Spatial impacts and sustainability of farm biogas diffusion in Italy

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Introduction

In 2009, the Italian government has introduced feed-in tariffs for renewable energy production, which, in the case of biogas, remunerate eligible producers with fifteen- year-flat price for each unit of electricity (€ 0.28/kWh) plugged into the national grid. Recent research (e.g., Chinese et al., 2014) has found that those incentives were the main driver for biogas diffusion in Italy. Major eligibility criteria for the incentives are auto-producing at least 51% feedstock and outsourcing the rest within 70km. These two prescriptions affect the demand for both land and agricultural labour in plants' neighbourhood, which results in spillover effects due to marshallian externalities. To the best of our knowledge, no study has assessed *ex post* the impact of farm biogas diffusion on the viability of EU's rural areas, despite ongoing policy debates at the single member state and Community level. Mainly, economic analysis focused on the EU have assessed the impact and spillover effects of agroenergy diffusion on the viability of rural areas *ex ante*; though, *ex post* assessments about domestic plants in developing countries are available. We consider hosting at least one operating agricultural biogas plant a treatment to Italian municipalities; provided comparable municipality features, the non-hosting ones form the control group. Measuring treatment effects can help estimate the contribution of farm biogas' diffusion the viability of rural areas. We analyse the spillover effects on neighbouring municipalities by means of a spatial propensity score model on censuses' data aggregated at the municipality level, to pinpoint the patterns of change at the meso level. The next paragraph briefly reviews the literature about biogas impacts. The methodology provides the framework for the spatial propensity score methodology, besides some details about used indicators and the dataset. Then, we present the results of software elaborations and conclude by a critical discussion around the proposed study.

Impacts of biogas diffusion

The anaerobic digestion of agricultural residues and food waste (biomass) help mitigate the negative externalities on the environment of agriculture and food industries, for example by abating climate altering emissions (Battini et al., 2014). Biogas, a low-grade natural gas substitute, is the added value output of digestion and digestate is the by-product. When consciously spread on cropland, the digestate balances nutrient mining, improves soil organic content, and increases microbiological diversity (Holm-Nielsen et al., 2009; Torquati et al., 2014; Sapp et al., 2015). Supplementing digester's diet with dedicated crops – notably maize, given the exceptional biogas yield potential – helps offset energy production costs (Walla & Schneeberger, 2008). Still, the intensification of feedstock cropping around biogas plants have modified habitats' suitability to locally adapted species and simplified landscapes' structure (Burel, 1989; Pearson, 1993; Gevers et al., 2011; Sauberei et al., 2014), though biodiversity estimates based on indicators are ambiguous (see Gevers et al., 2011 for a discussion).

On-farm digesters are generally coupled with cogenerators for combined heat and power generation; in Italy, plugging electricity into the national grid (i.e. selling electricity to the national authority) is compulsory. Apart from offsetting greenhouse gas emissions that would follow the use of fossil fuels (Sims et al., 2003; OECD, 2010; Gloy, 2011), supplying electricity diversifies farmers' revenue. Profit can drive land, and water, use change from food to energy production. Direct land use change (commonly, just land use change) is the shift of a share cropland from food to energy supply, while indirect land use change is the conversion of natural areas into (energy)cropland, which affects the carbon sequestration service of above ground vegetation.

The retrieved literature did not allow to understand the extent to which the global development of a bio-economy is compatible with sustainable agricultural practices (see, for example, Muller, 2009).

Social acceptance is key for bioenergy to widespread: odour, noise, visual impact, and suspected health threats are major sources of complaint by citizens who live in the vicinity of a plant (Faaij and Domac (2006) pinpointed significant barriers to bioenergy diffusion); job creation, contribution to local economy and raised farm income are recognised plants' benefits (Domac et al., 2005 provide a reasoned framework of socio-economic aspects of bioenergy). Shared biogas installations had delivered increased social cohesion and stability, for example by revitalising the cultural heritage of hosting remote communities, thanks to increased energy self-sufficiency, reduced supply costs, labour creation and integration of the energy plant within local activities (Faaij and Domac, 2006).

Biogas systems have evolved adaptively – i.e. through learning, creation, and growth – and achieved their own technological designs and bounded network organizations (Buchholz et al., 2007; Mol, 2014). For example, Denmark's centralised biogas concept is unique: a community of farmers cooperate to supply and digest the feedstock in a centrally located biogas plant (Raven and Gregersen, 2007; Holm-Nielsen et al., 2009). Finnish installations date early 1900s; biogas was addressed to the transport sector (Biogas Fachverband, 2012 , in Pollman et al., 2014).

In Italy, farm biogas had spread via capital-risk investors (energy system companies), which promote and design plant with the purpose of maximising the profit from the state's incentive system (Cannemi et al., 2014). The economic sustainability of installations has relied on the incentive system in force until 2012 (Torquati et al., 2014). Four legal constraints (Italian law: D.M. 18/12/2008) mainly affected the selection of plant location and its sustainability: (i) at least 51% feedstock had to be auto-produced; (ii) feedstock sourcing from outside farm was limited to 70 km from plant location; (iii) 15-year-flat feed-in tariff was dedicated to plants under 1 MWh rated power; (iv) a plan for the agronomic use of digestate, to be approved by the local political authority, is needed for spreading the digestate.

Methodology

Spatial propensity score analysis

We attempt at drawing causal inference about spatial impacts and sustainability of the diffusion of biogas installations in Italian municipalities. Having a non-random sample we turn to Rosenbaum and Rubin (1983)'s propensity score analysis. We consider agricultural anaerobic digesters coupled with combined heat and power installations as treatments to hosting municipalities, i.e. the treated (*i*). Biogas impact over a given geographical area (*Y*) accounts for the average treatment effect on the treated (*ATT*), the extent of which is understandable only if compared to the average treatment effect on the same set of municipalities had they not hosted the plant (the average treatment effect on the untreated, *TT*), i.e. the control. Realistically, however, the selection of control's items bases on analogy with plant-hosting municipalities, provided the absence of treatment. Each municipality belongs to either the treated or the control group, which makes treatment assignment (*T*) a dummy variable. The average treatment effect (*ATE*) arises from the difference between the potential outcomes associated with *T* for each observation ($Y_i(\mathrm{T}_i)$):

$$ATE = Y_i(1) - Y(0)_0$$

Despite analogy, pre-treatment differences (or covariates, *x*) lead treatment and control groups to systematically diverge, thus avoiding a straightforward comparison. The propensity score ($p(x)$) is a function of the observed covariates that associates to each observation its relative probability (*Pr*) to be among the treated ($T=1$):

$$p(x) = \Pr(T = 1 \mid x)$$

Contrary to randomized experiments, $p(x)$ is unknown in case of non-random sampling and, thus, is estimated from observed data, generally via a logit model. When both $Y_i(T_i)$ do not depend on *T*, given a vector of covariates (*X*) (so called unconfoundedness) and each *i* may fall among both the treated and the control (so called overlap), treatment assignment is strongly ignorable; respectively:

$$(Y_i(1), Y_i(0)) \perp T \mid X \qquad \text{and} \qquad 0 < \Pr(T_i = 1 \mid X) < 1$$

In that case, the difference between *ATT* and *TT* (the control) at each value of *p*(*x*) is an unbiased estimate of the *ATE*:

$$ATE = ATT - TT \qquad \forall p(x) \mid X$$

An additional requirement for correctly implementing a propensity score analysis is the "stable unit treatment value" assumption (Rubin, 1980), i.e. being treated is conditional to *i* only and the observed $Y_i(1)$ is independent of treatment assignment methodology, as well as of any other *i* receiving treatment. We estimate the *ATT* on plant-hosting municipalities and approximate *TT* using the average result of the self-selected group of the non-hosting ones. Measuring spatial impacts implies consider spatial dependence, i.e. the reciprocal influence of every *i* included in the system under study. This turns into the combination of statistical dependence with the notion of space (Anselin, 1988). We model the municipalities – the observations *i* – as a set of pairs (i_1, i_2) and build a spatial contiguity matrix (*W*), the elements of which are *i*'s weights (w_{i_1,i_2}):

$$Y_{i_1,i_2} = Wy \qquad \text{with} \qquad w_{i_1,i_2} = \{1 \text{ if } i_1 \text{ and } i_2 \text{ are neighbours; } 0 \text{ if } i_1 \text{ and } i_2 \text{ are not neighbours}\}$$

Plant managers hardly rely on a single type of feedstock (regardless if self-supplied or purchased), needing to meet digesting bacteria needs, to secure continuously the maximum energy output, and to deal with economic constraints. Italian farmers feed their anaerobic digesters with livestock and cropping waste, food manufacturing waste, the organic fraction of municipal solid waste, and dedicated energy crops in different proportions. Given the sustainability concerns associated with energy cropping, we consider hosting a plant fed with waste as a second treatment to municipalities. Properly adapted, the above methodology applies to this second treatment as well.

Selected sustainability indicators

Indicators and conceptual frameworks for assessing sustainability are widely available from the literature as well as from official statistical institutes, as e.g. EUROSTAT (see Singh et al. (2009) for a review). We selected five indicators able to deliver concise and readily intelligible results, across the three dimensions of sustainability. The five sustainability indicators are hired labour (No. working days/year), household labour (No. working days/year), number of farms, EUROSTAT's livestock units (LSU).

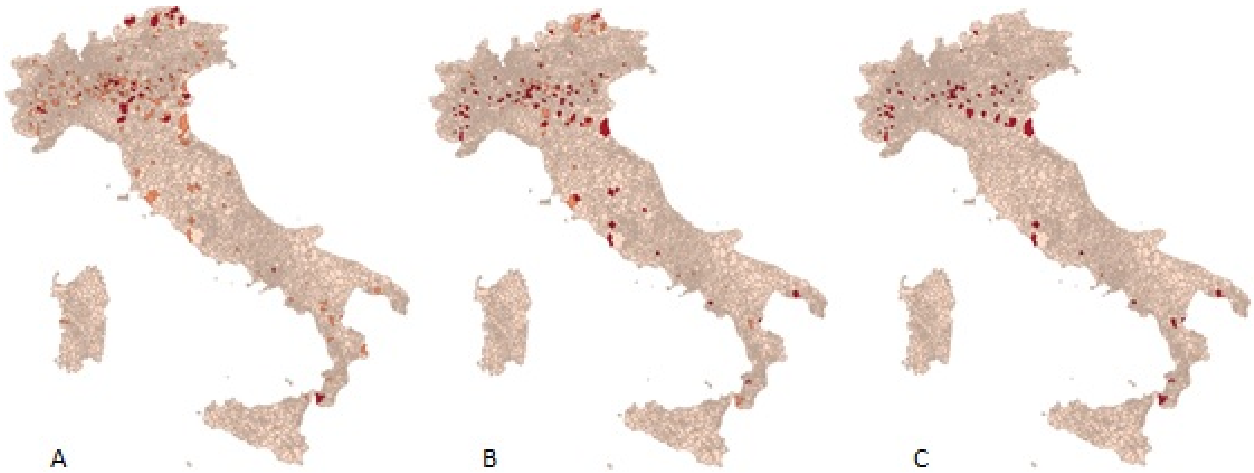
Data

We compared the most recent official information on Italian municipalities that host operating biogas plants to ten-year-older municipality microdata from the same source, notably the Italian Statistical Institute (ISTAT), over the same set of variables. We organised a dataset by supplementing ISTAT's Agriculture (2000 and 2010) censuses with plant feeding material and energy supply microdata from the 2010 biogas plant inventory of the Research Centre on Animal Production (CRPA). Data are aggregated at the municipality level. The descriptive statistics are available from Annex 1.

Results

Treatment 1 and 2 ($T_{1,2} = 1$) to observations (i = Italian municipalities) are hosting at least one operating agricultural biogas plant and hosting a plant fed with agri-food waste, respectively; assigning $T_{1,2} = 0$ to untreated municipalities is straightforward. The figure (Figure 1) and table (Table 1) below display the outputs of software elaborations. Both T_1 and T_2 affect the sustainability indicators. Major impacts are on agricultural labour, though with marked differences between household and hired labour: both treatments affect positively agricultural hiring on neighbouring municipalities, but negatively household labour. The results associated to the hired labour indicator are significant and the confidence interval is positive. Instead, the household labour indicator is not significant and the confidence interval has both negative and positive values. This latter result may be due to the lack of data about job sectorial mobility: a control variable informing about off-farm income may help explain that uncertainty.

Figure 1. Distribution of operating biogas plants in Italy in 2010 (A) and subgroups of plants fed (B) or not (C) with agri-food waste.



Source: Authors' elaboration

Table 1. Average effects of treatments T_1 and T_2.

Outcome: difference between 2010 and 2000	Treatment	ATE	StdandardError	z	P>z	Confidence Interval 95%	
Hired labour [No. working days / year]	T_1	1268.79	212.21	5.98	0	852.84	1684.73
	T_2	931.19	343.53	2.71	0.007	257.88	1604.51
Household labour [No. working days / year]	T_1	-542.86	1740.52	-0.31	0.755	-3954.24	2868.50
	T_2	-1177.11	1235.36	-0.95	0.341	-3598.39	1244.16
Utilised agricultural area [ha / year]	T_1	39.57	69.35	0.57	0.568	-96.34	175.50
	T_2	17.40	89.25	0.19	0.845	-157.54	192.34
Number of farms per year	T_1	-47.27	16.69	-2.83	0.005	-79.99	-14.55
	T_2	-46.58	16.60	-2.81	0.005	-79.13	-14.04
Livestock units / year	T_1	0.52	0.23	2.19	0.028	0.05	0.98
	T_2	0.46	0.255881	1.83	0.068	-0.03	0.96

Source: Authors' elaboration

As we expected, the diffusion of biogas affects both farms' number and the utilised agricultural area, thus confirming published studies assessing biogas impacts on land demand and the profitability of agricultural activities. Spatially, biogas diffusion affects negatively the number of farms. This result may be understood by noting that larger farms are more likely than the smaller ones to endorse energy contracts with plant managers for energy cropping and feedstock supply. In fact, larger farms are willing to pay more for energy contracts, than the smaller ones, given the fixed transaction costs of energy contracts, e.g. cost for information during plant planning and cost for looking for and preparing the contract. Thus, those contract are more profitable for larger farms, which, in turn, would, more likely, keep farming. The results for the utilised agricultural area are positive, though not significant and with confidence interval between negative and positive values. Despite literature evidence on biogas driven increased demand for land, the spatial impacts may have other causes, such us, e.g., urban pressure, competition for land with added value farming systems, e.g. vine and fruit farming or embedding EU quality labels. We approximate environmental impacts with EUROSTAT's livestock units (LSU) indicator, accounting for animal pressure over the utilised agricultural area. The spatial impacts of biogas diffusion are positive and significant on neighbouring municipalities, maybe due to the increased demand for animal waste, which, in turn, help the profitability of livestock farming.

Conclusion

Despite the ongoing debate about the sustainability of farm biogas for heat and energy selling, few studies have carried out ex-post analysis. Here, we investigate the spatial impacts of biogas diffusion in Italy, by means of a spatial propensity score method, to try assess the spatial contribution of biogas on the viability of rural areas. We chose such a methodology due to legal constraints about feedstock sourcing area and feedstock transport costs. We found a strong biogas impact on rural economy, with trade-off among the tree-dimensional indicators of sustainability. On one hand, our results show a positive effects on income and job availability in rural areas. On the other hand, we highlight increased environmental pressure, with agricultural intensification and marginalisation of small farms. Undoubtedly, this study is biased; we recognise at least two limitations:

- the viability of rural areas depend on non-rural drivers, such as, e.g., sector mobility, off-farm income, and availability of infrastructures, that we did not model; improving the dataset by including data from outside the agricultural sector may return more accurate results;

- biogas plants are mainly concentrated in northern Italy, thus in a further study we would apply a generalised propensity score and dose-response model, to simulate the effects of non-binary treatments.

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Annex 1: descriptive statistics

Category	code	Variable	Obs	Mean	Std.Dev.	Min	Max
Treatment	t1	Municipality with at least one biogas plants	7159	0.02	0.16	-	1.00
	t2	Municipality with at least one biogass plant using biomass from livestock or dedicated crops	7159	0.02	0.15	-	1.00
Outcome	w_lab_ex1	Difference in hired labour in neighbour municipalities (working days)	7159	371.47	25,220	-378,248	322,337.00
	w_lab_hh1	Difference in household labours in neighbour municipalities (working days)	7159	-58,356	75,284	-779,094	165,042.00
	w_uaa1	Difference in UAA in neighbour municipalities (ha)	7159	-325.31	1,986.44	-15,855	23,645.18
	w_farm1	Difference in farm no. in neighbour municipalities (#)	7159	-530.93	772.89	-7,974	1,050.00
	w_livch1	Difference in livestock charge no. in neighbour municipalities (#LSU/ha)	7159	-8.98	64.88	-2,100	37.37
Municipality localisation	Mount	Location in mountain	7159	0.53	0.50	-	1.00
	Lit	Location coastal area	7159	0.08	0.27	-	1.00
	diff_density	Change in inhabitants density between 2010 and 2000	7159	16.34	56.24	-967.01	1,082.32
	Urb	Main Urban	7159	0.03	0.16	-	1.00
	Inturb	Intermediary urban	7159	0.01	0.11	-	1.00
	Belt	Urban belt	7159	0.43	0.49	-	1.00
	Interm	Intermediary	7159	0.31	0.46	-	1.00
	Perip	Periphery	7159	0.19	0.39	-	1.00
	remper	Remote areas	7159	0.04	0.19	-	1.00
	Central	Centre	7159	0.47	0.50	-	1.00
	remote	Marginal area	7159	0.53	0.50	-	1.00
Farming systems	Ave_farm	Average farm size (ha)	7157	0.34	0.24	-	1.00
	cereal_farm	Farms with arable area (#)	7157	94.57	163.44	-	2,186.00
	lsu00	Livestock size units in2000 (#)	7159	1,210.91	3,046.73	-	81,528.46
	tractown_num	Mechanisation intensity (number of tractors)	7157	276.35	441.58	1.00	6,458.00
	uaa_ha	UAA (ha)	7157	1,264.94	1,856.05	-	27,776.93
	uaa_rent_ha	UAA rented_in (ha)	7157	99.73	281.13	-	7,106.20