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Not in My Backyard, Not on My Grid? Data-Centre Proximity and Public Scepticism Towards Digital Technology in Europe's Sustainable Digital Transition

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Abstract

The expansion of artificial intelligence is turning data centres into a source of territorial and resource conflict, making their social acceptance a condition for a sustainable digital transition. We examine whether Europeans who live closer to data centres evaluate digital technology differently, and whether institutional trust and local water stress condition that association. We link Eurobarometer 101.4 microdata (April–May 2024; 22,889–23,581 respondents in 228 EU-27 regions) with 1187 geocoded data-centre sites and water-stress indicators, and estimate three-level mixed models. Residents of more exposed regions evaluate digital technology more negatively: one standard deviation of exposure is associated with 0.057 points on a 1–4 scale (95% CI 0.014–0.100), and ten nearby data centres versus none with 17% of a standard deviation. The association holds with exposure reconstructed as mapped at the survey date, on a 1 km population grid and under country fixed effects, but it is small and not significant in every specification. Exposure is not associated with demand for AI regulation on average, although institutional trust moderates that slope. Water-stress interactions are not robust. We interpret them as spillover scepticism consistent with, but not a direct test of, digital NIMBYism, and discuss implications for transparency and participation in data-centre governance.

Keywords: data centres; digital infrastructure; public attitudes; NIMBY; institutional trust; water stress; sustainable digital transition; environmental justice; multilevel models; Eurobarometer

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1. Introduction

The cloud has an address. Every large language model, streaming platform and digital public service runs on buildings that draw electricity from regional grids, consume water for cooling and occupy land zoned by municipalities. Global data-centre electricity use was already about 1% of final electricity demand before the arrival of generative artificial intelligence (AI) [1], and the International Energy Agency expects it to more than double by 2030, driven by AI workloads [2]. Cooling withdraws substantial volumes of water [3], and a quarter of the world's data centres are already located in areas that experience recurrent water gaps [4]. Whether digital technology contributes to sustainable development therefore depends not only on its applications but also on how its physical footprint is governed [5].

Infrastructure studies have long argued that infrastructure becomes visible only when it breaks, expands or is contested [6,7]. Data centres were designed to stay out of sight, framed by the metaphor of a weightless "cloud" that obscures the land and resources they

use [8]. That invisibility is ending. In Frankfurt, the "Digital Gateway to Europe", the spatial and environmental footprint of data centres has become an object of public controversy and new regulation [8]. In Ireland, the digital transition has become a material reality that reshapes energy and land-use politics [9,10]. Dutch public debate has developed a critical "reactive imaginary" around hyperscale projects [11], and in Aragón (Spain) planned data centres and green hydrogen together could multiply regional electricity demand several times over by 2035 amid growing local opposition [12]. Similar conflicts over water and land have been documented in Chile and the United States [13,14]. The digital transition is therefore also a story of territorial friction, and its social sustainability depends on whether host communities accept the infrastructure it requires.

The European Union pursues a twin transition: digital sovereignty and AI competitiveness on one side, climate neutrality by 2050 on the other. The two objectives meet in the same places. Data-centre clusters concentrate around the FLAP-D hubs (Frankfurt, London, Amsterdam, Paris and Dublin), where they compete with heat pumps, electric vehicles and industry for grid capacity, and with households and agriculture for water. The EU has begun to regulate this footprint. The recast Energy Efficiency Directive (EU) 2023/1791 requires operators above 500 kW to report energy and water performance [15], and Delegated Regulation (EU) 2024/1364 establishes a Union-wide rating scheme for data centres [16]. Yet the public debate on AI remains dominated by algorithmic risks such as bias, privacy and automated decision-making. Much less is known about how citizens who live next to the material side of AI respond to it.

Two literatures address parts of this question but do not meet. Public-opinion research on AI and digitalisation treats attitudes as a function of individual traits such as education, digital skills, ideology and trust, and rarely asks where respondents live. The literature on facility siting and NIMBYism, built mainly on wind farms, transmission lines and waste facilities, has not yet absorbed digital infrastructure. The emerging social-science literature on data centres is rich but consists largely of qualitative case studies [8,13,17]; the few surveys cover single jurisdictions [18]. To our knowledge, no cross-national study has examined whether proximity to data centres is associated with public attitudes.

This article addresses that gap with three questions. First, is residential exposure to data centres associated with how Europeans evaluate digital technology and with whether they want it regulated? Second, does local water stress or the cost of electricity condition that association? Third, does institutional trust condition it? We answer them with a data-fusion design that links Eurobarometer 101.4 microdata to spatial indicators of data-centre exposure, water stress and regional economic structure across 228 regions in all 27 Member States, estimated with three-level multilevel models and spatial autoregressive specifications.

The article makes three contributions. Conceptually, it proposes digital NIMBYism as a lens for the attitudinal consequences of digital infrastructure and distinguishes it from established accounts of facility opposition, environmental justice and technology acceptance. Empirically, it provides the first EU-wide evidence on the association between proximity to data centres and attitudes towards digital technology, with exposure validated against the state of mapping at the time of the survey and against an independent facility register. For policy, it indicates where transparency and participation are most likely to matter for the social sustainability of the digital transition. Because the survey does not ask about data centres, the design tests an observable implication of digital NIMBYism, a spillover of scepticism from place to technology, rather than local opposition itself; we return to this distinction throughout.

2. Theoretical Framework and Hypotheses

We propose that data centres can generate a distinct form of spatial scepticism, which we call digital NIMBYism. It may arise because a facility makes a placeless technology locally tangible, and its political form may depend on resource scarcity and institutional trust. The argument draws on four literatures: the materiality of digital infrastructure, proximity and NIMBY research, energy and environmental justice, and the role of trust in technology acceptance.

2.1. From the Cloud to the Backyard: The Materiality of Digital Infrastructure

Digital technologies have long been framed as weightless. Infrastructure studies contest this framing by showing that infrastructures recede from view when they work and become objects of contention when they fail, expand or compete for resources [6,7]. AI accelerates this shift. Robbins and van Wynsberghe argue that AI is becoming an infrastructure in its own right, one that locks societies into energy- and water-intensive pathways that are hard to reverse [19]. Political-ecology research traces the same dynamic in specific places: the water demands of a large data centre in a drought-prone US state [20], the reorganisation of Irish post-extractive peatlands around the energy needs of data centres [10], and the resource relations obscured by the political economy of "climate AI" [21].

A growing body of work shows that data centres are now politicised in their host regions. Monstadt and Saltzman trace how the footprint of Frankfurt's data-centre cluster moved to the forefront of public controversy and municipal regulation [8]. Sovacool and colleagues document community risks and benefits of Nordic data-centre development [17], and Cáceres and colleagues show that Swedish municipalities lack the power to plan the land, energy and heat implications of new facilities coherently [22]. Studies in the United States and Latin America describe opposition centred on water insecurity, utility rates and institutional distrust [13,14]. Impact-assessment practice, which relies on aggregate employment and fiscal multipliers, systematically overlooks the locally concentrated costs borne by host communities [23].

Two features of this literature matter for our argument. First, it relies mostly on case studies and says little about how the wider public responds to the footprint it describes. Second, research on smaller digital infrastructure offers a first indication of how such responses work. Local opposition to 5G antennas follows a NIMBY logic distinct from general attitudes to mobile connectivity [24]. Data centres are larger, more resource-intensive and less visible to their users than antennas, so proximity may matter at least as much for them.

2.2. Proximity, NIMBYism and the Generalisation of Local Costs

The NIMBY literature began with a simple claim: residents support facilities that provide diffuse public goods but oppose them nearby, because the costs are local [25]. Three decades of research have qualified this claim in three ways.

First, the effect of proximity is real but contingent. In an early review, van der Horst concluded that proximity strongly influences attitudes to proposed projects, but that its strength and spatial scale vary with local context and the value of the land [26]. Surveys of energy facilities such as carbon capture and storage confirm proximity effects [27], and experimental work supports NIMBY motives [28]. A large US study, by contrast, finds little evidence of proximity-based opposition once research designs are harmonised [29].

Second, the distance gradient is not linear. Studies of waste-to-energy plants report "ripple", "typhoon-eye" and marginal-zone effects, in which perceived risk peaks at intermediate distances [30], and concerns about wind-turbine noise travel well beyond the zone of physical impact [31]. Exposure to infrastructure should therefore be measured at several radii rather than with a single cut-off.

Third, the image of the selfish resident has given way to accounts based on place attachment, fairness and identity [32–34]. Local disputes can evolve into broader movements that question the purpose of a facility, not only its location [35], and opposition spreads through neighbourhood interaction [36].

A recent strand asks whether proximity affects attitudes beyond the facility itself. Zhou, Li and Prakash show that proximity to utility-scale renewable projects is associated with lower support for climate-mitigation policy in general [37]. Local costs can thus spill over into evaluations of the policy domain that the facility represents. We expect such spillover to be particularly likely for data centres. Their output is computation consumed elsewhere, they create few permanent local jobs per megawatt, and for most residents the facility is the only visible part of "digital technology". The facility can therefore become a proxy for the technology as a whole, and local concern can spill over into general judgements about digital technology and its governance.

2.3. What Is Distinctive About Digital NIMBYism?

Digital NIMBYism overlaps with three established literatures, and it is worth stating where it departs from each. Classic NIMBY and facility-siting research explains opposition to a specific project by residents who bear its local costs [25,26,32]. Its object is the facility. Digital NIMBYism, as we use the term, concerns the technology that the facility serves: the attitudinal target moves from the building to digital technology and its governance. Environmental-justice research asks how the burdens and benefits of infrastructures are distributed and who decides [38,39]. Digital NIMBYism adds an attitudinal consequence of that distribution, namely that unequal exposure to digital infrastructure may translate into unequal scepticism towards the digital transition itself. The technology-acceptance literature, finally, distinguishes socio-political, market and community acceptance [40] and documents a "social gap" between general support and local opposition [41], with trust as a central determinant [42]. Digital NIMBYism describes a path that runs in the opposite direction to the social gap: community-level exposure may erode socio-political acceptance of the technology.

Three features of data centres make this path plausible. Their benefits are delocalised and largely invisible to residents; they are rarely identified by name or function in the landscape, so residents may attribute their costs to "digital technology" rather than to a specific operator; and their resource claims are increasingly reported in the media. Digital NIMBYism is therefore a theoretical proposal, not an established mechanism. The data available to us allow a test of one of its observable implications, the association between exposure and general evaluations of digital technology, but not of local opposition, awareness of nearby facilities or the attribution process itself.

Hypothesis 1 (proximity association)**.** *Greater residential exposure to data centres is associated with (a) more negative evaluations of digital technology and (b) greater demand for its regulation.*

2.4. Resource Scarcity and the Materialisation of the Invisible

Environmental- and energy-justice scholarship asks who bears the burdens of a technology, who benefits and who decides [38,39,43]. Applied to the digital transition, this lens shows that digital energy systems create winners and losers [44] and that AI introduces new questions of distribution and procedure into energy systems [45]. At the European level, the twin transition has been criticised for treating its distributive consequences as an afterthought [9,46].

Resource scarcity sharpens these distributive questions. When a resource is abundant, a large industrial user is an abstraction; when it is scarce, every unit the facility

consumes is visibly withheld from households, agriculture or ecosystems. Water is the clearest case, because allocation in a stressed basin is close to zero-sum and conflicts peak during droughts [14,47]. Energy-siting studies show a related logic of relative fairness: communities judge a facility by whether they already carry more than their share, for example when a region exports electricity it does not need [48,49]. We therefore expect scarcity to make the invisible infrastructure more salient, turning a data centre from a neutral neighbour into a competitor for a local resource. The most direct expression of this salience would be concern about the facility's resource consumption, which the survey does not measure. We expect scarcity to carry over to the two outcomes we observe in the same way as proximity itself. By making the costs of digital technology more tangible, it should strengthen negative evaluations of the technology; and because the allocation of scarce water is a matter of public rules, it should also strengthen support for rules that constrain how the technology is deployed. H2 therefore applies to both outcomes. High electricity prices could work in the same way, but two features make that channel weaker: prices are set largely at the national level, and they are not attributable to a single facility.

Hypothesis 2 (resource-stress moderation)**.** *The association between data-centre exposure and evaluations or regulatory demand is stronger where regional water stress is high and, more weakly, where electricity prices are high.*

2.5. Institutional Trust and the Channelling of Local Concern

Trust is one of the most consistent predictors of acceptance of energy and industrial technologies. Huijts and colleagues place trust in responsible actors at the centre of a comprehensive acceptance framework [42], and social-licence research shows that trust built through procedural fairness and contact quality allows communities to accept extractive operations [50]. Studies of waste facilities, offshore wind and grid expansion converge on the same finding: procedural fairness builds trust in the actors involved, and trust lowers perceived risk and raises acceptance [51–53]. Government information disclosure, in turn, raises acceptance of nearby facilities [54].

Most of this literature treats trust as a direct determinant of acceptance. We emphasise a second possible role: trust may condition the form that local concern takes. Institutional trust predicts support for some environmental policy instruments but not others, and it matters most where citizens must believe that public authorities will design and enforce a rule effectively [55]. Applied to data centres, this suggests a channelling mechanism. Residents who trust institutions may translate proximity-related concern into support for regulation, because they expect regulation to work. Residents who distrust institutions have no such outlet, and their concern may be expressed as generalised scepticism towards the technology.

Hypothesis 3 (institutional-trust moderation)**.** *Institutional trust moderates the association with data-centre exposure. The association with demand for regulation is more positive among residents with high trust, and the association with negative evaluations is more positive among residents with low trust.*

Figure 1 summarises the framework. Exposure is measured at the regional level and has two possible attitudinal correlates; resource stress and institutional trust may condition which of them dominates.

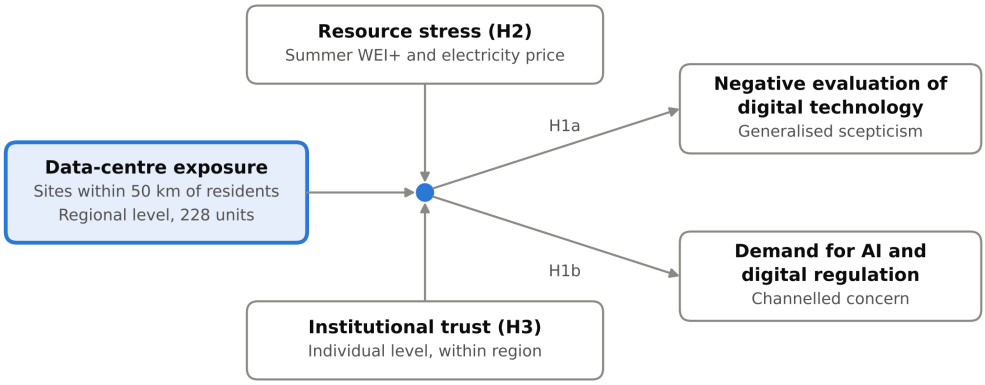


Figure 1. Conceptual framework. Data-centre exposure may be associated with generalised scepticism (H1a) or with demand for regulation (H1b); resource stress (H2) and institutional trust (H3) may condition which response dominates. The survey measures attitudes towards digital technology, not attitudes towards data centres.

3. Materials and Methods

The analysis combines survey microdata with spatial data in three steps. First, we link each respondent to a regional unit and attach to that unit measures of data-centre exposure, water stress and economic structure (Section 3.1). Second, we construct the outcomes, moderators and controls (Section 3.2) and define the analytic samples (Section 3.3). Third, we estimate three-level linear mixed models in which respondents are nested in regions and countries, test cross-level interactions, and assess robustness with alternative measures, estimators, samples and spatial models (Section 3.4).

3.1. Data Sources and Integration

The analysis links one individual-level survey to spatial sources through the respondent's region of residence (Table 1).

Fusion. Eurobarometer reports the region of residence in country-specific variables. These are mostly NUTS-2, but NUTS-1 for Germany and Sweden and NUTS-3 for Estonia, Ireland, Latvia, Lithuania and Slovenia. We parse the NUTS code from each label and rebuild the polygon of each survey unit from the GISCO vintage in which that code exists. Merged units (e.g., Piemonte and Valle d'Aosta) are unions of their components; Cyprus, Luxembourg and Malta form one unit each; and Riga and Pieriga are merged to match the NUTS 2024 reform. Eurostat NUTS-3 data are assigned to survey units through each NUTS-3 region's representative point. The result is 228 regional units nested in 27 countries, with a median of 94 respondents per unit (range 8–507).

Data-centre exposure. Site geometries are projected to ETRS89-LAEA (EPSG:3035), and buildings nested inside a larger campus polygon are counted once (156 removed). For every NUTS-3 region we count the sites within 25, 50 and 100 km of its representative point. Regional exposure is the population-weighted mean across a unit's NUTS-3 regions, that is, the number of data centres within 50 km of the average resident. As an alternative that does not depend on NUTS-3 representative points, we compute the same quantity on the 1 km GHS-POP population grid, counting the sites within 50 km of every populated cell. We use 50 km as the main radius for three reasons. First, the distance at which infrastructure shapes attitudes varies and often extends beyond the zone of physical impact (Section 2.2), so a radius of a few kilometres would miss the wider area in which a facility is visible in local media and politics. Second, exposure is measured from NUTS-3 representative points rather than from respondents' addresses. The median NUTS-3 region of the EU-27 has

the area of a circle with a 25 km radius (90th percentile: 49 km), so a 50 km radius covers the resident's own NUTS-3 region and its surroundings in most cases, whereas a 25 km radius is sensitive to where the representative point falls. Third, the median survey unit has the area of a circle with a 62 km radius, so a 100 km radius extends well beyond the respondent's region. We report results for 25 and 100 km and for the population grid, which removes the dependence on NUTS-3 points.

Table 1. Data sources.

Level	Source	Content Used	Spatial Unit	Period
Individual	Eurobarometer 101.4, GESIS ZA8844 v1.0.0 [56]	Digital technology and AI, energy, rule of law, socio-demographics	Respondent; region of residence	April–May 2024
Regional	OpenStreetMap via osm2rdf/QLever [57]; object histories [58]	1187 data-centre sites (`telecom` or `building` = `data_center`); footprint; date first tagged	Point/polygon	Snapshot October 2026; 790 sites tagged before May 2024
Regional	PeeringDB [59]	1349 colocation and interconnection facilities with record creation dates (validation)	Point	1233 listed before May 2024
Regional	European Environment Agency, WEI+ (ECRINS sub-basins) [60]	Seasonal Water Exploitation Index plus	390 sub-basins	2010–2014 average
Regional	European Drought Observatory, Combined Drought Indicator [61]	Share of land in drought warning or alert (validation)	5 km grid	March 2022–February 2024
Regional	GHS-POP R2023A [62]; Eurostat `demo_r_pjanaggr3`, `nama_10r_3gdp` [63]	Population (1 km grid and NUTS-3); GDP per inhabitant (PPS)	1 km; NUTS-3 (2024)	2020; 2024; latest year
Country	Eurostat `nrg_pc_204`, `nrg_pc_205`, `nrg_ind_ren`, `sdg_06_60` [63]	Electricity prices; renewable share of electricity; national WEI+	NUTS-0	2024-S1; 2023; 2022
Geometry	Eurostat GISCO [63]	NUTS 2013, 2016, 2021 and 2024 boundaries (1:10M)	NUTS-0 to NUTS-3	–

Use and validation of OpenStreetMap. No open, EU-wide register of data centres with locations and capacities exists. Commercial registries are not openly licensed, and the database created under Delegated Regulation (EU) 2024/1364 is not published at site level. OpenStreetMap is the only open source with EU-wide coverage of individual sites, but it is incomplete. The global file contains 4834 objects tagged as data centres, compared with 9347 facilities in a recent global inventory [4]; the two counts are not strictly comparable, because an OpenStreetMap object can be one building of a multi-building campus. Within the EU-27 there are 1343 such objects, which become 1187 sites once buildings nested in a campus are merged. Enterprise and edge facilities are likely to be under-recorded, whereas large campuses occupy extensive, visible plots that are mapped from aerial imagery; 77% of the EU sites are mapped as building polygons and 160 exceed one hectare. We assess the consequences of incomplete coverage in three ways. First, we compare OpenStreetMap exposure with exposure built from PeeringDB, an independent register of colocation and interconnection facilities: across the 228 regions the two measures correlate at $r = 0.83$. Second, we use a population-weighted distance to the FLAP-D hubs, which uses no facility data. This measure does not validate the accuracy of the OpenStreetMap layer; it is an alternative proxy for exposure that is immune to its omissions. Because proximity to the hubs also reflects urbanisation and affluence (its correlation across regions is 0.55 with log GDP per inhabitant and 0.43 with log density), we use it only in models that control for both. Third, we re-estimate the models with each alternative. If under-coverage is unrelated

to attitudes it attenuates the estimates; if it is related to attitudes, for example because controversial facilities are mapped more often, it could bias them in either direction, which is why the independent measures matter.

Temporal alignment. Attitudes were measured in April–May 2024, whereas the OpenStreetMap layer is a snapshot from October 2026. To reconstruct exposure as it was mapped at the time of the survey, we retrieved the full version history of every site from the OpenStreetMap API and dated each site by the first version tagged as a data centre [58]. Of the 1187 sites, 790 were tagged before 1 May 2024 and 397 afterwards; the latter include facilities opened or planned after the survey as well as older facilities mapped later. Exposure built only from sites tagged before the survey correlates at $r = 0.96$ with the full measure across regions. We also use PeeringDB facilities whose records existed before the survey (1233 of 1349). Water stress poses a different problem. The sub-basin WEI+ series ends in 2014. We use it because WEI+ measures structural pressure on renewable freshwater, which changes slowly, and because no more recent EU-wide series exists at sub-basin resolution. To check that the results do not depend on its age, we use two alternatives: national WEI+ for 2022 and the share of land in drought warning or alert according to the Combined Drought Indicator in the 24 months before the survey (March 2022–February 2024) [61], which captures recent, salient water stress. The recent-drought measure correlates only weakly with the structural index across regions ($r = 0.20$), so the two capture different aspects of water stress.

Water stress. We overlay the European Environment Agency's seasonal WEI+ sub-basin polygons on the survey units and compute, for each unit, the area-weighted mean of the summer (third-quarter) WEI+ for 2010–2014, the season when allocation conflicts peak. Four units with less than 50% sub-basin coverage (Canarias, Malta, and Severozapaden and Severen tsentralen in Bulgaria) receive the national WEI+ and are flagged; we exclude them in a robustness check.

3.2. Variable Operationalisation

Dependent variables. The survey contains no item on data centres, on local siting or on awareness of nearby facilities. We therefore model outcomes that capture general attitudes towards digital technology and its governance, and we interpret them as such rather than as attitudes towards a specific facility.

Demand for AI and digital regulation (`ai_reg`) is the mean importance of five rules for "digital technologies, including artificial intelligence" (QB11_1–5: protecting workers' privacy, prohibiting fully automated decisions, limiting automated monitoring of employees, transparency of human-resource decisions, and involving workers and their representatives), on a 1–4 scale ($\alpha = 0.85$). The rules are framed for the workplace, and the question asks how important such rules are rather than who should set them. We therefore read the index as a disposition towards rules that constrain how AI is deployed, not as support for government regulation in general or for regulating the local data centre. Eurobarometer 101.4 contains no item on rules for digital infrastructure or its environmental footprint, so this is the closest available measure of support for constraining digital technology. An association between exposure and this index would require local concern to extend from the infrastructure to the rules governing the technology, which makes it a demanding test. Because the items differ in content, we also estimate the models for each item separately and for an index that omits the item on worker involvement, which refers to participation rather than to constraint.

Negative evaluation of digital technology (`digital_neg`) is the mean of the perceived impact of "the most recent digital technologies, including Artificial Intelligence" on society and on one's quality of life (QB1_2 and QB1_3; 1 = very positive, 4 = very negative).

As a supplementary outcome, *energy-saving priority* (`prio_save`, 0/1) captures whether the respondent names "saving energy wherever possible (e.g., in industrial processes, in digital uses...)" as the first priority for climate neutrality (QC4a); it is estimated as a linear probability model.

Individual moderator. Institutional trust is the mean of seven items on judicial independence (QA2_1, QA2_3 and QA2_4 reversed) and on the impartiality, transparency and integrity of public authorities (QA4_1, QA4_3, and QA4_2 and QA4_4 reversed). The items were not designed as a single scale, and its internal consistency is modest ($\alpha = 0.66$, $\omega = 0.66$, mean inter-item correlation 0.22; [64]). The two sub-scales correlate at $r = 0.45$ and have lower reliabilities on their own ($\alpha = 0.49$ and 0.54). We use the composite because both components refer to the trustworthiness of the institutions that would design and enforce rules, and we re-estimate the trust models with each sub-scale separately (Appendix B). Trust is centred within regions, and its regional mean is entered separately [65].

Individual controls. The models include age, gender, age at the end of full-time education, left–right self-placement (with a missing-value indicator), subjective social class, type of community, daily internet use, difficulty paying bills (a proxy for energy-cost sensitivity) and naming climate neutrality as an EU energy priority (a proxy for climate concern).

Regional and country predictors. Data-centre exposure enters as the logarithm of one plus the number of sites within 50 km, and water stress as the logarithm of one plus summer WEI+. We also include log GDP per inhabitant (PPS) and log population density at the regional level, and the household electricity price (2024-S1) and the renewable share of electricity (2023) at the country level. All level-2 and level-3 predictors are standardised across units. Descriptive statistics are reported in Appendix A.

3.3. Sample, Missing Data and Weights

Missing values are not imputed. Each model uses the respondents with valid values on its outcome, controls and moderators (listwise deletion), with one exception: left–right self-placement, which 12.6% of respondents did not report, is set to its mean for those respondents and flagged with an indicator, so that they are retained. Of the 26,404 respondents in the EU-27, 26,362 have a valid region of residence. The regulation-demand index is observed for 24,785 respondents and the negative-evaluation index for 24,047. Listwise deletion on the controls leaves 23,581 and 22,889 respondents for models M1–M3, and adding institutional trust leaves 23,137 and 22,452 for model M4 (Table A2). Most item non-response comes from the outcomes themselves (6.0% and 8.8% missing), followed by institutional trust (3.4%) and subjective social class, climate priority and education (1.5–2.1% each). Respondents excluded from the analytic samples are older, less educated, less often daily internet users and more likely to decline a left–right placement than those included (standardised differences of 0.35–0.57), and they live in slightly less exposed regions (0.13). The analytic samples therefore under-represent older and less digitally connected Europeans, which limits generalisation to these groups.

Eurobarometer provides a national post-stratification weight (`w1`, by gender, age, region and community type) and an EU-27 weight (`w22`). The main multilevel models are unweighted, because the variables used to build the weights are included as covariates, which makes unweighted estimates of the conditional associations consistent and more efficient [66], and because likelihood-based multilevel estimation with sampling weights requires weights at each level that Eurobarometer does not provide. As design-based checks, we estimate weighted least-squares models with each weight and standard errors clustered by region, with and without country fixed effects.

3.4. Analytical Strategy

We estimate three-level linear mixed models with random intercepts for countries (k) and regions (j) by maximum likelihood:

$$y_{ijk} = \beta_0 + \boldsymbol{\beta}'\mathbf{x}_{ijk} + \gamma_1 \mathrm{DC}_{jk} + \gamma_2 \mathrm{WEI}_{jk} + \gamma_3 (\mathrm{DC} \times \mathrm{WEI})_{jk} + \gamma_4 (\mathrm{DC}_{jk} \times \mathrm{TRUST}_{ijk}) + \boldsymbol{\delta}'\mathbf{z}_{jk} + u_k + v_{jk} + \varepsilon_{ijk}. \quad (1)$$

Models are built in steps: M0 (null), M1 (individual controls), M2 (exposure and regional and country controls; H1), M3 (cross-level interactions of exposure with water stress and electricity price; H2) and M4 (institutional trust, its regional mean, and their interactions with exposure; H3). Each model is fitted with several numerical optimisers, and the solution with the highest log-likelihood is retained.

Inference follows four rules. First, we report exact p-values and 95% confidence intervals for the confirmatory estimates. Second, because the three hypotheses involve eight confirmatory tests (H1a, H1b, four interactions for H2 and two for H3), we report p-values adjusted with the Holm and Benjamini–Hochberg procedures [67,68]. Third, we interpret moderation with marginal effects and their confidence intervals at substantively relevant values of the moderator [69], and, for the cross-level interaction with trust, we add a random slope for trust at the regional level, without which the standard error of such interactions can be too small [70]. Fourth, we express the size of the exposure association in numbers of data centres, not only in standard deviations.

Random intercepts absorb level differences but not dependence between neighbouring regions. We therefore test Moran's I on the regional empirical-Bayes intercepts (k-nearest neighbours, $k = 6$, row-standardised, 999 permutations) and estimate spatial autoregressive lag (SAR) models by maximum likelihood on composition-adjusted regional means,

$$\bar{y}_j^{adj} = \rho W \bar{y}^{adj} + X_j \beta + \varepsilon_j, \quad (2)$$

with and without within-country demeaning. Following Gibbons and Overman [71], we treat the spatial models as checks on robustness to spatial dependence. They do not address confounding by unobserved regional characteristics.

Robustness checks use eight alternative exposure measures (sites within 25 and 100 km, footprint within 50 km, sites per million inhabitants, population-weighted distance to the FLAP-D hubs, sites tagged before the survey, PeeringDB facilities listed before the survey, and exposure on the 1 km population grid); two alternative water measures; country fixed-effects and design-based weighted least-squares models with region-clustered standard errors; and subsamples that exclude the FLAP-D countries (Germany, France, the Netherlands and Ireland), restrict the analysis to NUTS-2 units, exclude units with imputed WEI+ and exclude capital regions. We summarise the robustness of the exposure association with a specification curve [72] that crosses nine exposure measures, four samples and weighted and unweighted estimation (72 specifications per outcome). All analyses were run in Python 3.13 (`statsmodels` 0.15, `geopandas` 1.2, `libpysal` 4.15, `esda` 2.10 and `spreg` 1.9); the replication package is openly available [73].

Use of generative AI. During the preparation of this study, the authors used Claude Opus 5.5 (model claude-opus-5-5; Anthropic), accessed through Claude Code, to assist in writing the data-processing and analysis code, in preparing figures and in drafting and editing the text. The authors reviewed and verified all code, results and text, and take full responsibility for the content of the publication.

4. Results

4.1. Descriptive and Spatial Patterns

Data centres and water stress occupy different parts of Europe: their correlation across regions is $r = -0.01$ (Figure 2). Exposure peaks in Paris (Île-de-France, 139 sites), Frankfurt

(Hessen, 115), Dublin (79) and Amsterdam (Noord-Holland, 63), with secondary clusters in Milan, Lyon, Stockholm and Brussels. In 32% of regions the average resident has no data centre within 50 km. Summer water stress is highest in Cyprus (75%) and in central and south-eastern Spain (43–55%). Madrid is the main region where both pressures coincide. This near-orthogonality means that the exposure × water-stress interaction rests on a small number of high–high regions, which limits statistical power for H2.

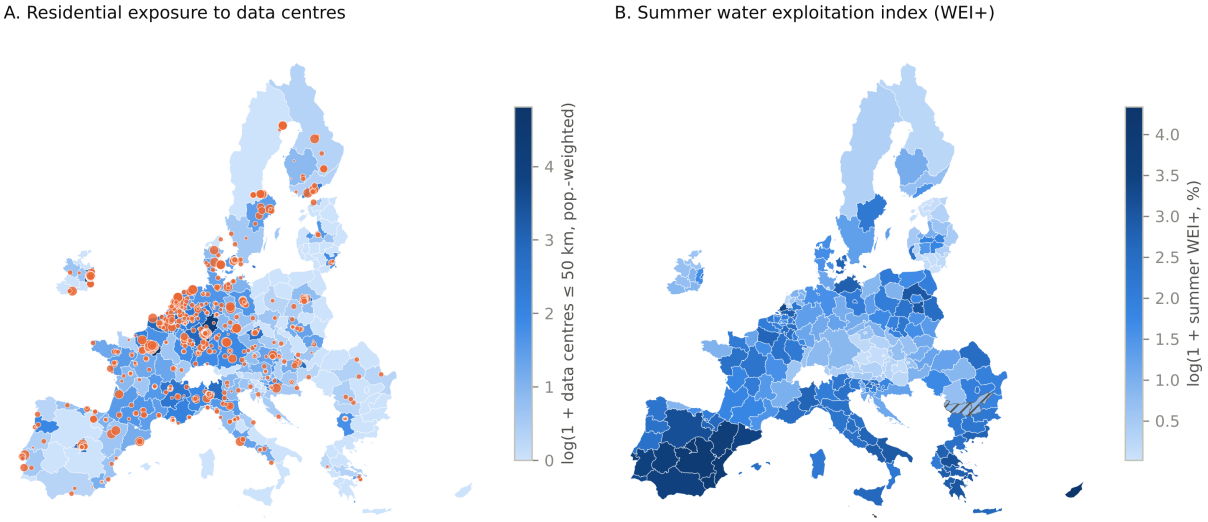


Figure 2. Residential exposure to data centres (**A**) and summer water stress (**B**) in 228 Eurobarometer regions of the EU-27. Points are OpenStreetMap data-centre sites sized by footprint; hatched units use national WEI+.

Attitudes cluster regionally. In the null models, regions account for 10.3% of the variance in demand for regulation and 7.2% in negative evaluations of digital technology, and countries for 3.7% and 2.1%, respectively. After adjusting for composition, regional scepticism is spatially clustered (Moran's $I = 0.28$, $p = 0.001$; Figure 3), with hotspots in much of France, Tuscany, Sardinia and parts of Greece and Romania, and lower scepticism in the Baltic states, Spain and Ireland.

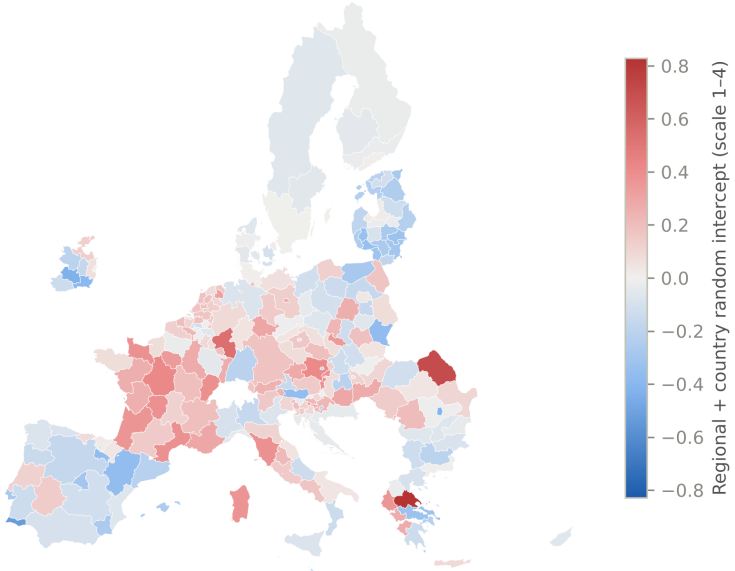


Figure 3. Compositionally adjusted regional scepticism about digital technology: regional plus country random intercepts from model M1 for negative evaluation of digital technology (1–4 scale).

4.2. Exposure and Attitudes Towards Digital Technology

Exposure to data centres is associated with more negative evaluations of digital technology but not, on average, with demand for its regulation (Tables 2 and 3; models M0–M2 are reported in Table A5). The exposure coefficient is almost identical in M2, before the cross-level interactions are added (0.056, $p = 0.010$). A one-standard-deviation increase in exposure is associated with an increase of 0.057 points in negative evaluations (95% CI 0.014–0.100, $p = 0.010$), net of regional GDP, density, energy prices and individual controls. The estimate remains significant after a Benjamini–Hochberg adjustment for the eight confirmatory tests ($p = 0.039$) but not after the more conservative Holm adjustment ($p = 0.067$). The same increase changes demand for regulation by only 0.013 (95% CI −0.034 to 0.061, $p = 0.58$) and the energy-saving priority by −0.006 ($p = 0.58$). H1a is therefore supported, with the qualification that the evidence is moderate, and H1b is not.

The association is small. Because exposure is log-transformed, its size depends on the starting point. Moving from a region whose average resident has no data centre within 50 km to one with a single site is associated with 0.036 points (5% of the outcome's standard deviation); moving to ten sites with 0.12 points (95% CI 0.03–0.22; 17%); and moving across the interquartile range of regions, from zero to 4.4 sites, with 0.086 points (12%) (Table A3). For comparison, daily internet users are 0.22 points less negative than other respondents, and a one-standard-deviation increase in difficulty paying bills is associated with 0.04 points. The exposure association is thus comparable to that of financial hardship and modest relative to the digital divide. Regional affluence pulls in the opposite direction: residents of richer regions want more regulation ($b = 0.085$, $p < 0.001$) and are less negative ($b = -0.053$, $p = 0.019$).

Table 2. Three-level linear mixed models (unstandardised coefficients, standard errors in parentheses).

	Regulation Demand		Negative Evaluation		Energy Saving
Predictor	**M3**	**M4**	**M3**	**M4**	**M3**
Data-centre exposure (DC, SD)	0.013 (0.024)	0.012 (0.024)	0.057 ** (0.022)	0.059 ** (0.021)	−0.006 (0.011)
Summer WEI+ (SD)	−0.002 (0.019)	−0.005 (0.019)	0.004 (0.018)	0.004 (0.018)	−0.007 (0.010)
DC × WEI+	0.027 (0.017)	0.028 $^{+}$ (0.017)	−0.026 $^{+}$ (0.015)	−0.022 (0.015)	0.004 (0.008)
Household electricity price (SD)	0.001 (0.024)	0.011 (0.024)	0.038 (0.025)	0.050 $^{+}$ (0.028)	−0.014 (0.013)
DC × electricity price	−0.001 (0.018)	−0.004 (0.019)	−0.003 (0.017)	−0.005 (0.017)	0.017 $^{+}$ (0.009)
Institutional trust, within region	–	−0.022 *** (0.005)	–	−0.119 *** (0.005)	–
Institutional trust, regional mean	–	−0.046 * (0.022)	–	−0.059 ** (0.022)	–
DC × trust (within)	–	0.025 *** (0.004)	–	−0.008 $^{+}$ (0.004)	–
DC × trust (regional mean)	–	0.013 (0.019)	–	0.018 (0.018)	–
WEI+ × trust (within)	–	−0.015 *** (0.004)	–	0.010 * (0.004)	–
GDP per inhabitant, PPS (log, SD)	0.085 *** (0.025)	0.096 *** (0.025)	−0.053 * (0.023)	−0.041 $^{+}$ (0.023)	−0.003 (0.011)
Population density (log, SD)	−0.053 * (0.025)	−0.057 * (0.025)	−0.011 (0.023)	−0.021 (0.023)	−0.003 (0.012)
Renewable share of electricity (SD)	0.020 (0.022)	0.031 (0.023)	−0.007 (0.023)	0.009 (0.026)	−0.005 (0.012)
Daily internet use	0.167 *** (0.014)	0.167 *** (0.014)	−0.223 *** (0.014)	−0.235 *** (0.014)	−0.042 *** (0.009)
Years of education (SD)	0.064 *** (0.005)	0.065 *** (0.005)	−0.029 *** (0.005)	−0.027 *** (0.005)	−0.008 * (0.004)
Difficulty paying bills (SD)	−0.017 *** (0.005)	−0.018 *** (0.005)	0.038 *** (0.005)	0.031 *** (0.005)	−0.010 ** (0.003)
Left–right (SD)	−0.022 *** (0.005)	−0.022 *** (0.005)	−0.018 *** (0.005)	−0.018 *** (0.005)	−0.018 *** (0.003)
Respondents	23,581	23,137	22,889	22,452	23,963
Regions/countries	228/27	228/27	228/27	228/27	228/27
Regional variance share	0.099	0.097	0.074	0.069	0.036

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All models also control for age, gender, social class, community type, missing left–right and climate priority. Sample sizes differ across columns because of item non-response in the outcomes and in institutional trust (Table A2). Full estimates are in the replication package [73].

Table 3. Confirmatory estimates with 95% confidence intervals, exact *p*-values and adjustment for multiple testing.

Hypothesis	Estimate (Outcome, Model)	b	95% CI	*p*	*p* (Holm)	*p* (BH)
H1a	DC (negative evaluation, M3)	0.057	0.014 to 0.100	0.010	0.067	0.039
H1b	DC (regulation demand, M3)	0.013	−0.034 to 0.061	0.584	1.000	0.779
H2	DC × WEI+ (negative evaluation, M3)	−0.026	−0.055 to 0.004	0.087	0.434	0.171
H2	DC × WEI+ (regulation demand, M3)	0.027	−0.006 to 0.059	0.107	0.434	0.171
H2	DC × price (negative evaluation, M3)	−0.003	−0.036 to 0.030	0.857	1.000	0.972
H2	DC × price (regulation demand, M3)	−0.001	−0.037 to 0.036	0.972	1.000	0.972
H3	DC × trust (regulation demand, M4)	0.025	0.017 to 0.034	<0.001	<0.001	<0.001
H3	DC × trust (negative evaluation, M4)	−0.008	−0.017 to 0.000	0.056	0.335	0.149

Holm: family-wise error rate; BH: Benjamini–Hochberg false discovery rate, both over the eight tests shown. With a random slope for trust, the H3 estimates are 0.018 (95% CI 0.001 to 0.035, $p = 0.038$) for regulation demand and −0.006 (−0.020 to 0.009, $p = 0.449$) for negative evaluation.

4.3. Cross-Level Interactions: Water Stress, Electricity Prices and Trust

H2 is not supported. In the main models, the exposure × WEI+ interaction is negative for negative evaluation ($b = -0.026$, 95% CI −0.055 to 0.004, $p = 0.087$) and positive for regulatory demand ($b = 0.027$, −0.006 to 0.059, $p = 0.107$), and neither survives adjustment for multiple testing (Table 3). The marginal effects in Figure 4A show the same pattern: the association with negative evaluation is clearly positive in regions with low water stress (0.082, 95% CI 0.031–0.134, at one standard deviation below the mean) and indistinguishable from zero in regions with high stress (0.031, −0.021 to 0.083), whereas the association with regulatory demand is not significant at any level of water stress. The interaction is significant in some specifications that use only within-country variation (country fixed effects: $b = -0.028$, $p = 0.023$; outside the FLAP-D countries: $b = -0.047$, $p = 0.030$), but it is not significant with recent drought instead of structural water stress ($b = -0.014$, $p = 0.41$) and only marginal with national WEI+ ($b = -0.041$, $p = 0.058$). Its direction is also the opposite of the one hypothesised, since water stress, if anything, weakens rather than strengthens the association with scepticism. We therefore treat any role of water stress as an exploratory pattern that requires better data, not as a finding. The interaction with household electricity prices is null for both attitudinal outcomes.

The evidence on trust is more consistent but narrower than the hypothesis. For regulatory demand, the exposure × trust interaction is positive and robust: $b = 0.025$ (95% CI 0.017–0.034, $p < 0.001$), significant after Holm adjustment, smaller but still significant with a random slope for trust ($b = 0.018$, 0.001–0.035, $p = 0.038$), present with each trust subscale and for each of the five regulation items separately (Appendix B). The random-slope variance is itself significant, which confirms that the within-region association between trust and regulatory demand varies across regions. The interaction means that the slope of exposure differs by trust. It does not mean that exposure raises regulatory demand among trusting residents: the conditional association is 0.038 (95% CI −0.011 to 0.086) at one standard deviation above mean trust and −0.013 (−0.061 to 0.035) at one standard deviation below, and neither differs significantly from zero (Figure 4B). For negative evaluation, the interaction with trust is small and not robust ($b = -0.008$, $p = 0.056$; with a random slope, $b = -0.006$, $p = 0.45$), and the interactions between exposure and regional-mean trust are not significant for either outcome. H3 is therefore supported only in its weakest form: trust shifts the association between exposure and regulatory demand, but the data do not show that exposure is channelled into regulatory demand among trusting residents. Trust is also the strongest attitudinal correlate of negative evaluation (−0.119 per standard deviation within regions).

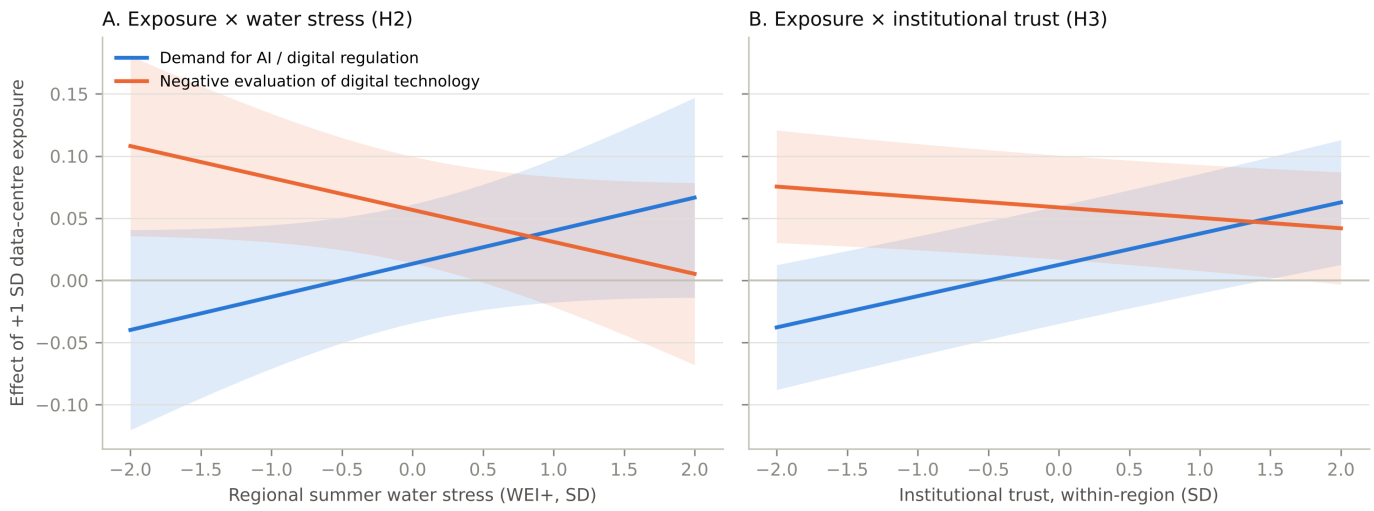


Figure 4. Marginal association of a one-standard-deviation increase in data-centre exposure with each outcome across regional water stress ((**A**), model M3) and within-region institutional trust ((**B**), model M4); shaded bands are 95% confidence intervals.

4.4. Robustness Checks and Spatial Dependence

Table 4 and Figure 5 report the main robustness checks. For negative evaluation, the exposure coefficient is positive in all sixteen specifications shown and significant at $p < 0.05$ in twelve. It is of similar size when exposure is restricted to sites mapped before the survey ($b = 0.055$, $p = 0.011$), computed on the 1 km population grid (0.055, $p = 0.013$), measured by distance to the FLAP-D hubs without any facility data (0.060, $p = 0.012$), estimated with country fixed effects (0.052, $p = 0.014$) and when the FLAP-D countries are excluded (0.062, $p = 0.040$). It is smaller and not significant with the 25 km radius ($p = 0.11$), footprint within 50 km ($p = 0.18$), PeeringDB facilities listed before the survey (0.036, $p = 0.16$) and the exclusion of capital regions ($p = 0.09$). In the NUTS-2 subsample, which homogenises the territorial scale, the coefficient is 0.062 ($p = 0.031$). Design-based weighted estimates without random effects give larger coefficients (0.068 with the national weight and 0.080 with the EU-27 weight, both $p < 0.01$), so the main estimate is not an artefact of ignoring the sampling design. For regulatory demand, exposure is significant only at the 100 km radius ($b = 0.048$, $p = 0.038$).

The specification curve summarises the evidence across 72 combinations of exposure measure, sample and weighting, all with country fixed effects and region-clustered standard errors (Figure 6). For negative evaluation, 92% of the coefficients are positive, with a median of 0.039, and 38% are significant at $p < 0.05$. The non-significant specifications are concentrated in the 25 km and footprint measures and in the smaller subsamples, where standard errors are larger. Because these specifications rely only on within-country variation, they are a demanding test, and we read them as indicating a consistently positive but imprecisely estimated association. For regulatory demand, the coefficients are centred on zero.

Attitudes are spatially dependent beyond the country level. Moran's I of the regional intercepts is 0.22 for regulatory demand and 0.28 for negativity in M1 (both $p = 0.001$) and 0.12 ($p = 0.003$) and 0.24 ($p = 0.001$) in M3. In the SAR-lag model of composition-adjusted regional means, the spatial autoregressive parameter for negativity is $\rho = 0.34$ ($p < 0.001$). Exposure retains its association after the spatial lag ($b = 0.059$, $p = 0.007$). With within-country demeaning, however, the exposure coefficient falls to 0.040 and is not significant at the 5% level ($p = 0.092$); the negative ρ in that specification is a known artefact of demeaning on a sparse within-country neighbour structure. The spatial models show

that the association is not an artefact of spatial dependence in the outcome, but they do not rule out confounding by unobserved regional characteristics that are correlated with data-centre location.

Table 4. Robustness of the exposure association and of the exposure × water-stress interaction (coefficients, standard errors in parentheses).

		Negative Evaluation		Regulation Demand	
Specification	**N (NE/RD)**	**DC**	**DC × Water**	**DC**	**DC × Water**
Main (M3): sites ≤ 50 km	22,889/23,581	0.057 ** (0.022)	−0.026 $^{+}$ (0.015)	0.013 (0.024)	0.027 (0.017)
Exposure measure					
Sites ≤ 25 km	22,889/23,581	0.033 (0.021)	−0.016 (0.015)	−0.011 (0.023)	0.019 (0.016)
Sites ≤ 100 km	22,889/23,581	0.047 * (0.022)	−0.026 (0.016)	0.048 * (0.023)	0.015 (0.017)
Footprint ≤ 50 km	22,889/23,581	0.026 (0.019)	−0.026 $^{+}$ (0.015)	0.002 (0.021)	0.023 (0.017)
Sites per million inhabitants	22,889/23,581	0.058 ** (0.020)	−0.014 (0.017)	0.004 (0.022)	0.020 (0.018)
FLAP-D hub proximity (no facility data)	22,889/23,581	0.060 * (0.024)	−0.001 (0.016)	0.022 (0.025)	0.003 (0.017)
OSM sites tagged before May 2024	22,889/23,581	0.055 * (0.021)	−0.019 (0.017)	0.011 (0.024)	0.016 (0.018)
PeeringDB facilities listed before May 2024	22,889/23,581	0.036 (0.025)	−0.033 * (0.014)	0.000 (0.027)	0.013 (0.015)
OSM sites, 1 km population grid	22,889/23,581	0.055 * (0.022)	−0.030 * (0.015)	0.013 (0.025)	0.025 (0.017)
Water measure					
Recent drought (CDI, 2022–2024)	22,889/23,581	0.055 * (0.022)	−0.014 (0.017)	0.012 (0.025)	0.014 (0.019)
National WEI+ (2022)	22,889/23,581	0.052 * (0.023)	−0.041 $^{+}$ (0.022)	0.019 (0.025)	0.045 $^{+}$ (0.024)
Estimator and sample					
Country fixed effects (WLS)	22,889/23,581	0.052 * (0.021)	−0.028 * (0.012)	−0.020 (0.018)	0.027 $^{+}$ (0.015)
Excluding FLAP-D countries	18,818/19,392	0.062 * (0.030)	−0.047 * (0.022)	0.022 (0.034)	0.040 (0.025)
NUTS-2 units only	14,979/15,560	0.062 * (0.029)	−0.014 (0.018)	0.034 (0.033)	0.034 $^{+}$ (0.020)
Excluding imputed WEI+	22,247/22,894	0.057 * (0.022)	−0.026 $^{+}$ (0.015)	0.011 (0.025)	0.027 (0.017)
Excluding capital regions	18,112/18,591	0.042 $^{+}$ (0.025)	−0.027 (0.019)	0.025 (0.028)	0.023 (0.021)

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. N: respondents in the negative-evaluation (NE) and regulation-demand (RD) models. Smaller samples result only from the subsample restrictions (excluding the FLAP-D countries, NUTS-2 units only, excluding imputed WEI+ and excluding capital regions); the NUTS-2 restriction, which drops the units coded at NUTS-1 (Germany, Sweden, Cyprus, Luxembourg and Malta) and at NUTS-3 (Estonia, Ireland, Latvia, Lithuania and Slovenia), yields the smallest samples. "Water" is summer WEI+ except in the two water-measure rows. All specifications include the individual controls, GDP and population density; mixed-model specifications also include electricity price and renewable share. FLAP-D countries: Germany, France, the Netherlands and Ireland. WLS: weighted least squares with post-stratification weights and region-clustered standard errors.

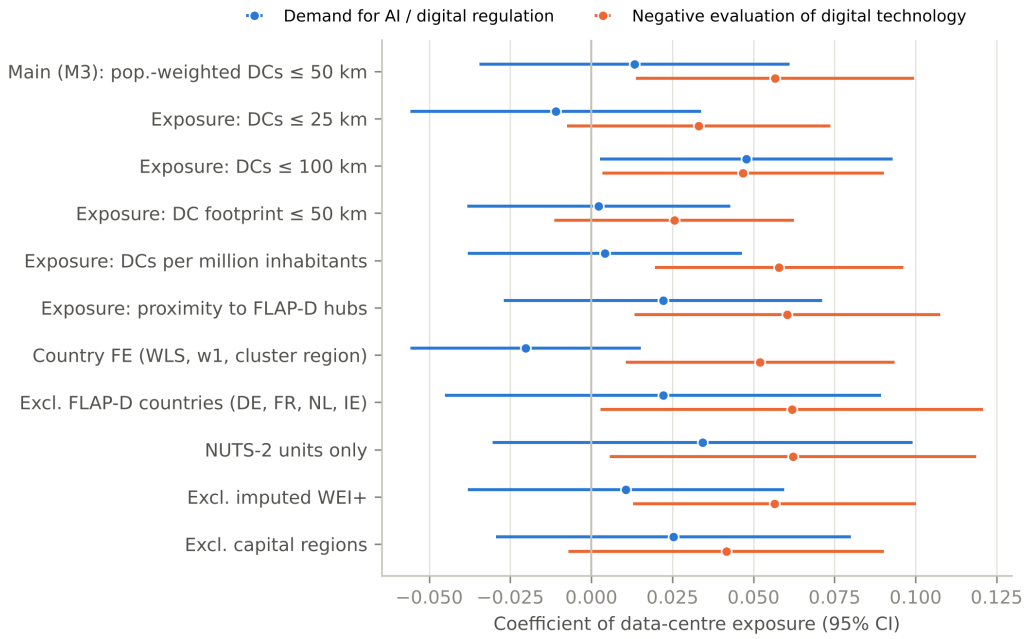


Figure 5. Coefficients of data-centre exposure (95% confidence intervals) for regulatory demand and negative evaluation across alternative exposure measures, estimators and subsamples.

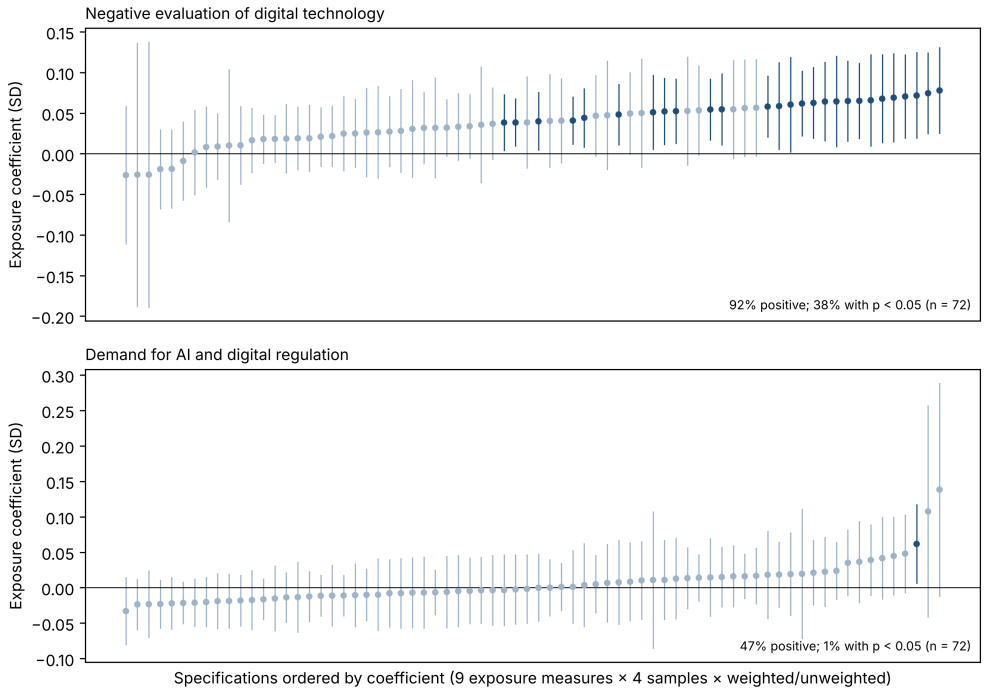


Figure 6. Specification curve for the exposure coefficient: nine exposure measures, four samples (full; excluding FLAP-D countries; NUTS-2 units only; excluding capital regions) and weighted or unweighted estimation, all with country fixed effects and region-clustered standard errors. Dark markers: $p < 0.05$.

5. Discussion

5.1. Interpreting the Evidence: Spillover Scepticism and Digital NIMBYism

The results establish a small but fairly consistent association: Europeans who live in regions with more data centres evaluate digital technology somewhat more negatively. The association survives exposure reconstructed as mapped at the survey date, a finer population grid, a hub-distance measure that uses no facility data, country fixed effects and design-based weighting. It is not significant in every specification, it is modest in size, and it would not survive the most conservative correction for multiple testing. The other hypothesised relationships receive weaker support. Exposure is not associated with demand for regulation on average; trust shifts that association without producing a significant positive effect at any level of trust; and the water-stress interactions are not robust.

How should this pattern be interpreted? One plausible account, consistent with the spillover literature [37], is that the data centre is the place where the cloud becomes visible and that residents generalise from its local costs to the technology it serves. The data are consistent with this account but do not test it. The survey does not measure awareness of nearby facilities, attitudes towards their siting, perceived local costs or competition for resources, so we cannot show that residents attribute their scepticism to data centres. Nor do the analyses test a sequence in which proximity first produces scepticism and scepticism then becomes demand for regulation; we therefore no longer describe the findings as a two-stage process. We use the term digital NIMBYism for the theoretical proposal and spillover scepticism for what the data show: an association between regional exposure and general evaluations of digital technology.

Several alternative explanations remain open. Data centres locate in regions with good connectivity, skilled labour and particular economic structures, and although the models control for GDP, density, energy prices and country, unobserved regional characteristics correlated with both siting and scepticism could produce the association. The hub-distance

measure and the exclusion of the hub countries make a pure hub or capital-city artefact unlikely, but they do not exclude all confounding. Reverse causation, in the sense of facilities avoiding sceptical regions, would bias the estimate towards zero rather than produce it. In a cross-sectional design, these possibilities cannot be eliminated, and we interpret the estimates as associations.

With these qualifications, the findings speak to an unresolved debate. Large harmonised studies find weak proximity effects on support for specific energy projects [29]. Our results suggest that a relevant outcome may lie elsewhere, in evaluations of the technology a facility represents. The trust result adds a second consideration. The literature often assumes that local costs breed opposition directly; the data suggest that institutional trust is associated with how exposure relates to support for rules, which echoes the procedural turn in siting research [32,33] and evidence that trust matters most for instruments whose effectiveness depends on credible enforcement [55]. The near-zero correlation between data-centre exposure and water stress is itself informative: Europe's data-centre geography is still driven by connectivity and markets, not by water availability, in contrast to the global picture, in which a quarter of facilities already face recurrent water gaps [4]. As AI-driven expansion moves towards the cheaper land and power of southern Europe, as current plans in Madrid and Aragón illustrate [12], it will become possible to test whether water stress conditions attitudes, which our data could not establish.

5.2. Policy and Governance Implications

The implications fall into two groups that rest on different kinds of evidence. The first group follows directly from the results. Because exposure is associated with more negative evaluations of digital technology as a whole, the social acceptance of the digital transition cannot be treated as independent of where its infrastructure is built. Data-centre siting is therefore part of the sustainability of the digital transition, not only a question of energy and water efficiency. The association is small at the individual level, but it applies to entire regional populations, and it will grow in relevance as AI-related capacity expands. Monitoring public attitudes in host regions, for example through regionally representative survey items on data centres, would allow regulators to see whether new capacity is accompanied by rising scepticism. The trust result suggests, more tentatively, that the relationship between exposure and support for rules is more favourable where institutions are trusted.

The second group consists of proposals grounded in the literature and in the regulatory context rather than tested here. Our data do not show that disclosure, participation or benefit sharing increase trust or acceptance; they show only that trust is associated with how exposure relates to support for rules. With that caveat, three proposals connect the findings to existing EU frameworks. On energy, Directive (EU) 2023/1791 and Delegated Regulation (EU) 2024/1364 already collect indicators such as energy consumption, power-usage effectiveness, the renewable energy factor and waste-heat reuse from facilities above 500 kW, but publish them only in aggregate [15,16]. Publishing these indicators at site level, together with each facility's contracted grid capacity, would let residents and regional planners see what a facility draws from the local system. On water, the same reporting includes water consumption, which could be published at site level together with the river basin or sub-basin of abstraction and linked to river-basin management under the Water Framework Directive [74]; sub-basin WEI+ is available for the whole EU and could be used to screen siting proposals in stressed basins, together with requirements for closed-loop cooling or water recycling where stress is high. On participation, large facilities fall under environmental impact assessment, whose public-participation provisions [75] could be applied early and could include data on energy, water and heat reuse. Community-benefit

agreements are another option, although their design itself shapes acceptance [76]. Survey evidence from Virginia indicates that residents support regulatory oversight of data centres and favour provisions that address direct and visible local impacts [18]. Whether such measures change attitudes in Europe is an empirical question that future research should address directly.

5.3. Limitations and Future Research

Several limitations qualify these conclusions and point to further research. The most important concerns the outcomes. Eurobarometer 101.4 does not ask about data centres, local siting or awareness of nearby facilities, and our regulatory index refers to workplace rules for AI. The analysis therefore cannot test digital NIMBYism directly, and we have reframed the article as a study of associations between exposure and general attitudes. A survey module on data-centre awareness, siting, perceived local costs and benefits, support for water-use disclosure and trust in operators would allow a direct test and would make it possible to separate attitudes towards facilities from attitudes towards the technology they serve.

The size of the associations is a second limitation. The exposure association amounts to between 5% and 17% of a standard deviation for realistic contrasts, it is not significant in all specifications, and it would not survive the most conservative correction for multiple testing. The findings should therefore be read as a consistent but modest regularity, not as evidence of a strong effect.

The exposure measure is a third limitation. OpenStreetMap under-records sites, particularly enterprise and edge facilities, and contains no capacity data. Exposure built from sites mapped before the survey, from a population grid and from distance to the hubs gives similar results, whereas the measure based on PeeringDB, which covers colocation rather than all facilities, gives a smaller and non-significant estimate. Linking the EU data-centre database created under Delegated Regulation (EU) 2024/1364, once published at site level, would allow exposure weighted by capacity in megawatts. The water data are also dated: the sub-basin WEI+ series ends in 2014. A recent drought indicator gives the same answer for the exposure association, but the water-stress interactions remain fragile, and newer sub-basin data would allow a better test of H2.

Measurement and sampling impose a fourth limitation. The institutional-trust scale has modest internal consistency, and although the trust interaction for regulatory demand holds for each of its sub-scales, a validated multi-item measure of trust in the authorities that regulate infrastructure would be preferable. Respondents excluded because of item non-response are older, less educated and less often online than those included, so the results may not generalise to these groups. Geography also matters: Germany and Sweden are coded only at NUTS-1, and respondents' exact locations are unknown. The NUTS-2 robustness check indicates that this error attenuates rather than inflates our estimates, but geocoded survey data would permit sharper tests of the distance gradient.

Finally, the data are cross-sectional and observational. The models control for regional affluence, density, energy prices and country, and the spatial models address dependence in the outcome, but unobserved regional characteristics correlated with data-centre location could still account for part of the association. Repeated survey waves combined with dated site openings, such as those reconstructed here from the OpenStreetMap history, would permit difference-in-differences designs that identify how attitudes change when a data centre arrives.

6. Conclusions

AI infrastructure is becoming part of the landscape that Europeans live in. Across 228 regions and 27 countries, residents with more data centres nearby evaluate digital technology somewhat more negatively. The association is modest and observational, it does not extend on average to demand for regulation, and we find no robust evidence that water stress conditions it. Institutional trust is associated with how exposure relates to support for rules, but the data do not show that exposure is channelled into regulatory demand among trusting residents. These findings are consistent with the proposal that digital infrastructure can generate spillover scepticism towards the technology it serves, which we call digital NIMBYism, but they do not test it directly. For a sustainable digital transition, they suggest that the social acceptance of digital technology and the siting of its infrastructure should be considered together, and that surveys designed to measure attitudes towards data centres directly are needed to establish how strong that link is.

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Data Availability Statement: The Eurobarometer 101.4 microdata are available from GESIS under its terms of use (https://doi.org/10.4232/1.14471). All open spatial data used in this study, the derived regional dataset, and the complete replication package—the code that rebuilds the regional data from the raw sources and regenerates every table and figure—are openly deposited in Zenodo at https://doi.org/10.5281/zenodo.23434478. PeeringDB records are not redistributed under the PeeringDB Acceptable Use Policy; the package includes the script that retrieves them.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
BH	Benjamini–Hochberg
CDI	Combined Drought Indicator
CI	Confidence interval
DC	Data-centre exposure
EEA	European Environment Agency

FLAP-D	Frankfurt, London, Amsterdam, Paris and Dublin
GDP	Gross domestic product
NIMBY	Not in my backyard
NUTS	Nomenclature of territorial units for statistics
OSM	OpenStreetMap
PPS	Purchasing power standard
SAR	Spatial autoregressive
SD	Standard deviation
WEI+	Water Exploitation Index plus
WLS	Weighted least squares

Appendix A. Descriptive Statistics

Table A1. Descriptive statistics of individual- and regional-level variables.

Variable	N	Mean	SD	Min	Max
Individual level (respondents)					
Demand for AI and digital regulation (1–4)	24,785	3.18	0.69	1	4
Negative evaluation of digital technology (1–4)	24,047	2.25	0.70	1	4
Energy-saving priority (0/1)	25,105	0.32	0.47	0	1
Institutional trust (1–4)	25,471	2.39	0.49	1	4
Difficulty paying bills (0–2)	26,171	0.41	0.62	0	2
Age (years)	26,362	51.72	18.40	15	98
Female (0/1)	26,362	0.53	0.50	0	1
Age at end of education (years)	25,956	19.85	4.11	2	30
Left–right self-placement (1–10)	23,032	5.37	2.08	1	10
Subjective social class (1–5)	25,832	2.44	0.99	1	5
Type of community (1–3)	26,355	1.98	0.80	1	3
Daily internet use (0/1)	26,362	0.82	0.38	0	1
Climate neutrality as energy priority (0/1)	25,820	0.20	0.40	0	1
Regional level (survey units)					
Data centres within 50 km (population-weighted)	228	5.61	14.25	0.00	121.91
Data centres within 25 km (population-weighted)	228	2.68	9.18	0.00	84.00
Data centres within 100 km (population-weighted)	228	13.94	23.95	0.00	147.99
Data-centre sites in unit	228	5.21	14.34	0	139
Summer WEI+ (%)	228	7.86	10.82	0.02	75.44
GDP per inhabitant (PPS)	228	36,124	16,929	14,700	154,300
Population density (inhabitants/km^2)	228	304.5	789.6	5.6	8474.8
Household electricity price (EUR/kWh)	228	0.26	0.07	0.11	0.40
Renewable share of electricity (%)	228	42.70	16.99	10.73	87.90

Appendix B. Additional Analyses

Table A2. Sample flow and comparison of included and excluded respondents (negative-evaluation sample, M3).

Sample Flow **Stage**		**Respondents**	
Eurobarometer 101.4, EU-27		26,404	
With a valid region of residence		26,362	
Regulation demand: outcome observed/+ controls (M1–M3)/+ trust (M4)		24,785/23,581/23,137	
Negative evaluation: outcome observed/+ controls (M1–M3)/+ trust (M4)		24,047/22,889/22,452	
Included vs. Excluded Respondents **Variable**	**Included**	**Excluded**	**Std. Diff.**
Age (years)	50.8	57.6	−0.35
Female	0.53	0.58	−0.11
Age at end of education (years)	20.1	18.2	0.46
Daily internet use	0.86	0.62	0.57
Type of community (1–3)	1.99	1.91	0.10
Subjective social class (1–5)	2.49	2.01	0.49
Left–right not reported	0.11	0.26	−0.41
Data-centre exposure (SD)	0.12	−0.02	0.13

Included: 22,889 respondents; excluded: 3473 respondents with a valid region (fewer for variables with item non-response).

Table A3. Size of the exposure association in numbers of data centres (negative evaluation, M3).

Contrast (Data Centres Within 50 km of the Average Resident)	Change (1–4 Scale)	95% CI	% of SD
0 vs. 1	0.036	0.009 to 0.062	5
0 vs. 5	0.092	0.022 to 0.161	13
0 vs. 10	0.123	0.030 to 0.216	17
0 vs. 50	0.201	0.049 to 0.354	29
Interquartile range of regions (0 vs. 4.4)	0.086	0.021 to 0.151	12

Table A4. Institutional trust and the regulation index: sub-scales, single items and random slopes.

Specification	b	SE	*p*
DC × trust, regulation demand (M4)			
Composite trust (main)	0.025	0.004	<0.001
Composite trust, random slope for trust	0.018	0.009	0.038
Justice sub-scale (QA2)	0.028	0.004	<0.001
Public-authorities sub-scale (QA4)	0.018	0.004	<0.001
DC × trust, negative evaluation (M4)			
Composite trust (main)	−0.008	0.004	0.056
Composite trust, random slope for trust	−0.006	0.007	0.449
Justice sub-scale (QA2)	−0.003	0.005	0.488
Public-authorities sub-scale (QA4)	−0.009	0.004	0.029
Single regulation items: DC (M2) and DC × trust (M4)			
Protect workers' privacy	0.031/0.033	0.028/0.005	0.273/<0.001
Prohibit fully automated decisions	0.007/0.025	0.025/0.006	0.773/<0.001
Limit automated monitoring of employees	0.010/0.023	0.026/0.006	0.703/<0.001
More transparency of HR decisions	−0.002/0.026	0.024/0.006	0.949/<0.001
Involve workers and representatives	0.007/0.020	0.024/0.005	0.783/<0.001
Index without worker involvement	0.015/0.026	0.025/0.004	0.541/<0.001

Trust reliability: composite $\alpha = 0.66$, $\omega = 0.66$; justice sub-scale $\alpha = 0.49$; public-authorities sub-scale $\alpha = 0.54$; correlation between sub-scales 0.45. Item–rest correlations range from 0.23 to 0.50.

Table A5. Sequential models M0–M2 (unstandardised coefficients, standard errors in parentheses).

	Regulation Demand			Negative Evaluation		
Predictor	**M0**	**M1**	**M2**	**M0**	**M1**	**M2**
Intercept	3.167 *** (0.032)	3.022 *** (0.030)	3.018 *** (0.026)	2.262 *** (0.025)	2.437 *** (0.030)	2.447 *** (0.029)
Age (SD)	–	0.003 (0.005)	0.002 (0.005)	–	0.088 *** (0.005)	0.088 *** (0.005)
Female	–	0.004 (0.008)	0.004 (0.008)	–	0.047 *** (0.009)	0.047 *** (0.009)
Years of education (SD)	–	0.064 *** (0.005)	0.064 *** (0.005)	–	−0.029 *** (0.005)	−0.029 *** (0.005)
Left–right (SD)	–	−0.022 *** (0.005)	−0.022 *** (0.005)	–	−0.018 *** (0.005)	−0.018 *** (0.005)
Left–right not reported	–	0.055 *** (0.014)	0.056 *** (0.014)	–	0.049 ** (0.015)	0.049 ** (0.015)
Subjective social class (SD)	–	0.002 (0.005)	0.002 (0.005)	–	−0.056 *** (0.005)	−0.056 *** (0.005)
Type of community (SD)	–	0.026 *** (0.005)	0.025 *** (0.005)	–	−0.010 * (0.005)	−0.010 * (0.005)
Daily internet use	–	0.168 *** (0.014)	0.167 *** (0.014)	–	−0.223 *** (0.014)	−0.223 *** (0.014)
Difficulty paying bills (SD)	–	−0.018 *** (0.005)	−0.017 *** (0.005)	–	0.038 *** (0.005)	0.038 *** (0.005)
Climate priority	–	0.026 * (0.011)	0.026 * (0.011)	–	−0.081 *** (0.011)	−0.080 *** (0.011)
Data-centre exposure (DC, SD)	–	–	0.014 (0.024)	–	–	0.056 ** (0.022)
GDP per inhabitant, PPS (log, SD)	–	–	0.084 *** (0.024)	–	–	−0.050 * (0.022)
Population density (log, SD)	–	–	−0.055 * (0.025)	–	–	−0.011 (0.023)
Household electricity price (SD)	–	–	0.001 (0.024)	–	–	0.038 (0.026)
Renewable share of electricity (SD)	–	–	0.022 (0.022)	–	–	−0.009 (0.024)
Country variance	0.018	0.013	0.006	0.010	0.013	0.011
Regional variance	0.050	0.047	0.046	0.036	0.037	0.035
Residual variance	0.419	0.402	0.402	0.457	0.419	0.419
Log-likelihood	−24,686.5	−22,999.5	−22,991.4	−24,954.4	−22,766.3	−22,760.7
Respondents	24,785	23,581	23,581	24,047	22,889	22,889

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. 228 regions in 27 countries. M0 uses all respondents with a valid outcome; M1 and M2 use the same listwise sample, so their log-likelihoods are comparable. Full estimates for all models and outcomes, including the energy-saving priority, are in the replication package.

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