Quantifying Biogas Plant Externalities Using Well-Being and Hedonic Price Data

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Abstract

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This paper quantifies the negative external effects of biogas plants using well-being data. We combine a new panel data set comprising more than $13,000$ installations in Germany with rich longitudinal household data from the German Socio-Economic Panel for the period 2000 to 2012. Our empirical strategy rests on a difference-in-differences design exploiting exact geographical coordinates of both installations and households. Propensity-score and spatial matching ensures comparability of the treatment and control group. Results show that the construction of biogas plants closer than 750 metres to households has significant negative impacts on the well-being of household members.

Keywords: Externalities, Renewable Energy, Biogas Plants, Life Satisfaction, Rental Prices, Social Acceptance, Spatial Analysis

JEL:

C23, Q42, Q51, R20

1. Introduction

Renewable energy sources play an ever increasing role in electricity generation. Globally, the share of renewables (excluding hydropower) grew from 1.3% in 1990 to 6.8% in 2015 (IEA, 2017). Beyond solar photovoltaics (PV) and wind power, world-wide biomass capacities for electricity generation more than trebled since 2000, reaching over 100 gigawatt in 2016 (IRENA, 2015; IRENA, 2017), which roughly corresponds to 100 large nuclear reactors. Electricity generation from biomass, unlike from wind and PV, does not depend on exogenous and variable weather conditions but can be scheduled when needed or profitable. This flexibility provides a valuable complement in the transition to renewables.

Of biomass, biogas plays a particularly large role in Germany, where more than a third of world-wide electricity generation from this source was located in 2014, followed by the US, Italy, and the UK (IRENA, 2017). In Germany, there were more than $7,500$ biogas plants with an overall capacity around $5,000$ megawatts in 2014, up from below 100 megawatts in 2000 (BMWi, 2017). Biogas plants use domestic energy crops such as maize, remnant or waste material, in particular liquid manure from livestock farming, or green waste from agriculture as inputs. These inputs are first fermented; the resulting gas is then combusted in an on-site combined power station to generate electricity and heat for nearby households.[1]

The welfare economic rationale for using renewables in electricity generation is clear: they are to avoid negative externalities associated with conventional technologies, especially greenhouse gas emissions arising from fossil fuel technologies. Contrary to coal or natural

[1] There are different technologies using biomass as input: *(i)* solid biomass, combusting inputs such as timber and pellets; *(ii)* liquid biomass, combusting inputs such as plant oils; *(iii)* biogas, turning biomass into gas, which is then combusted; and *(iv)* biomethane power stations, combusting gas from the gas grid, of which the same amount is fed into the grid at another site. In Germany, biogas is by far the most widespread technology, covering about 77% of all installations and about 72% of all electricity generated from biomass in 2014 (FNR, 2017).

gas, biogas is largely climate-friendly. While its combustion releases CO_2, the energy crops feeding the biogas plant previously absorbed roughly the same amount from the atmosphere.[2]

However, there are potential negative externalities when generating electricity from biogas. First, odour emissions may stem from the storage of inputs such as liquid manure, inappropriate operation of installations (especially when fermenting inputs under air closure), or application of inadequately fermented waste materials on fields (BSOE, 2011). Second, the operation of biogas plants can increase the transportation volume of inputs toward and waste materials from installations. Third and fourth, biogas plants can impact landscape aesthetics. Specifically, growing energy crops such as maize may lead to uniform mono-culture landscapes. For example, in Germany, about 13% of available arable land was covered by energy crops in 2016, and in particular, the share of maize as energy crop has increased considerably over the past decade (FNR, 2017). There is also a general fear of genetically modified maize, which is often used as input. Likewise, installations as such can be large, and may thus interfere with the landscape. Fifth, the application of fermented waste materials on fields may lead to a heightened nitrate concentration in ground water.

In 2013, a survey among 6,500 households found that biomass is by far the most unpopular renewable technology (Andor et al., 2015). Only 51% of residents living close to a biomass plant are supportive of the technology, compared to 89% for solar photovoltaic and 72% for wind (Meyerhoff et al., 2015). Choice experiments find a higher willingnes–to–pay to avoid a new build project in their surroundings than for other renewables. Installations are often perceived as interfering with landscape aesthetics, pointless in terms of energy policy, or even environmentally harmful (Meyerhoff et al., 2015). When asked about how

[2] In Germany, one megawatt hour of biogas electricity is estimated to have crowded out roughly 400 kilogram of CO_2 equivalents in 2014 (BMWi, 2017).

a new build project might affect property prices, respondents often give a negative outlook (Fraunhofer UMSICHT, 2012). However, besides few studies that directly ask individuals about how they would feel if a new biogas plant was constructed in their immediate surroundings, there exists little systematic evidence on biogas plant externalities.

To fill this research gap, we aim to study the causal effect of biogas plant externalities on nearby residents, and quantify externalities using both well-being and hedonic price data. To this end, we combine longitudinal household data from the German Socio-Economic Panel Study (SOEP) with a novel panel data set comprising more than $13,000$ installations in Germany for the time period between 2000 and 2012. We consider well-being and hedonic price data as complementary: if real estate market frictions preclude a full internalisation of externalities, well-being data can detect a residual effect. We quantify externalities monetarily: directly by considering their impact on real estate prices and indirectly by trading off the decrease in well-being caused by externalities against the increase caused by income.

Our empirical strategy employs a difference-in-differences design that exploits variation in biogas plant construction across space and time: residents are allocated to the treatment group if a plant is constructed within a pre-specified radius around their households, and to the control group otherwise. To ensure comparability of treatment and control group, and thus common trend behaviour, we apply spatial matching based solely on geographical locations of places of residence, and propensity-score matching based on local socio-demographic characteristics, macroeconomic conditions, and rich external land cover data.

We find that the construction of a biogas plant in a radius closer than 750 metres around a household decreases self-reported life satisfaction of household members, measured on a scale from zero to ten, by about 0.1 points. This effect is also economically significant:

assuming that it is permanent, it amounts to a shadow tax of about 100 Euro per affected household per year. Various treatment intensity measures, placebo tests, and a separate downwind analysis exploiting exogenous wind data will disentangle drivers and shed light on anticipation effects, whereas treatment decay measures will explore adaptation to newly built installations.

The rest of this paper is organised as follows: Section 2 reviews the related literature on externalities of biogas plants and different valuation approaches. Section 3 describes the data, and Section 4 the empirical strategy. Results are presented in Section 5. Finally, Section 7 concludes and outlines avenues for future research.

2. Related Literature

In the stated-preferences literature, evidence on externalities of biogas plants is scant, mixed, and if anything, case-study based rather than systematic.[3] Stated preference studies such as contingent valuation or choice experiments directly ask respondents about their attitudes towards a technology in general, a particular existing installation, or a hypothetical or planned new build project in their surroundings.

Kortsch et al. (2015) interviewed 423 persons in the Altmark region, Germany, between 2009 and 2011, showing that acceptance of biogas plants in the area is and remains high. Acceptance does not seem to be a fixed construct, but can change over time, depending on personal experiences with plants at a local level. Schumacher and Schultmann (2017) conducted a cross-national survey of 667 residents living near 11 biogas plants in French, German, and Swiss Upper Rhine region. In Germany, the majority of respondents rated

[3]For solid biomass based on timber, Botelho et al. (2016), using contingent valuation, find that the average willingness to accept a biomass plant is about 17 Euro per month for nearby residents in Portugal. This is somewhat higher than 6 and 13 Euro per month, which the same authors detect as average willingness-to-pay in order to avoid negative environmental externalities associated with conventional technologies for the general population (Botelho et al., 2015).

the biogas plant in their neighbourhood between neutral to very negative, and most are also willing to actively oppose a new build project. Only 19% of respondents are willing to live within a one kilometre radius around a plant; most people consider a minimum distance between three and eight kilometres as acceptable, in all countries. Perceived odour emissions decrease acceptance considerably, while visual contact seems less important. Some respondents also report a loss in value of nearby houses and properties as well as a loss in quality of life. Similar, mostly case-study based findings are obtained in Germany (Bertsch et al., 2016; Wüste and Schmuck, 2013; Zoellner et al., 2008), Switzerland (Soland et al., 2013), and in the UK (Upham, 2009; Upham and Shackley, 2006, 2007; Upreti, 2004; Upreti and van der Horst, 2004).[4] One study on landscape externalities points towards concern about built infrastructure rather than landscape aesthetics due to land use (Dockerty et al., 2012).

There is little evidence on heterogeneous impacts: for biomass combustion in general, attitudes are fairly unfavourable across the population, with some evidence that individuals who have more pro-environmental attitudes and preferences for renewables tend to be more in favour (Yoo and Ready, 2014). Susaeta et al. (2011) find that more sophisticated types in terms of educational level or knowledge about renewables exhibit a higher willingness–to–pay for green electricity generation. Community involvement as well as perceived procedural fairness and trust are often cited as important factors behind acceptance (Lantz et al., 2007; Wüstenhagen et al., 2007).

Using stated preferences to value environmental externalities can be problematic: the complexity, and associated cognitive burden, of valuing intangible externalities monetarily can yield biased statements. Likewise, symbolic valuation – consciously or subconsciously

[4] Among farmers, Emmann et al. (2013) find that personal innovativeness increase a farmer's acceptance and take-up of biogas technology, whereas negative externalities such as odour emissions or negative attitudes towards biogas originating from, for example, a rise in land lease prices decrease it.

– may yield expressions of intrinsic attitudes rather than extrinsic preferences. They can be prone to framing and anchoring effects (Kahneman and Sugden, 2005), and respondents may have incentives to answer in a strategical or socially desirable way, especially in face-to-face settings.

An alternative is to use revealed preference approaches such as hedonic pricing: here, environmental externalities are valued using observed changes in real estate prices resulting from a particular existing or newly planned installation. The hedonic method is standard in the literature.[5] Modica (2017) uses a difference-in-differences design covering the period 2006 to 2015 in which 167 new biogas plants were built in Piedmont province, Italy. He does not find that new installations have negative effects on house prices. Pechrova and Lohr (2016), using a simple hedonic regression, find small effects on rental prices for eight installations in the Czech Republic: decreasing the distance to the nearest installation by one kilometre (the mean distance is about 8.4 kilometres) decreases rental prices by 0.15% to 0.40%.

The hedonic method brings its own set of problems: for real estate prices to fully reflect environmental externalities, markets need to be in, or close to, equilibrium. Otherwise, estimates will be downward biased. Frictions may violate this condition, such as slow price adjustment, incomplete information, or large transaction costs, especially direct and indirect moving costs. Prices may also be prone to potentially distorted future risk perceptions, which are common to all market transactions.

Using well-being data is a third way to value environmental externalities. It may overcome disadvantages of both stated and revealed preference approaches. Here, a micro-econometric function relates self-reported life satisfaction – commonly referred to as experienced

[5]For recent applications on energy infrastructure externalities, see Gibbons (2015), Heintzelman and Tuttle (2012), and Jensen et al. (2013), for example.

utility (Kahneman et al., 1997) – to the potential disamenity to be valued, along with income and other variables.

The marginal rate of substitution between the influence of income and the influence of the externality under consideration allows inferring a monetary valuation (Welsch and Kühling, 2009). The relationship of interest itself remains covert. By now, this approach constitutes an established method in the literature on non-market valuation and has, for instance, been used to quantify external costs of air pollution (Ambrey et al., 2014; Ferreira et al., 2013; Levinson, 2012), landscape amenities (Kopmann and Rehdanz, 2013), intangible land use value (Bertram and Rehdanz, 2015; Krekel et al., 2016), noise pollution (Rehdanz and Maddison, 2008; van Praag and Baarsma, 2005), flood disasters (Luechinger and Raschky, 2009), and energy infrastructure (Krekel and Zerrahn, 2017; von Möllendorff and Welsch, 2017).

There is an ongoing debate about whether self-reported life satisfaction is a valid approximation of utility. Evidence shows that individuals do not always make choices that maximise their life satisfaction, for example, when making moving decisions (Glaeser et al., 2016). This suggests that life satisfaction is one component, among others, in an individual's utility function, as opposed to being utility itself (Becker and Rayo, 2008; Benjamin et al., 2012). Moreover, individuals may make prediction errors about their future life satisfaction when making decisions, be it systematically or white noise (Odermatt and Stutzer, 2015). This debate is of secondary importance for this paper: we are not interested in the content of life satisfaction *per se*, but use it as a vehicle to quantify an externality only. That said, we adopt *ex-post* perspective to evaluate the actually materialised impact.

Importantly, we approach the quantification of biogas externalities using both the life satisfaction and the hedonic approach. For imperfect real estate markets – probably the most realistic case – well-being data can detect complementary effects not fully internalised in house prices. Thus, well-being and hedonic prices should be seen in conjunction rather than separation to quantify externalities in total. This will be the methodological approach of our study.

The paper most closely related to ours is von Möllendorff and Welsch (2017): the authors study the effect of renewable energy externalities on the well-being of nearby residents, showing that biogas plants exert significant negative external effects. Compared to wind turbines, effect sizes are almost twice as large, and impacts seem to be persistent over time. However, this paper differs from ours in at least three important aspects: first, the authors do not account for self-selection of residents; the direction of bias resulting from this is not *ex-ante* clear. Second, data are analysed at the post-code level only, i.e. life satisfaction is regressed on the number of biogas plants in a given post-code area. Finally, the authors look at impacts on well-being only, whereas we look at impacts on well-being and property prices in conjunction. In Krekel and Zerrahn (2017), we adopted a similar methodology to study wind turbine externalities on residential well-being.

3. Data

3.1. Household Data

The German Socio-Economic Panel Study (SOEP) is representative panel study on private German households (SOEP, 2015). Since 1984, it contains almost $30,000$ individuals in more that $11,000$ households (Wagner et al., 2007, 2008). Essentially for our study, it provides the exact geographical coordinates of individuals' location of residents. This allows us to merge the SOEP data with our dataset of biogas plant based on geographical information.[6]

[6] Because of data protection reasons of the SOEP, users are not able to connect household data from their geographical location. Households characteristics are not accessible at the same time as the geographical coordinates. See Goebel and Pauer (2014) for details.

For our analysis, we use the dependent variables *(i)* life satisfaction and *(ii)* the monthly net rent of the dwelling. To assess individuals' life satisfaction, participants answer the question "How satisfied are you with your life, all things considered?" on a standard eleven-point single-item Likert scale. As an evaluative measure of subjective well-being, life satisfaction can be defined as cognitive evaluation of the circumstances in life (Diener et al., 1999). Moreover, the SOEP contains two types of rents: While the actual rents is reported by renters, a hypothetical rents is reported by house owners. The latter are obtained from an item in the SOEP that asks house owners to convert their house prices into fictitious rental prices. In our hedonic price regressions, we use both types of rents next to each other to contrast impacts on renters with those on house owners. In our well-being regressions, we combine them into a single indicator which we routinely control for.

Besides that, we select a rich set of observables. On the micro level, controls include demographic and human capital characteristics as well as economic and housing conditions. On the macro level, controls include the unemployment rate and average household income.

3.2. Data on Biogas Plants

Our study builds on official biomass plant data from the German electricity transmission system operators. It includes all 13,493 biomass plants connected to the grid through the end of the year 2012.[7] As our analysis draws on spatial and temporal variation, the most important attributes are the geographic coordinates, the commencement of operation as well as some information on the size and technology type of the plant. While the official data have a decent quality concerning the latter, we needed to specify the geo-coding in

[7] We downloaded the raw data set, the so-called *Anlagenstammdaten* (translation: installations master data) of all renewable energy plants on September 8, 2014 from `http://www.netztransparenz.de`. The *Anlagenstammdaten* are the official German account of renewable energy plants in Germany.

greater detail. Specifically, we carried out comprehensive manual refinements and merged in data from other sources when suitable.

First, the original data set contains address information that we converted into geographical coordinates. As such, the spatial data is sufficiently exact on the bulk of plants in rendering the specific addresses. However, we could localize a third of the installations with only approximate accuracy, meaning that inferred coordinates are about more than one hundred metres away from the actual site.

Second, for the plants with approximate geo-coding quality, we manually checked addresses on the web and used satellite images. We could increase accuracy for more than a third of them by eliminating obvious typing or locational errors.

Third, we merged in locational data using a newer version of the German registry of renewable plants from June 2016. This newer registry, the so-called *Anlagenregister* (translation: registry of installations), holds exact information on geo-coordinates for that part of plants for which certain regulatory changes applied between 2014 and 2016, for instance, a change in the subsidy.[8] Thus, we could improve the geographical coordinates of about a further ten percent of plants with approximate accuracy.

Fourth, we validated our data set against data on biomass plants from the German website `www.energymap.info`.[9] This website collected the official German renewable plants registry data, carried out extensive sanity checks, implemented corrections, and published the improved data on their website. Whenever we detected substantial differences between out and the *energymap.info* data set, we checked addresses and satellite images to update

[8]The *Anlagenregister* was downloaded from `https://www.bundesnetzagentur.de/DE/Sachgebiete/ElektrizitaetundGas/Unternehmen_Institutionen/ErneuerbareEnergien/ZahlenDatenInformationen/EEG_Registerdaten/EEG_Registerdaten_node.html` on August 29, 2016.

[9]The website is run by the *International Solar Energy Society, German Section*, a German solar energy lobby group. The web project aimed at a more transparent, and partly corrected, public documentation of German data on renewable plants. The data set was downloaded on October 24, 2016.

our data.

Fifth, to be conservative, we flag plants for which relevant information is still given with insufficient accuracy. This comprises the 21% of plants only feature approximate accuracy in their geographical coordinates. Moreover, we classify about 7% of plants as data deficient in a sense that different data sources provide substantially deviating information on size, the type of fuel or the beginning of operation: for the operational date, a spread of over 30 days; for the size, a divergence in the sense that one data source reports the plant having a capacity less than 75 kilowatts and another source above this threshold. These plants receive special attention in defining our treatment and control groups as Section 4.1 explains.

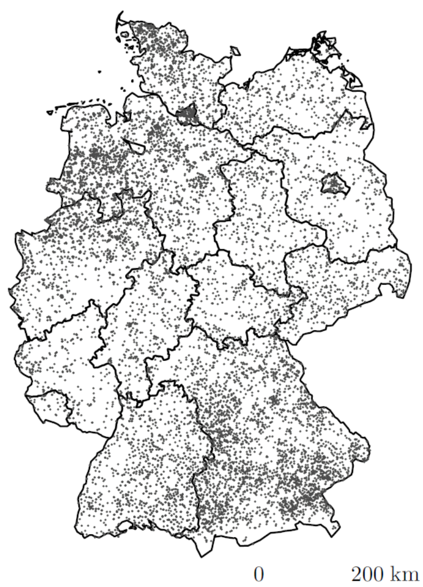

Figure 1: Biogas plants with grid connection through end of 2012 in Germany.
Dots are biomass plants, lines are borders of Federal States.
Source: Data on biomass plants as described in Section 3.2

Sixth, not all recorded biomass plants use biogas as fuel, but about two percent directly combust liquid or solid biomass, for instance plant oils or pellets. For these installations, one can also expect negative externalities such as an increased transport volume or interference with the landscape. As default, we keep these plants in our data set; however, we also run a sensitivity analysis excluding those. Likewise, for 48% of the installations, no data source provides information on the type of fuel. Yet, given that close to 100% all of installations for which we have information are biogas plants, we can plausibly assume that the bulk of the installations without type information also use biogas. In any case, we adopt an intention-to-treat framework, and interpret estimates as lower bound.

Finally, we carried out plausibility checks on all variables for a random draw of a number of plants. We arrived at a new and comprehensive panel data set on biomass plants in Germany on a high quality level. Figure 1 illustrates the geographical distribution of the biomass plants in our data set with grid connection through end of 2012.

3.3. Merge

We merge the SOEP data on individuals with our newly constructed data set on biomass plants through geographical coordinates. The coordinates allow us to compute the distance between a household and a biomass plants in its surroundings in every interview year. Specifically, each household is annually merged to all biomass plants closer than 21 kilometres.[10] As we also include plants so far away that they are unlikely to trigger any negative effect, we do not exclude any possible source of nuisance *ex ante*.

The resulting panel data set contains both individual characteristics and biomass plants information in the period 2000 to 2012.

[10]This corresponds to a maximum of 57 biomass plants per interview year.

4. Empirical Strategy

4.1. Defining Treatment and Control Group

To empirically identify external effects of neighbouring biogas plants on subjective well-being, we group individuals either into a treatment or a control group. An individual assigned to the treatment group if a biomass plant within a pre-specified treatment radius is operational in the respective year. The treatment radii 500, 750, 1000, and 1500 metres define the neighborhood of an individual. We select different treatment radii for several reasons.

First, there is no uniform legislation in Germany that could serve as a natural point of reference. Environmental impact assessments of installations are location-specific, and impact radii vary across time and states.[11] Analysing these different radii allows us to investigate the range of the external effect of biogas plants, and thus, serves as a sensitivity analysis.

Moreover, we define conservative minimum requirements for a biomass plant in order to trigger treatment of an individual. The reason for this lies in the assumption that different types of biomass plants have different external effects. Besides biomass plants that are identified to be data deficient, we exclude all small biomass plant with an installed capacity below 150 kilowatts since we expect them to exhibit no or only negligibly small external effects.[12] We also exclude all plants with only approximate spatial accuracy.

[11]There is no legal mandate for a minimum setback distance between biomass plants and residential areas in Germany; rather, this is a case-by-case decision, depending on the specific location, type of building area, types of neighbouring building areas, type and size of installation, availability of a development plan, and whether the new build project is located within an inner or outer zone under German building law. See, for example Administrative Court Munich (2016). The *Biogashandbuch Bayern* (Biogas Handbook for Bavaria) specifies minimum separation distances between 300 metres and 500 metres for open and closed installations, respectively, but installations can come below these distances under certain technical conditions (BSOE, 2011)

[12]Moreover, we neglect all 530 installations at which biogas is drawn from the natural gas network. These installations are no different from conventional micro power plants; they are only part of the original dataset

To be conservative, all plants that cannot trigger treatment are instead triggering the exclusion of residents in their vicinity from our analysis, if such plants are observed previous to plants that do trigger treatment. For example, if a biogas plant with inaccurate geo-coordinates is built "close" to a household, we cannot be sure whether it actually affects residents. For a sensitivity analysis, we weaken the conservative approach and also assume for data deficient, small, and approximately localised plants to trigger treatment. Likewise, we exclude households that already had a plant close to their place of residence before the year 2000, that is, before our period of analysis. Formally, these individuals would enter the control group despite having an installation in their vicinity.

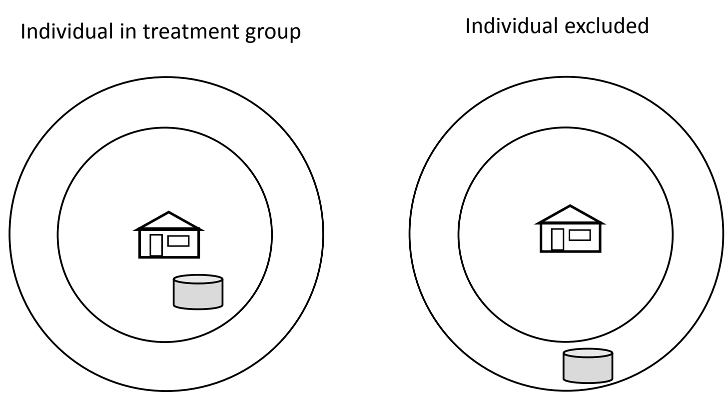

Figure 2: An individual is allocated to the treatment group if there is a biogas plant within the treatment radius. It is excluded if the nearest plant is within the ban radius.

Individuals with no biomass plant in operation close by are assigned to the default control group. To obtain a clear-cut distinction between treatment and control group, we use additional ban radius: For each treatment group, we define a constant ban radius of 6,000 metres. Figure 2 illustrates this setup. Hence, all individuals with no biomass plant

for administrative reasons.

in their treatment radius but within the ban radius are neither assigned to the treatment nor control group. Apart from this the same minimum requirements for biomass plants are applied as for the corresponding treatment group.

4.2. Identifying Assumptions

We make three identifying assumptions to estimate the causal effect of biogas plant externalities on individuals living in their surroundings: *ignorability*, *stable unit treatment value*, and *common trends*. Moreover, our strategy is an intention-to-treat framework and estimates should be interpreted as lower bound.

4.2.1. Ignorability

Ignorability means that allocation of an individual to the treatment or control group is independent of the outcome of that individual, conditional on covariates. Threats to ignorability come from within-sample selection; in particular, from *endogenous residential sorting* and *endogenous construction*.[13]

Regarding *endogenous residential sorting*, individuals with a lower preference for biogas plants might be systematically more likely to live farther away from the nearest plant, and *vice versa*. Such sorting can occur either prior to or during the observation period. In case it occurs prior to the observation period, we face preference heterogeneity, and to the extent that preferences are stable, we account for such time-invariant unobserved heterogeneity by routinely including individual fixed effects.

However, in case it occurs during the observation period, or in case of endogenous preference formation, we face simultaneity, which we work around in our baseline specification

[13] Alternatively, individuals might select out of the sample, which could bias estimates if such out-of-sample selection is correlated with outcomes. To the extent that individuals who are most adversely affected from biogas plant construction are most likely to select out of the sample, our estimates could be interpreted as lower bounds.

by focusing only on stayers and exclude individuals who move. The rationale for focusing only on stayers is that the direction of bias resulting from residential sorting is not *ex-ante* clear. Individuals may move away from biogas plants, switching from the treatment to the control group, if the installation strongly affects them. This moving pattern would bias estimates downward. However, individuals could also move toward biogas plants for reasons unrelated to them, despite having a low preference for installations in their surroundings. This would bias estimates upwards. Other movers may relocate without switching groups: remaining in the treatment group, they may move to a location that is less prone to biogas plant externalities, or remain in the control group for reasons that are entirely unrelated. Yet another type of movers may not realise their original moving intention because of biogas plant construction at their destination, a counterfactual with welfare implications that is not directly observable.

Thus, to arrive at a clear-cut interpretation of our treatment effect, in our baseline specification, we focus only on stayers. In Section 6.2, we evaluate in more detail the extent to which residential sorting affects our estimates by including movers, either jointly or different types of movers individually.

Regarding *endogenous construction*, it might be systematically more likely for some individuals that biogas plants are constructed in their surroundings. This is especially true for farmers who owned about 72% of biogas in Germany in 2010. Private persons, on the contrary, made up less than 1% (KNI, 2011).[14] The dominance of farmers in the ownership structure of biogas plants is also reflected in siting decisions: in line with a transportation costs framework, most plants are located where biomass in form of remnant or waste material is readily available, or where energy crops can be cheaply cultivated.

[14] Other owners were mostly institutional: the most important ones were project planners (about 13%) and funds or banks (about 6%) (KNI, 2011).

We therefore exclude all farmers (about 1.7% of individuals) from our analysis. They are more likely to be owners, let land to commercial operators, or generate profits from selling biogas or inputs into production to energy producers, thus generating both monetary and non-monetary benefits from installations in their surroundings.

4.2.2. Stable Unit Treatment Value

The stable unit treatment value assumption states that the allocation of an individual to the treatment or control group is independent of the outcome of another individual, implying that there should be no behavioural spillovers. There is no reason to believe that this is the case in our setting.

4.2.3. Common Trends

The common trend assumption states that, in the absence of treatment, the treatment and control group would have followed a common trend in outcomes over time. To ensure common trend behaviour, we apply spatial and propensity-score matching techniques drawing on external land cover data, as described in more detail in Sub-Section 4.3, prior to running our difference-in-differences regressions. Although there is no formal way of testing the common trend assumption, we can show graphically that the treatment group, prior to treatment, and the matched control group exhibit common trend behaviour in outcomes over time.

4.2.4. Intention-to-Treat and Lower Bound

In our setting, we do not know for sure whether a household that is allocated to the treatment group is indeed subjected to externalities caused by a biogas plant in its surroundings. Therefore, our identified effects should be interpreted as intention-to-treat, and in particular, as intention-to-treat for stayers in our baseline specification.

This is due to several reasons: first and foremost, we proxy externalities caused by a biogas plant through a treatment radius, which implicitly assumes that externalities decrease in distance to the nearest plant, and are present for any individual at any time. This, however, is unlikely to be the case: for example, local wind conditions may greatly reduce externalities.[15] Second, households may adopt mitigating behaviour, for example, by installing air filters, better sealings, or simply opening windows less often. Finally, we only have information on private households: individuals living in places like nursing homes are excluded, and so are temporary visitors to the area such as tourists. Of course, we cannot make counterfactual inference about individuals who might have moved into the area, and did not do so because of installations. In terms of time use, some individuals spend considerable amounts of time outside their private homes, for example at work, and may thus be less permanently affected. Our identified effects should therefore be, additionally, interpreted as lower bounds.

4.3. Matching Treatment and Control Group

So far, individuals inside the treatment radius are compared to all individuals outside the ban radius. However, this control group is likely to be considerably different from the treatment group. As such, the treatment group is concentrated in rather rural, agrarian areas rather than evenly spread across the country (compare Figure 1), whereas the control group consists of individuals from all parts of the country, including urban areas. Comparability and, thus, the assumption of a common trend between treatment and control group may not be justified.

To account for this, we restrict our sample to those residents not living in major population centres and exclude all individuals living in a county with above $500,000$

[15] We will investigate this issue further in Section 6.3 by performing a downwind analysis.

inhabitants. An additional sensitivity check lowers this requirement to 100,000 inhabitants.[16] Moreover, we apply different types of matching techniques.

4.3.1. Spatial Matching

The first type of matching – spatial matching – matches individuals in the treatment group with individuals in the control group based solely on the geographical locations of their places of residence. This type of matching is rooted in the first law of geography, stating that objects which are closer are also more similar to each other (Tobler, 1970). To operationalise it, we introduce – in addition to the treatment and ban radii – a larger matching radius: the matching radius goes beyond the ban radius, restricting the control group to individuals living in the ring between the ban and the matching radius. In other words, the control group is restricted to individuals living close to a biogas plant but just not close enough to be treated. A matched individual is unlikely to be exposed to external effect of a plant, but likely to live in similar spatial conditions than treated individuals.

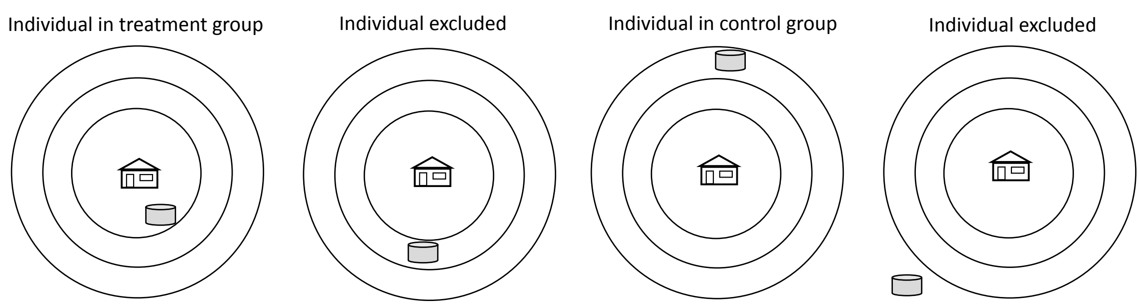

Figure 3: Depending on the distance to the nearest biogas plant, an individual is assigned to the treatment group, the control group, or does not enter the analysis.

[16] As a *county*, we designate the German administrative areas *Landkreise* and *kreisfreie Städte*. This corresponds to the roughly 400 German NUTS-3 regions, according to the NUTS classification scheme. To account for time-variant populations sizes, we exclude an individual if the county had a population above 500,000 (100,000) in at least one year of the observation period.

Figure 3 illustrates this setting. The individual to the left is in the treatment group because a biogas plant is present within the treatment radius; the next individual is excluded because a plant is located within the ban radius. The third individual is part of the control group because there is a plant in the matching radius. The individual on the right-hand side does not enter any group as there is no plant in any vicinity.

As a default matching radius, we choose $15,000m$. Beyond this default matching radius, we will carry out sensitivity analyses using a smaller matching radius of $9,000$ metres and a medium one of $12,000$ metres.

The following figure plots the predicted outcomes, covariate-adjusted, for the treatment group, prior to treatment, and the matched control group over the observation period. It shows both groups exhibit common trend behaviour in pre-treatment outcomes over time.

Work in progress – Figure will be available at the time of the IZA Workshop

4.3.2. Propensity-Score Matching (work in progress)

The second type of matching – propensity-score matching – will match individuals in the treatment group with individuals in the control group based on their predicted likelihood of being treated.

We will apply a one-to-one nearest neighbour matching on macro-level controls. They include the county-level unemployment rate, average household income, population density, and federal state-specific dummy variable. As reflected in their ownership structure consisting predominantly of farmers, a distinct feature of biogas plants is their proximity to places where biomass in form of remnant or waste material is readily available, or where energy crops can be cheaply cultivated.

To better predict these places, and thus better match individuals in the treatment group with individuals in the control group, we will additionally match on external land cover data. In particular, we will merge our dataset with data from the most current wave (2012) of the CORINE Land Cover inventory (EEA, 2017). This inventory classifies different categories of land cover based on highly detailed satellite imagery, being able to identify and differentiate surface areas with a minimum size of 0.25 hectares. It also covers a variety of agricultural areas: from this category, we calculate the total area covered by *(i)* arable land, *(ii)* permanent crops, *(iii)* pastures, and *(iv)* heterogeneous agricultural areas per county.

We will additionally include these variables in our scoring function. Different from spatial matching, the sizes of the treatment and control group will be equal under propensity-score matching. A figure will graphically illustrate our external land cover data.

4.4. Regression Equations

We estimate two sets of regressions, depending on the outcome: well-being regressions and hedonic price regressions. Each set, in turn, includes three regressions.

The first estimates the overall treatment effect, with $treatment_{it,r}$ as the variable of interest. $treatment_{it,r}$ is a dummy variable that equals one in time period t if a biogas plant is present within treatment radius r around the household of individual i, and zero else.

The second regression estimates treatment effect intensity, with interaction $treatment_{it,r} \times intensity_{it,r}$ as the variable of interest. $intensity_{it,r}$ is a placeholder for different measures of treatment intensity: $revdist_{it,r}$ is the treatment radius minus the distance to the nearest installation, $invdist_{it,r}$ is the inverse of the distance to the nearest installation, that is the treatment radius divided by the distance, and $cumul_{it,r}$ is the number of installations within the treatment radius. Note that the two distance-based measures make different parametric assumptions and that treatment intensity can change over time. Moreover, we estimate a non-parametric distance-decay specification. To this end, we specify the intensity as dummy $treatring_{it,\underline{r},\overline{r}}$, equal to one if a biogas plant is operational within a ring around the individual with a radius larger than $\underline{r}$ but smaller than $\overline{r}$. We take the default treatment radii 500, 750, 1000, and 1500 metres to define the concentric rings.

The third regression estimates treatment effect persistence. The variable of interest, $trans_{it-\tau,r}$, is a dummy variable that equals one in time period t, which is τ periods after the construction of the first biogas plant within the treatment radius, and zero else.

4.4.1. Well-Being Regressions

For our well-being regressions, we employ linear models estimated by fixed-effects (within) estimators.[17] Robust standard errors are clustered at the state level.

For our analysis, we estimate the following regression equations, where Equation (1) estimates the overall intention-to-treat effect (ITE) on subjective well-being, Equation (2)

[17] Since subjective well-being is recorded as a discrete, ordinal variable, applying a linear models introduces a measurement error. But as for example Ferrer-i-Carbonell and Frijters (2004) for panel data, and Brereton et al. (2008) and Ferreira and Moro (2010) for repeated cross-section data show, the resulting estimation bias can be neglected.

the treatment effect intensity, and Equation (3) treatment effect persistence.

$$y_{it} = \beta_0 + \mathbf{MIC'_{it}}\boldsymbol{\beta}_1 + \mathbf{MAC'_{it}}\boldsymbol{\beta}_2 + \delta_1 treatment_{it,r} + \\ + \sum_{n=0}^{12} \gamma_n Year_{2000+n} + \mu_i + \epsilon_{it} \tag{1}$$

$$y_{it} = \beta_0 + \mathbf{MIC'_{it}}\boldsymbol{\beta}_1 + \mathbf{MAC'_{it}}\boldsymbol{\beta}_2 + \delta_1 treatment_{it,r} \times intensity_{it,r} + \\ + \sum_{n=0}^{12} \gamma_n Year_{2000+n} + \mu_i + \epsilon_{it} \tag{2}$$

$$y_{it} = \beta_0 + \mathbf{MIC'_{it}}\boldsymbol{\beta}_1 + \mathbf{MAC'_{it}}\boldsymbol{\beta}_2 + \sum_{\tau=1}^{9} \delta_\tau trans_{it-\tau,r} + \\ + \sum_{n=0}^{12} \gamma_n Year_{2000+n} + \mu_i + \epsilon_{it} \tag{3}$$

The dependent variable is life satisfaction, y_{it}, of individual i in year t. MIC_{it} is a vector of micro level controls and MAC_{it} a vector of macro level controls. Moreover, we include a full set of year dummy variables $Year_{2000+n}$. μ_i controls for time-invariant unobserved heterogeneity at the individual level. ϵ_{it} is the idiosyncratic error term. The variables of interests are $treatment_{it,r}$, $treatment_{it,r} \times intensity_{it,r}$, and $trans_{it-\tau,r}$, depending on the regression equation. Their coefficients, δ_1 and δ_τ, estimate the corresponding intention-to-treat effects.

4.4.2. Hedonic Price Regressions

Our hedonic price regressions will be modelled in a similar way, but will rely on a log-level linear model. Our approach follows Luechinger (2009) and the hedonic literature: We use dwelling fixed effects θ_d to control for different dwelling and amenity characteristics. Equation (4) again estimates the treatment effect, Equation (5) treatment effect intensity, and Equation (6) treatment effect persistence.

$$\begin{aligned} ln(R_{dt}) = \beta_0 + \delta_1 treatment_{dt,r} + \\ + \sum_{n=0}^{12} \gamma_n Year_{2000+n} + \theta_d + \epsilon_{dt} \end{aligned} \tag{4}$$

$$\begin{aligned} ln(R_{dt}) = \beta_0 + \delta_1 treatment_{dt,r} \times intensity_{dt,r} + \\ + \sum_{n=0}^{12} \gamma_n Year_{2000+n} + \theta_d + \epsilon_{dt} \end{aligned} \tag{5}$$

$$\begin{aligned} ln(R_{dt}) = \beta_0 + \sum_{\tau=1}^{9} \delta_\tau trans_{dt-\tau,r} + \\ + \sum_{n=0}^{12} \gamma_n Year_{2000+n} + \theta_d + \epsilon_{dt} \end{aligned} \tag{6}$$

In these models the dependent variable is $ln(R_{dt})$, the log monthly net rent of dwelling d in time period t. All other controls remain the same as in Equation (1) to (3).

5. Results

5.1. Treatment Effect

By estimating Equation (1), we obtain estimates of the overall intention-to-treat effect of large biogas plants on subjective well-being.[18] Table 5.1 shows the coefficient estimates of the overall treatment effect and of log annual net household income on the self-reported life satisfaction of household members for different treatment radii.

[18]We consider all biomass plants with an installed capacity larger or equal to 150 kW as large. We apply a ban radius of $6,000$ metres and a matching radius of $15,000$ metres. Further calculations are work in progress.

Table 5.1: Results: overall treatment effect

Dependent variable: satisfaction with life

Treatment radius in metres	500	750	1000	1500
$Treatment_{it,r}$	-0.1127^{*}	-0.0750^{**}	-0.0580	-0.0520
	(0.5955)	(0.0311)	(0.04289)	(0.0597)
Macro controls included	yes	yes	yes	yes
Micro controls included	yes	yes	yes	yes
amongst which				
$log\, household\, income_{it}$	0.3698^{***}	0.3627^{***}	0.3609^{***}	0.3607^{***}
	(0.0453)	(0.0485)	(0.0470)	(0.0462)
Observations	47,862	48,285	48,666	165,908
Individuals in treatment group	103	215	317	531
Individuals in control group	10,494	10,397	10,319	10,170
R^2	0.1002	0.0790	0.0791	0.0798

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $treatment_{it,r}$ is a dummy variable equal to one if a biogas plant operates within the given treatment radius r of an individual i in year t, and zero otherwise. All regression equations include a full set of dummy variables for years and the full set of controls at the micro and macro level. Robust standard errors are clustered at the federal state level. We use a ban radius of 6,000 metres and a matching radius of 15,000 metres. All numbers are rounded to four decimal places.
Source: SOEP (2015), 2000–2012, individuals aged 17 or above, and data on biomass plants as described in Section 3.2, own calculations.

Results show that the sign of the coefficient is always negative regardless of treatment radius. It is statistically significant for the smaller radii, 500 metres and 750 metres, at the 10% and 5% level, respectively, and insignificant for the larger radii, 1,000 metres and 1,500 metres. For the 500 metres treatment radius, a neighbouring biogas plant, *ceteris paribus*, lowers an individual's self-reported life satisfaction on average by 0.1127 points. A one percent decrease in household income, *ceteris paribus*, lowers an individual's self-reported life satisfaction on average by 0.3698 points. Given that the average annual net household income in our final sample is about 33,895 Euro, this implies, assuming a permanent impact with no adaptation, that an affected household would be willing-to-pay about 100 Euro per year in order to avoid a biogas plant being located within this radius.

To the extent that negative external effects are (at least partly) internalised in real estate prices, and given that we control for real estate prices in our well-being regressions, this estimate can be interpreted as a residual, and thus as a lower bound.

For larger treatment radii, the size of the coefficient decreases: while it amounts to -0.1127 for the 500 metres treatment radius, it decreases to -0.0520 for the $1,500$ metres treatment radius. These findings are in line with the intuition that biomass plants exhibit negative externalities that are spatially limited.

The hedonic regressions are work in progress. Results will be available by the time of the IZA Workshop, and will complement our well-being regressions.

5.2. Treatment Effect Intensity

Different measures of treatment intensity provide further insights into the spatial dimension of biogas plant externalities. To initially explore this dimension, we multiply our treatment dummy variable $treatment_{it,r}$ with the intensity measure $revdis_{it,r}$ defined as the treatment radius minus the distance to the closest biomass plant. We thus impose a linear distance-decay effect on treatment intensity.[19]

We use Equation (2) to obtain results. Table 5.2 summarizes the estimated treatment intensities for different treatment radii.

Table 5.2: Results: treatment intensity

Dependent variable: satisfaction with life

Treatment radius in metres	500	750	1000	1500
$treatment_{it,r} \times revdist_{it,r}$	-0.00028	-0.00023^{**}	-0.00041^{**}	-0.00006
	(0.00042)	(0.00010)	(0.00006)	(0.0597)

Continued on next page

[19]Further treatment intensities are currently work in progress. Results will be available at the time of the IZA Workshop.

Continued from previous page

Dependent variable: satisfaction with life				
Treatment radius in metres	500	750	1000	1500
Micro controls included	yes	yes	yes	yes
Macro controls included	yes	yes	yes	yes
Observations	47,862	48,285	48,666	165,908
Individuals in treatment group	103	215	317	531
Individuals in control group	10,494	10,397	10,319	10,170
R^2	0.1002	0.1012	0.0995	0.0964

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Note: $treatment_{it,r}$ is a dummy variable equal to one if a biogas plant operates within the given treatment radius r of an individual i in year t, and zero otherwise. $revdist_{it,r}$ is equal to the treatment radius r minus the distance to the nearest biogas plant. All regression equations include a full set of dummy variables for years and the full set of controls at the micro and macro level. Robust standard errors are clustered at the federal state level. We use a ban radius of $6,000$ metres and a matching radius of $15,000$ metres. All numbers are rounded to five decimal places.
Source: SOEP (2015), 2000–2012, individuals aged 17 or above, and data on biomass plants as described in Section 3.2, own calculations.

Results show that treatment intensities have a negative sign for all radii, indicating the decrease in subjective well-being is higher the closer the next biogas plant is located. For instance, for the 750 metres treatment radius, an individual's life satisfaction *ceteris paribus* declines on average by 0.00023 points for each metre a biogas plant is constructed more closely to the place of residence; this corresponds to 0.23 points per kilometre. The direction of the effect is in line with the results from our basic specification above and, again, indicates the negative external effects are spatially limited.

Estimates are statistically significant at the five percent level for the 750 and the $1,000$ metres treatment radii. For the larger $1,500$ metres radius, they turn out insignificant. The insignificance for the 500 metres radius may be due to small sample size.

5.3. Treatment Effect Persistence

Further results will shed light in treatment effect persistence. To this end, we will estimate Equation (3) that specifies a treatment dummy, $trans_{it-\tau,r}$, equal to one for each year t τ years after the first treatment and zero else.

Results will be available by the time of the IZA Workshop.

5.4. Treatment Effect Heterogeneity

We will also estimate treatment effect heterogeneity. Specifically, we will carry out subgroup analyses differentiating between politically "green" individuals, owners and renters as well as for different quantiles of the income distribution.

Results will be available by the time of the IZA Workshop.

6. Robustness Checks

6.1. Placebo Tests

We will carry out placebo tests concerning both anticipation effects and a random assignment of the treatment status across individuals.

Results will be available by the time of the IZA Workshop.

6.2. Residential Sorting

As such, endogenous residential sorting seems to be a minor issue; only about 5% of individuals in the SOEP move per year. Likewise, most movers seem to move for other reasons than newly constructed biogas plants in their surroundings as the moving reasons, recorded in the SOEP indicate.

Specifically, movers can change between treatment and control group and, thus, endogenously assign themselves. The direction of the bias is, however, *ex ante* unclear; see Section 4.2.

A robustness including all movers and only different subgroups will shed light on the repercussions.

Results will be available by the time of the IZA Workshop.

6.3. Downwind Analysis

Finally, we will perform a downwind analysis based on detailed data on wind speeds and direction on a highly resolved geographical scale. Specifically, this downwind analysis will allow disentangling odour emissions from other negative external effects.

Results will be available by the time of the IZA Workshop.

7. Conclusion

Biogas is an important technology to generate climate-friendly electricity. It avoids negative external costs, notably CO_2 and noxious local emissions, of conventional technologies such as coal and natural gas-fired power stations. However, biogas plants are not entirely free of negative externalities themselves. These comprise potential odour emissions, an increased transport volume around sites, undesired land-use change for energy crops, and the presence of installations themselves. Accordingly, studies regularly rank biomass as the least popular renewable energy source. Systematic large-scale evidence, however, is largely missing.

We close this gap by quantifying the negative external effects of biogas plants using both well-being and hedonic data. To this end, we combine a new panel data set comprising more than $13,000$ biogas plants in Germany for the period 2000 to 2012 with rich longitudinal household data from the SOEP. Based on exact distances, we match households to the nearest biogas facilities. Exploiting temporal and spatial variation, we identify causal effects in a difference-in-differences design. Spatial and propensity-score matching technical ensure comparability between treatment and control group.

Our preliminary findings show that the construction of a biogas plant in a 750 metres radius around a household significantly lowers the self-reported life satisfaction of household members by, on average, 0.075 points on an eleven-point scale. This impact is not only statistically but also economically significant: trading off the negative effect of the installation against the positive effect of household income, we find that affected households would be willing to pay about 100 Euro per year in order to avoid an installation being located in their surroundings. Our hedonic regressions, which will be available by the time of the IZA Workshop, will shed more light on the exact nature of internalisation and its dynamics, allowing to quantify the total amount of the externality including both its spatial and its temporal dimension.

From a welfare economic perspective, external cost of biogas plants cannot be neglected. However, our figures are much smaller than the damage done by conventional electricity generation in terms of climate change. Assuming a moderate CO_2 damage of 50 Euro per ton, biogas electricity generation mitigated external cost of somewhat below 700 million Euro in Germany in 2016. Nevertheless, policy-makers should address distributive effects. Prudent zoning laws can minimize the impacts on residents; likewise, efficient and equitable compensation schemes could target more heavily affected households. Both could substantially contribute to increasing the deployment of renewables.

Our research adds new and systematic evidence on the debates of external costs in energy and land-use change. Several points are left for further research. For instance, studies on other countries could shed light on the question whether findings apply globally. Likewise, more fine-grained land-use data could more explicitly target land use and, thus, help disentangling channels. Finally, social and natural scientific research should keep on analysing best practices how to mitigate the impact of biogas energy generation.

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