.3384 (1.6114)	2.9312 (3.6685)	3.3185 (2.2134)
(Within) R Squared	*0.2692*	*0.2621*	*0.2795*	*0.0859*	*0.0886*	*0.0854*
Patch Density (PDe_k)	0.0089 (0.0222)	0.0500 (0.0492)	0.0077 (0.0254)	-0.0017 (0.0341)	0.1296* (0.0754)	0.0126 (0.0488)
(Within) R Squared	*0.2691*	*0.2615*	*0.2794*	*0.0859*	*0.0887*	*0.0853*
Edge Density (EDe_k)	0.0041 (0.0034)	0.0179** (0.0076)	0.0029 (0.0039)	0.0023 (0.0052)	0.0160 (0.0124)	0.0055 (0.0073)
(Within) R Squared	*0.2691*	*0.2619*	*0.2794*	*0.0859*	*0.0887*	*0.0853*
Largest Patch Index (LPI_k)	0.0601** (0.0277)	0.1444*** (0.0508)	0.0386 (0.0339)	0.0539 (0.0495)	0.0581 (0.0923)	0.1600** (0.0784)
(Within) R Squared	*0.2693*	*0.2623*	*0.2795*	*0.0859*	*0.0886*	*0.0856*

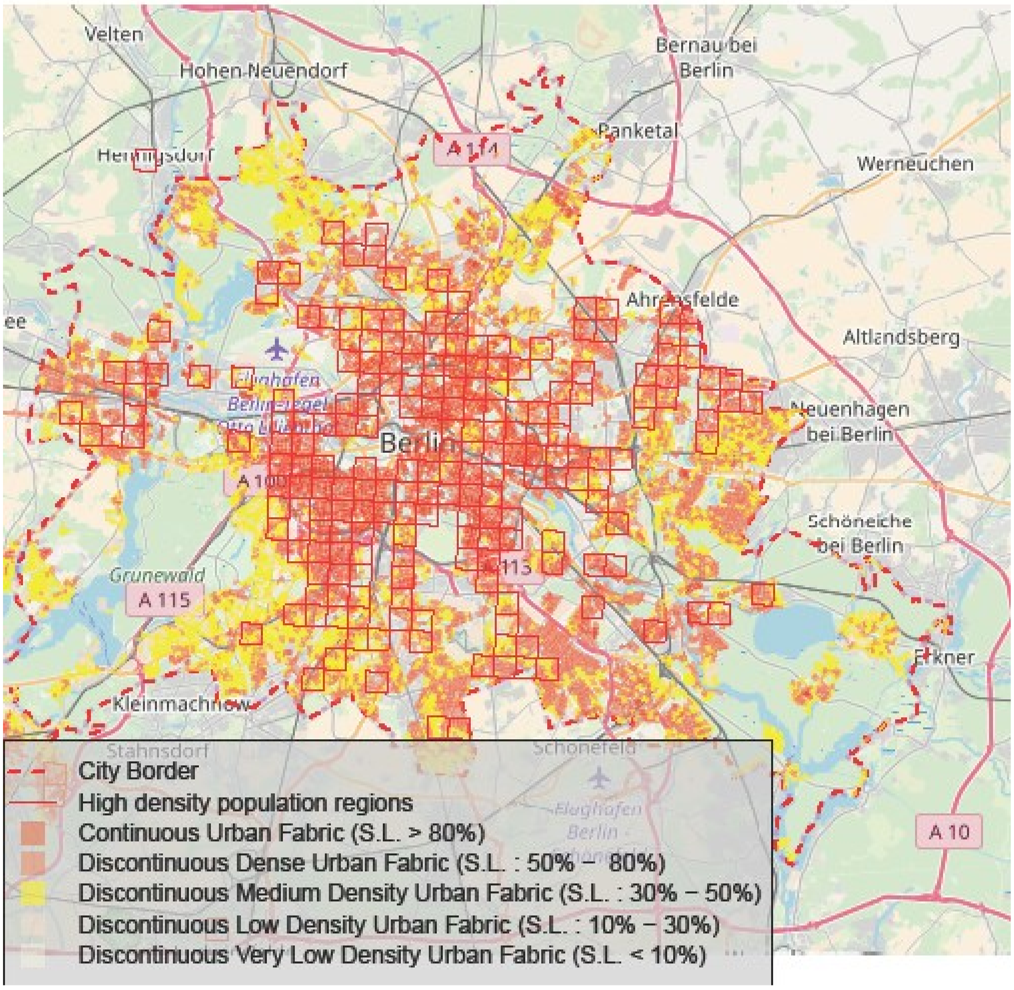
Mean Patch Size (MPS_k)	0.0043*** (0.0016)	0.0089*** (0.0030)	0.0034* (0.0020)	0.0092*** (0.0027)	0.0108** (0.0051)	0.0164*** (0.0048)
(Within) R Squared	*0.2694*	*0.2623*	*0.2796*	*0.0862*	*0.0889*	*0.0860*
Panel E: Discontinuous Very-Low-Density Urban Fabric						
Percentage of Landscape (POL_k)	-17.2911 (17.6957)	3.5672 (49.4269)	-19.1312 (19.4835)	14.9589 (21.4278)	40.0129 (33.5691)	-15.1408 (25.9687)
(Within) R Squared	*0.2691*	*0.2614*	*0.2795*	*0.0859*	*0.0886*	*0.0853*
Patch Density (PDe_k)	-0.0813 (0.1512)	-0.1334 (0.3982)	-0.0672 (0.1677)	0.1944 (0.2158)	0.1787 (0.4064)	0.0790 (0.2717)
(Within) R Squared	*0.2691*	*0.2614*	*0.2794*	*0.0859*	*0.0886*	*0.0853*
Edge Density (EDe_k)	-0.0277 (0.0412)	-0.0159 (0.1039)	-0.0271 (0.0467)	0.0528 (0.0404)	0.0751 (0.0468)	0.0165 (0.0573)
(Within) R Squared	*0.2691*	*0.2614*	*0.2794*	*0.0859*	*0.0886*	*0.0853*
Largest Patch Index (LPI_k)	-0.2229 (0.1944)	0.3179 (0.3772)	-0.2973 (0.2186)	0.0761 (0.2620)	0.3421 (0.4932)	-0.2652 (0.3049)
(Within) R Squared	*0.2691*	*0.2614*	*0.2796*	*0.0859*	*0.0886*	*0.0853*
Mean Patch Size (MPS_k)	-0.0082 (0.0066)	0.0121 (0.0112)	-0.0115 (0.0075)	0.0008 (0.0090)	0.0085 (0.0172)	-0.0100 (0.0104)
(Within) R Squared	*0.2691*	*0.2614*	*0.2796*	*0.0859*	*0.0886*	*0.0853*
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	No	No	No	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57 588	23 332	34 256	57 588	23 332	34 256
Individuals	14 744	6 267	9 392	14 744	6 267	9 392

*Robust standard errors clustered at household level in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Notes: Each estimate comes from a separate regression of Equation 1. The outcome is *life satisfaction* on a 0/10 scale. MPS has been rescaled (divided by 1,000). The treatment radius is 1,000 metres. The census is the mean number of residents per square kilometre (which is about 5,908), as defined by the Federal Statistical Office's 2011 Microcensus. All regressions include city and year fixed effects and a constant. All figures are rounded to four decimal places. See Section 2 for variable definitions and descriptive statistics.
Sources: SOEP, 2000-2014, individuals aged 17 or above; EUA, 2006, 35 major German cities with inhabitants equal to or greater than 100,000; own calculations.

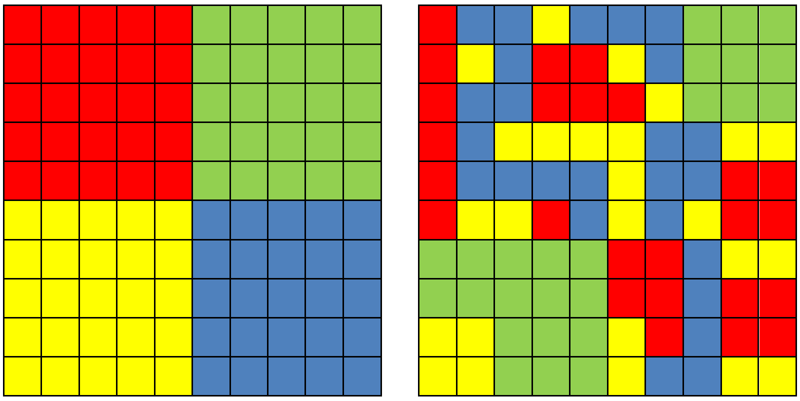
Figures

Figure 1: Distribution of Different Types of Urban Fabric in Berlin, Germany



Source: European Urban Atlas, Berlin, 2006, own calculations

Figure 2: Illustration of Stylised Landscapes (Landscape A on Left, Landscape B on Right)



Endnotes

[1] Particularly hedonic pricing studies have investigated the effect of landscape (dis-)amenities on housing prices (e.g., Klaiber and Phaneuf, 2010). Meta-analyses of hedonic pricing studies valuing urban open spaces can be found in Perino et al. (2014) and Brander and Koetse (2011). One of the few studies looking at the effects of spatial fragmentation and housing prices is Kuethe (2012).

[2] In this approach, self-reported life satisfaction – a cognitive evaluative measure of subjective wellbeing which is sometimes referred to as *experienced utility* (Kahneman et al. 1997, Kahneman and Sugden 2005) – is regressed on the non-market good alongside income and other covariates. The non-market good is then valued by calculating the marginal rate of substitution between the good and income.

[3] Regarding environmental factors, noise, air, and scenic pollution are the disamenities that have been most often studied (e.g., see Yuan et al. 2018, Zhang et al. 2017a,b, Ambrey and Fleming 2014a, Ferreira et al. 2013, Levinson 2012, Menz and Welsch 2012, Ferreira and Moro 2010, Luechinger 2009, MacKerron and Mourato 2009, and Rehdanz and Maddison 2008 for air pollution; Weinhold 2013, Rehdanz and Maddison 2008, and van Praag and Baarsma 2005 for noise pollution; and von Möllendorff and Welsch 2017 and Krekel and Zerrahn 2017 for scenic pollution).

[4] In this paper, patch types in a landscape are differentiated according to the different land use types described in Section 2.2. We use the terms *patch type*, *land use type*, and *land use class* interchangeably.

[5] See Uuemaa et al. (2009) for a detailed overview of the use of landscape metrics in landscape research.

[6] Geographical coordinates at the street-block level are very precise in urban areas.

[7] Calculations must be made on-site in the SOEP Research Data Centre at the German Institute for Economic Research (DIW Berlin). Access to the data is subject to rigorous data protection rules; it is never possible to derive household data from the geographical coordinates of households, as both are not shown to the researcher at the same time. See Goebel and Pauer (2014) for a detailed description of the data protection concept.

[8] *Demographic and human capital characteristics* include age, gender, marital status, health, migration background, and the highest degree obtained. *Economic conditions* include the labour force status, employment type, and household income. *Household characteristics and housing conditions* include the number of children in the household, number of rooms per individual, building type, and rental price. *Neighbourhood characteristics* include the local unemployment rate and average household income.

[9] Table W1a in the Web Appendix shows descriptive statistics on outcome and control variables for our estimation sample.

[10] These are: *Augsburg*, *Berlin*, *Bielefeld*, *Bonn*, *Bremen*, *Darmstadt*, *Dresden*, *Düsseldorf*, *Erfurt*, *Frankfurt (Oder)*, *Frankfurt am Main*, *Freiburg im Breisgau*, *Göttingen*, *Halle an der Saale*, *Hamburg*, *Hannover*, *Karlsruhe*, *Kiel*, *Koblenz*, *Köln*, *Leipzig*, *Magdeburg*, *Mainz*, *Mönchengladbach*, *München*, *Nürnberg*, *Regensburg*, the *Ruhrgebiet*, *Saarbrücken*, *Schwerin*, *Stuttgart*, *Trier*, *Weimar*, *Wiesbaden*, and *Wuppertal*.

[11] The EUA is estimated to have a thematic accuracy of greater than 85% (EEA 2011).

[12] Table W1b in the Web Appendix gives an overview including fragmentation metrics of the different types of urban land use available in the EUA.

[13] Figures W1a and W1b in the Web Appendix illustrate this distribution for two other major German cities: Bonn and Stuttgart.

[14] City centres, downtown areas, and central business districts are classified as urban fabric as long as there are traces of residential use.

[15] Besides composition and spatial configuration metrics, there also exist other metrics of landscape fragmentation. In this paper, we restrict ourselves to the composition and spatial configuration metrics that are most frequently used in the literature on landscape research.

[16] McGarigal (2012) gives an overview of different approaches to capture the potentially complex spatial patterns of landscapes. For the purposes of this paper, using metrics based on so-called *categorical map patterns* are the most suitable approach.

[17] Tables W1c and W1d in the Web Appendix show means, standard deviations, and the number of observations for landscape fragmentation (Table W1c) and fabric fragmentation metrics (Table W1d), respectively, for all individuals and for movers only in our estimation sample.

[18] When looking at overall fragmentation, we aggregate across all k=20 types of urban land use so that the subscript k becomes obsolete. When looking at fabric fragmentation, we consider the $k=5$ types of urban fabric, which are (i) *continuous urban fabric* (average degree of soil sealing greater than 80%), (ii) *discontinuous dense urban fabric* (sealing between 50% and 80%), (iii) *discontinuous medium-density urban fabric* (sealing between 30% and 50%), (iv) *discontinuous low-density urban fabric* (sealing between 10% and 30%), and (v) *discontinuous very-low-density urban fabric* (sealing less than 10%).

[19] The mean number of residents per square kilometre is about 5,908 in our estimation sample.

[20] At the time when doing the calculations, the EUA had only one verified wave.

[21] See Figures W2a to W2c in the Web Appendix.
[22] See Tables W5a and W5b in the Web Appendix.
[23] The results are available upon request.
[24] The SOEP includes a filter question that asks respondents about whether they moved in the previous wave, and a follow-up item that asks about primary moving reasons. These include *notice given by landlord*; *buying a house or an apartment*; *inheritance*; *job reasons*; *marriage, breakup, or other family reasons*; *the size of the dwelling*; *the price of the dwelling*; *the standard of the dwelling*; *the standard of the location*; *the standard of the surroundings*; and *other reasons*. We combine all categories except for the standard of the location and the standard of the surroundings into one category that we assume *not* to be directly linked to the surroundings of respondents.
[25] See Tables W6a and W6b in the Web Appendix.
[26] See Tables W7a and W7b as well as Tables W8a and W8b in the Web Appendix.
[27] The results are available upon request.
[28] See Tables W9a and W9b as well as Tables W10a and W10b in the Web Appendix.
[29] Tables W2a and W2b in the Web Appendix presents findings for a treatment radius of 500 metres around households, whereas Tables W3 and W4 present findings including the complete set of controls, using, for illustrative purposes, Shannon's Evenness Index (SEI_i) and a treatment radius of 1,000 and 500 metres, respectively.
[30] We do not find statistically significant effects within a smaller treatment radius of 500 metres either, except for the *Largest Patch Index* (LPI_i), which turns out to be significant at the 5% level. Note, however, that we are testing a large number of hypotheses, and the fact that we do not find a consistent pattern for this landscape fragmentation metric between urban areas above or below the mean population density as well as across models points towards a false positive.
[31] *Shannon's Diversity Index* (SDI) and *Shannon's Evenness Index* (SEI) are perfectly correlated with each other if the number of patch types remains constant. Our results regarding the effect of SEI are thus directly transferable to using SDI. Our results for using SDI in our regressions are available upon request.
[32] The authors employ the concept of *functional urban areas* developed by the OECD, which are comparable territorial and functional units with a minimum population size of 500,000 in which people live, work, access amenities, and interact socially. Hence, the total area covered is much larger than ours, including both core city and periphery, whereas our analysis is restricted to inner cities, excluding the urban fringes.
[33] Table W4 in the Web Appendix presents findings for a treatment radius of 500 metres around households.
[34] See Tables W1c and W1d in the Web Appendix.
[35] We ignore the singleton finding for *Largest Patch Index* (LPI_i) under *continuous urban fabric*: there is again no consistent pattern for this landscape fragmentation metric between urban areas above or below the mean population density as well as across models, which may point again towards a false positive.