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Original research article

Affluence, Spatial Spillovers, and Inequality in Household Energy Transitions: Exploring the Determinants of Sustainable Technology Adoption in Ireland

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A R T I C L E I N F O

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A B S T R A C T

This study investigates the spatial and socioeconomic determinants of household adoption of sustainable technologies in Ireland—specifically heat pumps (HP), solar photovoltaic (PV) systems, electric vehicles (EV), and EV home chargers (EVHC). Using a Spatial Seemingly Unrelated Regression Generalised Nested Model (SPSUR-GNM) at the electoral division (ED) level, we analyse 2804 EDs combining socioeconomic, housing, transport, and demographic data. Results show that a one-point increase in the Deprivation Index (less deprived areas) is associated with 1.2–2.9% higher adoption across all technologies, while a 1-percentage-point rise in management professionals increases uptake by 0.8% for PV, 1.6% for EV, and 2.5% for EVHC. In contrast, higher fossil-fuel dependence sharply reduces HP uptake (−4.6% for oil, −7.0% for wood heating). Spatial spillovers are substantial: for example, EV adoption in one ED induces an additional 2.6% increase in neighbouring areas. These results confirm that adoption is strongly concentrated in affluent, owner-occupied, and professionally employed communities. Current "pay-then-reimburse" grant schemes and limited public infrastructure disproportionately benefit higher-income households, reinforcing equity gaps. The study recommends upfront, means-tested subsidies and geographically targeted outreach to promote a more inclusive energy transition.

1. Introduction

The transition to sustainable energy and transport technologies is central to achieving climate mitigation targets. In Ireland, however, progress remains constrained by continued fossil-fuel dependence and persistent gaps in residential and transport decarbonisation. While Ireland has made significant progress in renewable electricity generation—wind farms provided a third of the island's electricity in 2024 [1]—it continues to lag behind other EU nations in the adoption of household-level low-carbon technologies, such as heat pumps (*HP*), solar photovoltaic (*PV*), electric vehicles (*EV*) and electric vehicles home chargers (*EVHC*) [2].

Historically, indoor heating has accounted for 44% of Ireland's total energy use, 93% of which came from fossil fuels, with the residential sector responsible for nearly half of that consumption [3]. Recognising this, the Irish government's 2019 Climate Action Plan [4] identifies HP as a key solution for decarbonising home heating, setting a target of 600,000 installations by 2030, with 400,000 in existing homes. Grants are available to mitigate the high upfront costs compared to fossil fuel systems, yet uptake remains modest, as in 2023, 47,953 HP grants were offered by the Sustainable Energy Authority of Ireland (SEAI). Although these figures remain well below those of countries such as France (394,000 installations), they represent substantial year-on-year growth when compared with previous years, such as 2022 (27,200 HP grants) and 2020 (8750). The same plan sets ambitious goals across other sectors, including the deployment of nearly one million EV [5]. Similar to slow progress in home energy retrofits, EV uptake has been lagging far behind national targets. As of 2024, EV accounted for less than 14.4% of new car sales in Ireland—which is a considerable increase from 4.5% in 2020, yet still below the European average of 22.7% [6,7]. The gap between targets and real-world adoption highlights the need to understand the factors influencing the uptake of these technologies. This gap is not merely technical; it reflects structural socioeconomic and spatial inequalities embedded within Ireland's housing and transport systems.

The adoption of green technologies is not merely a technological choice but a fundamentally socioeconomic process. Households' investment decisions in technologies such as solar photovoltaic systems or heat pumps are shaped by income constraints, housing characteristics,

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tenure structure, commuting patterns, education, and local labour market conditions. These factors determine not only financial capacity but also risk perception, information access, and environmental preferences. Technology diffusion therefore reflects spatially embedded social structures rather than purely individual optimisation. Understanding adoption therefore requires examining the socioeconomic composition of local areas and the interaction between households within those areas.

Much of Ireland's sustainable technology policy relies on financial incentives. These include Sustainable Energy Authority of Ireland's (SEAI) grants—such as, up to €15,000 as rebates for EV purchase price, tax exemptions, toll reductions, and subsidies for EVHC grants [8]. SEAI reported an investment of €616 million in 2024, primarily directed toward the clean energy transition. This funding supported initiatives such as the Warmer Homes Scheme grant for home energy upgrades, including PV and HP [9]. However, pay-then-reimburse schemes, that is, schemes that require households to pay significant costs upfront before being reimbursed, are less accessible to low-income groups, disproportionately benefitting the higher-income individuals who can afford the initial investment [10]. Additionally, Ireland's EV rollout is hindered by an underdeveloped public charging network, with 80% of charging still occurring at home [11]. This raises equity concerns, as apartment dwellers and renters lack the same access to private charging, reinforcing socioeconomic disparities in EV adoption.

This study examines the spatial and socioeconomic determinants of household adoption of sustainable technologies—HP, PV, EV, and EVHC—in Ireland. Using a Spatial Seemingly Unrelated Regression Generalised Nested Model (SPSUR-GNM), it analyses geographic data across electoral division (ED) to uncover key predictors of adoption. Given that adoption occurs within spatially interconnected and multi-technology environments, a modelling framework capable of capturing cross-technology correlations and spatial spillovers is required to avoid biased inference. A modelling approach capable of capturing these interdependencies is therefore required to avoid biased inference and misleading policy conclusions.

The research focuses on income, deprivation index categories, housing structure types, and commuting patterns, identifying factors that facilitate or hinder the transition to sustainable technologies. Ignoring spatial interdependence in this context risks producing biased policy conclusions. Empirical evidence increasingly suggests that green technology adoption exhibits local clustering driven by peer effects, neighbourhood visibility, installer networks, and shared infrastructure conditions. When households observe nearby installations, informational and behavioural barriers may decline, accelerating diffusion. Conversely, areas with low initial uptake may remain locked into low-adoption equilibria. Standard non-spatial models implicitly assume independence across regions and therefore fail to capture these feedback mechanisms. As a result, they may underestimate multiplier effects or misidentify the role of socioeconomic determinants.

Despite growing research on individual technologies, limited work jointly models multiple household technologies while explicitly accounting for spatial interdependence in the Irish context. Residential renewable technologies are often adopted in bundles or sequentially, and their diffusion may be interconnected through shared socioeconomic drivers and installer markets. Moreover, Ireland's settlement structure—characterised by a strong urban–rural divide, dispersed housing patterns, and regionally differentiated commuting systems—creates heterogeneous spatial interaction processes. Estimating technologies separately would ignore shared socioeconomic drivers and common spatial shocks, leading to incomplete or biased conclusions. A joint spatial modelling framework therefore allows us to identify both technology-specific determinants and interdependent diffusion patterns, providing a more accurate representation of the adoption process.

Results reveal that adoption of HP and PV, as well as EV and EVHC, is concentrated in higher-income, owner-occupied, and professionally employed areas, while lower-income and more deprived regions—often with higher fossil fuel reliance—remain underrepresented. The study also highlights regional spillover effects, emphasizing the importance of spatial dependencies and local demonstration effects in shaping technology uptake. The findings underscore that current pay-then-reimburse grant schemes and infrastructure gaps disproportionately benefit affluent households, leaving renters, apartment dwellers, and lower-income groups at a disadvantage. These inequities reveal the limits of uniform subsidy design. Achieving a just and inclusive energy transition requires geographically targeted outreach, upfront and means-tested supports, and policies aligned with the structural realities of Ireland's housing and settlement patterns.

2. Literature review

The transition to sustainable household technologies—heat pumps (HP), photovoltaic systems (PV), electric vehicles (EV), and electric vehicle home charging (EVHC)—is central to reducing the environmental footprint of Irish households and achieving national climate targets. Despite substantial policy support, adoption remains uneven across regions and socioeconomic groups [11]. Existing research highlights the importance of financial incentives, infrastructure provision, and demographic characteristics, yet adoption patterns continue to exhibit strong spatial and social heterogeneity. This section synthesizes international and Irish evidence with a particular focus on three interrelated dimensions: (i) socioeconomic determinants of household adoption, (ii) spatial spillovers and infrastructure constraints, and (iii) the specific Irish institutional and policy context.

2.1. Socioeconomic determinants of sustainable technology adoption

International research shows that adoption of low-carbon household technologies is shaped by a combination of economic, demographic, behavioural, and policy factors. For EV adoption, financial incentives and charging availability are consistently identified as key drivers [12]. Subsidy schemes across Europe—including purchase grants, tax reliefs, and toll reductions—have increased uptake, although their effectiveness depends on demand elasticity and income distribution [13]. Germany's dual strategy of consumer subsidies and infrastructure funding, for example, contributed to an increase in EV market share from 2.9% in 2019 to 25.7% in 2021 [14,15], while similar strategies in the UK emphasised residential charging access for households without private driveways [16].

However, financial incentives alone do not ensure equitable or widespread adoption. High upfront costs remain a central barrier, particularly for lower-income households. EV typically cost €15,000–€20,000 more than conventional vehicles, even after subsidies, which reinforces wealth-driven adoption patterns [10]. Evidence from the California Clean Vehicle Rebate Project shows that rebate programmes often disproportionately benefit wealthier and well-educated neighbourhoods [17], while targeted income-based schemes in New England demonstrate attempts to address this imbalance [18]. In several contexts, including Nordic countries and China, EV adoption has also been associated with status signalling, further reinforcing socioeconomic stratification [19].

For home energy technologies such as HP and PV, similar patterns emerge. Adoption is influenced by income, education, age, housing type, and social norms [20,21]. Technical feasibility and economic considerations—particularly upfront investment costs—are frequently identified as dominant determinants [22,23]. Although policy efforts have expanded, HP adoption has lagged behind PV in several European countries [24,25]. Social networks and peer effects may further influence adoption decisions, yet these mechanisms are often underrepresented in policy design [26].

Socioeconomic disparities are closely intertwined with energy poverty. In Ireland, approximately 17.5% of households experience energy poverty [27], with disproportionate impacts on low-income, rural, and minority populations [28]. These households often face higher relative energy costs and limited access to efficient heating technologies [29,30]. Structural inequalities in housing quality and infrastructure access further constrain participation in the energy transition [31,32]. Without targeted interventions, adoption of sustainable technologies risks reinforcing existing socioeconomic divides.

2.2. Spatial factors, infrastructure gaps, and spillover dynamics

Beyond individual household characteristics, spatial context and infrastructure provision play a critical role in shaping adoption patterns. A robust and accessible charging network is widely recognised as essential for facilitating EV uptake and reducing range anxiety [33–35]. The absence of conveniently located charging stations remains a primary barrier [36], with demand differing across residential, workplace, en-route, and destination settings [37].

Empirical evidence suggests that infrastructure availability may, in some contexts, be more influential than direct financial subsidies [38]. Workplace charging can also generate peer effects, promoting adoption through social visibility and interaction [39]. However, home charging—while cost-effective—requires access to private parking, creating structural barriers for renters and residents of multi-unit dwellings [40]. These spatial constraints are particularly pronounced in urban areas.

In Ireland, public charging infrastructure has expanded but remains unevenly distributed, with approximately 80% of charging occurring at home [11]. GIS-based analyses have identified high-priority charging locations in Dublin and beyond [36], highlighting the importance of detached and semi-detached housing for EVHC installation. Rural and disadvantaged urban neighbourhoods face more pronounced infrastructure gaps [19,41], reinforcing spatial inequalities in adoption opportunities. Inefficient infrastructure placement may undermine decarbonisation goals and lead to suboptimal public expenditure [42–44].

Spatial clustering in adoption has been documented not only for EV but also for broader sustainable technologies [45]. Burra et al. [46] demonstrate significant county-level heterogeneity in EV registrations, even after controlling for subsidies and infrastructure endogeneity. These findings suggest that adoption decisions are embedded within local socioeconomic structures and spatial interdependencies. Yet, much of the existing literature treats technologies independently, rather than considering potential cross-technology spillovers or spatial diffusion across neighbouring regions.

2.3. The Irish context and remaining gaps

Ireland presents a distinctive institutional and structural context for sustainable technology adoption. Government incentives for EV include purchase grants, road-tax relief, and toll reductions, amounting to approximately €15,000 per vehicle [8], alongside a €600 grant for home charging installations [5]. Nevertheless, electrification of transport has progressed slowly, with EV comprising less than 5% of new car sales in 2020 [5], and evaluations raising concerns about the cost-effectiveness of certain funding schemes [47]. The 2019 Climate Action Plan sets ambitious targets for both transport and residential decarbonisation [48], including 600,000 HP installations by 2030 [49].

Despite this policy ambition, several structural challenges persist. Ireland's housing stock, commuting patterns, and rural settlement structure create heterogeneous conditions for adoption. Detached housing facilitates technologies such as EVHC and HP, whereas renters and residents of multi-unit dwellings face additional barriers [36]. Moreover, energy poverty remains significant, and existing schemes have been criticised for limited inclusiveness [27,50].

While prior research has examined individual technologies or specific barriers, three important gaps remain. First, limited empirical work jointly examines multiple household technologies within a unified analytical framework, despite potential complementarities and shared socioeconomic determinants. Second, spatial interdependencies across counties are rarely modelled explicitly, even though infrastructure and social diffusion processes are inherently geographic. Third, the interaction between socioeconomic structure, spatial clustering, and cross-technology adoption remains insufficiently understood in the Irish context.

Addressing these gaps is essential for designing equitable and spatially efficient climate policies. Without a clearer understanding of how socioeconomic and spatial factors jointly shape adoption patterns, policy interventions risk reinforcing existing inequalities and regional disparities.

3. Data description and exploration

The datasets employed in this analysis include:

1) **SEAI dashboard data**: The primary dataset used for this analysis is the SEAI's dashboard data providing information on the grants awarded by the Sustainable Energy Authority of Ireland (SEAI) up to the year 2023 at the electoral division or ED level. The relevant data includes number of grants per ED awarded for HP, PV, EV, and EVHC.
2) **POBAL Deprivation data:** The deprivation index used in this study is the 2022 Pobal HP [51,52] Relative Deprivation Index. This index provides a summary measure of socioeconomic deprivation at the level of Electoral Divisions (EDs). Each ED is assigned an absolute index score, which is then converted into relative categories: Extremely Disadvantaged, Very Disadvantaged, Disadvantaged, Marginally Below Average, Marginally Above Average, Affluent and Very Affluent (this last category is not present in the data after the data cleaning process). The absolute deprivation scores are calculated as a weighted function of several socio-economic indicators, including:

- Total Population
- Age Dependency Rate
- Lone Parent Rate
- Low Education and High Education levels
- Professional/Managerial and Low-Skilled Employment
- Male and Female Unemployment Rates
- Housing Tenure: Owner Occupied, Private Rental, Local Authority Rental
- Persons per Room

The Pobal HP Deprivation Index is derived from a statistical model framework that integrates ten Census-based measures of social and economic conditions, rather than a single equation. This model captures multiple dimensions of disadvantage, allowing robust comparison of deprivation scores across areas and over time. Higher positive scores indicate greater affluence, whereas lower negative scores indicate greater deprivation. For our analysis, we used the most recent 2022 ED-level relative scores to categorize areas as described above.

3) **Income data:** The income data is compiled from the Central Statistics Office which provides household median gross income (€) by Electoral Division. The most recent available income data originates

from the 2016 CSO records and is assumed to approximate current household incomes (at the time of writing this paper, 2016 data was the most up to date data available[1]).

4) **SAPS (Small Area Population Statistics) data:** This data is compiled from the Central Statistics Office (2022) at the Electoral Division or ED level, which offers information on:
   a. Population Demographics (Total Population, Male Population, Female Population (Under 19, 20–60, Above 60))
   b. Occupational Categories (Percentage in Management and Professional Occupations, Non-Manual Occupations, Skilled Occupations, and Agricultural and Own-Account Work)
   c. Socioeconomic Indicators (Average Income)
   d. Household Composition (Percentage of Single Households (With and Without Children); Percentage of Couples (With and Without Children); Percentage of Households with Children)
   e. Heating Types (Percentage Using Oil, Gas, Coal, Peat, LPG, and Wood Heating)
   f. Transport and Commuting Modes (Percentage Using Active Commuting Modes; Percentage Using Public Transport)

These datasets from various sources were merged into a single dataset organized by ED. Geospatial analysis was also incorporated by calculating centroids for EDs and counties using a shapefile of ED. This allowed for the assessment of spatial autocorrelation within the data and facilitated visualization in QGIS. In this study, we utilized multiple datasets, some with varying classifications of EDs and subject to changes in ED boundaries over time. To ensure consistency and accuracy, we excluded EDs from the analysis when their boundaries did not align across datasets or when they had been amended in one dataset but not in others. This approach resulted in the inclusion of a subset of EDs (2804 out of a total of 3440 legally defined EDs) for analysis. Rather than calculating the percentage of missing data for each variable, we prioritized the inclusion of EDs with consistent and complete data across all variables. This methodology was essential to maintain the integrity of our spatial analysis and to avoid potential biases from partial data.

Finally, data is analysed at the ED level, with 2804 EDs incorporated after data cleaning. The dependent variables, representing adoption rates, are *Natural* log *of HP grants,*[2] *Natural log of PV grants, Natural log of EV grants,* and *Natural log of EVHC grants*. The distributions of these four dependent variables of interest are shown in Figs. 1, 2, 3, and 4. Fig. A1 (Appendix A) offers a pairwise scatter plot matrix for the four variables of interest.

The Tables 1, 3 and 4 reveals significant disparities in the adoption and availability of renewable energy technologies (HP and PV) and electric vehicle infrastructure (EV and EVHC) across EDs, socio-economic and income categories. From Table 1, we note that "*HP grants per ED*" variable has no zeros and relatively fewer entries below 10 (1337 out of a total dataset). This indicating a potentially broader uptake of HP grants across different regions, compared to PV, EV or EVHC. Table 2 provides the descriptive statistics of the exogenous variables examined in this analysis.

From Table 3, EDs categorised as *affluent* as per deprivation-index

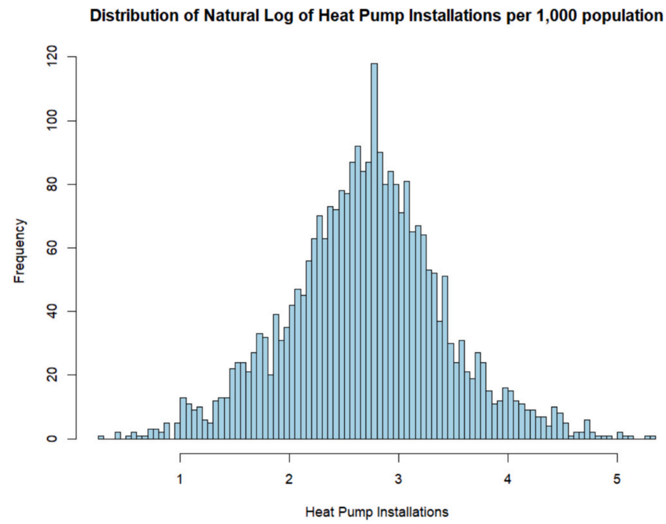

Fig. 1. Distribution of Natural log of HP grants per 1000 population.

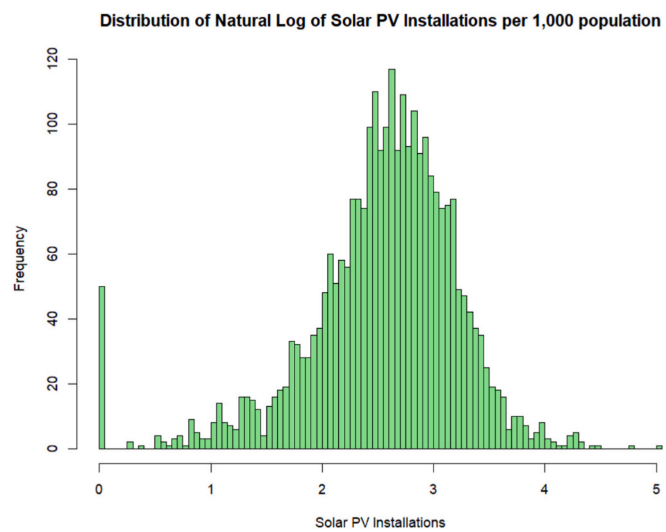

Fig. 2. Distribution of Natural log of PV grants per 1000 population.

data areas exhibit the highest adoption rates across all categories, with mean values for HP grants (24.39 per 1000 population), PV grants (21.01 per 1000 population), EV grants (17.28 per 1000 population), and EVHC grants (15.85 per 1000 population). In contrast, *very disadvantaged* areas show much lower adoption rates, particularly for EV-related grants, with mean values of 2.61 per 1000 population for EV grants and 1.69 per 1000 population for EVHC grants. A clear trend emerges, indicating that adoption increases as socio-economic status improves, underscoring the strong correlation between affluence and access to these technologies.

From Table 4, income categories reflect stark disparities in adoption rates. Low-income households (earning less than €25,000 annually) have the lowest adoption rates, particularly for EV-related grants, where the means are 4.99 per 1000 population for EV grants and 3.50 per 1000 population for EVHC grants. These figures point to affordability and accessibility challenges for lower-income groups in adopting renewable energy technologies. Middle-income households, particularly those earning €45,000–€65,000, exhibit moderate adoption rates that fall between lower- and higher-income groups. For example, HP grants in the middle-income group average 19.16 per 1000 population, compared to 35.13 in the high-income group. High-income households (earning more than €85,000) show the highest adoption rates across all

[1] A limitation of this study is the reliance on household income data from 2016, which may not accurately reflect current income levels. Changes in household income over time could introduce bias, potentially affecting the accuracy of income-related analyses. Although the 2016 CSO data were the most recent available at the time of this study, readers should interpret findings with caution regarding current income distributions.

[2] Each of the dependent variables contained zero observations (as seen in Table 1 below). To address the issue of undefined logarithms for zero values while retaining these cases in the estimation, we applied a *natural logarithm (x + 1)* transformation. This approach is commonly used when variables represent counts or rates with a meaningful zero value [53,54]. The transformation preserves monotonicity and scale comparability while enabling the inclusion of zero-valued observations in the model.

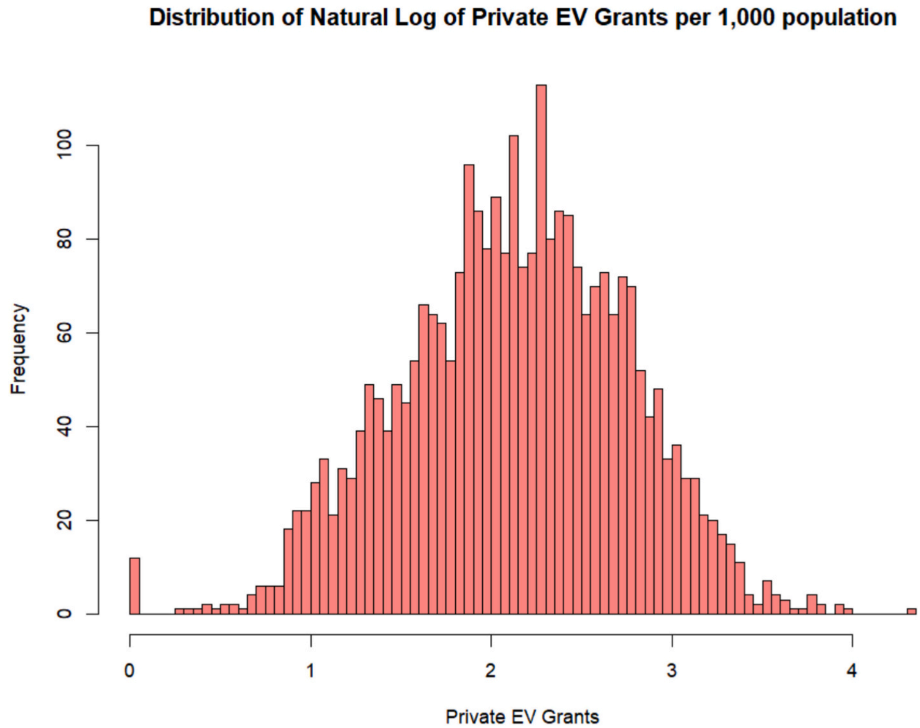

Fig. 3. Distribution of Natural log of EV grants per 1000 population.

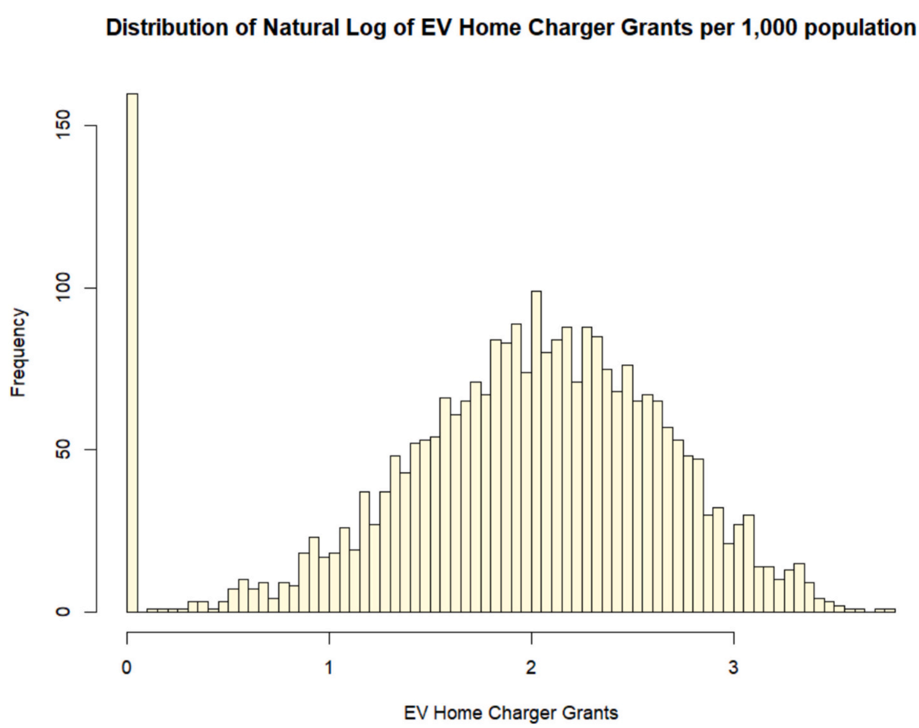

Fig. 4. Distribution of Natural log of EVHC grants per 1000 population.

technologies, with EV grants and EVHC grants reaching mean values of 26.81 and 26.57 per 1000 population, respectively. These patterns underscore the critical role of income and affluence in shaping access to renewable energy and EV technologies, highlighting the need for targeted policy interventions to reduce disparities and enhance equitable access for underrepresented and lower-income groups.

Fig. A2 provides scatterplots illustrating relationships between deprivation index values and adoption rates of the four sustainable technologies. Fig. A3 provides scatterplots illustrating relationships between income levels and adoption rates of the four sustainable technologies. Fig. A4 provides heatmaps showing adoption levels of HP, PV, EV, and EVHC across EDs. Fig. A5 provides a spatial distribution of Deprivation index categories and Income categories across Ireland for all EDs.

Table 1
Frequency distribution of dependent variables.

Frequency of EDs with grants (total = 2804)		Zero Count	Less Than 10	Less Than 100
HP grants	Absolute	0	1337	2594
	Per 1000 population	0	881	2785
PV grants	Absolute	50	1411	2683
	Per 1000 population	50	950	2802
EV grants	Absolute	12	1869	2732
	Per 1000 population	12	1844	2804
EVHC grants	Absolute	160	2006	2746
	Per 1000 population	160	2027	2804

4. Methodology and model development

This study employs a ***SP****atial* ***S****eemingly* ***U****nrelated* ***R****egression*-***Gener-alised*** ***N****ested* ***M****odel* (SPSUR-GNM) to analyse adoption patterns of four dependent variables: (1) HP grants, (2) PV grants, (3) EV grants, and (4) EVHC grants. These variables are measured per 1000 population and transformed using natural logarithm to address skewness and interpret coefficients as elasticities. The SPSUR-GNM framework [55,56] is well-suited for modelling the seemingly unrelatedness between dependent (endogenous) variables and their complex relationships with independent (exogenous) variables while accounting for spatial dependencies and interdependencies across equations. This approach captures both the direct determinants of adoption and spatial spillover effects arising from geographic proximity. The purpose of this framework is to isolate socioeconomic and spatial mechanisms driving adoption, rather than to prioritise methodological complexity.

Although PV, EV, HP, and EVHC represent distinct technologies with different purchase and usage contexts, they share overlapping socio-economic, infrastructural, and policy determinants. Empirical studies [57,58] show that households' adoption of low-carbon technologies often co-occurs due to shared latent traits—such as pro-environmental values, financial capacity, or compatibility of housing type—and local contextual factors such as policy incentives, installer availability, or visibility of peer adoption. At the household level, factors such as environmental orientation, financial liquidity, and dwelling characteristics (e.g., detached housing with sufficient roof and driveway space) can simultaneously raise the likelihood of adopting multiple technologies. At the spatial level, local authority actions—such as one-stop grant programmes, installer availability, or demonstration effects—tend to influence several technologies in parallel. Consequently, unobserved contextual factors may create systematic co-movements in adoption rates even when individual decision processes differ. The correlated-error structure in the SPSUR-GNM captures these shared unobservable rather than implying that consumers make joint purchase decisions. This approach allows us to identify structural patterns of inequality and diffusion across technologies that emerge from common socioeconomic and infrastructural conditions rather than from direct substitution or complementarity in consumer choice.

The SPSUR-GNM framework extends classical spatial models by jointly estimating multiple interdependent adoption equations (PV, EV, HP and EVHC) while accounting for spatial spillovers and correlated errors across technologies. Formally, each technology-specific equation includes endogenous and exogenous spatial lags, similar to SAR and SDM specifications, but estimation proceeds through a Seemingly Unrelated Regression (SUR) system to capture contemporaneous correlation across equations. This general structure nests well-known models as special cases:

1. SAR model: when only spatial lag of the dependent variable is included, and cross-equation correlations are zero.

Table 2
Descriptive statistics of the exogenous variables examined.

Variable Name	Mean	Std. Dev.	Min.	Max.
Absolute Deprivation Index	−1.16	5.65	−27.13	14.56
Estimated Average Income (ED)	45,776.44	11,228.53	17,232.00	105,943.00
Demographic Characteristics (ED Level)				
Percentage of Males Under 19	26.94	4.87	4.63	54.09
Percentage of Males Aged 20 to 60	50.13	5.71	30.02	84.28
Percentage of Males Over 60	22.93	5.76	4.64	46.05
Percentage of Females Under 19	25.71	4.58	6.67	43.49
Percentage of Females Aged 20 to 60	50.69	5.47	35.68	82.58
Percentage of Females Over 60	23.60	5.94	4.80	51.11
Marital Status (ED Level)				
Percentage of Population Single	51.13	5.21	37.57	85.06
Percentage of Population Married	40.03	5.56	12.17	53.11
Percentage of Population Separated	2.11	0.85	0.00	7.75
Percentage of Population Divorced	2.28	0.95	0.00	6.98
Percentage of Population Widowed	4.45	1.48	0.93	11.57
Employment Characteristics (ED Level)				
Percentage in Management or Professional Occupations	20.17	7.92	2.58	59.59
Percentage in Agricultural or Own-Account Work	15.23	8.62	0.32	54.41
Percentage in Non-Manual Work	30.60	5.77	4.70	49.82
Percentage in Skilled Occupations	18.16	5.87	0.00	47.91
Percentage in Unskilled or Miscellaneous Occupations	14.84	7.37	0.65	62.47
Health of population (ED Level)				
Percentage Reporting Very Good Health	54.79	6.83	18.11	72.31
Percentage Reporting Good Health	29.91	3.39	12.23	41.18
Percentage Reporting Fair Health	8.64	2.24	1.44	19.41
Percentage Reporting Bad Health	1.28	0.67	0.00	5.04
Percentage Reporting Very Bad Health	0.31	0.26	0.00	2.97
Percentage with Health Status Not Stated	5.07	5.28	0.00	62.97
Household Structure (ED Level)				
Percentage of Single-Adult Households	22.86	6.23	7.56	55.42
Percentage of Single-Adult Households with Children	8.59	3.32	0.00	33.07
Percentage of Couple Households without Children	20.43	3.95	5.27	39.56
Percentage of Couple Households with Children	36.85	9.06	3.95	63.10

(*continued on next page*)

Table 2 (*continued*)

Variable Name	Mean	Std. Dev.	Min.	Max.
Percentage of Multi-Adult Households without Children	6.70	5.56	0.00	61.97
Percentage of Multi-Adult Households with Children	4.57	2.12	0.00	16.69
Household Dwelling Unit (ED Level)				
Percentage of Households in Houses	94.17	12.93	0.00	100.00
Percentage of Households in Flats	5.37	12.97	0.00	100.00
Percentage of Households in Bedsits	0.04	0.34	0.00	12.38
Percentage of Households in Caravans	0.42	0.72	0.00	7.01
Household dwelling heating characteristics (ED Level)				
Percentage of Households Using Oil for Heating	55.01	22.85	0.00	91.67
Percentage of Households Using Gas for Heating	12.58	24.17	0.00	90.14
Percentage of Households Using Coal for Heating	4.37	3.83	0.00	24.61
Percentage of Households Using Peat for Heating	8.03	12.32	0.00	63.20
Percentage of Households Using LPG for Heating	0.79	1.07	0.00	15.63
Percentage of Households Using Wood for Heating	3.61	3.26	0.00	24.05
Percentage of Households Using Electricity for Heating	8.24	7.35	0.00	68.27
Percentage of Households Using Other Heating Sources	7.36	4.09	0.00	58.80
Household Transport Mode (ED Level)				
Percentage Using Public Transport to Commute	7.05	3.67	0.00	22.59
Percentage Using Active Transport (e.g., walk/ bike)	6.11	6.57	0.00	49.01
Percentage Using Private Transport to Commute	46.82	11.28	2.62	68.16
Percentage Working from Home	5.40	1.87	0.93	13.89
Percentage Using Other Means of Transport	34.62	6.97	16.75	76.76
Household Commute Time (ED Level)				
Percentage with Commute Time Under 15 Minutes	23.92	5.80	9.04	51.70
Percentage with Commute Time Between 15 and 30 Minutes	17.36	5.00	3.45	37.07
Percentage with Commute Time Between 30 and 45 Minutes	10.82	3.88	2.14	29.59
Percentage with Commute Time Between 45 Minutes to 1 Hour	3.60	1.76	0.00	10.38
Percentage with Commute Time Over 1 Hour	44.30	5.10	28.40	66.43
Household Car Ownership (ED Level)				
Percentage of Households with No Car	14.01	12.22	0.00	91.92
Percentage of Households with One Car	33.83	7.43	7.53	53.93
Percentage of Households with Two Cars	38.36	10.68	0.40	60.55
Percentage of Households with Three Cars	9.30	4.11	0.00	25.53
Percentage of Households with Four or More Cars	4.09	2.54	0.00	15.79

2. SDM model: when both spatially lagged dependent and independent variables are included.
3. SDEM model: when spatial dependence is restricted to the error term.
4. SARAR model: when both spatially lagged dependent and autoregressive errors are included.

The GNM generalization allows us to encapsulate all these specifications within one flexible estimation structure, more details of which can be found in [55].

When multiple adoption outcomes (e.g., PV, EV, HP, and EVHC) are analysed independently, conventional regressions assume that unobserved factors affecting one outcome are unrelated to those affecting another. However, in practice, the same latent characteristics—such as environmental awareness, access to finance, housing suitability, or local policy support—can influence several technologies simultaneously. If such unobserved factors are omitted, the error terms across equations become correlated, violating the assumption of independence. Estimating each equation separately under these circumstances can lead to inefficient estimates and biased standard errors, especially if cross-equation correlation aligns with spatial dependence. The SPSUR-GNM approach [55,56] addresses this by jointly estimating all equations, allowing contemporaneous correlation among their disturbance terms, and accounting for spatial autocorrelation among neighbouring units. In this setup, each technology equation is estimated conditional on both the spatial lag of its own outcome and the correlated errors across technologies. This improves estimation efficiency, enables joint hypothesis testing on cross-technology dependence, and allows interpretation of spatial spillovers and inter-technology effects within a unified system.

The inclusion of multiple socioeconomic controls is theoretically motivated by the heterogeneous nature of green technology adoption. Prior literature consistently shows that adoption decisions depend on income structure, housing typology, commuting behaviour, demographic composition, and deprivation levels. Excluding these dimensions risks omitted-variable bias in spatial models where structural heterogeneity is pronounced. The specification therefore aims to capture underlying socioeconomic structure rather than inflate explanatory power through redundant regressors.

To assess potential multicollinearity arising from the inclusion of multiple percentage-based socioeconomic variables, Variance Inflation Factors (VIFs) were calculated for all regressors. The maximum observed VIF is 5.36, with the majority of variables below 4. These values fall well within conventional acceptability thresholds, indicating that multicollinearity does not materially affect coefficient stability. A full correlation matrix and VIF statistics are reported in Appendix Tables A1 and A2.

4.1. Model formulation

The Seemingly Unrelated Regression (SUR) model system may have M equations, (each representing a different outcome or variable), and for each equation, there are N spatial units (for example, EDs). For equation $m = 1..., M$, the model is:

$$\boldsymbol{y}_m = \boldsymbol{X}_m\boldsymbol{\beta}_m + \boldsymbol{\varepsilon}_m \tag{1}$$

where, y_m is the N x 1 vector of dependent variable for equation m,
X_m is N x K_m matrix of regressors,
β_m is K_m x 1 vector of coefficients,

Table 3
Cross tabulation of sustainable technologies' grants, by deprivation index category.

Deprivation Index Category	HP*		PV*		EV*		EVHC*	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Very Disadvantaged	15.26	20.92	11.40	11.54	2.61	1.49	1.69	1.10
Disadvantaged	18.05	25.42	9.25	9.72	4.59	2.98	3.09	2.40
Marginally Below Average	16.61	14.54	12.43	8.05	7.25	5.00	5.93	3.94
Marginally Above Average	19.47	17.55	16.38	10.31	10.48	6.70	9.21	5.83
Affluent	24.39	24.91	21.01	17.67	17.28	8.82	15.85	9.53

*Grants per 1000 population.

Table 4
Cross tabulation of sustainable technologies' grants, by income category.

Income Category	HP*		PV*		EV*		EVHC*	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Low (<25,000)	19.37	18.31	14.53	17.70	4.99	4.17	3.50	4.62
Lower-Middle (25,000 - 45,000)	16.90	15.78	11.91	8.06	6.94	4.99	5.65	4.12
Middle (45,000 - 65,000)	19.16	17.22	16.47	9.76	10.44	6.43	9.08	5.45
Upper-Middle (65,000 - 85,000)	24.48	24.79	23.31	17.80	17.82	7.42	16.78	6.75
High (>85,000)	35.13	39.50	24.35	14.74	26.81	8.06	26.57	10.70

*Grants per 1000 population.

ε_m is N x 1 vector of errors for equation m.

Stacking all equations gives:

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \tag{2}$$

where, $y = \begin{matrix} y_1 \\ \vdots \\ y_M \end{matrix}$,

$X = \text{block-diag}(X_1, \ldots, X_M)$,

$\beta = \begin{matrix} \beta_1 \\ \vdots \\ \beta_M \end{matrix}$,

and, $\text{Cov}(\varepsilon) = \Sigma \bigotimes I_N$, where Σ is the M x M covariance matrix of errors across equations.

Now, adding the spatial lags of the explained variables, regressors and spatial errors will offer us the following generalised equation system:

$$\boldsymbol{y_m} = \boldsymbol{\rho_m W y_m} + \boldsymbol{X_m \beta_m} + \boldsymbol{W X_m \theta_m} + \boldsymbol{\varepsilon_m} \tag{3}$$

where, y_m is the N x 1 vector of dependent variable for equation m,

W is the N x N spatial weights matrix (row-standardised)

ρ_m is the scalar spatial autoregressive coefficient (for lag of y_m)

X_m is N x K_m matrix of regressors,

β_m is K_m x 1 vector of coefficients,

θ_m is the coefficient on spatially lagged X_m, (that is, WX_m).

ε_m is error term, described in the next equation.

Each error term ε_m follows a spatial error model specification:

$$\boldsymbol{\varepsilon_m} = \boldsymbol{\lambda_m W \varepsilon_m} + \boldsymbol{u_m} \tag{4}$$

where, λ_m is the spatial autocorrelation parameter for errors,

$$\mathrm{u_m} = \mathcal{N}\left(0, \sigma_m^2 \mathrm{I_N}\right)$$

So, the full error-process becomes:

$$\boldsymbol{\varepsilon_m} = (\boldsymbol{I_N} - \lambda_m \boldsymbol{W})^{-1} \boldsymbol{u_m} \tag{5}$$

Now, stacking all m-equations (to accommodate cross-equation correlations):

$$\boldsymbol{y} = \boldsymbol{Ay} + \boldsymbol{X\beta} + \boldsymbol{WX\theta} + \boldsymbol{\varepsilon} \tag{6}$$

where, $\text{Cov}(\boldsymbol{u}) = \Sigma \bigotimes I_N$ where Σ is the M x M covariance matrix of errors across equations,

A = block-diag($\rho_1 W$, …, $\rho_M W$), represents the spatial lags of the dependent variables and is block-diagonal

For each equation m, the **SPSUR-GNM** is:

$$\boldsymbol{y_m} = \boldsymbol{\rho_m W y_m} + \boldsymbol{X_m \beta_m} + \boldsymbol{W X_m \theta_m} + (\boldsymbol{I_N} - \lambda_m \boldsymbol{W})^{-1} \boldsymbol{u_m} \tag{7}$$

And stacked system:

$$\boldsymbol{y} = \boldsymbol{Ay} + \boldsymbol{X\beta} + \boldsymbol{WX\theta} + (\boldsymbol{I} - \boldsymbol{\Lambda W})^{-1} \boldsymbol{u} \tag{8}$$

where, Λ is the block-diag($\lambda_1 I_N$, …, $\lambda_M I_N$),

$$u_m = \mathcal{N}(0, \Sigma \bigotimes I_N)$$

Each equation within the system represents one of the dependent variables and incorporates a set of independent variables tailored to explain adoption patterns. The specification accounts for spatial spillovers by including a spatial autoregressive term, which reflects the influence of adoption rates in neighbouring regions. Spatial dependencies are captured using a spatial weights matrix based on a 10-nearest neighbours' approach, ensuring that geographically proximate areas are more strongly connected. The model also explicitly accounts for interdependencies between the four equations by estimating the variance-covariance matrix of the error terms, allowing for shared unobserved factors that influence multiple forms of technology adoption. In addition to modelling spatial spillovers, the SPSUR-GNM explicitly estimates the inter-equation variance–covariance matrix of residuals (Σ). This allows for cross-equation error correlation, reflecting the influence of unobserved factors that jointly affect multiple technology-adoption outcomes. For example, local policy awareness, environmental attitudes, or access to skilled installers may simultaneously increase the likelihood of adopting both EVs and solar PV. Traditional spatial models estimated separately for each technology (e.g., SAR, SDM, or SDEM) assume independent error structures and therefore ignore these latent interdependencies. Estimating Σ provides two advantages. First, it improves statistical efficiency, as joint estimation uses information from the covariance structure to yield more precise coefficient estimates [59]. Second, it enables substantive interpretation of inter-technology relationships: significant off-diagonal covariances indicate shared unobserved drivers of adoption, offering insights into complementarities (e.g., households adopting both EVs and home chargers) or substitution effects (e.g., PV vs. heat pumps). This feature is especially relevant for integrated climate-technology transitions, where policy instruments and behavioural norms overlap across sectors. The estimation process uses Maximum Likelihood Estimation (MLE) in R using the package "spsur" [60], which is well-suited to handle the simultaneous nature of the equations, spatial dependencies, and potential heteroskedasticity in the error terms.

4.1.1. Computation of direct and indirect spatial effects

To quantify the magnitude of spatial spillovers, we decomposed the estimated coefficients of the SPSUR–GNM model into average direct, indirect, and total impacts following [55,56]. For a spatial process of the form

$$\boldsymbol{y}_m = \rho_m \boldsymbol{W}\boldsymbol{y}_m + \boldsymbol{X}_m\beta_m + \varepsilon_m \tag{9}$$

the total marginal effect of a change in X on y can be expressed as:

$$(\boldsymbol{I} - \rho\boldsymbol{W})^{-1}\beta = \beta + (\rho\boldsymbol{W})\beta + (\rho\boldsymbol{W})^2\beta \tag{10}$$

The diagonal elements of this matrix represent direct (within-area) effects, and the off-diagonal elements capture indirect (spillover) effects transmitted through spatial neighbours.

4.2. Assessing and modelling spatial dependence

To evaluate the presence and form of spatial dependence in sustainable technology adoption across Irish EDs, a spatial weights matrix was constructed using the 10-nearest neighbours ($k = 10$) based on geographic coordinates (longitude–latitude). Spatial dependence tests were then performed using lm.RStests [61] to identify the appropriate model specification. While the Moran test is a common measure of global spatial autocorrelation, it does not provide guidance on the appropriate form of spatial regression model. Therefore, we applied LM, Spatial Lag, Spatial Error, and SARMA tests, which are designed to detect the presence and type of spatial dependence and to inform model specification [55,56,62].

The results revealed strong spatial autocorrelation. The Spatial Error Test indicated significant spatial dependence in the residuals (Test Statistic = 93.843, $p < 2.2\text{e–}16$), suggesting that unobserved regional factors may influence adoption patterns. Similarly, the Spatial Lag Test confirmed significant spatial dependence in the dependent variable (Test Statistic = 113.89, $p < 2.2\text{e–}16$), implying that adoption in one ED is affected by neighbouring areas.

When accounting for both effects, the Robust Spatial Error Test showed no remaining error dependence (Test Statistic = 0.242, $p = 0.623$), while the Robust Spatial Lag Test remained significant (Test Statistic = 20.288, $p = 6.66\text{e–}06$), indicating that spatial interactions operate primarily through lagged diffusion rather than unmodeled spatial shocks. The SARMA Test (Test Statistic = 114.13, $p < 2.2\text{e–}16$) confirmed strong joint spatial dependence across both lag and error components.

To validate these findings, we also applied the Lagrange Multiplier (LM) tests adapted to the Seemingly Unrelated Regression (SUR) framework [59], following the misspecification approach of [62]. The LM–SUR–SLM test was significant, confirming the presence of spatial lag dependence across technologies, whereas the LM–SUR–SEM test was not significant once spatial lag effects were controlled for, suggesting that spatial dependencies primarily manifest through lag structures rather than unmodeled error processes. This interpretation follows standard guidance in spatial econometrics [55,56,62], where significant LM-Lag and insignificant LM-Error statistics indicate that dependence arises through the endogenous interaction term rather than through residual autocorrelation.

Taken together, these results suggest that spatial dependencies in adoption patterns primarily manifest through spatial lags—that is, the influence of neighbouring EDs' adoption levels—rather than through unmodeled spatial errors. Consequently, a Seemingly Unrelated Regression Generalised Nested Model (SPSUR–GNM) is employed. This framework generalises classical spatial models (SAR, SARAR, SDM, and SDEM) and allows for cross-equation correlations, providing a robust and flexible approach to capturing spatial spillovers and estimating the socioeconomic and regional determinants of sustainable technology adoption.

5. Model estimation results

5.1. SPSUR-GNM model estimation results

Model specifications were developed using a structured specification search strategy combining bottom-up and top-down procedures. Variables were retained in the final models only when statistically significant and theoretically consistent. This approach ensures parsimony, mitigates multicollinearity, and enhances interpretability. Intermediate specifications including non-significant regressors were tested but are not reported in the main tables to preserve clarity of presentation.

The results are interpreted jointly across technologies, consistent with the SPSUR-GNM framework. This approach allows comparison of coefficient magnitudes and spatial effects within a unified system, capturing interdependencies and common socioeconomic drivers. Rather than presenting four isolated models, the emphasis is placed on identifying shared determinants and meaningful differences in effect size and spillover intensity. The discussion below therefore emphasises the socioeconomic interpretation of coefficients and spatial spillovers, rather than the statistical properties of the estimators themselves.

The spatial seemingly unrelated regression-generalised nested model (SPSUR-GNM) results (Tables 5a and 5b) reveals distinct but interrelated drivers of low-carbon technology adoption across HP grants, PV grants, EV grants, and EVHC grants. All dependent variables are expressed as natural logarithms, so the estimated coefficients can be interpreted as elasticities—indicating the percentage change in the outcome variable associated with a one-unit change in the predictor. The results are provided in Tables 5a and 5b and discussed below.[3]

The *Deprivation Index* is positively associated with all four adoption outcomes, indicating that higher deprivation index scores (less deprived or more affluent areas) see higher uptake of low-carbon technologies. A 1-point increase in the Deprivation Index is associated with a 1.16% increase in HP grants, 2.89% increase in PV grants, 1.87% increase in EV grants, and 0.89% increase in EV charger grants, controlling for other factors. These findings underscore the importance of economic capacity and access to resources in fostering sustainable technology adoption, with wealthier areas leading adoption across the board. Interestingly, the *household median gross income* has a very small but statistically significant positive elasticity for EV grants and marginally for EV chargers, but no significant relationship with HP or PV grants. This suggests that while income matters for EV adoption, it is less influential for home energy upgrades like HP or solar panels, of course impacted by presence of deprivation index values. The lack of significance for HP and PV systems suggests that other socioeconomic or structural factors, beyond income, may dominate their adoption decisions. These findings are consistent with established evidence that affluence enhances access to capital-intensive technologies through greater liquidity, creditworthiness, and exposure to sustainability norms [63,64]. Deprivation, by contrast, constrains both financial and informational access, reinforcing geographic disparities in energy transition [65,66].

While household income and deprivation index are positively correlated, they capture distinct aspects of socioeconomic advantage. The Deprivation Index reflects a composite of education, employment,

[3] It is important to note that all results presented here are based on observational data. While we report statistically significant associations between socioeconomic, demographic, and spatial factors and low-carbon technology adoption, these findings should not be interpreted as causal effects. The observed relationships highlight patterns and potential influences but do not establish definitive cause-and-effect links.

Table 5a
SPSUR-GNM results (part 1).

SPSUR-GNM (part 1 of 2)	Natural Log of HP grants		Natural Log of PV grants	
	Estimate	t value	Estimate	t value
Intercept	3.4424	6.81	1.6689	4.72
Deprivation Index	0.0116	2.54	0.0289	7.48
Household median gross income (€)	0.0000	0.55	–	–
Demographic Characteristics (ED Level)				
Percentage of males between 20 and 60 years	−0.0126	−3.17	–	–
Percentage of females under 19 years	0.0179	4.30	0.0086	2.33
Percentage of females between 20 and 60 years	0.0185	4.29	–	–
Employment Characteristics (ED Level)				
Percentage of management professionals	0.0077	2.58	0.0081	3.02
Percentage of agricultural professionals	−0.0137	−5.57	−0.0116	−5.69
Household Structure (ED Level)				
Percentage of HH with single adult and child	0.0255	5.07	0.0058	2.44
Percentage of HH with multi-adult and no-child	−0.0167	−3.39	–	–
Percentage of HH with multi-adult and children	−0.0124	−1.74	–	–
Household Dwelling Unit (ED Level)				
Percentage of HHs which live in a house (compared to apartments, etc.)	0.0157	7.46	0.0072	4.42
Household dwelling heating characteristics (ED Level)				
Percentage of HH with heating via oil	−0.0455	−16.58	–	–
Percentage of HH with heating via gas	−0.0429	−16.26	–	–
Percentage of HH with heating via coal	−0.0274	−4.82	–	–
Percentage of HH with heating via peat	−0.0493	−15.64	–	–
Percentage of HH with heating via LPG	−0.0545	−4.64	–	–
Percentage of HH with heating via wood	−0.0696	−13.39	–	–
Household Transport Mode (ED Level)				
Percentage of HH with Public Transport commute-mode	−0.0199	−4.50	−0.0081	−2.58
Household Commute Time (ED Level)				
Percentage of population with commute-time less than 15-min	−0.0161	−3.65	−0.0163	−4.81
Percentage of population with commute-time 15–30 min	−0.0130	−2.66	−0.0141	−4.01
Percentage of population with commute-time 30–45 min	–	–	−0.0177	−4.41
Percentage of population with commute-time 45–60 min	−0.0374	−3.06	−0.0169	−2.00
Health of population (ED Level)				
Percentage of population with very good health	0.0183	4.55	–	–
Percentage of population with good health	0.0238	4.75	–	–
Household Car Ownership (ED Level)				
Percentage of population with zero cars	–	–	–	–
Lag of independent (exogenous) variables				
Lag (Percentage of HHs which live in a house (compared to apartments, etc.))	–	–	−0.0063	−3.16
Lag (Deprivation Index)	–	–	−0.0139	−3.62
Lag (Percentage of HH with multi-adult and no-child)	−0.0277	−4.45	–	–
Lag (Percentage of HH with heating via coal)	−0.0275	−3.76	–	–
Lag (Percentage of HH with heating via oil)	–	–	–	–
Lag (Percentage of HH with heating via gas)	–	–	–	–
Lag (Percentage of population with commute-time 30–45 min)	−0.0276	−3.27	–	–
Lag (Percentage of population with commute-time 45–60 min)	0.0450	2.51	–	–
Lag coefficients				
Spatial autoregressive coefficient (Rho)	0.1073	0.75	0.5700	12.35
Spatial autocorrelation parameter for errors (Lambda)	0.1794	1.13	−0.3840	−4.03
R-squared:	0.272		0.3361	

Note: Only variables with statistically significant total effects ($p < 0.05$) are reported. "–" denote the variables which are statistically insignificant at 95% confidence interval.

and housing quality, which jointly shape households' structural capacity to adopt low-carbon technologies. Once this multidimensional measure is included, the marginal effect of income alone becomes small and only remains significant for more liquid investments—namely EVs and home chargers—where decisions depend primarily on disposable cash flow rather than property-level characteristics. In contrast, heat-pump and PV adoption are more closely tied to housing suitability, retrofitting potential, and the presence of professional installer networks, factors embedded in the deprivation measure but not in income itself. The heterogeneity across technologies also reflects their differing behavioural and infrastructural contexts. EVs and chargers are high-visibility, mobile technologies, often influenced by peer effects and spatial diffusion, explaining their sensitivity to income and spatial lags. PV and HP systems are home-integrated and less visible, relying on structural readiness and policy facilitation rather than neighbourhood imitation. Finally, EV grants are designed as direct financial rebates, whereas heat-pump and PV schemes often require complex application or reimbursement processes, potentially deterring lower-income or time-constrained households. Together, these patterns underscore that observed income elasticities are not simply statistical artefacts of deprivation but reveal distinct pathways of access and constraint across different sustainable technologies.

Although income and deprivation are positively correlated, they capture distinct dimensions of socioeconomic advantage. The deprivation index incorporates housing quality, education, and employment structure, which shape structural readiness for technology adoption. Once this multidimensional measure is included, the marginal role of income becomes limited to more liquidity-dependent investments such as EVs and chargers. This pattern suggests that adoption is embedded in longer-term spatial and housing trajectories rather than short-term income fluctuations, reflecting path dependence in Ireland's built environment.

The demographic structure also plays a role in technology uptake. Areas with more *females under 19 years* see higher adoption of both HP (1.79%) and PV (0.86%), while a higher share of *females aged 20–60* increases HP uptake by 1.85%. Conversely, a higher share of *males aged 20–60* reduces HP uptake by 1.26%, suggesting potential gendered patterns in decision-making or household energy behaviour. These variables are not significant in the EV-related models. These results align with emerging literature on gendered dimensions of energy and technology adoption. Prior studies show that female-headed or female-majority households tend to display stronger environmental concern and greater willingness to invest in comfort- and efficiency-oriented technologies such as heat pumps and home retrofits [67]. Conversely, higher shares of males in the 20–60 age range may correspond to greater reliance on traditional heating systems or higher sensitivity to the financial risks of technology adoption [58,68]. These patterns suggest

Table 5b
SPSUR-GNM results (part 2).

SPSUR-GNM (part 2 of 2)	Natural Log of EV grants		Natural Log of EVHC grants	
	Estimate	t value	Estimate	t value
Intercept	−0.3167	−2.70	0.8015	1.01
Deprivation Index	0.0187	6.63	0.0089	2.36
Household median gross income (€)	0.0000	2.95	0.0000	1.91
Demographic Characteristics (ED Level)				
Percentage of males between 20 and 60 years	–	–	–	–
Percentage of females under 19 years	–	–	–	–
Percentage of females between 20 and 60 years	–	–	–	–
Employment Characteristics (ED Level)				
Percentage of management professionals	0.0161	7.75	0.0246	9.31
Percentage of agricultural professionals	–	–	−0.0085	−3.56
Household Structure (ED Level)				
Percentage of HH with single adult and child	0.0070	2.64	0.0498	3.42
Percentage of HH with multi-adult and no-child	0.0499	4.30	–	–
Percentage of HH with multi-adult and children	–	–	–	–
Household Dwelling Unit (ED Level)				
Percentage of HHs which live in a house (compared to apartments, etc.)	0.0061	4.67	0.0061	3.12
Household dwelling heating characteristics (ED Level)				
Percentage of HH with heating via oil	–	–	–	–
Percentage of HH with heating via gas	–	–	–	–
Percentage of HH with heating via coal	–	–	−0.0123	−2.56
Percentage of HH with heating via peat	–	–	−0.0054	−1.67
Percentage of HH with heating via LPG	–	–	–	–
Percentage of HH with heating via wood	–	–	–	–
Household Car Ownership (ED Level)				
Percentage of population with zero cars	–	–	−0.0124	−3.08
Lag of independent (exogenous) variables				
Lag (Percentage of HHs which live in a house (compared to apartments, etc.))	−0.0048	−2.57	0.0064	1.70
Lag (Deprivation Index)	−0.0218	−7.00	–	–
Lag (Percentage of HH with multi-adult and no-child)	–	–	0.0069	1.79
Lag (Percentage of HH with heating via coal)	–	–	–	–
Lag (Percentage of HH with heating via oil)	–	–	−0.0113	−2.21
Lag (Percentage of HH with heating via gas)	–	–	−0.0100	−2.01
Lag (Percentage of population with commute-time 30–45 min)	–	–	–	–
Lag (Percentage of population with commute-time 45–60 min)	–	–	–	–
Lag coefficients				
Spatial autoregressive coefficient (Rho)	0.6274	20.25	0.3928	6.09
Spatial autocorrelation parameter for errors (Lambda)	−0.5840	−7.79	−0.2868	−2.77
R-squared:	0.4396		0.441	

Note: Only variables with statistically significant total effects ($p < 0.05$) are reported. "–" denote the variables which are statistically insignificant at 95% confidence interval.

that demographic composition shapes adoption through differentiated environmental attitudes and risk perceptions.

Employment composition strongly predicts adoption, particularly the share of *management professionals*, which is consistently positive across all four technologies. A 1 percentage point increase in this group corresponds to increases of 0.77% (HP), 0.81% (PV), 1.61% (EV), and 2.46% (EV chargers). These results point to the role of socioeconomic privilege and environmental awareness typically associated with professional occupations in driving sustainable technology adoption. In contrast, areas with more *agricultural professionals* experience lower adoption across three outcomes: -1.37% (HP), −1.16% (PV), and − 0.85% (EV chargers), reflecting possibly lower awareness, accessibility, and perceived relevance of these technologies in rural settings. This likely reflects infrastructural constraints, dispersed settlement patterns, and weaker installer networks in rural areas. The strong positive effect of management professionals aligns with prior studies showing that professional and managerial occupations are correlated with higher education levels, environmental awareness, and early-adopter behaviour [69]. Conversely, agricultural employment is associated with lower technology diffusion due to dispersed settlements, limited installer networks, and lower perceived relevance of urban-oriented grants [70].

Household structure also influences adoption patterns. Areas with more *single adult with child* households are associated with higher uptake across all technologies—most notably a 2.55% increase in HP adoption and a substantial 4.98% for EV chargers. These households may prioritise sustainable technologies due to policy incentives targeting energy efficiency and reduced running costs. *Multi-adult no-child* households exhibit divergent effects: negatively associated with HP uptake (−1.67%), positively associated with PV (only in the lagged form), and strongly positive for EV grants (4.99%). These findings underscore how household composition influences capacity or motivation to adopt certain technologies. This divergence suggests that lifestyle and energy preferences in these household types influences technology adoption. These differences mirror literature on household lifecycle and consumption patterns, where single-parent households often prioritise efficiency and long-term cost reduction, while multi-adult households may exhibit "split incentive" dynamics and coordination barriers [71,72].

The percentage of households living in detached or semi-detached *houses* significantly boosts adoption across all technologies, with elasticities ranging from 0.61% (EV charger) to 1.57% (HP). Since these technologies often require physical space (e.g., roof space for PV or outdoor units for HP), the results reflect practical constraints in apartment living. Interestingly, the *spatial lag* of this variable is negative for EV grants (−0.48%) and PV (−0.63%), implying that in areas where neighbouring regions have higher shares of houses, local adoption may slightly decline— potentially reflecting spatial substitution effects or localised saturation dynamics. Detached and semi-detached homes facilitate installation of PV panels, heat pumps, and chargers due to greater physical space and ownership autonomy. Prior studies highlight that apartment dwellers face landlord–tenant split incentives, shared infrastructure barriers, and limited retrofit authority [73].

Areas with higher shares of households using *oil*, *gas*, *coal*, *peat*, or *wood* heating are significantly less likely to adopt HP, with large negative elasticities (e.g., −4.55% for oil and − 6.96% for wood). For EV charger grants, coal heating is also negatively associated (−1.23%). These findings may reflect infrastructural inertia: households reliant on traditional heating fuels may face greater financial or technical barriers to adopting electric-based technologies like HP. This reflects compatibility issues or entrenched reliance on traditional heating systems, which may require costly retrofitting to accommodate HP. The negative association between fossil-fuel heating and adoption of electric systems reflects technological lock-in and capital stock inertia [74]. Transitioning from oil or solid-fuel systems to electric heat pumps requires costly retrofits and technical upgrades, which disproportionately deter lower-income or rural households [75].

The share of households using *public transport* for commuting is negatively associated with all relevant technologies—most notably, HP (−1.99%) and PV (−0.81%) uptake—suggesting that car-dependent areas may be more prone to adopting home energy and vehicle technologies. *Commute times* also matter areas with higher shares of people commuting under 60 min generally exhibit lower adoption, particularly for PV and HP. For example, a 1-point increase in the share of 15–30-min commuters reduce PV uptake by 1.41% and HP by 1.30%. Areas with greater car dependence are more likely to invest in home-based energy and transport technologies, while high public-transport shares may indicate urban settings with limited space and less need for private energy assets. This pattern echoes findings that lifestyle and transport behaviour co-evolve with technology adoption choices [76,77].

Commuting patterns further reflect Ireland's dispersed settlement structure. Longer commuting times are characteristic of suburban and peri-urban areas where detached housing facilitates installations, while dense urban cores face structural constraints. The contrasting direct and indirect effects suggest that adoption diffuses along functional commuting regions rather than strictly administrative boundaries.

Self-reported *health status* is positively related to HP adoption: a 1-point increase in the share of people with “very good” or “good” health raises adoption by 1.83% and 2.38%, respectively. For EV chargers, a higher share of people with *zero car ownership* reduces adoption by 1.24%, reinforcing the idea that EV infrastructure uptake is most feasible in already car-dependent contexts.

Several lagged variables are significant, indicating spatial spillovers or interdependencies. For instance, the *lagged deprivation index* is negatively associated with both PV (−1.39%) and EV grants (−2.18%), suggesting that lower adoption in neighbouring areas may discourage local uptake. Lagged commuting and heating variables also influence outcomes—such as the positive effect of long commutes (45–60 min) on HP adoption (4.5%).

The significant spatial autoregressive and error coefficients confirm that adoption behaviour diffuses across neighbouring areas—a classic “neighbour effect” observed in clean technology diffusion [78]. The magnitude of the autoregressive parameter for PV (0.57) and EV grants (0.63) indicates that adoption is strongly spatially reinforced rather than purely locally determined. These effects likely reflect social learning, visibility, and installer-network spillovers that reduce uncertainty and transaction costs once a critical mass of adopters emerges. In contrast, the weaker spillover intensity for heat pumps suggests that technologies requiring more complex retrofitting generate slower and more locally anchored diffusion. Spatial clustering therefore reflects both behavioural imitation and structural compatibility within neighbouring areas.

5.2. Residuals and model fit

Variance-Covariance Matrix of inter-equation residuals (Table 5c) shows the **covariances** between the residuals (errors) from each of the four equations in the model system. Diagonal values represent the residual variances for each model (e.g., 0.3723 for HP). These indicate the unexplained variation after accounting for independent variables. Off-diagonal values are the covariances between the residuals of different equations. The non-zero off-diagonal entries imply that the residuals are correlated across equations, meaning some unobserved factors (e.g., attitudes, local policies, infrastructure) may simultaneously influence adoption of multiple technologies. Example: The relatively large covariance between EV Grants and EV Chargers (0.1090) suggests strong shared unobserved influences (e.g., policy incentives, EV awareness).

5.2.1. Correlation matrix of inter-equation residuals

The correlations among the residuals across the four adoption equations are not merely statistical by-products—they reveal the presence of shared, unobserved factors influencing adoption of these sustainable technologies simultaneously. These factors could include local installer or supplier networks, area-level awareness of sustainable technologies, shared infrastructure (such as, electrical upgrades, planning permissions), or socio-cultural preferences for *green* investments. The strongest residual correlation (0.41) between EV and EV home charger (EVHC) adoption confirms that even after controlling for income, housing type, and spatial effects, there remain latent policy and behavioural linkages—for instance, grant design coupling, coordinated household investment, or clustering of dealership-led marketing. Similarly, moderate residual correlations between PV and EVHC (0.16) or HP and PV (0.13) suggest underlying “green bundle” preferences, where early adopters are inclined toward multiple clean technologies. The SPSUR-GNM framework, in contrast to single-equation spatial models (SAR, SDM, SDEM, SARAR), jointly estimates the system, improving parameter efficiency and capturing cross-technology linkages that reflect real-world co-adoption mechanisms.

Table 5c
Inter-equation residuals results.

	Natural Log of HP grants	Natural Log of PV grants	Natural Log of EV grants	Natural Log of EVHC grants
Variance-Covariance Matrix of inter-equation residuals				
Natural Log of HP grants	0.3723	0.0435	0.0245	0.0256
Natural Log of PV grants	0.0435	0.3198	0.0301	0.0512
Natural Log of EV grants	0.0245	0.0301	0.2203	0.1090
Natural Log of EVHC grants	0.0256	0.0512	0.1090	0.3177
Correlation Matrix of inter-equation residuals				
Natural Log of HP grants	1.0000	0.1262	0.0856	0.0743
Natural Log of PV grants	0.1262	1.0000	0.1133	0.1605
Natural Log of EV grants	0.0856	0.1133	1.0000	0.4120
Natural Log of EVHC grants	0.0743	0.1605	0.4120	1.0000
R-sq. pooled			0.4732	
Breusch-Pagan:			664.8	
p-value:			2.47E-140	

5.2.2. R-squared (pooled)

The value of 0.4732 represents the overall goodness-of-fit for the entire system of equations if estimated as a pooled regression, ignoring inter-equation correlations. At 47.3%, it suggests that a good portion of variation in technology adoption is explained by the model, but there's still room for unexplained variance, likely due to behavioural, institutional, or policy variables not included. The relatively high R^2 values are consistent with cross-sectional spatial models that incorporate structured socioeconomic heterogeneity and spatial dependence, both of which substantially improve explanatory power compared to non-spatial single-equation specifications.

5.2.3. Breusch-Pagan Test for independence of equations ($\chi^2 = 664.8$, $p < 2.47e\text{-}140$)

This test evaluates the null hypothesis that the residuals of the different equations are uncorrelated (i.e., that a pooled model would be sufficient). The extremely small *p*-value (< 0.000001) leads us to reject the null hypothesis, confirming that the system benefits significantly from the SUR-GNM structure. In simpler terms: the equations are not independent. Modelling them together captures important interdependencies and improves efficiency.

5.3. Direct and indirect spatial effects

Tables A3 and A4 (appendix): *Decomposition of Direct, Indirect, and Total Spatial Effects* report the average direct and indirect effects, along with percentages derived from the SPSUR–GNM model. For Solar PV, EVs, and EV chargers, the estimated indirect effects are large and statistically significant, indicating substantial spatial diffusion.

For the Heat-Pump equation, the decomposition of total impacts into direct and indirect (spatial spillover) components reveals that most of the observed variation in adoption operates through within-area effects rather than neighbourhood diffusion. For example, a one-unit increase in the Deprivation Index—indicating greater affluence—is associated with a direct elasticity of 0.0129 and an indirect elasticity of 0.0029, yielding a total effect of 0.0159 on the log of heat-pump installations. Thus, approximately 81% of the total impact arises locally, while 19% is transmitted through neighbouring electoral divisions. Interpreted in level terms, the total coefficient corresponds to an estimated 1.6% increase in heat-pump uptake for a one-unit improvement in the Deprivation Index, of which about 1.3% is due to local socioeconomic capacity and 0.3% to positive spillover effects from adjacent areas. These results indicate that although spatial diffusion exists, the heat-pump market in Ireland remains primarily driven by local affluence and structural readiness rather than by strong inter-area demonstration effects.

This distinction across technologies reinforces the idea that visibility and modularity condition spatial diffusion. Solar panels and EV chargers are externally visible and incrementally adoptable, making peer observation and neighbourhood signalling particularly influential. Heat pumps, by contrast, are less visible and more technically invasive, which dampens demonstration effects despite the presence of statistically significant spatial structure. Policy instruments designed to leverage peer effects may therefore be more effective for PV and EV technologies than for heating retrofits, where financial and structural barriers dominate.

An interesting offsetting pattern is observed for the share of commuters with travel times between 45 and 60 min. The estimated direct elasticity is -0.0375, indicating that, within an electoral division, a higher proportion of long-distance commuters is associated with lower local uptake of heat pumps—possibly reflecting time-constrained households or greater car dependence that diverts investment away from home energy improvements. However, the corresponding indirect effect is positive (0.0365), implying that neighbouring areas with higher shares of long commuters experience higher heat-pump adoption, likely due to spatial spillovers linked to regional commuting corridors or cross-boundary demonstration effects. The near-complete offset between these two opposing mechanisms (total effect $= -0.0011$) suggests a spatial suppression phenomenon, where local deterrence is balanced by regional reinforcement. In this case, direct and indirect effects contribute roughly $+3470\%$ and -3370% of the small net total effect, underscoring the importance of interpreting directional shares rather than proportional magnitudes when direct and spillover effects act in opposite directions.

5.4. Model framework limitations

The distribution of adoption rates exhibits a large mass at zero, especially for technologies such as heat pumps and EV home chargers. This pattern reflects both the early stage of market diffusion and the spatial concentration of adopters in higher-income or urban areas. Our current specification treats these adoption rates as continuous outcomes; however, the high share of zeros implies a potential mixture of non-adoption (structural zeros) and low-intensity adoption (sampling zeros). While the *natural* $\log(x + 1)$ transformation allows us to retain zero observations, it does not explicitly model the two-stage decision process—whether to adopt and how extensively to adopt. Future extensions could apply spatial two-part (hurdle) models or spatial Tobit approaches to distinguish the binary adoption decision from the continuous adoption intensity. Nonetheless, the current approach remains informative for spatial diffusion dynamics, as it captures both spatial spillovers and socioeconomic correlates of adoption across all regions, including those yet to adopt.

6. Comparative discussion: Ireland in the European and global context

The present study provides a detailed spatial and socioeconomic analysis of household adoption of sustainable technologies—HP, PV, EV, and EVHC—across Ireland, using a Spatial Seemingly Unrelated Regression Generalised Nested Model (SPSUR-GNM).

Across all model-equations, socioeconomic advantage emerges as the strongest and most consistent driver of sustainable technology adoption. A one-point increase in the Deprivation Index corresponds to 1.16–2.89% higher uptake, while areas with a greater share of management professionals see 0.77–2.46% higher adoption depending on the technology. Conversely, fossil-fuel reliance exerts a large negative effect—oil-heated households are 4.6% less likely, and wood-heated households 7% less likely, to install heat pumps. These quantitative effects underscore how economic capacity and housing characteristics dominate adoption patterns in Ireland.

Spatial dynamics play a critical role. The estimated autoregressive coefficients (ρ) of 0.57 for PV and 0.63 for EV indicate strong diffusion effects, meaning that up to 60% of total adoption gains arise from neighbourhood demonstration and network effects. Heat pumps, by contrast, show weaker spillovers, consistent with their lower visibility and higher installation complexity. This highlights that the visibility and social diffusion of technologies, as much as affordability, shape the pace of transition.

Equity disparities remain stark. Adoption rates in affluent EDs average 24.4 HP and 17.3 EV grants per 1000 residents—five to seven times higher than in disadvantaged areas (15.3 HP and 2.6 EV per 1000). These figures reflect both income constraints and infrastructural access gaps, particularly for renters and apartment dwellers. Current pay-then-reimburse models thus amplify inequalities, as upfront capital requirements prevent lower-income households from benefiting from subsidies.

To close these gaps, targeted policy reforms are essential. Front-loaded or means-tested grants, low-interest retrofit loans, and publicly accessible EV chargers in disadvantaged neighbourhoods could mitigate the uneven distribution of benefits. The evidence also suggests that interventions that increase local visibility—such as community demonstration projects—can trigger substantial spatial spillovers, amplifying adoption beyond direct beneficiaries.

Importantly, the presence of statistically significant indirect spatial effects implies that policy impacts are unlikely to remain confined to treated areas. Targeted interventions in strategically selected regions—particularly those exhibiting early adoption clusters—may generate local multiplier effects through social learning and installer-network expansion. This suggests that spatially concentrated pilot programmes or community-level demonstration schemes could yield broader regional gains beyond directly subsidised households. Conversely, failure to intervene in persistently low-adoption areas risks reinforcing spatial inequality through cumulative disadvantage.

Table 6
Summary table: Ireland vs. EU and world.

Technology	Ireland	EU Leaders	Key Determinants	Policy Innovations
HP	Low adoption, fossil fuel inertia	France, Germany	Income, housing, deprivation	Up-front grants, zero-interest loans
Solar PV	Low adoption	Germany, Netherlands	Income, urban/rural	Community solar, feed-in tariffs
EV	Below EU average	Norway, Sweden, Netherlands	Income, education, home charging access	Income-scaled rebates, public charging
EVHC	Home-dominated, equity issues	UK, Germany	Housing tenure, deprivation	Public residential charging, targeted grants

6.1. Comparison with the EU and global findings

When compared internationally, Ireland's adoption rates and the determinants identified in this study align with, but also diverge from, patterns observed elsewhere in Europe and globally.

For heat pumps and solar PV, Ireland remains among the lowest adopters within the EU. In 2020, only 8430 heat pumps were sold in Ireland, compared to 394,000 in France and over 1.6 million across the EU [2,49]. PV adoption is similarly lagging despite high technical potential [79]. Across the EU, income, housing type, and urban–rural divides are consistent predictors of adoption [80–83]. However, countries such as Germany and the Netherlands have more effectively targeted low-income households through up-front grants and zero-interest loans, mitigating some of the equity concerns that remain pronounced in Ireland [84]. Part of this divergence reflects structural differences in urban density and housing typology. Ireland's comparatively dispersed settlement pattern and high share of detached housing increase reliance on individual heating systems, particularly oil-fired boilers, which creates inertia in the transition away from fossil fuels. In contrast, higher-density countries often benefit from district heating networks or more uniform housing stock, which can facilitate coordinated retrofitting. Commuting structures also differ such that longer average commuting distances in peri-urban and rural Ireland reinforce car dependence, shaping both EV demand and the importance of home charging access.

A similar pattern emerges in the case of electric vehicles and home charging. In 2020, EVs accounted for less than 5% of new car sales in Ireland, only slightly above the EU average of 3.5% [85]. By contrast, Norway (54%), the Netherlands (20%), and Sweden (32%) achieved substantially higher market shares, supported by strong financial incentives, dense charging infrastructure, and complementary non-monetary benefits [15,79]. Research across Europe and North America consistently find that EV adoption is concentrated among higher-income, highly educated, and urban households [10,41,86]. The Irish findings regarding deprivation and professional status are therefore broadly consistent with international evidence. At the same time, the Irish case highlights the specific challenge of home charging access for renters and apartment dwellers, an issue also observed in the UK, Germany, and the US [16,87]. Leading EV markets have responded through targeted investments in public residential charging and income-scaled subsidies [41,88,89].

The spatial dependencies identified in Ireland, whereby adoption in one area encourages uptake in neighbouring areas, are likewise consistent with findings from other countries [80,81]. This suggests that policies leveraging local demonstration effects and peer influence can accelerate diffusion beyond directly subsidised households. Moreover, evidence from Germany and the UK indicates that infrastructure subsidies may, in some cases, be more cost-effective than direct purchase grants [14,88]. Ireland's current emphasis on up-front rebates may therefore benefit from rebalancing toward infrastructure expansion and more targeted support for disadvantaged groups.

To situate these findings more systematically, Table 6 summarises Ireland's position relative to leading EU adopters and highlights the dominant socioeconomic and policy determinants identified in the literature. The comparison clarifies not only differences in adoption levels but also structural differences in housing systems, urban density, and energy infrastructure that shape diffusion dynamics. By explicitly linking the Irish results to these broader structural conditions, the table provides context for interpreting both the magnitude of socioeconomic effects and the observed spatial spillovers. Ireland's progress continues to lag behind EU leaders, largely due to persistent socioeconomic and infrastructural barriers. International experience suggests that more equitable and targeted interventions—such as up-front support for low-income households and expanded public charging infrastructure—are critical for accelerating adoption and ensuring a just transition. Addressing spatial spillovers through local demonstration projects and community engagement can further enhance the diffusion of sustainable technologies.

The comparison underscores that Ireland's lower adoption rates cannot be explained by income effects alone. Structural features—such as fossil-fuel-based heating systems, dispersed settlement patterns, and reliance on private vehicles for commuting—interact with socioeconomic disparities to slow diffusion. In this context, the strong deprivation and professional-status coefficients identified in the SPSUR-GNM models reflect not only purchasing power but also differences in housing quality, tenure structure, and infrastructural access. The Irish case therefore illustrates how spatial form and socioeconomic structure jointly condition the pace of the green transition.

6.2. Understanding spatial spillovers in green technology adoption

The presence of statistically significant spatial effects suggests that green technology adoption in Ireland is not randomly distributed but influenced by local interaction mechanisms. Several channels may explain these spillovers. First, peer effects and social learning likely play an important role. The visibility of rooftop solar installations or heat pump retrofits can reduce informational asymmetries and perceived uncertainty. Observing neighbours' investments may signal financial viability and technical reliability, thereby lowering behavioural barriers. Second, installer networks and local supply chains may generate geographic clustering. Once installers establish presence in an area, marginal installation costs decline, and word-of-mouth diffusion accelerates. This can create self-reinforcing local adoption dynamics. Third, spatial spillovers may reflect shared structural characteristics such as housing typology, grid infrastructure, or planning regimes, which are themselves spatially correlated. These mechanisms imply that policy interventions may produce local multiplier effects: targeted incentives in early-adopting regions could amplify diffusion beyond directly subsidised households.

Finally, these spillovers should not be interpreted purely as behavioural imitation. They also reflect market formation dynamics: once a threshold level of local demand is reached, installers, financiers, and complementary service providers enter the market, reducing search costs and increasing reliability perceptions. Adoption clusters therefore emerge from the interaction between social learning and supply-side scaling. Recognising this dual mechanism is crucial for policy design, as interventions that stimulate initial demand may catalyse longer-term self-sustaining diffusion processes.

7. Conclusions

This study set out to examine the spatial and socioeconomic drivers of household adoption of sustainable technologies—specifically HP, PV, EV, and EVHC—across Ireland. Leveraging a Seemingly Unrelated Regression Generalised Nested Model (SUR-GNM), we assessed adoption patterns at the ED level, focusing on how variables such as income, deprivation, housing, and commuting shape uptake.

The results offer clear evidence that adoption is not evenly distributed. High-income areas and professional households—particularly in counties like Dublin, Meath, and Kildare—show significantly higher adoption rates, while lower-income regions such as Leitrim, Longford, and Donegal remain underrepresented. Spatial correlation among residuals further supports the presence of regional spillovers and shared unobserved drivers, affirming the utility of the SUR framework.

The decomposition of marginal effects confirms that spatial spillovers play a significant role in the diffusion of green technologies in Ireland. Technologies with greater visibility and social signalling potential—such as rooftop PVs and EV ownership—exhibit pronounced inter-area dependencies, while building-integrated systems like heat pumps remain locally determined. This heterogeneity in diffusion strength suggests that policies encouraging visible demonstration projects, local EV charging networks, and community-led retrofitting initiatives could accelerate nationwide technology uptake.

One of the most notable findings is the equity gap in EV grant uptake. Regression analysis and correlation matrices both highlight a system skewed toward affluent, multi-car households with long commutes—early adopters most able to leverage subsidies. Conversely, lower-income, single-car households, and short-distance commuters remain excluded from the transition. This aligns with earlier research showing that unemployment negatively affects EV adoption [90] and that larger or multi-car households are more likely to adopt [11,14].

7.1. Policy implications

7.1.1. Enhancing equity in electric vehicle adoption

The analysis highlights a pronounced equity gap in EV grant uptake across Ireland. Early adopters tend to be affluent, multi-car households with long commutes, leaving lower-income and single-car households largely excluded. This skew reflects structural barriers: existing pay-then-reimburse schemes favour households with disposable income, while renters and apartment dwellers face challenges in accessing home charging infrastructure. Spatial spillovers further compound these inequities, as adoption in affluent EDs reinforces uptake in neighbouring areas, while low-adoption regions remain marginalized.

To address these challenges, policy must move beyond universal rebates toward targeted, inclusive interventions. Means-tested or location-based subsidies, informed by deprivation indices, could ensure support reaches the households most constrained by upfront costs. Low- or zero-interest EV loans provide another mechanism to lower financial barriers, particularly for households unable to pre-finance grants. Additionally, expanding public charging infrastructure in rental-dominated urban areas would democratize access and reduce reliance on personal driveways, drawing on international best practices such as the UK and Germany's shared residential charging schemes [16,87]. Programs like France's "social leasing" model and Norway's zero-emission zones demonstrate the potential for combining financial and regulatory incentives to accelerate adoption among underrepresented populations [91,92].

Further interventions could leverage the second-hand EV market to broaden accessibility. Schemes such as scrappage incentives and trade-in programs—already implemented in France (€5000 rebate) and South Korea (2% rebate)—lower barriers for lower-income households [93–95]. Complementary innovations, including battery-swapping networks, Vehicle-to-Grid (V2G) integration, and urban shared charging infrastructure initiatives, can alleviate logistical constraints and range anxiety, fostering wider uptake across socio-demographic groups [96,97].

7.1.2. Promoting heat pump and solar PV adoption

The adoption of heat pumps (HP) and solar PV in Ireland exhibits similar socioeconomic and spatial disparities. Uptake is concentrated in affluent, owner-occupied areas, while regions with high fossil fuel reliance, rental-dominated housing, or lower-income populations remain underserved. The pay-then-reimburse nature of current grant schemes further disadvantages low- and middle-income households, highlighting the need for policy mechanisms that reduce upfront financial burdens.

International evidence offers viable strategies. Leading EU countries, including France, Germany, and the Netherlands, have successfully increased HP and PV adoption through up-front grants, zero-interest loans, and targeted outreach to low-income households [49,84]. These approaches reduce both financial and informational barriers, enabling broader participation and faster diffusion.

In Ireland, this could be operationalized through a suite of complementary interventions. Firstly, transitioning to up-front, means-tested grants or zero-interest loans would directly alleviate cost barriers for disadvantaged households. Secondly, community and cooperative solar schemes could expand access for renters and apartment dwellers lacking suitable roof space, replicating successful models from the Netherlands and Germany. Thirdly, targeted outreach and technical support in regions with high fossil fuel dependency—delivered via trusted local authorities and intermediaries—would address informational gaps and build trust in emerging technologies. Finally, streamlining permitting and grid connection processes for PV installations and promoting neighbourhood-scale or bulk retrofits for HP systems could reduce administrative friction, lower costs through economies of scale, and generate local demonstration effects, encouraging wider adoption.

7.1.3. Leveraging spatial spillovers and local demonstration effects

Spatial analysis indicates that adoption is not independent across regions. Visible technologies such as EVs and rooftop PVs generate inter-area spillovers, whereby adoption in one ED positively influences neighbouring EDs. This suggests that policies designed to create local demonstration effects can accelerate technology diffusion. For instance, subsidised pilot projects in strategically selected communities could serve as visible examples, signalling feasibility and normalizing adoption among peer networks. Similarly, neighbourhood-scale HP retrofits or community PV installations not only reduce costs but also cultivate local awareness and expertise, fostering longer-term behavioural change. By explicitly considering spatial dependencies, policy can move beyond isolated interventions and harness peer influence to amplify the impact of subsidies and infrastructure investments.

7.1.4. Integrating policy instruments for a just transition

A key insight from this study is the interdependence of financial, infrastructural, and behavioural factors in shaping sustainable technology adoption. Isolated subsidies are insufficient where structural and logistical constraints remain. Therefore, a holistic policy approach is required—one that aligns financial incentives with infrastructure development, targeted outreach, and market interventions. For EVs, this means combining means-tested grants or loans with investments in public charging and support for second-hand markets. For HP and PV, up-front financing must be complemented by streamlined permitting, neighbourhood retrofits, and cooperative schemes to overcome structural housing barriers. Cross-cutting measures, such as leveraging spatial spillovers through local demonstration projects, can amplify these interventions, ensuring that adoption accelerates equitably across diverse regions and demographics. International experience reinforces the importance of differentiated context-sensitive approaches. Countries that have successfully increased uptake among low-income or hard-to-reach populations typically combine financial support with technical assistance, infrastructure provision, and community engagement [88]. Ireland's lagging adoption is not an inevitable consequence of geography or technology costs; rather, it reflects the design of existing policies and their accessibility. By learning from these international examples, Ireland can foster an inclusive, accelerated transition to low-carbon technologies.

CRediT authorship contribution statement

Abhilash C. Singh: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Brian Caulfield:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that there is no conflict of interest regarding the publication of this paper. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix A

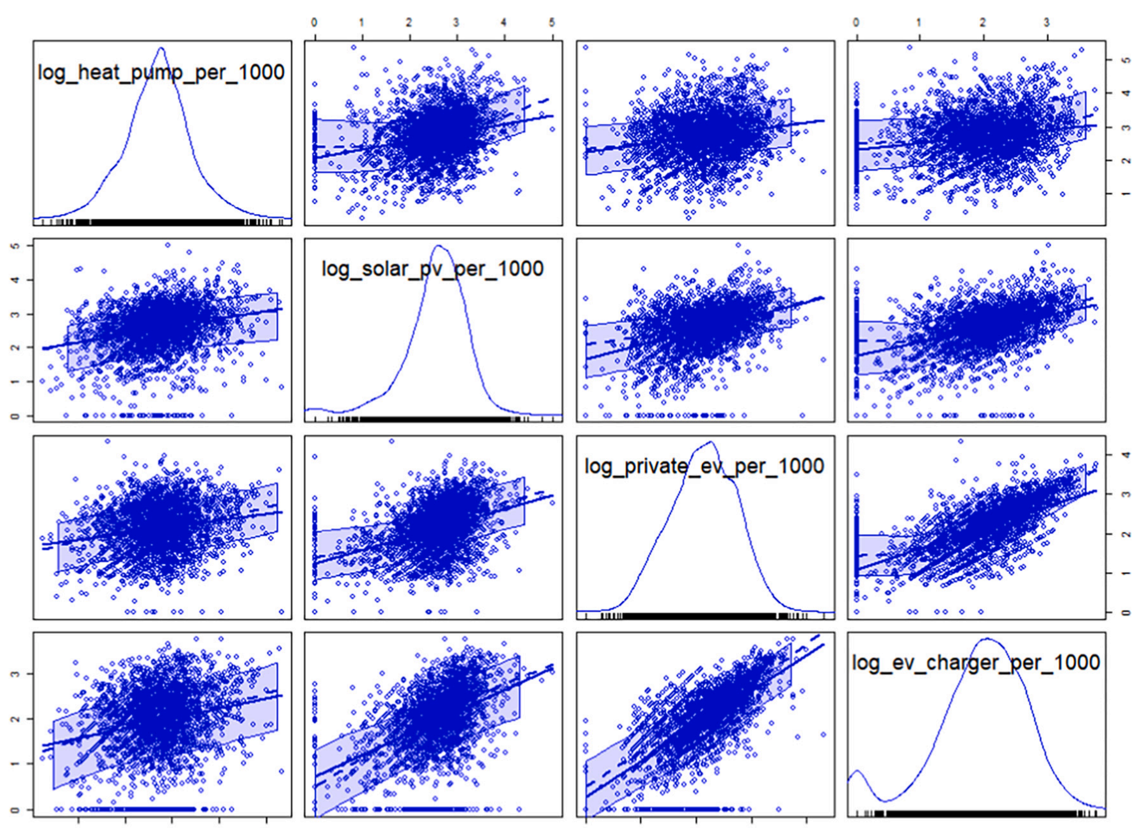


Fig. A1. Pairwise scatter plot matrix of dependent variables

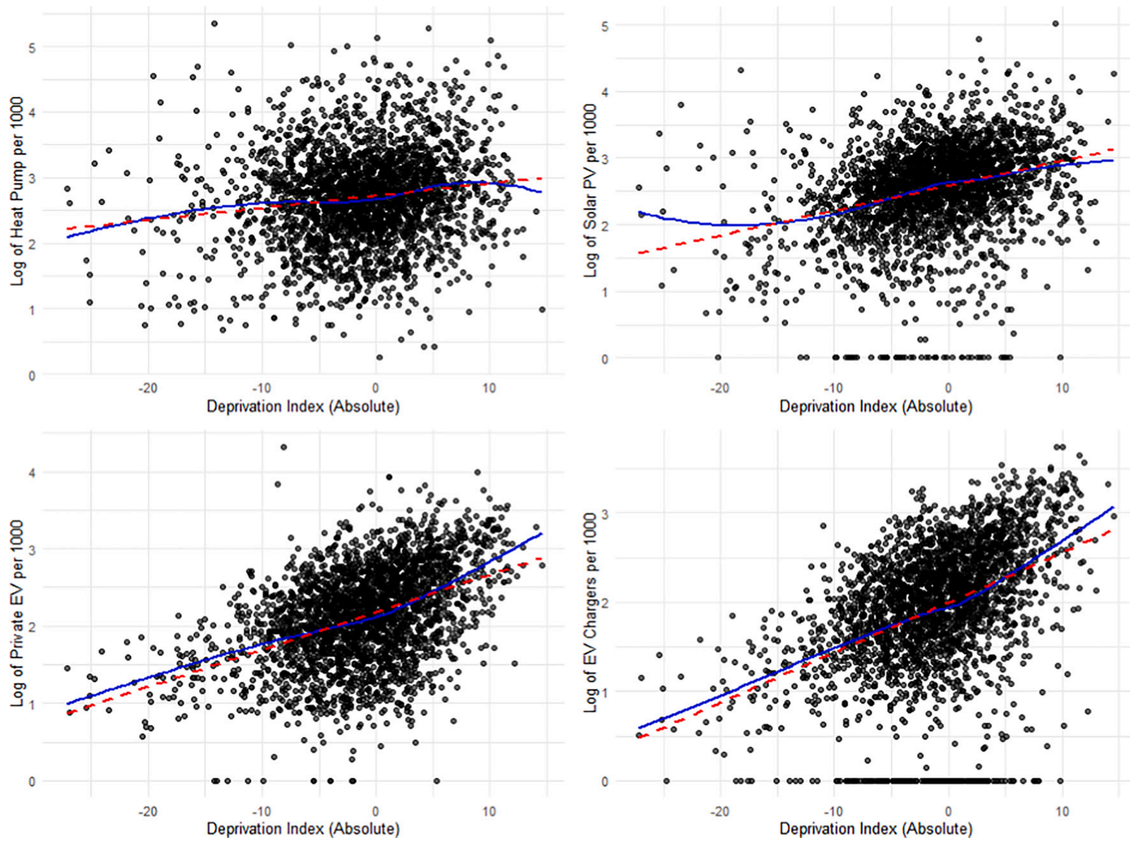


Fig. A2. Scatterplots illustrating relationships between deprivation index values and adoption rates of the four sustainable technologies.

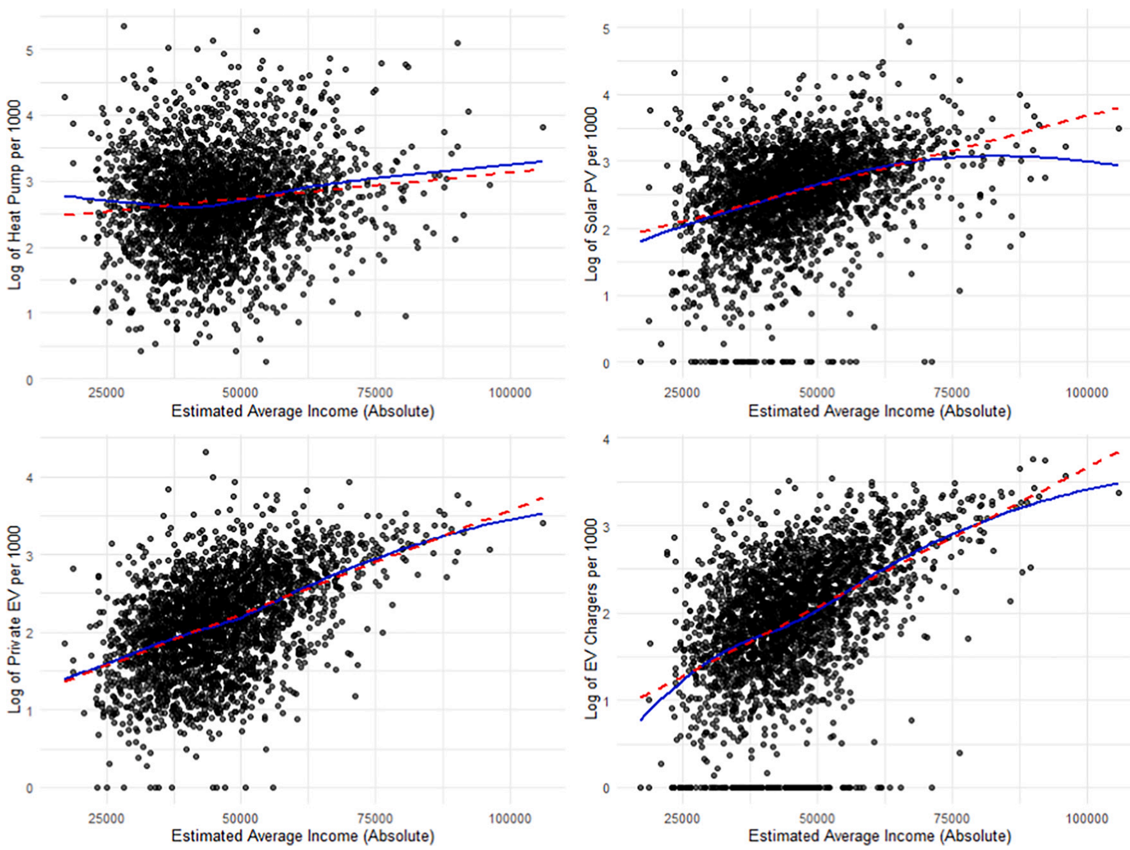


Fig. A3. Scatterplots illustrating relationships between income levels and adoption rates of the four sustainable technologies.

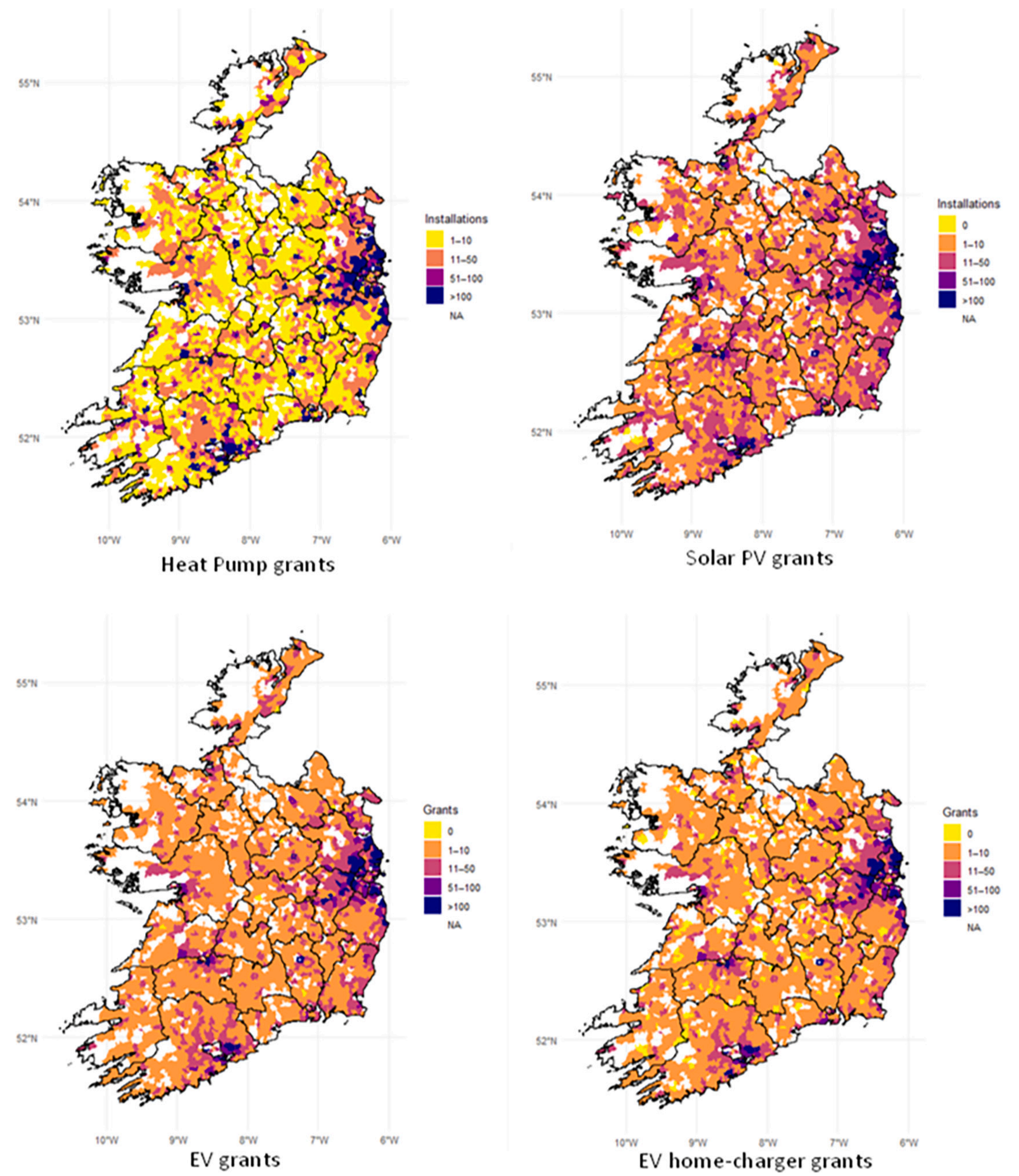
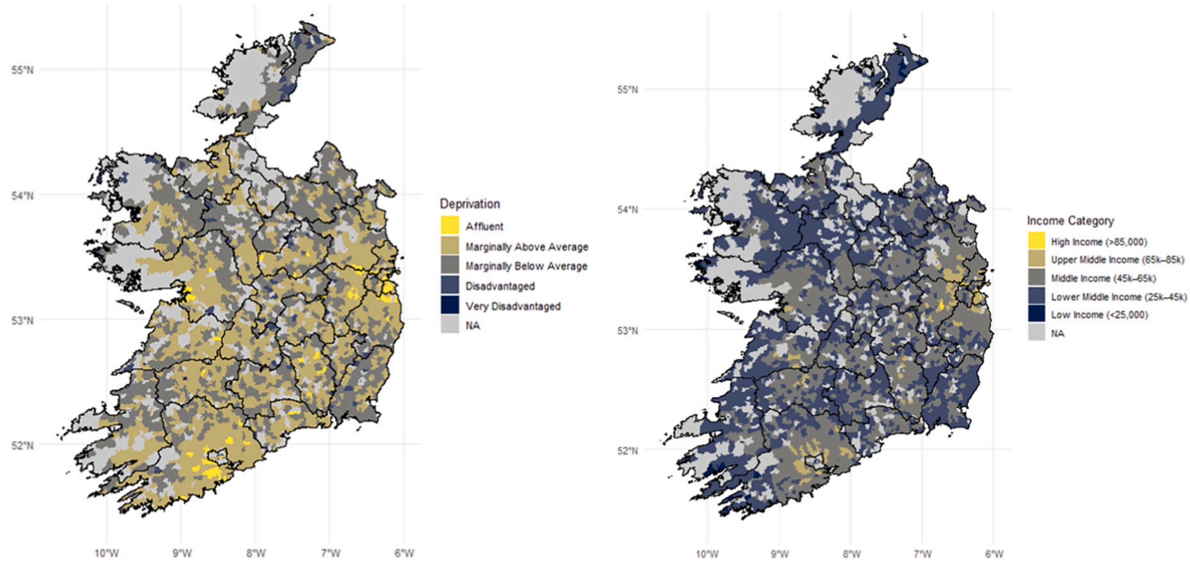


Fig. A4. Heatmaps showing adoption levels of HP, PV, EV, and EVHC across Ireland for all the EDs.



Deprivation index categories Income categories

Fig. A5. Spatial distribution of Deprivation index categories and Income categories across Ireland for all.

Table A1
Correlation matrix (1/2).

	Absolute Deprivation Index	Median Household Income	% Males Aged 20–60	% Females Under 19	% Females Aged 20–60	% Management & Professional Occupations	% Agricultural Self-Employed	% Single-Parent Households	% Multi-Adult Households with Children	% Detached/ Semi-Detached Houses	% Households Using Oil Heating	% Households Using Gas Heating
Absolute Deprivation Index	1	0.501	0.125	0.103	0.153	0.692	0.013	−0.555	−0.167	−0.099	0.041	0.043
Median Household Income	0.501	1	0.073	0.19	0.081	0.721	−0.119	−0.358	0.138	−0.012	−0.071	0.241
% Males Aged 20–60	0.125	0.073	1	−0.272	0.801	0.051	−0.466	0.063	0.083	−0.723	−0.514	0.435
% Females Under 19	0.103	0.19	−0.272	1	−0.312	0.034	0.253	0.02	0.144	0.386	0.396	−0.313
% Females Aged 20–60	0.153	0.081	0.801	−0.312	1	0.051	−0.447	0.091	0.106	−0.672	−0.449	0.368
% Management & Professional Occupations	0.692	0.721	0.051	0.034	0.051	1	−0.317	−0.336	−0.011	−0.07	−0.114	0.307
% Agricultural Self-Employed	0.013	−0.119	−0.466	0.253	−0.447	−0.317	1	−0.293	−0.116	0.487	0.558	−0.625
% Single-Parent Households	−0.555	−0.358	0.063	0.02	0.091	−0.336	−0.293	1	0.217	−0.034	−0.219	0.261
% Multi-Adult Households with Children	−0.167	0.138	0.083	0.144	0.106	−0.011	−0.116	0.217	1	0.08	−0.093	0.187
% Detached/ Semi-Detached Houses	−0.099	−0.012	−0.723	0.386	−0.672	−0.07	0.487	−0.034	0.08	1	0.594	−0.427
% Households Using Oil Heating	0.041	−0.071	−0.514	0.396	−0.449	−0.114	0.558	−0.219	−0.093	0.594	1	−0.839
% Households Using Gas Heating	0.043	0.241	0.435	−0.313	0.368	0.307	−0.625	0.261	0.187	−0.427	−0.839	1
% Households Using Coal Heating	−0.355	−0.383	−0.234	0.069	−0.204	−0.309	0.196	0.15	−0.091	0.238	0.406	−0.382
% Households Using Peat Heating	−0.159	−0.167	−0.252	0.043	−0.243	−0.246	0.268	−0.086	−0.098	0.219	−0.091	−0.306

(continued on next page)

Table A1 (*continued*)

	Absolute Deprivation Index	Median Household Income	% Males Aged 20–60	% Females Under 19	% Females Aged 20–60	% Management & Professional Occupations	% Agricultural Self-Employed	% Single-Parent Households	% Multi-Adult Households with Children	% Detached/ Semi-Detached Houses	% Households Using Oil Heating	% Households Using Gas Heating
% Households Using LPG Heating	0.142	0.021	−0.129	0.099	−0.099	0.065	0.069	−0.069	−0.058	0.123	0.199	−0.183
% Households Using Wood Heating	0.07	−0.039	−0.271	0.209	−0.225	−0.143	0.534	−0.189	0.005	0.33	0.386	−0.47
% Commuting by Public Transport	0.156	0.244	0.263	0.037	0.251	0.193	−0.094	−0.01	0.127	−0.29	−0.318	0.344
% Active Commuting (Walking/ Cycling)	0.02	0.021	0.647	−0.452	0.573	0.16	−0.65	0.176	−0.004	−0.704	−0.697	0.699
% Commute Time Below 30 Minutes	0.05	−0.004	0.229	0.173	0.263	−0.045	−0.213	0.059	−0.015	−0.126	0.04	−0.021
% Reporting Very Good Health	0.615	0.596	−0.273	0.461	−0.209	0.528	0.303	−0.389	−0.021	0.369	0.371	−0.192
% Reporting Good Health	−0.39	−0.422	−0.191	−0.172	−0.22	−0.355	0.123	0.199	−0.068	0.195	0.088	−0.121
% Married Population	0.349	0.355	−0.604	0.254	−0.574	0.28	0.506	−0.504	−0.097	0.622	0.544	−0.442
% Divorced Population	−0.266	−0.372	0.133	−0.308	0.14	−0.119	−0.314	0.338	−0.071	−0.228	−0.198	0.18
% Households with ≥1 Car	0.291	0.306	−0.666	0.479	−0.602	0.228	0.537	−0.292	−0.02	0.784	0.643	−0.481

Table A2
Correlation matrix (1/2).

	% Households Using Coal Heating	% Households Using Peat Heating	% Households Using LPG Heating	% Households Using Wood Heating	% Commuting by Public Transport	% Active Commuting (Walking/ Cycling)	% Commute Time Below 30 Minutes	% Reporting Very Good Health	% Reporting Good Health	% Married Population	% Divorced Population	% Households with ≥1 Car
Absolute Deprivation Index	−0.355	−0.159	0.142	0.07	0.156	0.02	0.05	0.615	−0.39	0.349	−0.266	0.291
Median Household Income	−0.383	−0.167	0.021	−0.039	0.244	0.021	−0.004	0.596	−0.422	0.355	−0.372	0.306
% Males Aged 20–60	−0.234	−0.252	−0.129	−0.271	0.263	0.647	0.229	−0.273	−0.191	−0.604	0.133	−0.666
% Females Under 19	0.069	0.043	0.099	0.209	0.037	−0.452	0.173	0.461	−0.172	0.254	−0.308	0.479
% Females Aged 20–60	−0.204	−0.243	−0.099	−0.225	0.251	0.573	0.263	−0.209	−0.22	−0.574	0.14	−0.602
% Management & Professional Occupations	−0.309	−0.246	0.065	−0.143	0.193	0.16	−0.045	0.528	−0.355	0.28	−0.119	0.228
% Agricultural Self-Employed	0.196	0.268	0.069	0.534	−0.094	−0.65	−0.213	0.303	0.123	0.506	−0.314	0.537
% Single-Parent Households	0.15	−0.086	−0.069	−0.189	−0.01	0.176	0.059	−0.389	0.199	−0.504	0.338	−0.292
% Multi-Adult Households with Children	−0.091	−0.098	−0.058	0.005	0.127	−0.004	−0.015	−0.021	−0.068	−0.097	−0.071	−0.02
% Detached/Semi-Detached Houses	0.238	0.219	0.123	0.33	−0.29	−0.704	−0.126	0.369	0.195	0.622	−0.228	0.784
% Households Using Oil Heating	0.406	−0.091	0.199	0.386	−0.318	−0.697	0.04	0.371	0.088	0.544	−0.198	0.643
% Households Using Gas Heating	−0.382	−0.306	−0.183	−0.47	0.344	0.699	−0.021	−0.192	−0.121	−0.442	0.18	−0.481
% Households Using Coal Heating	1	−0.215	0.026	0.139	−0.193	−0.225	−0.004	−0.104	0.2	0.016	0.11	0.102

(*continued on next page*)

Table A2 (*continued*)

	% Households Using Coal Heating	% Households Using Peat Heating	% Households Using LPG Heating	% Households Using Wood Heating	% Commuting by Public Transport	% Active Commuting (Walking/ Cycling)	% Commute Time Below 30 Minutes	% Reporting Very Good Health	% Reporting Good Health	% Married Population	% Divorced Population	% Households with ≥1 Car
% Households Using Peat Heating	−0.215	1	−0.089	0.057	−0.117	−0.305	−0.115	−0.032	0.211	0.198	−0.183	0.2
% Households Using LPG Heating	0.026	−0.089	1	0.082	−0.116	−0.159	−0.016	0.126	−0.046	0.143	0.088	0.163
% Households Using Wood Heating	0.139	0.057	0.082	1	−0.087	−0.445	−0.135	0.227	0.012	0.305	−0.108	0.371
% Commuting by Public Transport	−0.193	−0.117	−0.116	−0.087	1	0.196	−0.211	0.11	−0.168	−0.149	−0.105	−0.162
% Active Commuting (Walking/ Cycling)	−0.225	−0.305	−0.159	−0.445	0.196	1	0.135	−0.349	−0.085	−0.696	0.28	−0.747
% Commute Time Below 30 Minutes	−0.004	−0.115	−0.016	−0.135	−0.211	0.135	1	−0.028	−0.186	−0.172	−0.038	−0.162
% Reporting Very Good Health	−0.104	−0.032	0.126	0.227	0.11	−0.349	−0.028	1	−0.43	0.566	−0.428	0.696
% Reporting Good Health	0.2	0.211	−0.046	0.012	−0.168	−0.085	−0.186	−0.43	1	−0.001	0.18	0.077
% Married Population	0.016	0.198	0.143	0.305	−0.149	−0.696	−0.172	0.566	−0.001	1	−0.425	0.801
% Divorced Population	0.11	−0.183	0.088	−0.108	−0.105	0.28	−0.038	−0.428	0.18	−0.425	1	−0.352
% Households with ≥1 Car	0.102	0.2	0.163	0.371	−0.162	−0.747	−0.162	0.696	0.077	0.801	−0.352	1

Table A2
Variance inflation factors (heat pump equation).

Variable	VIF
Deprivation Index	4.03
% Males (20–60)	3.66
% Females (<19)	1.92
% Females (20–60)	3.58
% Management/Professional	3.68
% Agricultural Own-Account	3.13
% HH Single with Child	1.95
% HH Multi-Adult with Child	1.3
% HH House	5.12
% HH Heating Oil	2.22
% HH Heating Gas	2.08
% HH Heating Coal	2.37
% HH Heating Peat	5.36
% HH Heating LPG	1.18
% HH Heating Wood	2.05
% Public Transport Commuting	1.51
% Commute <30 min	1.47
% Health Very Good	4.64
% Health Good	1.87

Note: All VIF values remain below conventional critical thresholds (10.0), indicating that multicollinearity does not materially affect coefficient stability.

Table A3
Decomposition of direct, indirect, and total spatial effects.

Independent Variables	Natural Log of Heat-Pump Installations					Natural Log of Solar PV Installations				
	Direct	Percentage (%)	Indirect	Percentage (%)	Total	Direct	Percentage (%)	Indirect	Percentage (%)	Total
Absolute value of Deprivation Index (affluence indicator)	0.0129	81.4	0.0029	18.6	0.0159	0.0343	83.7	0.0067	16.3	0.0410
Percentage of males aged 20–60 years	−0.0118	81.4	−0.0027	18.6	−0.0145	–	–	–	–	–
Percentage of females under 19 years	0.0199	81.4	0.0045	18.6	0.0244	0.0161	41.4	0.0228	58.6	0.0390
Percentage of females aged 20–60 years	0.0194	81.4	0.0044	18.6	0.0238	–	–	–	–	–
Percentage of management and professional workers	0.0075	81.4	0.0017	18.6	0.0092	0.0107	41.4	0.0151	58.6	0.0257
Percentage of agricultural workers (own account/farmers)	−0.0132	81.4	−0.0030	18.6	−0.0162	−0.0072	41.4	−0.0102	58.6	−0.0174
Percentage of single-adult-with-child households	0.0277	81.4	0.0063	18.6	0.0340	0.0179	41.4	0.0254	58.6	0.0433
Percentage of multi-adult-without-child households	−0.0164	33.1	−0.0331	66.9	−0.0495	–	–	–	–	–
Percentage of multi-adult-with-children households	−0.0143	81.4	−0.0033	18.6	−0.0175	–	–	–	–	–
Percentage of households living in a house (vs. apartment)	0.0167	81.4	0.0038	18.6	0.0204	0.0103	64.8	0.0056	35.2	0.0159
Percentage of households using oil for heating	−0.0450	81.4	−0.0103	18.6	−0.0553	–	–	–	–	–
Percentage of households using gas for heating	−0.0440	81.4	−0.0100	18.6	−0.0541	–	–	–	–	–
Percentage of households using coal for heating	−0.0271	42.1	−0.0374	57.9	−0.0645	–	–	–	–	–
Percentage of households using peat for heating	−0.0473	81.4	−0.0108	18.6	−0.0580	–	–	–	–	–
Percentage of households using LPG for heating	–	–	–	–	–	–	–	–	–	–
Percentage of households using wood for heating	−0.0532	81.4	−0.0121	18.6	−0.0653	–	–	–	–	–
Percentage of households with zero cars	−0.0677	81.4	−0.0154	18.6	−0.0831	–	–	–	–	–
Percentage of population commuting by active modes (walk/cycle)	−0.0014	81.4	−0.0003	18.6	−0.0017	–	–	–	–	–
Percentage of population commuting by public transport	−0.0211	81.4	−0.0048	18.6	−0.0259	−0.0001	41.4	−0.0002	58.6	−0.0004
Percentage of commuters with commute <15 min	−0.0150	81.4	−0.0034	18.6	−0.0184	−0.0172	41.4	−0.0244	58.6	−0.0416
Percentage of commuters with commute 15–30 min	−0.0118	81.4	−0.0027	18.6	−0.0145	−0.0135	41.4	−0.0192	58.6	−0.0327
Percentage of commuters with commute 30–45 min	0.0032	−10.3	−0.0343	110.3	−0.0311	−0.0179	41.4	−0.0254	58.6	−0.0433
Percentage of commuters with commute 45–60 min	−0.0375	3470.7	0.0365	−3370.7	−0.0011	−0.0170	41.4	−0.0241	58.6	−0.0411
Percentage of population reporting very good health	0.0188	81.4	0.0043	18.6	0.0230	−0.0003	41.4	−0.0005	58.6	−0.0008
Percentage of population reporting good health	0.0240	81.4	0.0055	18.6	0.0295	−0.0005	41.4	−0.0008	58.6	−0.0013

Table A4
Decomposition of direct, indirect, and total spatial effects.

Independent Variables	Natural Log of EV Grants					Natural Log of EV Home-Charger Grants				
	Direct	Percentage (%)	Indirect	Percentage (%)	Total	Direct	Percentage (%)	Indirect	Percentage (%)	Total
Absolute value of Deprivation Index (affluence indicator)	0.0209	−1884.9	−0.0220	1984.9	−0.0011	0.0129	58.2	0.0093	41.8	0.0222
Percentage of males aged 20–60 years	–	–	–	–	–	–	–	–	–	–
Percentage of females under 19 years	–	–	–	–	–	–	–	–	–	–
Percentage of females aged 20–60 years	–	–	–	–	–	–	–	–	–	–
Percentage of management and professional workers	0.0212	35.7	0.0382	64.3	0.0594	0.0283	58.2	0.0203	41.8	0.0486

(*continued on next page*)

Table A4 (*continued*)

Independent Variables	Natural Log of EV Grants					Natural Log of EV Home-Charger Grants				
	Direct	Percentage (%)	Indirect	Percentage (%)	Total	Direct	Percentage (%)	Indirect	Percentage (%)	Total
Percentage of agricultural workers (own account/farmers)	−0.0005	35.7	−0.0008	64.3	−0.0013	−0.0098	58.2	−0.0070	41.8	−0.0168
Percentage of single-adult-with-child households	0.0022	35.7	0.0039	64.3	0.0061	−0.0014	−3.3	0.0434	103.3	0.0420
Percentage of multi-adult-without-child households	−0.0006	35.7	−0.0010	64.3	−0.0016	–	–	–	–	–
Percentage of multi-adult-with-children households	–	–	–	–	–	–	–	–	–	–
Percentage of households living in a house (vs. apartment)	0.0060	63.6	0.0035	36.4	0.0095	0.0068	55.9	0.0054	44.1	0.0122
Percentage of households using oil for heating	–	–	–	–	–	–	–	–	–	–
Percentage of households using gas for heating	–	–	–	–	–	–	–	–	–	–
Percentage of households using coal for heating	–	–	–	–	–	−0.0101	−700.2	0.0115	800.2	0.0014
Percentage of households using peat for heating	–	–	–	–	–	−0.0041	495.1	0.0033	−395.1	−0.0008
Percentage of households using LPG for heating	–	–	–	–	–	−0.0081	58.2	−0.0058	41.8	−0.0139
Percentage of households using wood for heating	–	–	–	–	–	–	–	–	–	–
Percentage of households with zero cars	–	–	–	–	–	–	–	–	–	–
Percentage of population commuting by active modes (walk/cycle)	–	–	–	–	–	–	–	–	–	–
Percentage of population commuting by public transport	–	–	–	–	–	–	–	–	–	–
Percentage of commuters with commute <15 min	–	–	–	–	–	–	–	–	–	–
Percentage of commuters with commute 15–30 min	–	–	–	–	–	–	–	–	–	–
Percentage of commuters with commute 30–45 min	–	–	–	–	–	–	–	–	–	–
Percentage of commuters with commute 45–60 min	–	–	–	–	–	–	–	–	–	–
Percentage of population reporting very good health	–	–	–	–	–	–	–	–	–	–
Percentage of population reporting good health	–	–	–	–	–	–	–	–	–	–

Note: Only variables with statistically significant total effects ($p < 0.05$) are reported.

Data availability

The authors do not have permission to share data.

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