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ABSTRACT

The Value of a Park in Crises: Quantifying the Health and Wellbeing Benefits of Green Spaces Using Exogenous Variations in Use Values*

Most people consider parks important for their quality of life, yet systematic causal evidence is missing. We exploit exogenous variations in their use values to estimate causal effects. Using a representative household panel with precise geographical coordinates of households linked to satellite images of green spaces with a nationwide coverage, we employ a spatial difference-in-differences design, comparing within-individual changes between residents living close to a green space and those living further away. We exploit Covid-19 as exogenous shock. We find that green spaces raised overall life satisfaction while reducing symptoms of anxiety (feelings of nervousness and worry) and depression. There is also suggestive evidence for reduced loneliness. Given the number of people in their surroundings, a compensating-surplus calculation suggests that parks added substantial benefits during the period studied.

JEL Classification: I10, I31, R23, H41, Q51

Keywords: parks, green spaces, mental health, wellbeing, quasi-natural experiment, compensating surplus

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1 Introduction

More than half of the world's population – about 55% or 4.2 billion people – are living in cities, and their share is expected to increase to 68% by 2050 (UN Department of Economic and Social Affairs, 2018). This rapid rate of urbanisation is putting increasing pressure on public open areas like parks to provide additional room for housing, especially in urban areas where land is scarce.

Yet, most people consider parks important for their quality of life, as reflected in the UN Sustainable Development Goals (SDGs). SDG 11 ("Sustainable Cities and Communities") aims at, amongst others, providing "universal access to safe, inclusive, and accessible green and public spaces" (UN Development Programme, 2022). Indeed, correlational evidence suggests that people put great value on green spaces, as places for recreation, physical activity, and social interaction with family or friends (cf. Berman et al., 2008; Leslie and Cerin, 2008; Richardson et al., 2013). However, systematic causal evidence on the health and wellbeing benefits of green spaces is missing, which means that they may not be (adequately) accounted for in social welfare analyses. This is because there are typically little to no exogenous variations in green spaces and because households' locational choices are endogenous.

We work around these issues by exploiting exogenous variations not in green spaces themselves but in their *use values*, brought about by Covid-19 restrictions. Our unique quasi-experimental setting is Germany, and our observation period covers both the strict lockdown period (March 22 to May 4, 2020) and an ensuing period of eased restrictions (May 5 to July 4, 2020). During the strict lockdown period, Covid-19 restrictions required residents to reduce social contact by meeting a maximum of one person outside of their household, maintaining social distancing, and avoiding leaving their house for reasons other than necessary work, essential shopping, medical appointments, or walking and exercising. Importantly, visiting a park was always permitted in Germany and parks remained open, unlike in other countries. During the ensuing period of eased restrictions, members of two households were allowed to meet, schools and shops of certain sizes were re-opened, and sports clubs were allowed to operate again, if outdoors (Federal Government of Germany, 2020). Restrictions were equal between all sixteen German federal states during the strict lockdown period, and they remained broadly equal thereafter.

We ask: was there a positive causal effect of living close to a green space on residents' wellbeing during that time? If so, what were the potential mechanisms? And, finally, what were, and are, the implications for social welfare, if any?

To estimate causal effects, we use a representative household panel with precise geographical coordinates of households linked to satellite images of green spaces with a nationwide coverage. We employ a spatial difference-in-differences design that compares within-individual changes between residents living close to a green space and those living further away, from before to during Covid-19. Our outcomes are overall life satisfaction as an overall welfare measure and, to explore potential mechanisms, mental health and loneliness. Finally, we calculate the compensating surplus to provide a willingness-to-pay estimate of the benefits added by parks during the period studied.

There are three reasons to expect positive effects. First, *biophilia* theory suggests that nature has a direct positive impact on health and wellbeing (Wilson, 1984). Experimental evidence from psychology shows that even short-term exposure to green natural environments can improve mood (Ulrich, 1984; Ulrich et al., 1991; Cackowski and Nasar, 2003), reduce stress (Agyemang et al., 2007; Nielsen and Hansen, 2007; van den Berg et al., 2010), restore cognition and memory capacity (Berman et al., 2008), and facilitate better self-regulation and executive function (Hartig et al., 2003; van den Berg et al., 2010; Bourrier et al., 2018).[1] Second, green spaces can have indirect impacts via the promotion of behaviours that are conducive to health and wellbeing, such as physical activity (Maas et al., 2008; Richardson et al., 2013), social interaction (Leslie and Cerin, 2008), or even pro-social behaviours (Weinstein et al., 2009). Finally, they may improve environmental quality, by reducing public bads such as air or noise pollution (Gidlöf-Gunnarsson and Öhrströn, 2007) while, at the same time, providing public goods such as scenic amenity (Seresinhe et al., 2019).

So far, however, most evidence is correlational and comes from cross-sectional studies (see Houlden et al. (2018) and Jiminez et al. (2021) for reviews) while findings from longitudinal studies have been mixed, with weak positive associations at best (Geneshka et al., 2021). Studies that have been able to estimate *causal* effects have been local interventions or experiments with small samples (see Hunter et al. (2019) and Wendelboe-Nelson et al. (2019) for reviews). In a natural experiment in Wuhan, China, Xie et al. (2022) find that residents living

[1] Using the day-reconstruction method (Kahneman et al., 2004), where participants keep diaries of their daily activities and feelings, White and Dolan (2009) show that outdoor activities are amongst the most pleasurable and purposeful activities. Similarly, using a smartphone app that randomly asks users about their momentary feelings and activities (so-called *experience-sampling*), MacKerron and Mourato (2013) show that people are happier in greener or more natural habitats.

within five kilometres to a greenway intervention – a landscaped and traffic-calm pathway for pedestrians and cyclists – show improved mental health compared to those living further away. Branas et al. (2011) examine the effects of *randomly* greening vacant lots in Philadelphia, US. The authors find that greening leads to less stress and more exercise, as well as reductions in gun assaults and vandalism. In contrast, our study covers all major German cities and metropolitan areas with more than 100,000 inhabitants.

We arrive at three results. First, living close to a green space during the pandemic had a positive effect on overall life satisfaction, a validated measure for personal wellbeing that is routinely asked by the Office for National Statistics (ONS) in the UK, amongst others (cf. Dolan and Metcalfe, 2012). Second, a potential mechanism through which this effect may have come about is better mental health: residents living close to a green space showed lower symptoms of anxiety (feelings of nervousness and worry) and depression, as measured by the Patient Health Questionnaire 4 (PHQ-4), a routine instrument for assessing symptoms of common mental health disorders amongst general and clinical populations (Kroenke et al., 2009). There is also suggestive evidence for reduced loneliness, measured by the UCLA 3-Items Loneliness Scale (Russell, 1996). As Covid-19 affected people around green spaces less adversely than others, green spaces played a buffering role against this stressful event. While larger patches of green space yield stronger returns to mental health and wellbeing, there is evidence for diminishing returns to the number of patches in people's surroundings. Finally, we calculate the compensating surplus, showing that an individual who did *not* live within 1,000 metres of a green space of at least 15 hectares would need to be compensated about €5,950 ($6,190) per year during Covid-19 (or similar) restrictions to achieve the same level of life satisfaction as an individual who did. Given the number of people in its surroundings (about 63% of individuals in our estimation sample, equivalent to about 16.1 million in Germany), this points towards substantial benefits added by parks during the period studied. In Section 5, we discuss the implications of our results for normal times, by adopting an actuarial perspective and calculating an *expected* compensating surplus per year.

We contribute to the literature on the health and wellbeing impacts of urban infrastructure, which includes, amongst others, low-emission zones (Margaryan, 2021), place-based programmes (Grossman, 2019), or housing retrofits (Kühn and Palacios, 2024), as well as residential segregation and sprawl (Zhao and Kaestner, 2010; Alexander and Currie, 2017;

Vu et al., 2024), local environmental quality (Giaccherini et al., 2021; Dave and Yang, 2022; Fan et al., 2023), or neighbourhood effects more generally (Bilger and Carrieri, 2013; Jacob et al., 2013). We add to this literature by looking at the health and wellbeing impacts of green spaces as an important type of urban amenity, for which systematic causal evidence is missing (see Richardson and Mitchell (2010), van den Berg et al. (2010), or Astell-Burt et al. (2022), amongst others, for important correlational evidence).

We also contribute to the literature on the monetary valuation of intangible benefits, in particular of green infrastructure. Studies in this literature typically regress either respondents' wellbeing (Ambrey and Fleming, 2014; Bertram and Rehdanz, 2015; Tsurumi and Managi, 2015; Krekel et al., 2016; Li and Managi, 2021) or house prices (Morancho, 2003; Panduro and Veie, 2013; Czembrowski and Kronenberg, 2016; Votsis, 2017; Liebelt et al., 2018; Daams et al., 2019; Stromberg et al., 2021) on the quantity of, or distance to, infrastructure in a pre-defined area around households, and then monetarily value these using either the compensating surplus (or marginal rate of substitution) between wellbeing and income or hedonic pricing.[2] Our paper differs, in that we are estimating the causal returns to green spaces using quasi-experimental methods, and in particular, exogenous variations in their use values, brought about by Covid-19 restrictions. The study most closely related to ours is Irwin and Livy (2021), who estimate the causal effects of Covid-19 stay-at-home orders on house prices in Baltimore, US. The authors observe changes in house prices near a major road. In contrast to house prices, which tend to be sticky, wellbeing data may be more susceptible to short-term fluctuations in use values. Our paper confirms correlational findings by Berdejo-Espinola et al. (2021) who, using data from Brisbane, Australia, show that living close to a green space during the pandemic was associated with reduced stress.

Finally, we contribute to the literature on public amenities and disamenities more generally, including open space provision (Lichtenberg et al., 2007; Lang, 2018; Picard and Tran, 2021) and conservation (Kotchen and Powers, 2006; Wu, 2014; Sims and Alix-Garcia, 2017), complementarities between parks and neighbourhood safety (Albouy et al., 2020), absence of environmental toxins (Billings and Schnepel, 2017), and better air, water, and climate (Tra, 2010; Baylis, 2020; Kuwayama et al., 2022).

[2] Another, less related, stream of literature uses stated preferences such as contingent valuation (cf. Sirina et al., 2017; Wang et al., 2018; Hui and Jim, 2022) or discrete choice experiments (cf. Bertram et al., 2017; Soto et al., 2018; Liu et al., 2020). An overview and comparison of different valuation methods can be found in Ferreira and Moro (2010) and Fleming and Ambrey (2017).

To our knowledge, we are the first to provide systematic causal evidence on the health and wellbeing benefits of green spaces using quasi-experimental methods. Our approach can be used to quantify the benefits of other public goods too, in particular those that have similar identification issues. Our findings offer important insights into the role of green spaces for the quality of life in cities, with implications for policy.

2 Data and Methods

2.1 Data

We use the German Socio-Economic Panel (SOEP), a large-scale, nationally representative panel of private households in Germany (SOEP, 2021). It has been conducted annually since 1984 and includes almost 40,000 individuals in over 19,000 households in its most recent pre-pandemic wave (the year 2019). For 2020, we use the first round of the SOEP Covid-19 questionnaires, which complemented the regular SOEP wave in 2020, covering the period from March 31 to July 4, 2020. It includes a random sub-sample of the regular respondents and asks a smaller Covid-19-specific set of questions.

An advantage of the SOEP and its Covid-19 wave is that they provide the precise geographical coordinates of every household in every year, allowing us to merge data on household members with data on green spaces in their surroundings (Goebel et al., 2019). For green spaces, we use the most recent European Urban Atlas (EUA) in 2018, which provides data on urban land use in all major German cities and metropolitan areas with more than 100,000 inhabitants.[3] The EUA is based on satellite images, recording patches of land as small as 0.25 hectares. A major advantage is that it records information on land *use*, not cover: the data preparation includes a validation stage that checks whether satellite imaging output is consistent with actual usage. This is important, considering that we exploit exogenous variations in use values to estimate causal effects.

Our variable of interest is *green space*, which is defined as all green publicly accessible land

[3] The cities in our estimation sample include the following (either by themselves or within metropolitan area boundaries): *Aachen*, *Augsburg*, *Berlin*, *Bielefeld*, *Bochum*, *Bonn*, *Bottrop*, *Braunschweig*, *Bremen*, *Bremerhaven*, *Chemnitz*, *Cottbus*, *Darmstadt*, *Dortmund*, *Dresden*, *Duisburg*, *Düsseldorf*, *Erfurt*, *Essen*, *Frankfurt am Main*, *Freiburg im Breisgau*, *Gelsenkirchen*, *Göttingen*, *Hagen*, *Halle (Saale)*, *Hamburg*, *Hamm*, *Hannover*, *Heidelberg*, *Heilbronn*, *Herne*, *Hildesheim*, *Ingolstadt*, *Jena*, *Karlsruhe*, *Kassel*, *Kiel*, *Koblenz*, *Köln*, *Krefeld*, *Leipzig*, *Lübeck*, *Ludwigshafen am Rhein*, *Magdeburg*, *Mainz*, *Mannheim*, *Moers*, *Mönchengladbach*, *Mülheim an der Ruhr*, *München*, *Münster*, *Nürnberg*, *Oberhausen*, *Oldenburg (Oldb)*, *Osnabrück*, *Paderborn*, *Pforzheim*, *Recklinghausen*, *Regensburg*, *Remscheid*, *Reutlingen*, *Rostock*, *Saarbrücken*, *Salzgitter*, *Siegen*, *Solingen*, *Stuttgart*, *Trier*, *Ulm*, *Wiesbaden*, *Wolfsburg*, *Wuppertal*, and *Würzburg*.

for predominantly recreational use.[4] Since we have precise information on location, size, and shape of every patch of green space as small as 0.25 hectares in all major German cities and metropolitan areas, we use a Geographical Information System (GIS) to calculate continuous green space areas with different minimum sizes, namely 5, 10, 15, and 20 hectares. Based on these minimum sizes, we also derive different patch sizes (from 5 to 10, 5 to 15, or 5 to 20 hectares; 10 to 15 or 10 to 20 hectares; or 15 to 20 hectares). We then calculate the Euclidean distance between every household and the nearest area (of varying sizes) to allocate households into treatment and control. Figure 1A plots the spatial distribution of green spaces in Germany in our estimation sample, Figure 1B plots this distribution in the capital, Berlin, as an example.

Figures 1A and 1B about here

Outcomes. We use *life satisfaction* as our overall welfare measure, which is obtained from a single-item eleven-point Likert-scale question asking: "How satisfied are you with your life, all things considered?" Responses range from 0 ("completely dissatisfied") to 10 ("completely satisfied"). This question has been validated and is routinely asked by the Office for National Statistics (ONS) in the UK, amongst others, to measure personal wellbeing (cf. Dolan and Metcalfe, 2012). As an evaluative measure of wellbeing, life satisfaction has been shown to capture a wide range of living conditions, including health, social relations, and employment (cf. Clark et al., 2018). Evidence from choice experiments and vignette studies suggests that life satisfaction is perceived as an important overarching life outcome (Benjamin et al., 2012; Adler et al., 2017, 2022). Importantly, accounts of life satisfaction can be used to monetarily value intangible impacts (Kahneman and Sugden, 2005; Welsch and Ferreira, 2014), and so have been frequently applied to value, amongst others, air and noise pollution (van Praag and Baarsma, 2005; Luechinger, 2009; Levinson, 2012), natural disasters (Luechinger and Raschky, 2009), the climate (Maddison and Rehdanz, 2011), public open space (Bertram and Rehdanz, 2015; Krekel et al., 2016), renewable energy plant externalities (Krekel and Zerrahn, 2017; von Möllendorff and Welsch, 2017), and public services and events (Dolan et al., 2019; Krekel

[4]Private gardens, cemeteries, agricultural areas, green fields not managed for recreational use, and sports and leisure facilities are not included. Appendix Table A11 shows raw correlations between green spaces and other types of urban land use in our estimation sample. As seen, most correlations are weak. Note that sports and leisure facilities, which can be part of a green space if located within its boundaries, remained closed during the strict lockdown period in Germany, and were only opened for outdoor activities thereafter. As seen in Section 4.2, our results are robust to the choice of period.

et al., 2024; Oparina, E. ⓡ C. Krekel ⓡ S. Srisuma ⓡ, 2024). Accounts of life satisfaction are also advocated for policy analysis by HM Treasury in the UK (HM Treasury, 2021b,a).[5]

To explore potential mechanisms, we look at mental health outcomes, which the literature has shown to be a major contributor to overall life satisfaction (cf. Clark et al., 2018). The SOEP and its Covid-19 wave include the Patient Health Questionnaire 4 (PHQ-4), a validated and routine instrument for assessing symptoms of common mental health disorders amongst general and clinical populations (Kroenke et al., 2009). It consists of four items, asking respondents whether they have felt *nervous* or *worried* (to assess symptoms of anxiety) or *depressed* or *no interest* (to assess symptoms of depression) during the last two weeks. Responses to each item are 0 ("Not at all"), 1 ("On some days"), 2 ("On more than half the days"), or 3 ("Almost every day"). A *summary scale* is then constructed by adding up these items, such that higher scores represent poorer mental health.

In addition, we look at loneliness as an outcome, given that Covid-19 restrictions in Germany allowed residents to meet a maximum of one person outside of their household and green spaces may provide places for social interaction. We use a version of the UCLA 3-Items Loneliness Scale (Russell, 1996) that has been incorporated into the SOEP and its Covid-19 wave (though only irregularly in the pre-pandemic waves). It is the sum of three single-item Likert-scale questions asking: "How often have you had the feeling that *(i)* you miss having other people around, *(ii)* you are left out, and *(iii)* you are socially isolated?". Responses to each item are 1 ("Hardly ever"), 2 ("Some of the time"), or 3 ("Often").

We complement our outcomes with covariates at the individual, household, and area level, as well as with alternative outcomes for placebo (household income) and confirmation tests (health and sleep satisfaction).[6] Appendix Table A1 shows summary statistics for our estimation sample

2.2 Estimation and Identification

Estimation. We employ a spatial difference-in-differences design which compares the changes in outcomes of individuals living close to a green space (treatment group) with those of individuals living further away (control group), from before to during the Covid-19 period. We

[5] In particular, HM Treasury allows the use of a *Wellbeing-Year (WELLBY)* as a measure of benefit in cost-benefit analyses, defined as one point of life satisfaction on a zero-to-ten Likert scale for one individual for one year (cf. Frijters et al., 2020; Frijters and Krekel, 2021; Frijters et al., 2024).

[6] See Section 4.4 for our placebo and confirmation tests and the definitions of these alternative outcomes.

estimate the following model:

$$y_{it} = \alpha + \beta_1 Green_s \times Post + \beta_2 Green_s + \beta_3 Post + t_y + t_m + t_{dw} + c + u_i + \epsilon_{it} \tag{1}$$

where y_{it} is the outcome of individual i at time t and $Green_s$ is a time-invariant dummy that is one if there is a green space with a minimum size of $s = \{5, 10, 15, 20\}$ hectares within a pre-defined treatment radius around the individual's residence, and zero else. As there is no clearly defined theoretical cut-off, we are guided by the literature and choose a default treatment radius of 1,000 metres, corresponding to a walking distance of up to 15 minutes, in line with previous correlational studies (cf. Bertram and Rehdanz, 2015; Krekel et al., 2016). Besides these minimum sizes, we also look at different patch sizes, as well as the number of green spaces in the intensive margin around the individual's residence. *Post* is a dummy that is one if the individual is interviewed during the Covid-19 period, and zero else. t_y, t_m, and t_{dw} are year, month, and day-of-week, and c and u_i city and individual fixed effects. The latter implicitly control for time-invariant observables and unobservables at the city and individual level.[7] In addition, we apply two types of matching to make treatment and control group more comparable to each other: *(i)* propensity-score matching based on pre-treatment observables and *(ii)* spatial matching based on geography, as described in detail below. As seen in Section 3, both types of matching produce similar results. Section 4.1 shows that our results are robust to *not* matching treatment and control group.

We consider only a short panel, $t = \{2019, 2020\}$, with 2020 constituting the Covid-19 period. We take the entire observation period in 2020 as the relevant treatment period, which is a conservative approach. When restricting the treatment period to the strict lockdown period in Germany (March 22 to May 4, 2020), our identified treatment effects become stronger (see Section 4.2 for these results).[8] To avoid concern about households' locational choices being endogenous, we exclude the very few individuals who move during our observation period. Note that Covid-19 restrictions made moving virtually impossible during the strict lockdown period in Germany. Equation 1 thus simplifies to:

[7] Note that we cannot control for time-varying observables X_{it}, given that most of the covariates in the SOEP are not available in its Covid-19 wave (which asks a smaller Covid-19-specific set of questions).

[8] Our results remain similar when using more pre-treatment years, e.g. from 2016 onwards (available upon request).

$$y_{it} = \alpha + \beta_1 Green_s \times Post + \beta_3 Post + t_m + t_{dw} + u_i + \epsilon_{it} \tag{2}$$

where $Green_s$, c, and t_y drop out due to collinearity. Our model is estimated using OLS, with robust standard errors clustered at the interview date level, which is justified by the daily variation in exposure to the pandemic, e.g. via changes in positive cases and media reporting over time. Our results are robust to clustering at the household level. As treatment occurs at a single point in time, we avoid bias due to treatment effect heterogeneity and dynamics found in two-way fixed-effects models with staggered designs, see Goodman-Bacon (2021) and de Chaisemartin and D'Haultfœuille (2020); Athey and Imbens (2022); Borusyak et al. (2022).

Identifying Assumptions. We are interested in β_1, which is the average treatment effect on the treated (ATT) if two identifying assumptions are satisfied:

1. *Exogeneity of Treatment.* Allocation to our treatment or control group is as good as random, conditional on temporal fixed effects $T = \{t_m, t_{dw}\}$ and individual fixed effects u_i, i.e. $Green_s \perp 0, 1 | T, u_i$.

2. *Common Trend.* In the hypothetical absence of treatment, our treatment group would have followed the same time trend in outcomes as our control group, conditional on temporal fixed effects $T = \{t_m, t_{dw}\}$ and individual fixed effects u_i, i.e. $E[y_t - y_{t-1} | T, u_i, Green_s = 1] = E[y_t - y_{t-1} | T, u_i, Green_s = 0]$.

Regarding *exogeneity of treatment*, Covid-19 and ensuing restrictions were sudden, unexpected, and binding, affecting most individuals in a similar way. They are thus largely exogenous to any single individual. By construction, our sample is relatively homogeneous, in that it is restricted to all major German cities and metropolitan areas with more than 100,000 inhabitants. By including individual fixed effects and excluding movers, our model estimates *within-individual changes* in *the same city*. This eliminates any time-invariant (observable or unobservable) confounders at the individual or city level (e.g. individual preferences, city-specific spatial distributions of urban land use) that may explain selection into the proximity to a green space. It also reduces concern that individuals may have been exposed to different Covid-19 restrictions in different federal states after the strict lockdown period in Germany had ended, i.e. when federal states were given more autonomy in certain areas of life (though restrictions remained broadly equal).

In addition, to make individuals in our treatment and control group more comparable, we apply two types of matching. First, we apply *propensity-score matching*, which matches treated individuals to their nearest control neighbours based on pre-treatment observables in 2019.[9] We then include only matched pairs in our model. Second, we use *spatial matching*, restricting control individuals to those who have a green space outside the treatment radius of 1,000 metres but inside a (matching) radius of 1,500 metres. The choice of this matching radius is guided agnostically by achieving roughly equal areas.[10] We perform both types of matching separately for green spaces with different sizes.[11] Under propensity-score matching, our estimation sample for green spaces with a minimum size of $s = 15$ hectares includes 10,336 observations, 4,040 of which belong to the treatment and 6,296 to the control group. Under spatial matching, it includes 5,602 observations (4,040 in the treatment and 1,562 in the control group). Without any matching (which produces similar though slightly attenuated estimates), we have 13,207 observations (5,099 in the treatment and 8,108 in the control group). As propensity-score matching is likely more precise when it comes to netting out potential differences between groups, it is our preferred specification.

Regarding *common trend*, we first look at level differences in pre-treatment observables between treatment and control. Appendix Table A2 presents scale-free normalised differences between both groups for our preferred specification, i.e. propensity-score matching.[12] Treatment here is defined as having a green space with a minimum size of $s = 15$ hectares within a treatment radius of 1,000 metres. According to Imbens and Wooldridge (2009), a normalised difference greater than 0.25 suggests covariate imbalance. As seen, we do not find any imbalances. This also reduces concern that individuals in our treatment group may be hit differently by the pandemic, e.g. because they may be better shielded due to higher income.

Next, we look at changes in overall life satisfaction as our overall welfare measure over

[9] We match on demographics (i.e. dummies for age in ten-year brackets and log annual net household income in quintiles) and housing conditions (i.e. dummies for dwelling type, ownership, log annual gross rent in quintiles, and area type). The choice of observables is guided by relative covariate imbalance in 2019.

[10] 3.1 million square kilometres versus 3.9.

[11] A third option is to combine both types of matching. This produces similar results, which are available upon request.

[12] Contrary to simple differences, normalised differences are independent of sample size, and hence more informative about the degree of covariate imbalance, if any, between relatively large groups (Imbens and Rubin, 2015). The normalised difference is calculated as $\Delta x = (\bar{x_t} - \bar{x_c})/\sqrt{(\sigma_t^2 + \sigma_c^2)}$, where $\bar{x_t}$ and $\bar{x_c}$ is the sample mean of variable x in the treatment and control group, respectively. σ^2 denotes the respective variance (Imbens and Wooldridge, 2009; Imbens and Rubin, 2015).

time. Appendix Figure A1 plots mean life satisfaction in the pre-treatment years 2016 to 2019 and the Covid-19 period by treatment status. While mean life satisfaction is slightly (though not statistically significantly) higher in our control group, both groups show similar changes up until the Covid-19 period, after which they diverge, suggesting a common trend while giving a first glance at our results. Note that level differences between our treatment and control group in the pre-treatment years are no threat to identification, as we are only interested in *relative changes* over time.

3 Results

3.1 Non-Parametric Results

Figure 2 plots the difference in overall life satisfaction as our overall welfare measure (averaged by interview date) between the Covid-19 period and 2019, between our treatment and control group, using our preferred specification, i.e. propensity-score matching. Treatment is defined as having a green space with a minimum size of $s = 15$ hectares within a treatment radius of 1,000 metres. The vertical line illustrates the end of the strict lockdown period in Germany (May 4, 2020). Overlaying each scatter plot are non-parametric Epanechnikov-kernel-weighted local quadratic polynomials. The figure thus provides a non-parametric, graphical illustration of our spatial difference-in-differences design in Equation 2.

Figure 2 about here

As seen, our treatment group showed an increase in life satisfaction in the Covid-19 period relative to 2019, compared to our control group.

3.2 Regression Results

Wellbeing. We now turn to parametric estimates of the relative differences in Figure 2. Table 1 presents the estimates of our spatial difference-in-differences design in Equation 2: Columns 1 to 4 show estimates from our preferred specification, i.e. propensity-score matching, Columns 5 to 8 from our alternative specification, i.e. spatial matching. Each column here is a separate estimation of Equation 2 for green spaces with a different minimum size, i.e. $s = \{5, 10, 15, 20\}$ hectares, respectively.

Table 1 about here

We find that having a green space within a treatment radius of 1,000 metres during the Covid-19 period had a significant positive effect on overall life satisfaction as our overall welfare measure. There is a concave relationship: life satisfaction is increasing at a decreasing rate in the minimum size of green spaces (up to a threshold of 15 hectares), under propensity-score matching from about 0.12 points on a zero-to-ten Likert scale (0.07 σ) for $s = 5$ hectares to about 0.22 points (0.13 σ) for $s = 15$ hectares. We observe similar impacts under spatial matching. However, whereas all effects are significant under propensity-score matching, only the effects for $s = \{5, 10, 15\}$ hectares reach statistical significance at conventional levels under spatial matching (where estimates are less precise). For green spaces with a large minimum size of $s = 20$ hectares, we generally find weaker impacts than for those with a minimum size of $s = 15$ hectares. A reason may be that green spaces of 20 hectares or greater do not tend to be located in dense inner cities but rather at the urban fringes, where public open areas like grassland or forests are already more abundant.

Appendix Table A3 looks at the intensive margin using our preferred specification, by estimating the effect of the *number* of green spaces of different minimum sizes (one, more than one, or more than two) on life satisfaction. In line with our estimates of the extensive margin, there is a concave relationship: life satisfaction is increasing at a decreasing rate in the number of green spaces of a particular minimum size, with a clear pattern that larger green spaces have stronger impacts. Note, however, that the treatment group reduces sharply the larger the number of green spaces of a particular minimum size, especially for larger sizes. Instead of minimum sizes, Appendix Table A4 looks at patch sizes (from 5 to 10, 5 to 15, or 5 to 20 hectares; 10 to 15 or 10 to 20 hectares; or 15 to 20 hectares). In line with our previous estimates, we find that larger green spaces have stronger impacts, with effect sizes between 0.22 and 0.52 points on a zero-to-ten Likert scale (0.07 and 32 σ) for green spaces between $s = 15$ and $s = 20$ hectares.

Compared to previous studies (cf. Bertram and Rehdanz, 2015; Krekel et al., 2016), effect sizes are large: living close to a green space with a minimum size of $s = 15$ hectares, which yields the strongest effects, increased life satisfaction by about 0.22 points on a zero-to-ten Likert scale (0.13 σ) during the Covid-19 period.[13] Although this may be in part due to

[13] Appendix Table A12 provides a literature review of effect sizes of green spaces during normal times.

methodological differences in the literature, it is most likely due to exogenous variations in their use values brought about by Covid-19 restrictions, when having a park close to home suddenly became very valuable.[14]

Mental Health. To explore potential mechanisms, we look at mental health, which has been shown to be positively correlated with the availability and use of green spaces (cf. Bratman et al., 2019). Arguably, these correlations should become stronger in times of heightened use values. Table 2 presents the estimates of our spatial difference-in-differences design in Equation 2 for mental health from the PHQ-4 and loneliness from the UCL 3-Items Loneliness Scale, using our preferred specification, i.e. propensity-score matching, and a green space with a minimum size of $s = 15$ hectares, for which we consistently found effects across specifications. Appendix Table A5 replicates our analysis for spatial matching: our results remain similar.

Table 2 about here

In line with our findings for wellbeing, we find that having a green space within a treatment radius of 1,000 metres during the Covid-19 period had significant positive effects on mental health. In particular, it reduced symptoms of anxiety, by decreasing feelings of nervousness and worry by about 0.08 and 0.04 points on a zero-to-three Likert scale (0.11 and 0.06 σ), as well as symptoms of depression, by decreasing feelings of depression by about 0.07 points (0.10 σ), in the two weeks prior to respondents' interviews. Overall, respondents' summary scores of mental ill health (the sum of the individual items) decreased by about 0.2 points on a zero-to-12 scale (0.09 σ), which is similar though somewhat smaller than the effect size for overall life satisfaction as our overall welfare measure. Instead of using the full support, Appendix Table A6 estimates linear probability models, dichotomising each mental health outcome such that zero denotes no and one or more denotes (any frequency) of symptoms, and the loneliness outcome such that three to five denotes no and six to nine denotes symptoms of loneliness (cf. Steptoe et al., 2013). When doing so, our results remain similar, with the exception that feelings of nervousness turn out insignificant and feelings of no interest significant.

Amongst others, green spaces are often seen as places for social interaction, and Covid-19 restrictions in Germany allowed residents to meet a maximum of one person outside of their

[14] In unreported regressions, we found little evidence for heterogeneous effects by dwelling type (whether a respondent lives in a large apartment building or a high rise) or dwelling characteristics (whether a respondent has a balcony or a garden). These results are available upon request.

household. In line with this, we find suggestive evidence for reduced loneliness, by about 0.12 points on a three-to-nine scale (0.08 σ), though statistical significance is at the 10% level only.[15] Under spatial matching, loneliness turns out insignificant (cf. Appendix Table A5).

As with life satisfaction, Appendix Table A7 looks at the intensive margin, by estimating the effect of the *number* of green spaces of different minimum sizes on mental health, proxied by respondents' summary scores of mental ill health to reduce dimensionality. As before, there is a concave relationship: mental health is increasing at a decreasing rate in the number of green spaces of a particular minimum size, with an even clearer pattern than for life satisfaction that larger green spaces have stronger impacts. As to patch sizes, Appendix Table A8 shows that, similar to life satisfaction, larger green spaces have stronger impacts on mental health, with effect sizes between 0.54 and 0.67 points on a zero-to-12 scale (0.23 and 29 σ) for green spaces between $s = 15$ and $s = 20$ hectares.

4 Robustness Checks

Next, we conduct several robustness checks based on our preferred specification, i.e. propensity-score matching, and a green space with a minimum size of $s = 15$ hectares. These are presented in Table 3.

Table 3 about here

4.1 No Matching and Extended Controls

So far, we matched our treatment and control group based on observables in the pre-treatment year (2019). In Table 3 Column 1, we do not match both groups. As they become less comparable, we expect our estimate to be attenuated downwards. Indeed, our estimate decreases slightly, from about 0.22 (cf. Table 1 Column 3) to about 0.19 points on a zero-to-ten Likert scale for overall life satisfaction as our overall welfare measure, while continuing to be significant at the 1% level. The fact that our results remain similar regardless of whether we apply matching or not suggests that omitted variable bias is, if anything, only a minor concern.

One might argue that weather could be a potential omitted variable affecting both life satisfaction and use values of green spaces – bias could be in either direction, depending on

[15] Unfortunately, the UCLA 3-Items Loneliness Scale was only irregularly included in the SOEP in the years prior to Covid-19, which is why we had to include more pre-treatment years, up until 2016.

conditions at the time. To be clear, weather is a threat to identification only if it affected our treatment group systematically differently than our control group, which is unlikely (especially in our spatial-matching specification). We nevertheless obtain data on daily average temperature, precipitation, and cloud cover at the city level from the German Meteorological Office (*Deutscher Wetterdienst*) and include them as extended controls. As Table 3 Column 2 shows, our estimate increases slightly, from about 0.22 to about 0.23 points. It continues to be significant at the 1% level.

4.2 Strict Lockdown Period

We exploit exogenous variations in use values of green spaces brought about by Covid-19 restrictions to estimate causal effects. We expect use values to be higher during times of harsher restrictions. In line with our expectation, when restricting our treatment period to the strict lockdown period in Germany (March 22 to May 4, 2020) in Table 3 Column 3, our estimate increases from about 0.22 (cf. Table 1 Column 3) to about 0.24 points for life satisfaction on a zero-to-ten Likert scale. It is highly significant at the 1% level. This finding also reduces concern that our results may be driven by different Covid-19 restrictions in different federal states after the strict lockdown period had ended (though restrictions remained broadly equal). Finally, it reduces concern that our results may be driven by facilities that may be located within the boundaries of green spaces, such as sports and leisure facilities, which remained closed during the strict lockdown period. In any case, Appendix Table A11 shows that raw correlations between green spaces and other types of urban land use in our estimation sample are weak.

4.3 Estimation

We applied a linear model for cardinal data to an ordinal outcome, life satisfaction. Empirically, it has been shown that both linear and ordered probit or logit models produce similar estimates (cf. Ferrer-i Carbonell and Frijters, 2004). We nevertheless re-estimate our model using a fixed-effects ordered logit model, using the more recent Blow-Up-and-Cluster (BUC-τ) estimator (Baetschmann, 2012; Baetschmann et al., 2015). Table 3 Column 4 presents our estimate as an odds-ratio: having a green space with a minimum size of $s = 15$ hectares within a treatment radius of 1,000 metres during the Covid-19 period continues to have a significant and strong positive effect on life satisfaction at the 5% level. In particular, it increased the probability of being in a higher category of life satisfaction (a one-point increase on the zero-to-ten Likert scale) by about 30%.

4.4 Placebo and Confirmation Tests

We conduct two placebo tests: first, we re-estimate our model for the placebo period 2018 to 2019, i.e. the years before the Covid-19 pandemic. We do not expect to detect an effect, as there were no exogenous variations in use values of green spaces during this period. Second, we re-estimate our model for the placebo outcome log annual net household income. Again, we do not expect to detect an effect, as exogenous variations in use values of green spaces should have no direct effect on household income. As Table 3 Columns 5 and 6 show, we indeed do not detect any effects in either test. The latter test is also supporting evidence that our identified effects are driven by exogenous variations in use values of green spaces brought about by Covid-19 restrictions, rather than different economic impacts of Covid-19 on our treatment and control group.

We further re-estimate our model for health and sleep satisfaction as confirmation outcomes.[16] If green spaces reduced symptoms of anxiety, by decreasing feelings of nervousness and worry, as well as symptoms of depression, one might expect this to translate into higher health and sleep satisfaction. As Table 3 Columns 7 and 8 show, we indeed find that having a green space with a minimum size of $s = 15$ hectares within a treatment radius of 1,000 metres during the Covid-19 period had significant and strong positive effects on both outcomes at the 5% level.

4.5 Further Robustness Checks

Selection on Unobservables and Coefficient Stability. Implicit in our argument that our results remain similar regardless of whether we apply matching or not is that coefficient movements are informative about relative omitted variable bias due to unobservables. Yet, this is only the case if observables are correlated with unobservables. In Appendix Section A, we follow the argument by Oster (2019) that both coefficient movements *and* R Squared movements need to be taken into account to make informative statements about the degree

[16]These outcomes are obtained from single-item eleven-point Likert-scale questions asking: "How satisfied are you right now with the following areas of your life?", followed by "Your Health" and "Your Sleep". Responses range from 0 ("Completely dissatisfied") to 10 ("Completely satisfied").

of selection on unobservables. In particular, we implement a bounding analysis based on the maximum attainable R Squared and the degree of selection on unobservables relative to observables. We find that, in our case, selection on unobservables is considerably *less* important than selection on observables and obtain an interval of $[0.15; 0.22]$ for β_1. As the lower bound excludes zero at the 5% significance level, selection on unobservables and resulting omitted variable bias is, if anything, only a minor concern.

Multiple Hypotheses Testing. In Appendix Section B, we implement the stepdown multiple testing procedure by Romano and Wolf (2005b,a) in our preferred specification, i.e. propensity-score matching, for life satisfaction and green spaces with a minimum size of $s = \{5, 10, 15, 20\}$ hectares (Table 1 Columns 1 to 4) and for mental health (including loneliness) and a green space with a minimum size of $s = 15$ hectares (Table 2). We find that our stepdown-adjusted P-values continue to show statistical significance at conventional levels for life satisfaction and green spaces with a minimum size of $s = \{10, 15\}$ hectares as well as respondents' summary scores of mental ill health and their feelings of nervousness and depression.

5 Social Welfare Implications

Finally, we put our findings into perspective, by calculating the compensating surplus for having a nearby green space during the Covid-19 period. We base our calculation on our preferred specification, i.e. propensity-score matching, and a green space with a minimum size of $s = 15$ hectares. Calculations for other minimum or patch sizes can be performed analogously. We then discuss the implications of our results for normal times.

The causal return to overall life satisfaction as our overall welfare measure from a nearby green space is about 0.15 points on a zero-to-ten Likert scale (cf. Table 1 Column 3). The causal return to life satisfaction from log annual gross household income is about 0.35 points (Lindqvist et al., 2020).[17] As there is little difference in our estimates between the strict lockdown period in Germany (cf. Table 1 Column 3) and the ensuing period of eased restrictions (cf. Table 3 Column 3), one can assume that the return to life satisfaction from a nearby

[17] Lindqvist et al. (2020) exploit exogenous lottery wins to estimate the causal effect of household income on life satisfaction in Sweden, with auto-enrolment into lotteries. To our knowledge, the authors' income coefficient is the most robust to date.

green space remains similar for as long as restrictions are in place. The median annual gross household income in our estimation sample is about €36,800 ($38,640). The compensating surplus (CS) can be calculated as:

$$CS = (1 - exp(\frac{-\beta_1}{\beta_Y})) \times Y \tag{3}$$

where β_1 is the causal effect of a nearby green space on life satisfaction, β_Y is the causal effect of log annual gross household income on life satisfaction, and Y is the median annual gross household income.

We arrive at about €15,460 ($16,080) per household per year.[18] With, on average, 2.6 individuals per household (cf. Appendix Table A1), this yields about €5,950 ($6,190) per individual per year – a large figure for a willingness-to-pay estimate. That is, an individual who does *not* have a nearby green space would need a compensation of about €5,950 ($6,190) per year to achieve the same level of life satisfaction as an individual who does, during Covid-19 (or similar) restrictions.

Covid-19 restrictions are, of course, exceptional. However, we can adopt an actuarial perspective to derive a more useful, lower-bound value for normal times. In particular, it is estimated that the annual probability of a pandemic with similar impact as Covid-19 is about 2% (Marani et al., 2021).[19] Adjusting our compensating surplus accordingly, an individual who does *not* have a nearby green space would be *expected* to need a compensation of about €119 ($124) per year to achieve the same level of life satisfaction as an individual who does, in any given year. This is a lower bound, as these expected benefits are *in addition* to any baseline benefits that green spaces may already provide during normal times.

About 63% of individuals in our estimation sample have a nearby green space. At about 25.5 million people in Germany living in cities and metropolitan areas with more than 100,000 inhabitants, this makes about 16.1 million individuals. Given this prevalence and the calcu-

[18] We converted € into $ using an exchange rate of 1:1.04 as of February 5, 2025.

[19] To arrive at this probability, Marani et al. (2021) use records of novel disease outbreaks over the past 350 years. Two percent is at the lower end of their 95% confidence interval. The authors find that this probability is, in fact, increasing rapidly, such that the probability of novel disease outbreaks may grow up to threefold in coming decades. Alternatively, using catastrophe risk modelling on a historical database of 2,600 disease outbreaks and epidemics since the 1918 Spanish Flu pandemic, and hundreds of thousands of simulated event catalogues, Microbiota – a US firm focused on tracking infectious disease risks and outbreaks – estimates the probability to be between 2.5% and 3.3% (Cheney, 2021). We take 2% as a lower bound to be conservative.

lated compensating surplus, green spaces added substantial benefits during the period studied, and are likely to add significant benefits during normal times too.

6 Discussion and Conclusion

We set out to answer three questions: was there a positive causal effect of living close to a green space on residents' wellbeing during the Covid-19 period? If so, what were the potential mechanisms? And, finally, what were, and are, the implications for social welfare, if any?

We found that having a nearby green space during the Covid-19 period had a significant positive effect on overall life satisfaction as our overall welfare measure. There was a concave relationship: life satisfaction was increasing at a decreasing rate in the minimum size of green spaces, although large green spaces had weaker impacts or turned out statistically insignificant, most likely because they tend to be located at the urban fringes, where public open areas like grassland or forests are already more abundant. A similar picture arose for the number of patches of a particular minimum size in the intensive margin. Finally, we found that larger green spaces had stronger impacts.

When it comes to potential mechanisms, we found that residents living close to a green space had significantly better mental health, and in particular, had reduced symptoms of anxiety (feelings of nervousness and worry) as well as symptoms of depression (feelings of depression) in the two weeks prior to respondents' interviews. We also found suggestive evidence for reduced loneliness. These findings resonate well with previous correlational evidence on the relationship between green spaces and health and wellbeing in the literature, in general and when it comes to their role as buffers against stressful life events (Leslie and Cerin, 2008; Maas et al., 2008; Richardson et al., 2013; Houlden et al., 2018; Geneshka et al., 2021; Jiminez et al., 2021).

We then looked at social welfare implications, by calculating the compensating surplus for having a nearby green space during the Covid-19 period. We showed that an individual who did *not* have a nearby green space would need a compensation of about €5,950 ($6,190) per year to achieve the same level of life satisfaction as an individual who did. Adjusting our compensating surplus by the annual probability of a pandemic with similar impact as Covid-19, we also derived a more useful, lower-bound value for normal times: an *expected* compensation of about €119 ($124) per individual per year. Given the number of people around green spaces, especially in dense inner cities, this points towards substantial benefits, during the period studied and likely during normal times too.

Our findings are based on a spatial difference-in-differences design, using a large-scale, nationally representative household panel with precise geographical coordinates of households linked to satellite images of green spaces with nationwide coverage. Our results are robust to different model specifications, sample restrictions, and various placebo and confirmation tests. They also withstand a correction for multiple hypotheses testing.

Although most people consider parks important for their quality of life, the lack of systematic causal evidence on their health and wellbeing benefits means that they may not be (adequately) accounted for in social welfare analyses. Our approach, which exploited exogenous variations in their use values, can be used to quantify the benefits of other public goods too, in particular those that have similar identification issues. A promising avenue for future research specifically on green infrastructure would be to look beyond average effects, and study which quality and spatial distribution of green spaces yield the strongest benefits.

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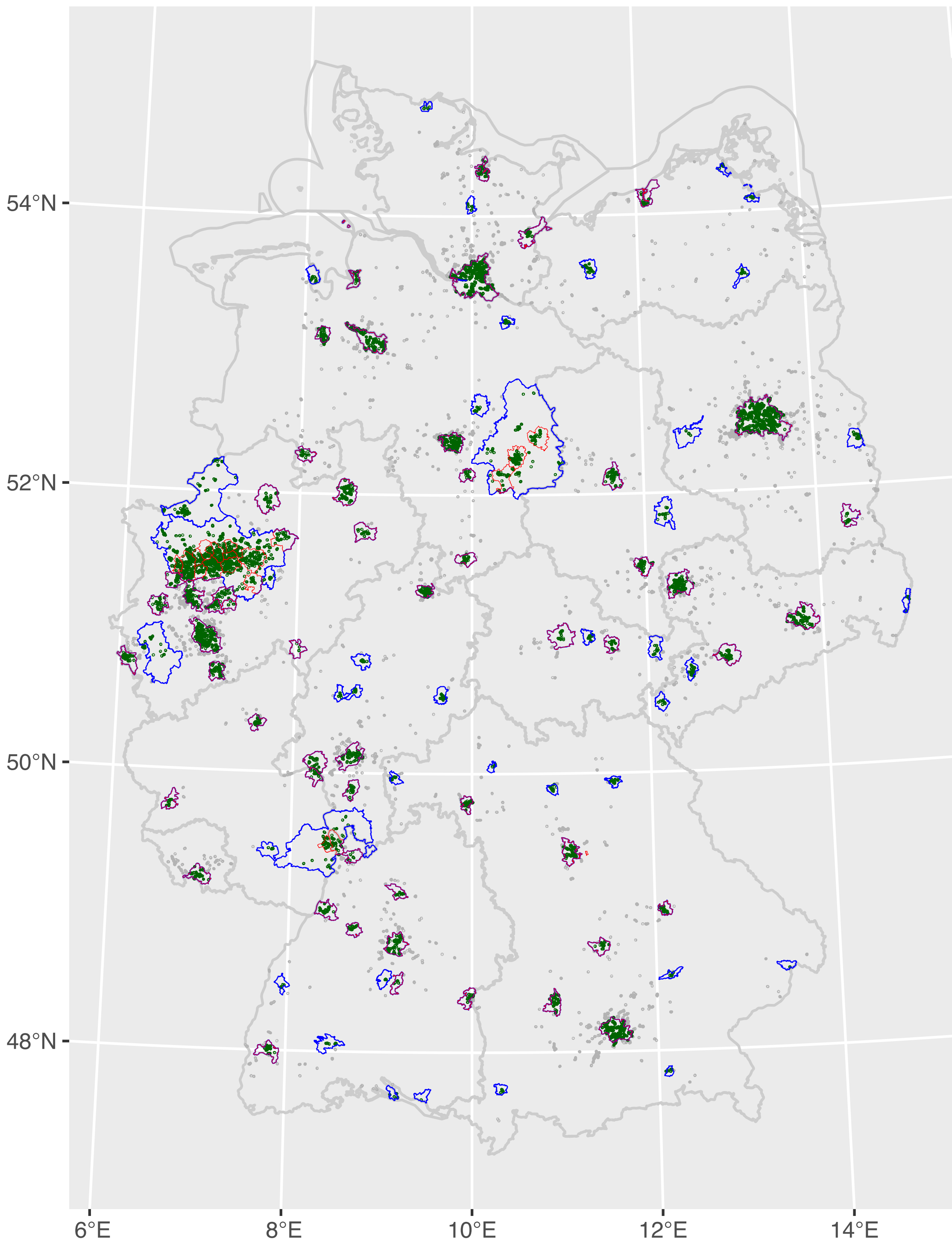
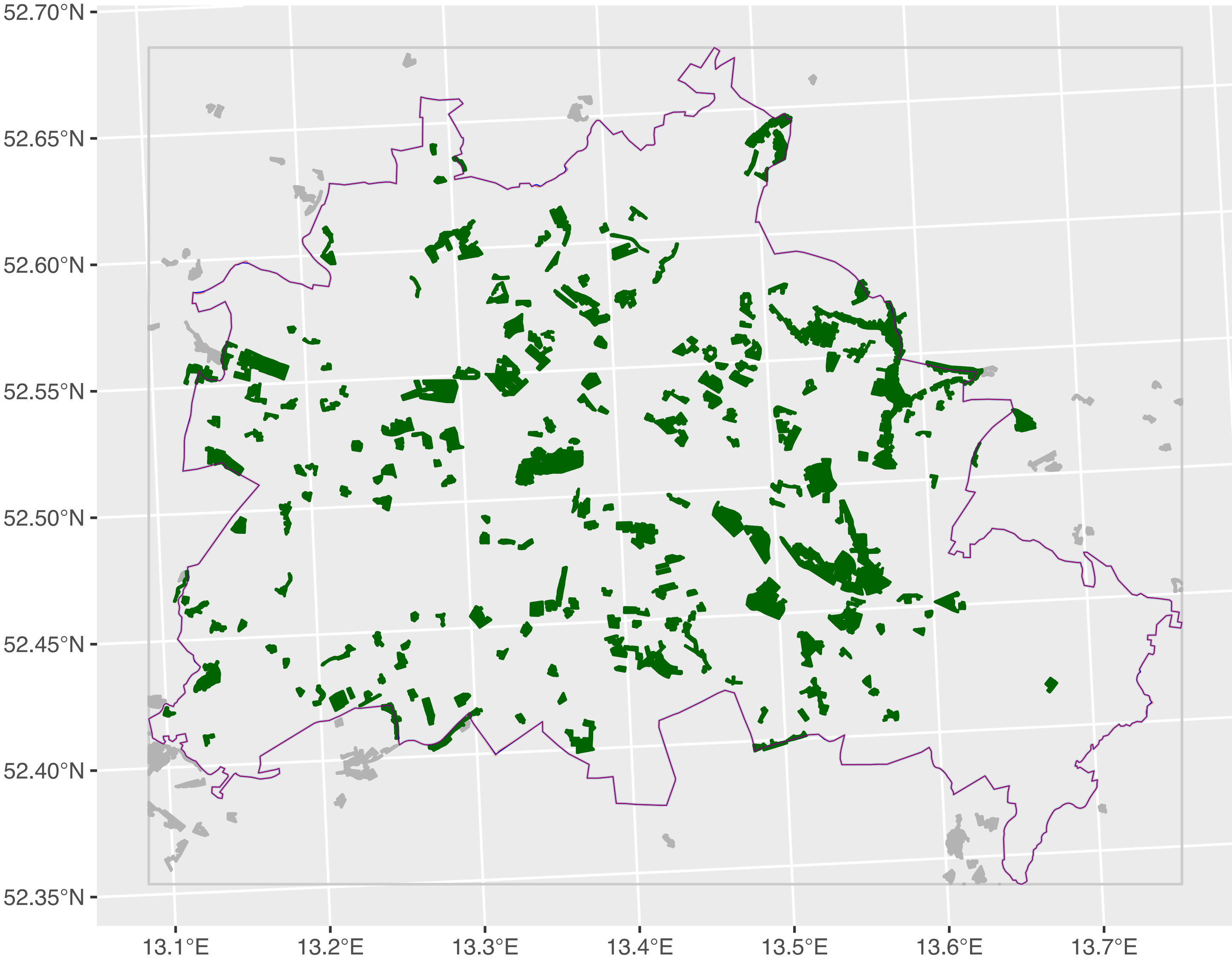
Figure 1A: Spatial Distribution of Green Spaces in Germany in Estimation Sample



Notes: The map shows the spatial distribution of green spaces in Germany in our estimation sample. The gray lines denote the federal states in Germany, the blue lines the core regions covered by the European Urban Atlas, and the red lines the German cities and metropolitan areas with more than 100,000 inhabitants. The gray dots denote green spaces with a minimum size of $s = 5$ *hectares covered by the European Urban Atlas, the green dots green spaces included in our estimation sample.*

Sources: EUA, 2018; own calculations.

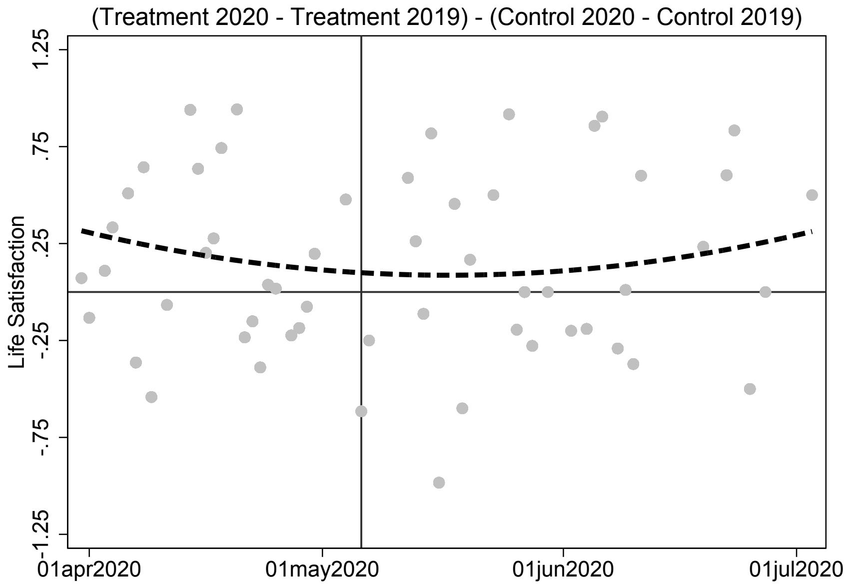
Figure 1B: Spatial Distribution of Green Spaces in Berlin, Germany, in Estimation Sample



Notes: The map shows the spatial distribution of green spaces in Berlin, Germany, in our estimation sample. The red line denotes the administrative boundaries of Berlin, the gray dots green spaces with a minimum size of $s = 5$ hectares covered by the European Urban Atlas, and the green dots green spaces included in our estimation sample.

Sources: EUA, 2018; own calculations.

Figure 2: Difference-in-Differences in Life Satisfaction Between Treated and Controlled, 2020-2019



Notes: Scatter plot shows the difference-in-differences in raw responses for *life satisfaction* (measured on a zero-to-ten Likert scale, whereby zero denotes "completely dissatisfied" and ten "completely satisfied") between the Covid-19 period (2020) and the pre-treatment year 2019, averaged by interview date, between the treated and controlled, after propensity-score matching on observables (without further manipulation). The propensity-score matching matches individuals in the treatment group to their nearest neighbours in the control group based on pre-treatment observables, including demographics (i.e. dummies for age in ten-year brackets and log annual net household income in quintiles) and housing conditions (i.e. dummies for dwelling type, ownership, log annual gross rent in quintiles, and area type). Treatment is defined as being located inside a treatment radius of 1,000 metres to a green space with a minimum size of $s = 15$ hectares. The vertical line illustrates the end of the strict lockdown period in Germany (May 4, 2020). In addition, each panel shows non-parametric Epanechnikov-kernel-weighted local quadratic polynomials. The SOEP Covid-19 wave ran from March 31 to July 4, 2020.

Sources: SOEP, 2019 to 2020; EUA, 2018; own calculations.

Table 1: Impacts of Nearby Green Spaces With Various Minimum Sizes on Life Satisfaction

	Life Satisfaction (0-10)							
	Propensity-Score Matching				**Spatial Matching**			
	≥ 5 Hectares	**≥ 10 Hectares**	**≥ 15 Hectares**	**≥ 20 Hectares**	**≥ 5 Hectares**	**≥ 10 Hectares**	**≥ 15 Hectares**	**≥ 20 Hectares**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Green$_5$ x 2020	**0.120****				**0.125***			
	(0.054)				**(0.065)**			
Green$_{10}$ x 2020		**0.150*****				**0.166****		
		(0.046)				**(0.068)**		
Green$_{15}$ x 2020			**0.218*****				**0.185****	
			(0.050)				**(0.076)**	
Green$_{20}$ x 2020				**0.109****				**0.130**
				(0.054)				**(0.081)**
2020	-4.280***	-5.921***	-5.967***	-4.145***	-1.602*	-2.265**	-0.766	-3.338***
	(0.280)	(0.443)	(0.432)	(0.282)	(0.844)	(1.017)	(1.354)	(0.257)
Propensity-Score Matching	Yes	Yes	Yes	Yes	No	No	No	No
Spatial Matching	No	No	No	No	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	7.478	7.478	7.478	7.478	7.476	7.484	7.474	7.483
σ	1.629	1.629	1.629	1.629	1.632	1.613	1.627	1.627
N	10,336	10,336	10,336	10,336	9,192	6,993	5,602	4,842
N Treated	7,632	5,431	4,040	3,280	7,632	5,431	4,040	3,280
N Controlled	2,704	4,905	6,296	7,056	1,560	1,562	1,562	1,562
Within R Squared	0.175	0.176	0.178	0.175	0.190	0.236	0.282	0.320

Robust standard errors clustered at interview date level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Treatment is defined as being located inside a treatment radius of 1,000 metres to a green space $Green_s$ with a minimum size of s hectares. Each column is a separate estimation of Equation 2. The propensity-score matching specification matches individuals in the treatment group to their nearest neighbours in the control group based on pre-treatment observables, including demographics (i.e. dummies for age in ten-year brackets and log annual net household income in quintiles) and housing conditions (i.e. dummies for dwelling type, ownership, log annual gross rent in quintiles, and area type). The spatial-matching specification restricts individuals in the control group to those who are located outside the treatment radius of 1,000 metres but inside a matching radius of 1,500 metres to a green space. Both types of matching are performed separately for green spaces with minimum size $s = \{5, 10, 15, 20\}$ hectares. See Section 2.1 for a detailed description of the data and Section 2.2 for the model.
Sources: SOEP, 2019 to 2020; EUA, 2018; own calculations.

Table 2: Impact of Nearby Green Space With Minimum Size of 15 Hectares on Mental Health and Loneliness (Propensity-Score Matching)

	Patient Health Questionnaire-4 (PHQ-4)					UCLA
		Anxiety		Depression		3-Items
	Summary Scale (0-12)	**Nervous (0-3)**	**Worried (0-3)**	**Depressed (0-3)**	**No Interest (0-3)**	**Loneliness Scale (3-9)**
	(1)	(4)	(5)	(3)	(2)	(6)
$Green_{15}$ x 2020	**-0.219*** **	**-0.080*** **	**-0.044** **	**-0.068*** **	**-0.027**	**-0.120* **
	(0.080)	**(0.026)**	**(0.022)**	**(0.025)**	**(0.033)**	**(0.064)**
2020	10.637***	2.563***	3.664***	1.767***	2.643***	-2.190***
	(0.471)	(0.246)	(0.275)	(0.283)	(0.252)	(0.816)
Propensity-Score Matching	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean	2.036	0.566	0.321	0.451	0.698	5.562
σ	2.328	0.746	0.655	0.715	0.795	1.590
N	10,336	10,336	10,336	10,336	10,336	11,711
N Treated	4,040	4,040	4,040	4,040	4,040	4,510
N Controlled	6,296	6,296	6,296	6,296	6,296	7,201
Within R Squared	0.219	0.179	0.185	0.179	0.218	0.182

Robust standard errors clustered at interview date level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Treatment is defined as being located inside a treatment radius of 1,000 metres to a green space $Green_s$ with a minimum size of $s = 15$ hectares. Each column is a separate estimation of Equation 2. The propensity-score matching specification matches individuals in the treatment group to their nearest neighbours in the control group based on pre-treatment observables, including demographics (i.e. dummies for age in ten-year brackets and log annual net household income in quintiles) and housing conditions (i.e. dummies for dwelling type, ownership, log annual gross rent in quintiles, and area type). See Section 2.1 for a detailed description of the data and Section 2.2 for the model. *Sources:* SOEP, 2019 to 2020; EUA, 2018; own calculations.

Table 3: Robustness Checks

	Life Satisfaction (0-10)			
	No Matching	**Meteorological Controls**	**Strict Lockdown Period**	**FE Ordered Logit (Odds Ratio)**
	(1)	(2)	(3)	(4)
Green$_{15}$ x 2020	**0.186***** **(0.050)**	**0.226***** **(0.063)**		**1.300**** **(0.146)**
2020	-2.771*** (0.261)	-4.751*** (0.513)		
Green$_{15}$ x Lockdown			**0.242***** **(0.066)**	
Lockdown			-0.246 (0.486)	
Propensity-Score Matching	No	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	No
Day-of-Week Fixed Effects	Yes	Yes	Yes	No
Individual Fixed Effects	Yes	Yes	Yes	Yes
N	13,207	10,336	10,136	3,074
N Treated	5,099	4,040	3,961	1,204
N Controlled	8,108	6,296	6,175	1,870
Within / Pseudo R Squared	0.156	0.189	0.197	0.014

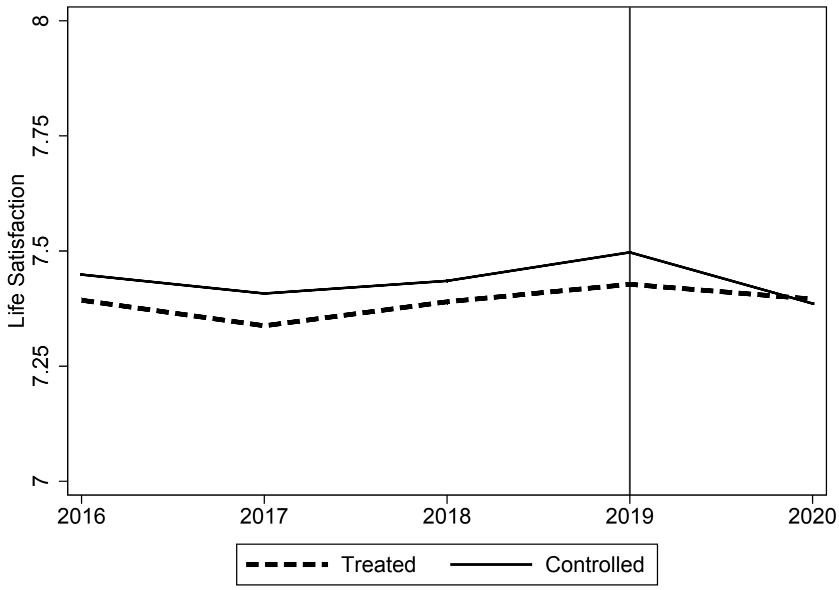
	Placebo Tests		Confirmation Tests	
	Life Satisfaction (0-10)	**Log Household Income**	**Health Satisfaction (0-10)**	**Sleep Satisfaction (0-10)**
	(5)	(6)	(7)	(8)
Green$_{15}$ x 2020		**-0.001** **(0.005)**	**0.146**** **(0.065)**	**0.157**** **(0.064)**
2020		-0.089 (0.081)	-1.946*** (0.478)	-5.306*** (0.620)
Green$_{15}$ x 2019	**-0.017** **(0.024)**			
2019	-0.792 (0.733)			
Propensity-Score Matching	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	No
Day-of-Week Fixed Effects	Yes	Yes	Yes	No
Individual Fixed Effects	Yes	Yes	Yes	Yes
N	18,237	10,336	10,336	10,336
N Treated	7,114	4,040	4,040	4,040
N Controlled	11,123	6,296	6,296	6,296
Within R Squared	0.080	0.203	0.233	0.177

Robust standard errors clustered at interview date level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Treatment is defined as being located inside a treatment radius of 1,000 metres to a green space $Green_s$ with a minimum size of $s = 15$ hectares. Each column is a separate estimation of Equation 2. Column 1 does not perform any matching (neither propensity-score nor spatial matching). In all other columns, propensity-score matching matches individuals in the treatment group to their nearest neighbours in the control group based on pre-treatment observables, including demographics (i.e. dummies for age in ten-year brackets and log annual net household income in quintiles) and housing conditions (i.e. dummies for dwelling type, ownership, log annual gross rent in quintiles, and area type). Column 2 additionally controls for meteorological conditions, including daily average temperature, precipitation, and cloud cover at the city level. Column 3 restricts the treatment period to the strict lockdown period in Germany (March 22 to May 4, 2020). Column 4 uses, instead of a linear model, an ordered logit model, i.e. the Blow-Up-and-Cluster (BUC-τ) estimator by Baetschmann (2012); Baetschmann et al. (2015). Columns 5 and 6 conduct placebo tests, by estimating our preferred specification for the years 2018 to 2019 instead of 2019 to 2020 (Column 5) and by replacing life satisfaction with log annual net household income as outcome (Column 6). Columns 7 and 8 conduct confirmation tests, by replacing life satisfaction with health and sleep satisfaction as outcomes. See Section 2.1 for a detailed description of the data and Section 2.2 for the model.
Sources: SOEP, 2018 to 2020; EUA, 2018; own calculations.

Appendix

Figure A1: Common Trend Between Treated and Controlled, 2016 to 2020



Notes: Scatter plot shows levels in raw responses for *life satisfaction* (measured on a zero-to-ten Likert scale, whereby zero denotes “completely dissatisfied” and ten “completely satisfied”) from the pre-treatment year 2016 to the Covid-19 period (2020), averaged by interview date, separately for the treated and controlled, after propensity-score matching on observables (without further manipulation). The propensity-score matching matches individuals in the treatment group to their nearest neighbours in the control group based on pre-treatment observables, including demographics (i.e. dummies for age in ten-year brackets and log annual net household income in quintiles) and housing conditions (i.e. dummies for dwelling type, ownership, log annual gross rent in quintiles, and area type). Treatment is defined as being located inside a treatment radius of $r = 1,000$ metres to a green space with a minimum size of $s = 15$ hectares.

Sources: SOEP, 2016 to 2020; EUA, 2018; own calculations.

Table A1: Summary Statistics for Estimation Sample (Table 1 Column 3)

	Mean	σ	Minimum	Maximum	N
Outcomes					
Life Satisfaction	7.478	1.629	0	10	10,336
Patient Health Questionnaire-4 (PHQ-4)					10,336
... Summary Scale	2.036	2.328	0	12	10,336
... Nervous	0.566	0.746	0	3	10,336
... Worried	0.321	0.655	0	3	10,336
... Depressed	0.451	0.715	0	3	10,336
... No Interest	0.698	0.795	0	3	10,336
UCLA 3-Items Loneliness Scale	5.562	1.590	5	9	11,711
Covariates					
Age	49.314	17.283	18	89	10,336
Is Male	0.443	0.497	0	1	10,336
Is Female	0.557	0.497	0	1	10,336
Is Single	0.292	0.455	0	1	10,336
Is Married	0.538	0.499	0	1	10,336
Is in Civic Partnership	0.003	0.057	0	1	10,336
Is Divorced	0.117	0.321	0	1	10,336
Is Widowed	0.050	0.217	0	1	10,336
Has Very Good Health	0.156	0.363	0	1	10,336
Has Good Health	0.413	0.492	0	1	10,336
Has Satisfactory Health	0.284	0.451	0	1	10,336
Has Bad Health	0.117	0.322	0	1	10,336
Has Very Bad Health	0.029	0.168	0	1	10,336
Has Migration Background	0.270	0.444	0	1	10,336
Is in Civil Service	0.000	0.022	0	1	10,336
Is in Training	0.030	0.170	0	1	10,336
Is Employed	0.633	0.482	0	1	10,336
Is Marginally Employed	0.026	0.159	0	1	10,336
Is on Parental Leave	0.019	0.137	0	1	10,336
Is Unemployed	0.050	0.218	0	1	10,336
Is Out of Labour Force	0.066	0.249	0	1	10,336
Log Annual Net Household Income	10.447	0.630	7.554	14.180	10,336
Lives in Farm House	0.002	0.048	0	1	10,336
Lives in Detached House	0.127	0.333	0	1	10,336
Lives in Terraced House	0.183	0.386	0	1	10,336
Lives in Small Apartment Building	0.100	0.300	0	1	10,336
Lives in Medium-Sized Apartment Building	0.287	0.452	0	1	10,336
Lives in Large Apartment Building	0.269	0.443	0	1	10,336
Lives in High Rise	0.032	0.177	0	1	10,336
Lives in Other Building Type	0.000	0.000	0	0	10,336
Is Owner	0.335	0.472	0	1	10,336
Is Renter	0.665	0.472	0	1	10,336
Log Annual Gross Rent	6.668	3.023	2.485	10.919	10,336
Number of Individuals in Household	2.590	1.419	1	12	10,336
Number of Children in Household	0.605	1.010	0	7	10,336
Lives in Old Residential Area	0.481	0.500	0	1	10,336
Lives in New Residential Area	0.228	0.420	0	1	10,336
Lives in Mixed Area	0.287	0.452	0	1	10,336
Lives in Commercial Area	0.003	0.050	0	1	10,336
Lives in Commercial or Industrial Area	0.002	0.042	0	1	10,336
Urban	0.932	0.252	0	1	10,336
Rural	0.068	0.252	0	1	10,336

Table A2: Balancing Properties for Estimation Sample (Table 1 Column 3)

	Mean		Normalised Difference
	Treated	**Controlled**	
Age	48.942	49.554	0.025
Is Male	0.443	0.443	0.000
Is Female	0.557	0.557	0.000
Is Single	0.306	0.283	0.035
Is Married	0.523	0.548	0.036
Is in Civic Partnership	0.005	0.002	0.041
Is Divorced	0.122	0.113	0.019
Is Widowed	0.044	0.053	0.029
Has Very Good Health	0.163	0.152	0.021
Has Good Health	0.405	0.419	0.020
Has Satisfactory Health	0.278	0.288	0.016
Has Bad Health	0.119	0.116	0.006
Has Very Bad Health	0.035	0.025	0.042
Has Migration Background	0.275	0.267	0.013
Is in Civil Service	0.000	0.000	0.001
Is in Training	0.032	0.028	0.014
Is Employed	0.631	0.635	0.005
Is Marginally Employed	0.028	0.024	0.018
Is on Parental Leave	0.021	0.018	0.018
Is Unemployed	0.050	0.051	0.004
Is Out of Labour Force	0.070	0.064	0.016
Log Annual Net Household Income	10.415	10.467	0.058
Lives in Farm House	0.001	0.003	0.027
Lives in Detached House	0.076	0.159	0.183
Lives in Terraced House	0.173	0.189	0.029
Lives in Small Apartment Building	0.095	0.103	0.021
Lives in Medium-Sized Apartment Building	0.300	0.279	0.032
Lives in Large Apartment Building	0.314	0.240	0.118
Lives in High Rise	0.041	0.027	0.055
Lives in Other Building Type	0.000	0.000	0.000
Is Owner	0.297	0.359	0.094
Is Renter	0.703	0.641	0.094
Log Annual Gross Rent	6.909	6.514	0.093
Number of Individuals in Household	2.528	2.630	0.051
Number of Children in Household	0.585	0.617	0.022
Lives in Old Residential Area	0.466	0.490	0.035
Lives in New Residential Area	0.223	0.232	0.015
Lives in Mixed Area	0.307	0.274	0.050
Lives in Commercial Area	0.003	0.002	0.021
Lives in Commercial or Industrial Area	0.001	0.002	0.007
Urban	0.946	0.923	0.067
Rural	0.054	0.077	0.067
N	4,040	6,296	-

Table A3: Impacts of Nearby Green Spaces With Various Minimum Sizes on Life Satisfaction – Intensive Margin (Propensity-Score Matching)

	Life Satisfaction (0-10)											
		$s = 5$			$s = 10$			$s = 15$			$s = 20$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Green$_s$[1] x 2020	**0.120****			**0.150*****			**0.218*****			**0.109****		
	(0.054)			**(0.046)**			**(0.050)**			**(0.054)**		
Green$_s$[1+] x 2020		**0.156****			**0.226*****			**0.267*****			**0.132**	
		(0.058)			**(0.064)**			**(0.066)**			**(0.081)**	
Green$_s$[2+] x 2020			**0.151****			**0.117**			**0.336*****			**0.357****
			(0.064)			**(0.076)**			**(0.128)**			**(0.169)**
2020	-4.280***	-2.779***	-2.341***	-5.921***	-10.281***	-4.402***	-5.967***	-4.551***	-4.529***	-4.145***	1.315	-3.485***
	(0.280)	(0.260)	(0.246)	(0.443)	(0.476)	(0.637)	(0.432)	(0.291)	(0.302)	(0.282)	(0.993)	(0.763)
Propensity-Score Matching	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	7.478	7.454	7.473	7.478	7.465	7.477	7.478	7.496	7.491	7.478	7.480	7.476
σ	1.629	1.646	1.647	1.629	1.658	1.651	1.629	1.626	1.628	1.629	1.631	1.628
N	10,336	7,402	5,349	10,336	7,209	5,893	10,336	7,702	6,748	10,336	7,978	7,285
N Treated	7,632	4,698	2,645	5,431	2,304	988	4,040	1,406	452	3,280	922	229
N Controlled	2,704	2,704	2,704	4,905	4,905	4,905	6,296	6,296	6,296	7,056	7,056	7,056
Within R Squared	0.175	0.226	0.301	0.176	0.250	0.310	0.178	0.237	0.256	0.175	0.223	0.234

Robust standard errors clustered at interview date level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Treatment is defined as being located inside a treatment radius of 1,000 metres to a green space $Green_s[x]$ with a minimum size of s hectares, whereby x denotes the number of green spaces inside the radius. Each column is a separate estimation of Equation 2. The propensity-score matching specification matches individuals in the treatment group to their nearest neighbours in the control group based on pre-treatment observables, including demographics (i.e. dummies for age in ten-year brackets and log annual net household income in quintiles) and housing conditions (i.e. dummies for dwelling type, ownership, log annual gross rent in quintiles, and area type). See Section 2.1 for a detailed description of the data and Section 2.2 for the model.
Sources: SOEP, 2019 to 2020; EUA, 2018; own calculations.

Table A4: Impacts of Nearby Green Spaces With Various Patch Sizes on Life Satisfaction (Propensity-Score Matching)

	Life Satisfaction (0-10)					
	5 to 10 Hectares	**5 to 15 Hectares**	**5 to 20 Hectares**	**10 to 15 Hectares**	**10 to 20 Hectares**	**15 to 20 Hectares**
	(1)	(2)	(3)	(4)	(5)	(6)
Green x 2020	**0.011**	**0.031**	**0.126***	**0.077**	**0.222*****	**0.521*****
	(0.082)	**(0.070)**	**(0.065)**	**(0.089)**	**(0.070)**	**(0.114)**
2020	-6.296***	-9.121***	1.100	-5.164***	-9.049***	-4.306***
	(0.382)	(0.403)	(0.997)	(0.402)	(0.373)	(0.831)
Propensity-Score Matching	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean	7.485	7.493	7.485	7.494	7.485	7.485
σ	1.645	1.626	1.626	1.626	1.626	1.626
N	4,905	6,296	7,056	6,296	7,056	7,056
N Treated	2,201	3,592	4,352	1,391	2,151	760
N Controlled	2,704	2,704	2,704	4,905	4,905	6,296
Within R Squared	0.332	0.264	0.236	0.264	0.237	0.241

Robust standard errors clustered at interview date level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Treatment is defined as being located inside a treatment radius of 1,000 metres to a green space *Green* with various patch sizes, from 5 to 10, 5 to 15, or 5 to 20 hectares; 10 to 15 or 10 to 20 hectares; or 15 to 20 hectares. Each column is a separate estimation of Equation 2. The propensity-score matching specification matches individuals in the treatment group to their nearest neighbours in the control group based on pre-treatment observables, including demographics (i.e. dummies for age in ten-year brackets and log annual net household income in quintiles) and housing conditions (i.e. dummies for dwelling type, ownership, log annual gross rent in quintiles, and area type). See Section 2.1 for a detailed description of the data and Section 2.2 for the model.
Sources: SOEP, 2019 to 2020; EUA, 2018; own calculations.

Table A5: Impact of Nearby Green Space With Minimum Size of 15 Hectares on Mental Health and Loneliness (Spatial Matching)

	Patient Health Questionnaire-4 (PHQ-4)					**UCLA**
		Anxiety		**Depression**		**3-Items**
	Summary Scale (0-12)	**Nervous (0-3)**	**Worried (0-3)**	**Depressed (0-3)**	**No Interest (0-3)**	**Loneliness Scale (3-9)**
	(1)	(4)	(5)	(3)	(2)	(6)
Green$_{15}$ x 2020	**-0.294****	**-0.122*****	**-0.060***	**-0.089****	**-0.024**	**-0.056**
	(0.124)	**(0.042)**	**(0.035)**	**(0.040)**	**(0.047)**	**(0.093)**
2020	0.674	0.050	0.496*	0.469	-0.341	-1.944***
	(1.159)	(0.311)	(0.294)	(0.443)	(0.317)	(0.093)
Spatial Matching	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean	6.040	1.559	1.320	1.458	1.703	5.580
σ	2.354	0.747	0.655	0.728	0.809	1.644
N	5,602	5,602	5,602	5,602	5,602	7,911
N Treated	4,040	4,040	4,040	4,040	4,040	5,601
N Controlled	1,562	1,562	1,562	1,562	1,562	2,310
Within R Squared	0.296	0.254	0.273	0.282	0.302	0.273

Robust standard errors clustered at interview date level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Treatment is defined as being located inside a treatment radius of 1,000 metres to a green space $Green_s$ with a minimum size of $s = 15$ hectares. Each column is a separate estimation of Equation 2. The spatial-matching specification restricts individuals in the control group to those who are located outside the treatment radius of 1,000 metres but inside a matching radius of 1,500 metres to a green space. See Section 2.1 for a detailed description of the data and Section 2.2 for the model.
Sources: SOEP, 2019 to 2020; EUA, 2018; own calculations.

Table A6: Impact of Nearby Green Space With Minimum Size of 15 Hectares on Mental Health and Loneliness – Linear Probability Models (Propensity-Score Matching)

	Patient Health Questionnaire-4 (PHQ-4)					**UCLA 3-Items**
		Anxiety		**Depression**		
	Summary Scale (0-1)	**Nervous (0-1)**	**Worried (0-1)**	**Depressed (0-1)**	**No Interest (0-1)**	**Loneliness Scale (0-1)**
	(1)	(4)	(5)	(3)	(2)	(6)
Green$_{15}$ x 2020	**-0.037***	**-0.012**	**-0.029****	**-0.038****	**-0.037***	**-0.042***
	(0.019)	**(0.018)**	**(0.014)**	**(0.017)**	**(0.021)**	**(0.022)**
2020	0.339*	0.489**	1.128***	0.264	0.221	-1.285***
	(0.188)	(0.247)	(0.146)	(0.269)	(0.195)	(0.326)
Propensity-Score Matching	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.680	0.445	0.240	0.347	0.533	0.522
σ	0.467	0.497	0.427	0.476	0.499	0.500
N	10,336	10,336	10,336	10,336	10,336	11,711
N Treated	4,040	4,040	4,040	4,040	4,040	4,510
N Controlled	6,296	6,296	6,296	6,296	6,296	7,201
Within R Squared	0.237	0.184	0.190	0.171	0.220	0.173

Robust standard errors clustered at interview date level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Treatment is defined as being located inside a treatment radius of 1,000 metres to a green space $Green_s$ with a minimum size of $s = 15$ hectares. Each column is a separate estimation of Equation 2. The propensity-score matching specification matches individuals in the treatment group to their nearest neighbours in the control group based on pre-treatment observables, including demographics (i.e. dummies for age in ten-year brackets and log annual net household income in quintiles) and housing conditions (i.e. dummies for dwelling type, ownership, log annual gross rent in quintiles, and area type). See Section 2.1 for a detailed description of the data and Section 2.2 for the model. *Sources:* SOEP, 2019 to 2020; EUA, 2018; own calculations.

Table A7: Impacts of Nearby Green Spaces With Various Minimum Sizes on Mental Health – Intensive Margin (Propensity-Score Matching)

	Patient Health Questionnaire-4 (PHQ-4) Summary Scale (0-12)											
	$s = 5$			$s = 10$			$s = 15$			$s = 20$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Green$_s$[1] x 2020	**-0.163***			**-0.327*****			**-0.219*****			**-0.082**		
	(0.085)			**(0.084)**			**(0.080)**			**(0.080)**		
Green$_s$[1+] x 2020		**-0.213****			**-0.473*****			**-0.467*****			**-0.330****	
		(0.089)			**(0.101)**			**(0.118)**			**(0.159)**	
Green$_s$[2+] x 2020			**-0.261****			**-0.543*****			**-0.694*****			**-0.843****
			(0.106)			**(0.152)**			**(0.231)**			**(0.364)**
2020	9.004***	6.319***	-2.641***	10.629***	12.201***	3.838***	10.637***	7.118***	7.085***	8.851***	0.955	3.062***
	(0.807)	(0.413)	(0.571)	(0.474)	(0.610)	(0.436)	(0.471)	(0.490)	(0.605)	(0.772)	(0.848)	(0.349)
Propensity-Score Matching	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	2.036	2.008	1.990	2.036	2.015	1.985	2.036	1.989	2.000	2.036	2.015	2.027
σ	2.328	2.289	2.278	2.328	2.300	2.261	2.328	2.276	2.273	2.328	2.300	2.299
N	10,336	7,402	5,349	10,336	7,209	5,893	10,336	7,702	6,748	10,336	7,978	7,285
N Treated	7,632	4,698	2,645	5,431	2,304	988	4,040	1,406	452	3,280	922	229
N Controlled	2,704	2,704	2,704	4,905	4,905	4,905	6,296	6,296	6,296	7,056	7,056	7,056
Within R Squared	0.218	0.270	0.324	0.221	0.297	0.345	0.219	0.269	0.295	0.218	0.263	0.285

Robust standard errors clustered at interview date level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Treatment is defined as being located inside a treatment radius of 1,000 metres to a green space $Green_s[x]$ with a minimum size of s hectares, whereby x denotes the number of green spaces inside the radius. Each column is a separate estimation of Equation 2. The propensity-score matching specification matches individuals in the treatment group to their nearest neighbours in the control group based on pre-treatment observables, including demographics (i.e. dummies for age in ten-year brackets and log annual net household income in quintiles) and housing conditions (i.e. dummies for dwelling type, ownership, log annual gross rent in quintiles, and area type). See Section 2.1 for a detailed description of the data and Section 2.2 for the model.
Sources: SOEP, 2019 to 2020; EUA, 2018; own calculations.

Table A8: Impacts of Nearby Green Spaces With Various Patch Sizes on Mental Health (Propensity-Score Matching)

	Patient Health Questionnaire-4 (PHQ-4) Summary Scale (0-12)					
	5 to 10 Hectares	**5 to 15 Hectares**	**5 to 20 Hectares**	**10 to 15 Hectares**	**10 to 20 Hectares**	**15 to 20 Hectares**
	(1)	(2)	(3)	(4)	(5)	(6)
Green x 2020	**0.132**	**-0.015**	**-0.171***	**-0.394*****	**-0.542*****	**-0.670*****
	(0.105)	**(0.097)**	**(0.100)**	**(0.128)**	**(0.120)**	**(0.176)**
2020	14.257***	11.796***	0.745	11.817***	11.634***	9.427***
	(0.392)	(0.267)	(0.938)	(0.615)	(0.316)	(1.008)
Propensity-Score Matching	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean	1.985	2.005	2.023	2.005	2.023	2.023
σ	2.252	2.273	2.297	2.273	2.297	2.297
N	4,905	6,296	7,056	6,296	7,056	7,056
N Treated	2,201	3,592	4,352	1,391	2,151	760
N Controlled	2,704	2,704	2,704	4,905	4,905	6,296
Within R Squared	0.400	0.317	0.295	0.320	0.302	0.300

Robust standard errors clustered at interview date level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Treatment is defined as being located inside a treatment radius of 1,000 metres to a green space *Green* with various patch sizes, from 5 to 10, 5 to 15, or 5 to 20 hectares; 10 to 15 or 10 to 20 hectares; or 15 to 20 hectares. Each column is a separate estimation of Equation 2. The propensity-score matching specification matches individuals in the treatment group to their nearest neighbours in the control group based on pre-treatment observables, including demographics (i.e. dummies for age in ten-year brackets and log annual net household income in quintiles) and housing conditions (i.e. dummies for dwelling type, ownership, log annual gross rent in quintiles, and area type). See Section 2.1 for a detailed description of the data and Section 2.2 for the model.
Sources: SOEP, 2019 to 2020; EUA, 2018; own calculations.

A Selection on Unobservables and Coefficient Stability

Implicit in our argument that our results remain similar regardless of whether we match individuals or not is that coefficient movements are informative about relative omitted variable bias due to unobservables. Yet, this is only the case if observables are correlated with unobservables. Oster (2019) shows that both coefficient movements *and* R Squared movements need to be taken into account to make informative statements about the degree of selection on unobservables. Note that our (Within) R Squared moves only slightly after matching, from 0.156 (cf. Table 3 Column 1) to 0.178 (cf. Table 1 Column 3) in our preferred specification, i.e. propensity-score matching, and a green space with a minimum size of $s = 15$ hectares.

Oster (2019) suggests a bounding analysis to make informative statements about selection on unobservables and coefficient stability, which is based on two key parameters: the maximum attainable R Squared (R^2_{max}) and the degree of selection on unobservables relative to observables (δ, whereby $\delta = 2$, for example, would imply that selection on unobservables is *twice* as important as selection on observables). In particular, the author argues that one should calculate the δ that would be necessary to explain away the treatment effect obtained in the full model, i.e. $\beta_1 = 0$ in Equation 2. Following this line of reasoning, and assuming that $R^2_{max} = 1$, we obtain $\delta = -0.01$. This implies that selection on unobservables is considerably *less* important than selection on observables.

An alternative is to calculate bounds around β_1, by varying δ and R^2_{max}. If we set $\delta = 0$ (i.e. unobservables are irrelevant for selection) and $R^2_{max} = 1$, we obtain $\beta_1 = 0.15$. If we set $\delta = 1$ (i.e. unobservables are as important as observables for selection) and $R^2_{max} = 0.018$ (i.e. the R Squared in our full model), we obtain $\beta_1 = 0.22$. This gives us an interval of $[0.15; 0.22]$ for β_1, whereby the lower bound excludes zero at the 5% significance level given a standard error of 0.05 in our full model, i.e. $0.15 - 1.96 \times 0.05 = 0.053$. Note that Oster (2019) considers $\delta = 1$ to be an appropriate seed value, as observables should, in theory, be at least as important as unobservables.

Taken together, our bounding analysis suggests that selection on unobservables and potentially resulting omitted variable bias is, if anything, only a minor concern.

B Multiple Hypotheses Testing

We test ten hypotheses in our preferred specification, i.e. propensity-score matching: four hypotheses for life satisfaction and green spaces with a minimum size of $s = \{5, 10, 15, 20\}$ hectares and six hypotheses for mental health (including loneliness) and a green space with a minimum size of $s = 15$ hectares.

To account for multiple hypotheses testing, we use the stepdown multiple testing procedure by Romano and Wolf (2005b,a), with the four-step algorithm by Romano and Wolf (2016). The algorithm constructs a null distribution for each of our ten hypothesis tests based on a set of null resampling test statistics (using a bootstrap with 1000 repetitions and robust standard errors clustered at the interview date level in both the original regression and the resampling procedure). We find that our stepdown-adjusted P values (corresponding to the significance of a hypothesis test where ten tests are implemented) continue to show statistical significance at conventional levels for life satisfaction and green spaces with a minimum size of $s = \{10, 15\}$ hectares as well as respondents' summary scores of mental ill health and their feelings of nervousness and depression. (Appendix Tables A9 and A10).

Table A9: Impacts of Nearby Green Spaces With Various Minimum Sizes on Life Satisfaction – Multiple Hypotheses Testing (Propensity-Score Matching)

	Life Satisfaction (0-10)			
	$\geq$ 5 Hectares	**$\geq$ 10 Hectares**	**$\geq$ 15 Hectares**	**$\geq$ 20 Hectares**
	(1)	(2)	(3)	(4)
Green$_5$ x 2020	**0.120****			
	(0.054)			
Original P Value	*0.025*			
Stepdown-Adjusted P Value	*0.145*			
Green$_{10}$ x 2020		**0.150*****		
		(0.046)		
Original P Value		*0.001*		
Stepdown-Adjusted P Value		*0.022*		
Green$_{15}$ x 2020			**0.218*****	
			(0.050)	
Original P Value			*0.000*	
Stepdown-Adjusted P Value			*0.005*	
Green$_{20}$ x 2020				**0.109****
				(0.054)
Original P Value				*0.042*
Stepdown-Adjusted P Value				*0.145*
2020	-4.280***	-5.921***	-5.967***	-4.145***
	(0.280)	(0.443)	(0.432)	(0.282)
Propensity-Score Matching	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
N	10,336	10,336	10,336	10,336
N Treated	7,632	5,431	4,040	3,280
N Controlled	2,704	4,905	6,296	7,056
Within R Squared	0.175	0.176	0.178	0.175

Robust standard errors clustered at interview date level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A10: Impact of Nearby Green Space With Minimum Size of 15 Hectares on Mental Health and Loneliness – Multiple Hypotheses Testing (Propensity-Score Matching)

	Patient Health Questionnaire-4 (PHQ-4)					**UCLA**
		Anxiety		**Depression**		**3-Items**
	Summary Scale (0-12)	**Nervous (0-3)**	**Worried (0-3)**	**Depressed (0-3)**	**No Interest (0-3)**	**Loneliness Scale (3-9)**
	(1)	(4)	(5)	(3)	(2)	(6)
Green$_{15}$ x 2020	**-0.219***	**-0.080***	**-0.044**	**-0.068***	**-0.027**	**-0.120***
	(0.080)	**(0.026)**	**(0.022)**	**(0.025)**	**(0.033)**	**(0.064)**
Original P Value	*0.001*	*0.001*	*0.031*	*0.000*	*0.218*	*0.062*
Stepdown-Adjusted P Value	*0.023*	*0.023*	*0.158*	*0.007*	*0.322*	*0.333*
2020	10.637***	2.563***	3.664***	1.767***	2.643***	-2.190***
	(0.471)	(0.246)	(0.275)	(0.283)	(0.252)	(0.816)
Propensity-Score Matching	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	10,336	10,336	10,336	10,336	10,336	11,711
N Treated	4,040	4,040	4,040	4,040	4,040	4,510
N Controlled	6,296	6,296	6,296	6,296	6,296	7,201
Within R Squared	0.219	0.179	0.185	0.179	0.218	0.182

Robust standard errors clustered at interview date level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A11: Correlations Between Green Urban Areas and Other Urban Land Use Types in Estimation Sample

EUA Code	**Urban Land Use Type**	**Correlation With Green Urban Areas**
14100	Green Urban Areas	1.000
11100	Continuous Urban Fabric (Soil Sealing > 80%)	0.121**
11210	Discontinuous Dense Urban Fabric (Soil Sealing 50% to 80%)	0.052**
11220	Discontinuous Medium Density Urban Fabric (Soil Sealing 30% to 50%)	-0.104**
11230	Discontinuous Low Density Urban Fabric (Soil Sealing 10% to 30%)	-0.127**
11240	Discontinuous Very Low Density Urban Fabric (Soil Sealing < 10%)	-0.103**
11300	Isolated Structures	-0.203**
12100	Industrial, Commercial, Public, Military, and Private Units	0.058**
12210	Fast Transit Roads and Associated Land	-0.041**
12220	Other Roads and Associated Land	0.238**
12230	Railways and Associated Land	-0.008
12300	Port Areas	-0.025**
12400	Airports	-0.028**
13100	Mineral Extraction and Dump Sites	-0.041**
13300	Construction Sites	-0.031**
13400	Land Without Current Use	-0.030**
14200	Sports and Leisure Facilities	0.150**
21000	Arable Land (Annual Crops)	-0.321**
22000	Permanent Crops	-0.091**
23000	Pastures	-0.319**
24000	Complex and Mixed Cultivation	-0.036**
31000	Forests	-0.272**
33000	Open Space With Little or No Vegetation	-0.006
40000	Wetlands	-0.030**
50000	Water	-0.005

** $p < 0.05$

Sources: SOEP, 2019 to 2020; EUA, 2018; own calculations.

Table A12: Literature Review on Effect Sizes and Monetary Valuations of Green Spaces

#	Study	Data and Methods	Effect Size on Life Satisfaction	Monetary Value	Notes
1	Present Study	All major German cities and metropolitan areas with more than 100,000 inhabitants; N=11,082. Data: survey data from German Socio-Economic Panel (SOEP), years 2019 to 2020, providing geographical coordinates of households, linked to data on urban land use from European Urban Atlas (EUA), year 2018. Methods: spatial difference-in-differences.	Effect of green space of at least 15ha within 1,000m radius of household on life satisfaction measured on 0-10 scale: +0.151 during Covid-19, +0.003 (=0.151x0.02) during normal times (lower bound).	EUR 1,664 per capita per year for green space of at least 15ha within 1,000m radius of household during Covid-19; EUR 63 during normal times (lower bound).	
2	Krekel et al. (2016)	All major German cities and metropolitan areas with more than 100,000 inhabitants; N=6,959 Data: survey data from German Socio-Economic Panel (SOEP), years 2000 to 2012, providing geographical coordinates of households, linked to data on urban land use from European Urban Atlas (EUA), year 2006. Methods: FE regression, selection on observables.	Effect of 1ha increase (mean of 23ha) in green space within 1,000m radius of household on life satisfaction measured on 0-10 scale: +0.007.	EUR 276 per capita per year for 1ha increase in green space within 1,000m radius of household.	
3	Bertram and Rehdanz (2015)	Berlin, Germany; N=316 Data: web survey (cross-section) including residential addresses, year 2012, linked to data on urban land use from European Urban Atlas (EUA), year 2006. Methods: ordered logit regression, selection on observables.	No significant linear effect of green space on life satisfaction, but significant inverse U-shaped effect (with peak above mean green space, suggesting undersupply).	EUR 322 per capita per year for 1ha increase (mean of 24ha) in green space within 750m radius of household.	Monetary value calculated for different point estimates of life satisfaction (given non-linear relationship).
4	Ambrey and Fleming (2014)	Capital cities in Australia; N=6,156. Data: survey data from Household, Income and Labour Dynamics in Australia (HILDA) panel at small area level (1.85sqkm), year 2005, linked to GIS data on public green space, year 2010. Methods: OLS regression, selection on observables.	Effect of 1ha increase (mean coverage unknown) in green space within 750m radius of household on life satisfaction measured on 0-10 scale: +0.22.	EUR 22,681 (AUD 32,797) per capita per year for 1ha increase in green space within 750m radius of household.	
5	Li and Managi (2021)	Sub-prefecture regions Japan; N=1,234. Data: aggregated survey data (sub-prefecture level), years 2015 to 2017, linked to aggregated land cover data (30m resolution) generated through remote sensing satellite data, years 2014 to 2016. Methods: OLS and others, selection on observables.	Effect of 1ha increase in grasslands in neighbouring city of respondent on life satisfaction measured on 0-10 scale: +0.118.	EUR 96,393 (JPY 13,210,565) per capita per year for 1ha increase in grasslands in neighbouring city.	Life satisfaction not associated with grassland in respondent's own region.
6	Tsurumi and Managi (2015)	Kanto and Kansai, Japan; N=2,158. Data: web survey data (cross-section) providing residential addresses, year 2012, linked to GIS data on green spaces (i.e. Digital Map 5000 from Geospatial Information Authority of Japan), various years. Methods: 2SLS IV models, with past income and past green spaces as IVs.	N/A.	Per household per year for 1% increase in green coverage: EUR 683 (JPY 93,714) within 100-300m, mean of 0.15; EUR 1,168 (JPY 160,065) within 300-500m, mean of 0.18.	No significant effect for green coverage within 100m radius; absolute mean coverage unknown.
7	Tsurumi et al. (2018)	Tokyo, Japan; N=2,758. Data: web survey data, year 2014, linked to high-resolution satellite images (which allow extraction of data at tree level, QuickBird, pixel resolution = 61cm) compiled using GIS software, year 2011. Methods: OLS regression, selection on observables.	Effect of 1sqm increase in green space within 1,000m radius of household on life satisfaction measured on 0-10 scale: +0.095.	EUR 18 (JPY 2,503) per household per year for 1sqm increase in green coverage within 0-100m radius of household, mean of 0.12; EUR 1 (JPY 109) within 100-500m, mean of 0.15.	Some types of greenery have higher monetary values than others.
8	Yuan et al. (2018)	China; N=18,441. Data: web survey data, year 2016, linked to city-level data on green coverage area, year 2013. Methods: OLS regression, selection on observables.	Effect of 1% increase in green coverage (mean of 0.4) at city level on life satisfaction measured on 0-10 scale: +0.010.	EUR 410 (CNY 2,808) per capita per year for 1% increase in green coverage at city level.	No information on size of city, but for context, one of cities is Beijing, which has 64,137ha of green space, making up 51% of total area.

Sources: Own research, own calculations.