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The diffusion of domestic energy efficiency policies: A spatial perspective

Craig Morton[a,*], Charlie Wilson[b], Jillian Anable[c]

[a] School of Architecture, Building, and Civil Engineering, Loughborough University, Loughborough LE11 3TU, United Kingdom
[b] Tyndall Centre for Climate Change Research, University of East Anglia, Norwich NR4 7TJ, United Kingdom
[c] Institute for Transport Studies, University of Leeds, Leeds, LS2 9JT, United Kingdom

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ABSTRACT

National domestic energy-efficiency policies are unlikely to be implemented in a geographically uniform manner. This paper demonstrates the importance of socioeconomic, contextual, and local policy conditions in shaping the spatially heterogeneous response to a national policy. Through an assessment of the geographical and temporal variation in domestic energy-efficiency assessments provided under the United Kingdom's Green Deal, the factors underpinning the spatial diffusion of this policy are identified. Spatial regression models show that the presence of young families, university educated residents, detached homes, and large households positively affects the uptake of energy-efficiency assessments whereas property market activity, personal incomes, the presence of self-employed residents, and the efficiency levels of the existing housing stock has a dampening effect. National incentives for policy implementation that are distributed through selected local authorities also work to promote the uptake of energy-efficiency assessments. Overall, the analysis clearly shows the importance of local factors in determining how national policies are implemented on the ground. This has important implications for policymakers in designing and administering national policy frameworks, in trading-off targeted implementation with fairness and uniformity, and in evaluating the local effectiveness of national policies.

1. Introduction

Achieving a successful transition to an environmentally sustainable energy system will be contingent on the widespread adoption of low-carbon technologies amongst consumers. This requirement is apparent in different energy sectors, such as the uptake of electric vehicles to service mobility needs (Dijk et al., 2013), solar photovoltaic systems to provide decentralised energy generation (Dewald and Truffer, 2012; Allan and McIntyre, 2017) and retrofits to the fabric of existing buildings to enhance their energy-efficiency (Wilson et al., 2015). Research which investigates the adoption of these low-carbon technologies tends to approach the subject either by considering the characteristics of the consumers that are likely to be receptive to the unique features of the innovation or by forecasting future rates of uptake based on expectations of demand. An important issue which has received less attention concerns how these technologies will diffuse across space (Balta-Ozkan et al., 2015). This lack of spatial sensitivity is also present in the development of policies to support diffusion, with governments tending to implement national policies including financial incentives to promote adoption, information campaigns to raise awareness, and industry grants to stimulate market development. However, the effectiveness of these policies will be dependent on local socioeconomic and environmental conditions which shape how the policy is received in a given location. Research that approaches adoption from a spatial perspective can help in identifying the effect that local conditions have on the diffusion of low-carbon technologies, assist in locating areas with the strongest adoption propensities, and provide evidence on the geography of sustainability transitions.

The objective of this paper is to demonstrate how local conditions affect the propensity of areas to adopt low-carbon technologies. This objective is pursued through an analysis of the geographical variation in the uptake of domestic energy-efficiency assessments under the United Kingdom's (UK) Green Deal energy policy to determine which factors effect spatial diffusion. Spatial regression models are used to evaluate the significance of socioeconomic characteristics of the population and the attributes of the properties to explain the observed spatial variation in Green Deal uptake. The analysis also tests whether the funding allocated to local governments to enable the pursuit of locally-designed strategies stimulated uptake. In doing so, this paper sheds light on the spatial processes at play in the diffusion of low-carbon technologies and demonstrates that the transition towards a sustainable energy system is unlikely to occur in a spatially uniform manner.

This paper is structured as follows. First, the existing literature on

* Corresponding author.
E-mail addresses: c.morton@live.co.uk (C. Morton), charlie.wilson@uea.ac.uk (C. Wilson), j.l.anable@leeds.ac.uk (J. Anable).

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spatial issues in energy policy and low-carbon technology adoption is discussed. Second, the Green Deal as a specific example of energy-efficiency policy is explained, alongside a synthesis of previous empirical research on the factors affecting household investment in energy efficient technologies. Third, the methodology and variables used in the spatial analysis are set out. Fourth, the results of the analysis are presented and interpreted, building up from descriptive statistics to spatial regression modelling. To conclude, the paper draws implications for energy policy, and argues that spatial heterogeneity is an important factor in national policy design, implementation, and evaluation.

2. Background

2.1. Spatial perspectives on energy policy implementation

The literature which considers the effectiveness of national policies aimed at enhancing domestic energy-efficiency employs a variety of approaches including temporal analyses of policy development (Geller et al., 2006; Mallaburn and Eyre, 2014), extensive reviews of existing scientific and policy evidence (Abrahamse et al., 2005; Harmelink et al., 2008; Kerr et al., 2017), and proposals for future strategies based on past experiences (Boardman, 2004; Jollands et al., 2010; Gooding and Gul, 2017). However, geographical issues such as space, location, and environmental context do not feature as prominent topics to date. Part of this might be due to lack of data, with Harmelink et al. (2008) noting that this represents a reoccurring problem when conducting ex-post policy assessments.

The need to account for geographical issues when considering the transition to a low-carbon society is increasing in prominence with researchers describing how regional and local situations can generate substantial impacts on transition pathways (Coenen and Truffer, 2012; Coenen et al., 2012; Hansen and Coenen, 2015). The benefits of introducing a spatial perspective to energy transitions are set out by Bridge et al. (2013), who note that energy systems are spatially situated (i.e. energy infrastructures have a geographical imprint) and are embedded in particular settings. To illustrate the ways in which geographical processes influence transition trajectories, Bridge et al. (ibid.) outline a set of geographical concepts which can be translated into transition studies. One of these concepts reflects the geographical variation which is inherent across the energy system, covering the spatial differences in such issues as energy generation, demand, and low-carbon resource availability. A similar perspective is put forward by Balta-Ozkan et al. (2015), who note that demographic structures are not spatially homogenous and that this will likely affect how receptive areas are to certain low-carbon technologies. The concept of geographical variation is also a prominent feature in Raven et al. (2012) proposed extension of transition frameworks to acknowledge the impact of spatial heterogeneity in endowments and circumstances on the processes of transition.

These conceptual contributions are complemented by a growing body of empirical studies which investigate the spatial diffusion of energy technologies. To date, the majority of such research has concentrated on the adoption of domestic solar photovoltaic (PV) systems (Allan and McIntyre, 2017; Dharshing, 2017). This is likely due to the prominence of solar PV in low-carbon transition pathways, their targeting by national energy policies (such as feed-in tariffs), as well as the 'visibility' of installed PV systems. Kwan (2012) investigates the effect that climate, economic, social, and political factors have on the installation rates of PV across different zip codes in the United States. He finds that the level of solar irradiance is the most useful factor in explaining spatial variation in PV adoption, with the cost of electricity and the presence of local incentives to encourage adoption also being relatively important. Davidson et al. (2014) similarly explore the rate of PV deployment at the zip code level in the state of California. They examine the effect of factors such as household size, car availability, home tenure, foreclosures, and the registration rates of alternative fuel vehicles (e.g. hybrid electric vehicles). Their modelling finds that property size, rate of foreclosure, and rate of hybrid electric vehicle adoption are important factors in the rate of PV uptake. Recently, attention has turned to investigating the importance of peer effects on the adoption of PV (Bollinger and Gillingham, 2012), with the work of Graziano and Gillingham (2015) clearly demonstrating that the installation of nearby PV systems in the past effects the likelihood of neighbours adopting PV systems in the present. These peer effects have also been observed in the work of Noonan et al. (2013) for heating, ventilation, and air conditioning systems, whereby the adoption of these systems in certain neighbourhoods is found to positively affect the rate of adoption in nearby areas.

The empirical analysis of Green Deal uptake presented in this paper contributes to this growing body of literature in two ways. First, it examines geographical variation in energy efficient technologies within the home, which is an under investigated area of critical importance to national emission reduction strategies. Second, it demonstrates that spatial heterogeneity in national policy implementation is linked to local socioeconomic population characteristics, property attributes, and local government strategies for channelling national incentives. More generally, the case study provides an example of how transitions towards a low-carbon society can progress in a spatially uneven manner, which has implications for how policies are designed and evaluated in both public institutions and commercial settings.

2.2. The Green Deal

The Green Deal was a domestic energy-efficiency policy implemented by the Department of Energy and Climate Change (DECC) in the UK. Introduced in January 2013, the Green Deal ran for over two years before financial support was withdrawn in July 2015. Although certain elements of the Green Deal remain in place, activity levels fell sharply after July 2015 (see Fig. 1). The structure of the Green Deal was quite innovative in nature, involving a number of different components designed to address widely-recognised barriers to energy-efficiency investments (Weber, 1997; Pelenur and Cruishank, 2012; Pettifor et al., 2015; Wilson et al., 2015). Mallaburn and Eyre (2014, p. 23) define the Green Deal as “a market-based, demand-led financial mechanism providing up-front loans for energy-efficiency measures, which are repaid using the energy savings”. The implementation of the Green Deal in a particular household progressed through a series of stages shown in Fig. 2.

The research presented in this paper concentrates on the uptake of Green Deal Assessment (GDAs) by households. These technical assessments involved the evaluation of the energy profile of a property by a qualified assessor with the production of an Energy Performance

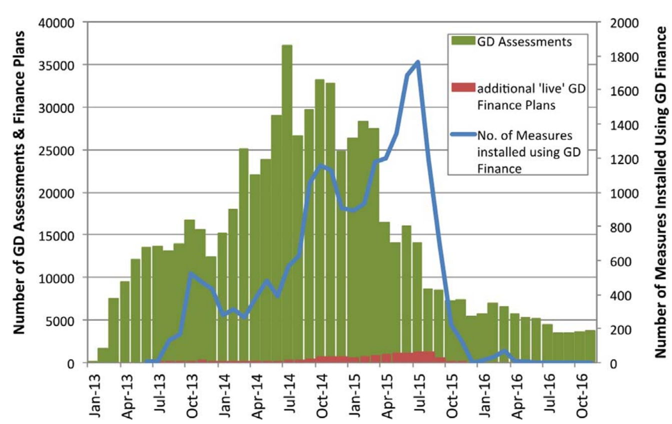

Fig. 1. Numbers of Green Deal Assessments (green columns, left y-axis), Green Deal Finance Plans (red columns, left y-axis) and measures installed using Green Deal Finance (blue line, right y-axis). (*Source*: BEIS, 2017). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

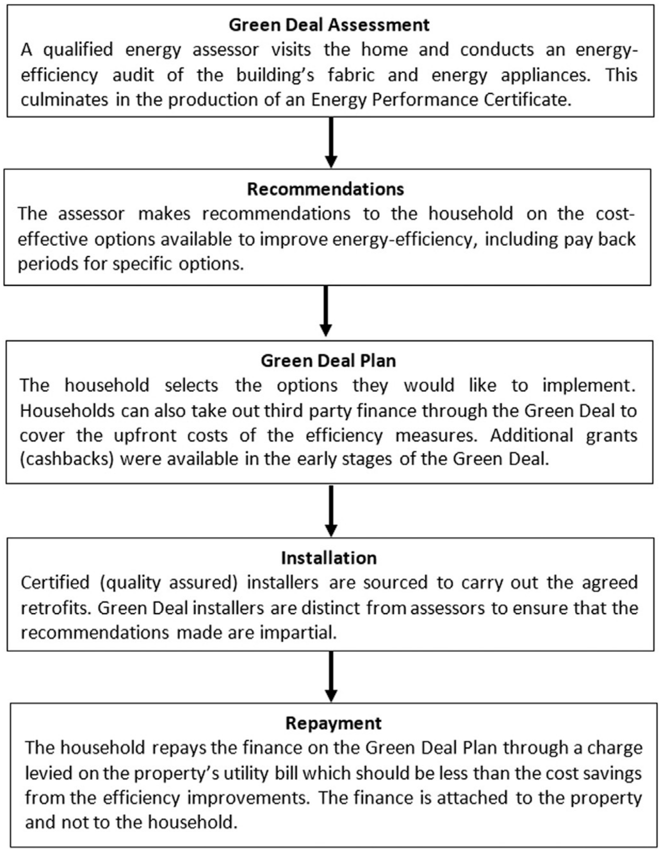

Fig. 2. Overview of the Green Deal process from a household's perspective.

Certificate (EPC), similar to the tailored energy audits discussed by Abrahamse et al. (2005). Following the evaluation, the assessor would report to the household on cost-effective retrofit options (i.e. energy savings over the lifetime of the retrofit option would exceed the upfront costs of installation and any ongoing maintenance costs). A separation existed between assessors and installers (i.e. the same company could not conduct the assessment, make the recommendations, and conduct the installation) in an effort to reassure householders that the advice being delivered was impartial (i.e. the assessor did not have anything to gain by recommending retrofits that would not be cost saving).

GDAs could be the result of either households requesting an assessment, or households being recommended for an assessment. This recommendation may have originated from an energy company under their legal obligations to reduce greenhouse gas emissions (the Carbon Emissions Reduction Obligations) and fuel poverty (the Carbon Savings Communities Obligation). The uptake of GDAs therefore contains elements of both demand-pull (initiated by households) and supply-push activities (initiated by utilities).

GDAs are used in this paper as a proxy for initial activity relating to domestic energy-efficiency retrofits. The DECC (2013) conducted a market survey on households' motivations for having GDAs (see Table 1). The principal stated motivation was to save money on household energy bills. Pettifor et al. (2015) found that the Green Deal helped raise the salience of energy-efficiency opportunities among households, particularly in the early stages of the retrofit decision process. During the lifetime of the Green Deal, over 475,000 GDAs were completed in England, which equates to approximately 2.1% of the housing stock. The different measures recommended through the GDAs are shown in Table 2.

Throughout the course of the Green Deal, the DECC opened a series of funding schemes to local government with the objective of enhancing Green Deal uptake (see Table 3). Two of these schemes (Pioneer Places and Green Deal Communities) involved a competitive bidding process. Local government bodies put forward strategies through which they would pursue the specific objectives associated with each funding scheme. Funding allocated to a third initiative, Core Cities, was part of a wider national strategy to empower regional conurbations outside of London to progress their economic development. Through these funding schemes, the DECC implicitly recognised that understanding local conditions is an important factor in promoting delivery of the national Green Deal, and that local government bodies, with their familiarity of the local population and housing stock, are well placed to pursue locally-appropriate strategies. The empirical analysis of GDA uptake in this paper examines if the allocation of funds to local government to pursue their own strategies resulted in an observable increase in GDAs.

Table 1
Household motivations for having a Green Deal Assessment (multiple responses allowed; n = 1506; DECC, 2013).

Motivation	Percentage
To save money on energy bills	64.02%
The assessment was free	58.01%
To find out how to make the property more energy efficient	42.71%
To reduce energy use for environmental reasons	28.71%
To access the Green Deal finance and cashback initiative	16.70%
Assessment was arranged by a landlord or local authority	15.34%
The availability of cashback or discounts	13.35%
Recommended by an energy company	13.32%
Recommended by an Energy Saving Advice Service	10.66%
Recommended by a friend or family member	9.67%

Table 2
Measures recommended in Green Deal Assessments (DECC, 2015a).

Efficiency Measure	Percentage of Recommendations
Boiler upgrade	10.0%
Cavity wall insulation	10.7%
Lighting upgrade	0.0%
Loft insulation	15.9%
Micro-generation (e.g. photovoltaic tiles)	23.1%
Other heating (e.g. thermostatic radiator valves)	9.3%
Other insulation (e.g. piping)	19.6%
Solid wall insulation	8.9%
Window glazing	2.4%

2.3. Factors effecting domestic energy-efficiency retrofits

There is a substantial body of research examining the factors affecting the uptake of domestic energy-efficiency measures (Wilson et al., 2015). A common typology of factors distinguishes: [1] personal factors, which can be further decomposed into the socioeconomic and psychological characteristics of household members (e.g. energy-related knowledge and capabilities); [2] economic factors such as energy prices; [3] policy factors such as taxes and subsidies; and [4] contextual factors such as property attributes (e.g. property age and size) and environmental conditions (e.g. climate and urban form).

In terms of socioeconomic characteristics, age profiles are routinely employed as independent variables in explanatory models, with Black et al. (1985) finding that the age of the oldest household member significantly affects general concerns about energy and the environment, which then shape the formation of individual energy-efficiency norms and behaviours. In his assessment of applications for US tax rebates associated with energy-efficiency retrofits, Long (1993) found that elderly households (with a taxpayer over the age of 64) tended to have higher levels of investment in home insulation and the installation of storm-proof doors and windows. However, Brechling and Smith (1994)

Table 3
Overview of national funding allocated to local authorities to enhance the uptake and impact of the Green Deal.

Funding	Introduced	Amount	Local Authorities	Objectives
Pioneer Places	January 2013	£10 million	39	Aimed at kick stating Green Deal activity by promoting local Green Deal strategies which take a street-by-street approach to identifying households and targeting uptake whilst also establishing a base for future activity by encouraging the formation of networks and partnerships.
Green Deal Communities	July 2013	£88 million	24	Enhance the street-by-street roll out of the Green Deal by providing direct assistance to 32,000 households.
Core Cities	February 2013	£12 million	8	Promote residential retrofits in entire communities with 2500 improvements targeted. Provide feedback on applying the Green Deal framework in urban settings outside of London.

analysed the installations of energy-efficiency measures in UK and found that households with a pensioner as the nominal head were significantly less likely to have cavity wall insulation. This result is supported by the findings of Nair et al. (2010), whose work on the installation of energy-efficiency measures in Sweden found that properties of individuals aged 65 and over displayed substantially lower rates of building fabric retrofits compared to all other age bands.

With respect to level of education, Mills and Schleich (2012) analysed domestic energy-efficiency in the EU and found that the attainment of a university degree produces a significant positive effect on the purchase of energy-efficient appliances, installation of compact fluorescent light bulbs, knowledge of energy use patterns, and the practice of energy curtailment behaviours (e.g. turning off appliances when not in use). Similar observations are made by Sütterlin et al. (2011) in their segmentation analysis of Swiss citizens. The two segments with the highest degree of energy curtailment behaviours and adoption of technical energy-efficiency measures have household members with relatively high levels of education.

With respect to income, Sardianou (2007) found that personal income has a significant positive effect on domestic energy conservation actions undertaken in Greece. Brechling and Smith (1994) similarly found that household income has a significant positive effect over the presence of loft insulation, cavity wall insulation, and double glazing in UK properties. In contrast, the segmentation analysis of Barr et al. (2005) found that the segment exhibiting the lowest level of habitual and purchase-related energy conservation behaviours have the highest prevalence of members earning in excess of £30,000 per annum. These varying results suggest that the effect of income on domestic energy-efficiency might depend on whether curtailment or investment-type activities are being evaluated.

In terms of property attributes, a host of different features have been evaluated to determine their effect on domestic energy-efficiency interventions. The number of residents is a commonly considered issue, with Black et al. (1985) noting that this feature positively effects investment in energy-efficiency retrofits with a comparable finding observed by Sardianou (2007) for curtailment activities. However, Long (1993) found mixed results, with household size having a significant positive effect on investments in renewable energy but a significant negative effect on retrofit investments.

Home tenure is commonly linked to a market failure in energy-efficiency investments, as rental properties have split incentives between owners (investing) and tenants (benefiting from lower bills). Brechling and Smith (1994) found that homes which are privately rented are significantly less likely to have building fabric retrofits. This observation is supported by the work of Sardianou (2007), who found that owner-occupiers are more likely to consider energy curtailment activities. The segmentation analysis by Barr et al. (2005) similarly found that the market segment most likely to engage with domestic energy-efficiency activities are also the most likely to own their home.

Dwelling type will likely constrain what variety of energy-efficiency measures can be pursued, with Brechling and Smith (1994) finding that terraced houses and flats are significantly less likely to have retrofits to the property fabric installed. Moreover, the results of Sardianou's (2007) analysis indicate that being a resident of a detached house generates a significant positive effect over curtailment behaviours. However, a different finding is observed by Barr et al. (2005), whose segmentation analysis demonstrates that committed environmentalists who engage with energy-efficiency behaviours and invest in energy efficient technologies have a higher likelihood of being resident in terraced houses as compared to other market segments.

2.4. Focus of this study

The empirical analysis reported in this paper focuses on a common set of socioeconomic factors, contextual factors, and policy factors as possible explanatory variables for the uptake of GDAs. This framework is illustrated in Fig. 3 and is informed by the findings of previous research concerning household response to energy efficient technologies.

Some of the specific variables used in the analysis correspond directly to those applied in earlier research. These include education level, personal income, tenure, household size, and dwelling type. Other variables are modified from those applied in earlier research. For instance, instead of evaluating the effect of population age, this analysis uses measures of life-stage based on the hypothesis that households in a more stable life-stage will be associated with higher levels of GDA uptake.

Additional variables are included to test specific hypotheses that are original to this work. First, the association between GDA uptake and economic status is examined to test the hypothesis that areas which have higher rates of employment are associated with higher rates of uptake. Second, the level of property market activity is included to test the hypothesis that higher turnover of ownership (i.e. 'churn') is associated with lower levels of uptake. Third, the energy-efficiency of the existing housing stock is included to examine whether uptake tends to be lower in areas with more efficient housing. Fourth, measures of fuel poverty are included to account for energy company activity associated with the Carbon Savings Communities Obligation, with the expectation being that higher levels of fuel poverty will be associated with higher levels of uptake. Finally, the allocation of national funding to local government bodies to pursue tailored strategies to promote GDAs is included to test whether areas which received funding tend to have higher levels of uptake.

It is important to emphasise that the dependent variable in the analysis is a measure of households'interest in and motivation towards

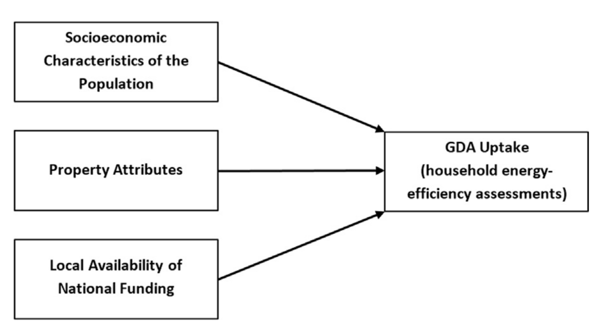

Fig. 3. Analytical framework for the empirical analysis.

energy efficiency, and not a measure of technology adoption. As a technical energy-efficiency audit, GDAs clearly signal households' intentions to at least consider improving their property's energy efficiency. However, there is strong evidence of a disparity or 'energy efficiency gap' between intention and adoption linked to numerous barriers to implementation (Jaffe and Stavins, 1994; Brown, 2001; Murphy, 2014). With spatial data being available concerning the uptake of GDAs and active Green Deal Plans (i.e. households that have implemented energy-efficiency retrofits through Green Deal finance), future research could explore where the disparity is greatest to identify the spatial characteristics of implementation barriers.

3. Methodology

3.1. Data sources

The UK government released detailed statistical information on the progression of the Green Deal, including the monthly numbers of assessments, finance plans, and measures installed (DECC, 2015a). This included geo-referenced data on the number of GDAs conducted quarterly from September 2013 to June 2015 in the 532 Westminster Parliamentary Constituencies (WPCs) of England (median size of 72,400 residents). This spatially-explicit dataset of GDAs is analysed in this paper.

Additional data on the socioeconomic characteristics and property profiles of the WPCs are sourced from the 2011 census of the UK (Office of National Statistics, 2011), Her Majesty's Revenue and Customs' (2015) income data, the DECC's (2015b) National Energy Efficiency Database, the DECC's (2015c) estimates of fuel poverty in England, and the Office of National Statistics' (2015) records of property sales. The variables included in the analysis are detailed in Table 4 (omitting the dummy variables used to distinguish WPCs which received central government funding).

3.2. Data preparation

The variables listed in Table 4 have been incorporated into a single dataset which lists the features of the WPCs inclusive of the number of GDAs conducted, socioeconomic characteristics of the population, property attributes, and funding allocations. This dataset has been spatially joined to a shapefile which contains the geographical layout of the WPCs of England (Office of National Statistics, 2016a).

3.3. Data limitations

The dataset is restricted in a number of ways which should be kept in mind when interpreting the results of the analysis. First, the results are for the WPC level of UK administrative geography. As described by Anselin (2002), results observed at one level of spatial resolution may not be transferable to other levels or to individual behaviour due to an effect of aggregation. This is generally referred to as the ecological fallacy problem, meaning that inferences about individual behaviour should be treated with caution. Second, the layout of WPC boundaries has been designed for purpose of electoral organisation and not for the consideration of domestic energy-efficiency. Generally referred to as the modifiable areal unit problem (Fotheringham and Wong, 1991), this issue may mean that the findings reported in the analysis could be sensitive to changes in spatial boundaries. Third, although the cumulative uptake of GDAs across the WPCs was measured in June 2015, the other socioeconomic and property characteristics used in this analysis were observed at different points in time. For instance, the majority of the socioeconomic and property characteristics are taken from the UK census which was conducted in 2011. This temporal disparity in the underlying data sources may affect the results if significant alterations in area characteristics have occurred during the intervening time period.

Table 4
Descriptive statistics of the variables employed in the analysis (n = 532).

Variable	Mean	S. D.	Min.	Max.
Green Deal Uptake				
Green Deal Assessments (per 1000 homes)[a]	21.86	10.11	0.80	90.90
Socioeconomics				
Life-Stage				
Single under 35 (%)[b]	4.19	2.24	1.11	18.55
Multi-person under 35 (%)[b]	6.01	3.85	1.99	24.11
Cohabiting under 35 with child (%)[b]	7.36	2.24	2.99	15.91
Single 35–54 (%)[b]	8.46	2.11	4.53	17.75
Multi-person 35–54 (%)[b]	10.68	0.95	6.99	13.15
Cohabiting 35–54 with child (%)[b]	20.06	2.83	9.77	29.01
Single 55–64 (%)[b]	4.95	0.61	3.30	7.27
Multi-person 55–64 (%)[b]	10.63	2.31	3.68	14.53
Cohabiting 55–64 with child (%)[b]	1.46	0.31	0.87	2.97
Single 65 and over (%)[b]	12.44	2.24	5.05	20.68
Multi-person 65 and over (%)[b]	13.46	3.71	3.91	25.56
Cohabitating 65 and over with child (%)[b]	0.30	0.10	0.14	0.84
Education Level				
No qualifications (%)[b]	22.69	5.65	9.57	39.23
High school (GCSE grades D-G) (%)[b]	13.39	2.31	5.68	19.20
High school (GCSE grades A*-C) (%)[b]	15.36	2.26	7.26	18.55
Pre-university (A-Levels) (%)[b]	12.33	2.35	8.34	27.65
University degree (%)[b]	27.02	8.51	12.07	57.39
Economic Status				
Part time employment (%)[b]	13.86	1.80	6.20	17.62
Full time employment (%)[b]	38.58	4.30	23.96	55.44
Self-employed (%)[b]	9.75	2.76	4.52	17.29
Unemployed (%)[b]	4.34	1.46	1.84	9.53
Retired (%)[b]	14.03	3.86	4.43	25.84
Income				
Mean personal income ('000 GBP)[c]	21.46	3.29	16.30	39.90
Fuel Poverty				
Households in fuel poverty (%)[d]	10.42	2.89	5.60	25.10
Property				
Dwelling Type				
Detached house (%)[b]	22.63	13.28	0.58	55.77
Semi-detached house (%)[b]	31.37	9.78	1.00	56.98
Terrace house (%)[b]	24.63	9.14	6.43	56.13
Flats (%)[b]	16.12	11.83	2.26	85.04
Tenure				
Owned outright (%)[b]	30.99	7.88	6.72	50.12
Owned mortgage (%)[b]	33.04	5.73	11.92	45.02
Rent social (%)[b]	17.42	7.68	4.59	50.63
Rent private (%)[b]	16.45	6.44	7.34	42.10
Dwelling Size				
Mean number of residents[b]	2.36	0.15	1.85	3.21
Mean number of rooms[b]	5.42	0.5	3.8	6.4
Mean number of bedrooms[b]	2.74	0.22	1.9	3.2
Real Estate Transactions				
House sales (% per annum)[e]	2.71	0.61	1.27	4.17
Energy Efficiency				
No central heating (%)[b]	2.67	1.31	0.44	10.11
Gas central heating (%)[b]	78.99	9.81	40.37	91.20
Electric central heating (%)[b]	8.11	3.85	1.59	29.61
Oil central heating (%)[b]	3.91	6.39	0.02	32.65
EPC grade A to C (%)[f]	29.05	6.80	13.59	63.67
EPC grade D to G (%)[f]	70.95	6.80	36.33	86.41

[a] DECC (2015a).
[b] ONS (2011).
[c] HMRC (2015).
[d] DECC (2015c).
[e] ONS (2015).
[f] DECC (2015b).

3.4. Statistical analysis

The statistical analysis of the dataset progresses through four stages.

3.4.1. Stage one

The first stage of the analysis concentrates on spatial and temporal depictions of the uptake of GDAs. A series of Choropleth maps are presented which illustrate the spatial variation in the uptake of GDAs per 1000 homes across the WPCs of England at quarterly intervals between September 2013 and June 2015. The same bin range (equal count) is used across all of the Choropleth maps which is derived from the GDA uptake in June 2015. This exploratory analysis assists in identifying if spatial heterogeneity is present regarding the uptake of GDAs across the WPCs.

To determine if any spatial dependence (i.e. non-random patterning) is present in the uptake of GDAs across the WPCs, spatial autocorrelation analysis is applied at both a global level, through the calculation of Moran's-I (Moran, 1948; Getis, 2009), and at a local level, through the estimation of the Local Indicator of Spatial Association (LISA; Anselin, 1995). A spatial weights matrix (W) is required for the spatial autocorrelation analysis, which classifies the geographical units (e.g. WPCs) based on their degree of connectivity with one another (Haining, 2009). A binary spatial weights matrix is specified following a queen contiguity approach which classifies geographical units as neighbours if they share a point or line boundary. This allows for the calculation of a spatially lagged variable of GDA uptake which permits the analysis to consider if uptake in a particular WPC tends to be correlated with the uptake observed in neighbouring WPCs.

3.4.2. Stage two

The second stage of the analysis considers if the allocation of national government funds to local authorities (i.e. through the Pioneer Places, Green Deal Communities, or Core Cities schemes) is associated with higher levels of GDA uptake. In order to classify WPCs as recipients or non-recipients of funding, look-up tables published by the Office of National Statistics (2016b) are used to nest WPCs into local authorities. Descriptive statistics (i.e. mean and standard deviation) are used to profile these recipient and non-recipient WPCs. Mann-Whitney U tests are applied in order to determine if WPCs that received funding tend to have higher levels of GDA uptake compared to those WPCs which did not receive funding.

3.4.3. Stage three

The third stage of the analysis examines the relationships between the uptake of GDAs per 1000 homes and the socioeconomic characteristics and property attributes of the WPCs. Two batches of Spearman's correlation analyses are reported to identify local conditions strongly connected to GDA uptake.

3.4.4. Stage four

In the fourth stage, regression models are specified with the cumulative uptake of GDAs per 1000 homes as of June 2015 across the WPCs as the model dependent variable in all instances. Across all the specified models, both the dependent and independent variables are transformed into their natural logarithms (expect in the instance of the dummy variables associated with the government funding). To begin, a benchmark Ordinary Least Squares (OLS) regression model is specified which introduces certain socioeconomic characteristics of the population, attributes of the properties, and dummy variables which distinguish recipients of central government funding as the model independent variables. Eq. (1) sets of the structure of the model.

$$y = \alpha + \beta_s x_s + \beta_p x_p + \beta_f x_f + \varepsilon \tag{1}$$

where:

y is a vector of observations of GDA uptake
α is a constant parameter
β_s is a vector of coefficients associated with socioeconomic independent variables
x_s is a vector set of observations of socioeconomic independent variables
β_p is a vector of coefficients associated with property independent variables
x_p is a vector set of observations of property independent variables
β_f is a vector of coefficients associated with the funding dummy variables
x_f is a vector set of observations of the funding dummy variables
ε is the model residual

To determine if the benchmark OLS needs to be extended to account for persisting spatial dependence (i.e. violating the assumptions of randomly distributed and independent error terms), the robust Langrange Multiplier spatial diagnostics (Anselin et al., 1996) are calculated which provide guidance on whether modelling for local or global spatial spillovers is appropriate. Following this, the Spatial Durbin Model is specified (SDM; LeSage and Pace, 2009; Elhorst, 2014) using the maximum likelihood method, which introduces an endogenous spatial interaction effect, measured by the spatial lag of the model's dependent variable, and allows for the estimation of direct, indirect, and total effects for each of the model's independent variables. The introduction of the endogenous spatial interaction effect allows the model to observe the degree to which GDA uptake in a particular WPC is effected by the uptake in neighbouring WPCs. The introduction of direct effects allows the model to measure the impact of an independent variable over the dependent variable in a particular area, indirect effects to measure the impact of an independent variable over the dependent variable in neighbouring areas (i.e. a spatial spillover), and total effects to measure the accumulation of direct and indirect effects. Thus, the SDM allows the analysis to consider how GDA activity is both effected by the situations directly present in a particular area and the wider environmental conditions present in neighbouring areas. The structural form of the SDM is reported in Eq. (2).

$$y = \alpha + \beta_s x_s + \beta_p x_p + \beta_f x_f + pWy + \theta Wx + \varepsilon \tag{2}$$

where:

p is a spatial interaction coefficient for the spatially lagged dependent variable
Wy is a vector of observations of the spatially lagged dependent variable
Θ is a vector of coefficients associated with the spatially lagged independent variables
Wx is a vector set of observations of the spatially lagged independent variables

4. Results

4.1. Spatial-temporal analysis

Fig. 4 illustrates the spatial dynamics in the uptake of GDAs across the WPCs of England between September 2013 and June 2015. Substantial geographical variability in GDA uptake is clearly visible. The WPC of the Cities of London and Westminster displays the lowest level of GDA uptake at 0.8 per thousand homes in June 2015. The WPC of Nottingham South (in the Midlands) exhibits the highest level of uptake at 90.9 GDAs per thousand homes. As the uptake of GDAs progresses through the observation period, WPCs in the North of England show relatively higher levels of adoption, especially surrounding some of the large conurbations. In contrast, the South East region displays comparatively low levels of GDA uptake. During the last three observation periods (December 2014 to June 2015), the uptake of GDAs stabilises in terms of the rank order of WPCs. This stabilisation is largely due to the legacy of completed assessments, with new uptake not significantly altering the existing rank of WPCs. One interpretation of this is that lead and laggard local markets for GDAs have been established in the time period where observations of uptake have been taken.

Although a substantial degree of spatial variation in the uptake of GDAs is observable in Fig. 4, it is possible that this variation is random in nature. Spatial autocorrelation analysis helps determine if any degree

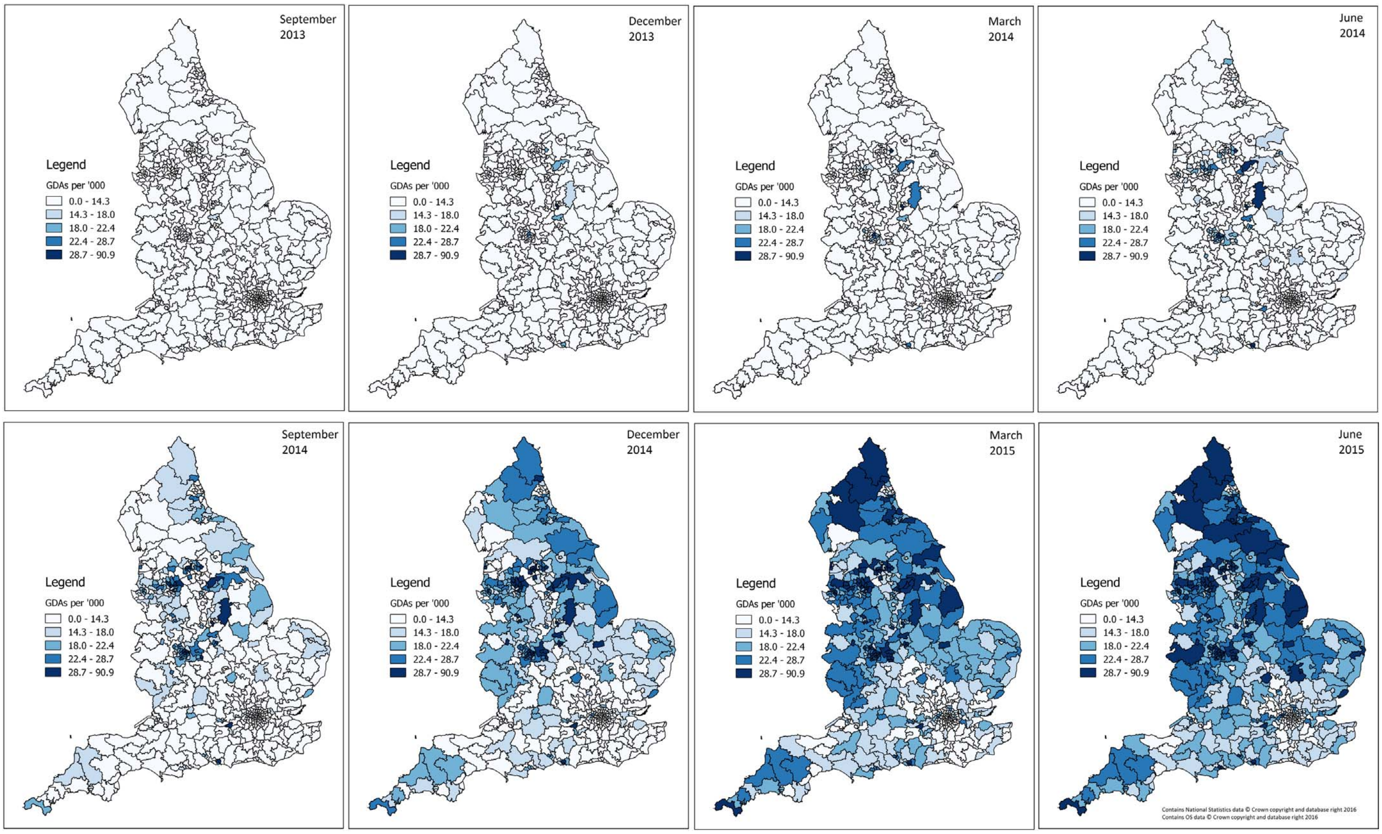

Fig. 4. Choropleth maps illustrating the level of Green Deal Assessments (per 1000 homes) conducted across the Westminster Parliamentary Constituencies of England quarterly from September 2013 to June 2015.

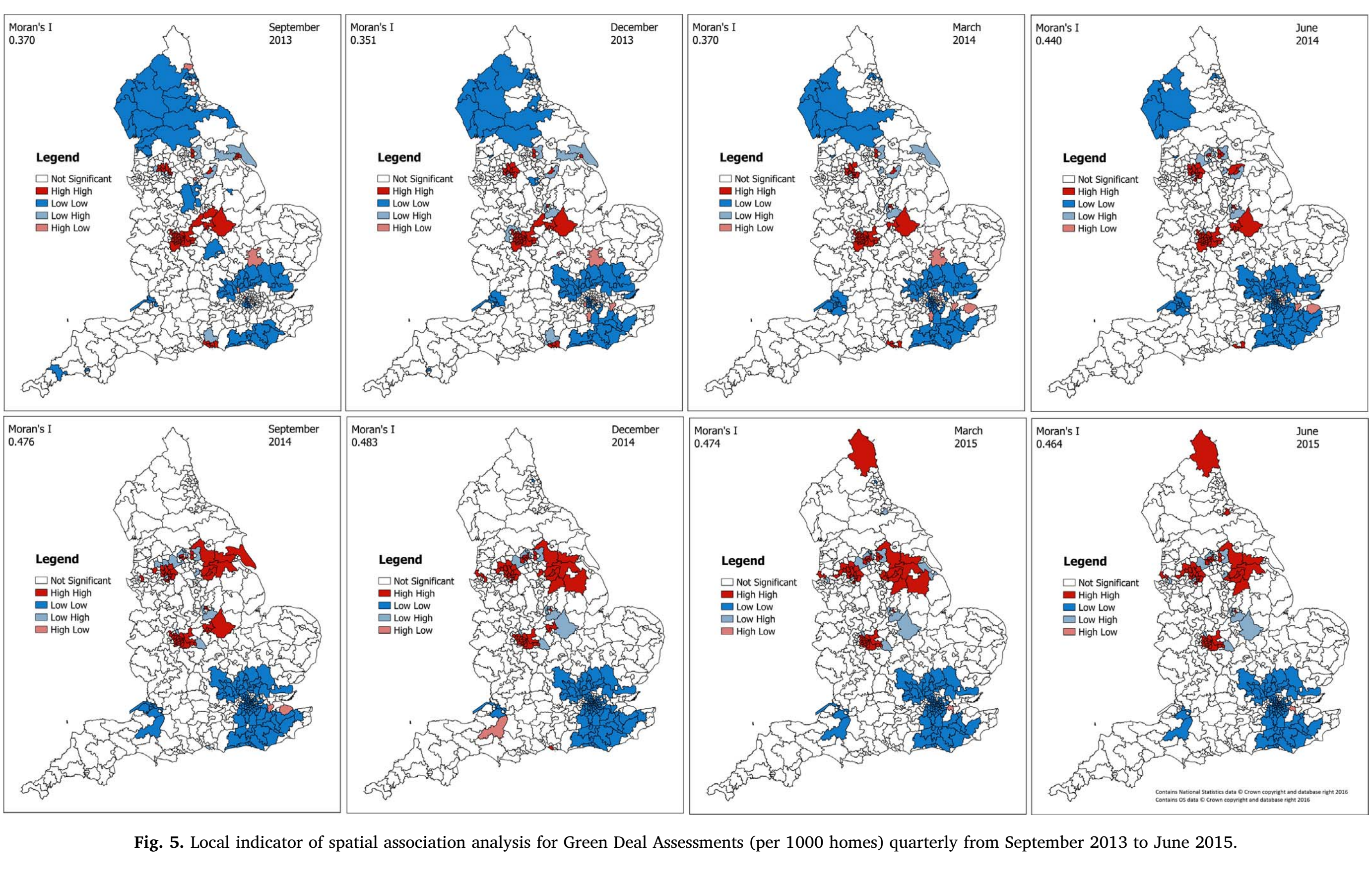

Fig. 5. Local indicator of spatial association analysis for Green Deal Assessments (per 1000 homes) quarterly from September 2013 to June 2015.

of spatial dependence is present in the uptake of GDAs. The results of the Moran's-I test of global spatial autocorrelation and the LISA analysis are displayed in Fig. 5 for all of the observation points. In each instance, Moran's-I returns a statistically significant result (p-value < 0.001), indicating that the uptake of GDAs in a particular WPC tends to be related to the uptake of GDAs in the neighbouring WPCs. The LISA analysis provides additional information concerning the areas which cluster around similar values (e.g. hotspots and coldspots of GDA uptake) and also WPCs which appear to be dissimilar to their neighbours, indicating the occurrence of spatial outliers.

From a visual inspection of the sequential LISAs, it is apparent that regional clusters of similar values (i.e. high-high and low-low) tend to be most prevalent, with the analysis identifying a series of coldspots (deep blue regions) and hotspots (deep red regions). Of particular interest is how these similar regions progress through the observation points. For instance, in the first observation point (September 2013), the North West of England is characterised as a large coldspot, implying that the WPCs contained within this region displayed low levels of GDA uptake when the Green Deal was initially introduced. Over the course of the first four observations, this coldspot gradually reduced and can no longer be observed from September 2014 onwards. This suggests that the North West of England was initially slow in its uptake of GDAs, but over the duration of the first year of the Green Deal, it steadily converged to the national average. In terms of hotspots, a visual inspection of the sequential LISAs illustrates how cities in the North (Liverpool, Manchester, and Leeds) and the Midlands (Birmingham and Nottingham) of England established as lead local markets for the Green Deal policy.

4.2. Funding scheme analysis

Throughout the course of the Green Deal, the DECC made available three different funding schemes to support and accelerate policy implementation. This section evaluates whether WPCs which received funding are significantly different in terms of their uptake of GDAs as compared to WPCs which did not receive funding. Table 5 provides relevant descriptive statistics as well as the results of the Mann-Whitney *U* tests. In terms of the Pioneer Places funding, no significant difference in the uptake of GDAs is observed between those WPCs which are located in local authorities that received funding and those which did not receive funding. For the Green Deal Communities and Core Cities funding, significant differences in the uptake of GDAs are observed, with those WPCs located in local authorities that did receive funding tending to display higher levels of GDA uptake compared to those WPCs which did not receive funding. This finding is consistent with expectations and indicates that the allocation of funding under the Green Deal Communities and Core Cities schemes is associated with increased uptake of GDAs.

Table 5
Descriptive statistics and Mann-Whitney *U* test results for the Green Deal Assessments (per 1000 homes) as of June 2015 across the three funding schemes.

	Mean	Std. Dev.	Min.	Max.
Pioneer Places (U = 11006, p-value = 0.136)				
Recipient (n = 67)	21.533	7.431	4.500	39.000
Non-recipient (n = 392)	20.527	8.888	0.800	73.900
Green Deal Communities (U = 6579, p-value = 0.020)				
Recipient (n = 45)	25.839	13.222	9.500	68.300
Non- recipient (n = 392)	20.527	8.888	0.800	73.900
Core Cities (U = 3250, p-value < 0.001)				
Recipient (n = 28)	28.460	12.840	11.800	64.000
Non- recipient (n = 392)	20.527	8.888	0.800	73.900

4.3. Correlation analysis

The results of the correlation analyses between the uptake of GDAs and the socioeconomic characteristics of the population are presented in Table 6. A number of significant interactions are observed, with GDA uptake displaying moderate to strong (coefficient between 0.3 and 0.7) positive associations with the proportion of cohabiting couples under 35 years old with children (r_s: 0.408), the proportion of the population with no formal qualifications (r_s: 0.521) as well as the proportion of the population classified as unemployed (r_s: 0.338) and in fuel poverty (r_s: 0.421). Moderate to strong negative correlations are observed between GDA uptake and the proportion of the population with a university degree (r_s: −0.504), the proportion of the population classified as self-employed (r_s: −0.417), and the mean personal income of the population (r_s: −0.544). These results indicate that socioeconomic characteristics are associated with initial activity related to energy-efficiency retrofits.

The results of the correlation analyses between the uptake of GDAs and property attributes are reported in Table 7. Moderate to strong positive correlation coefficients are observed between uptake and the proportion of homes categorised as semi-detached (r_s: 0.320) and terraced (r_s: 0.303). A pair of moderate to strong negative relationships are also identified between GDA uptake and the proportion of homes categorised as flats (r_s: −0.363) as well as the percentage of homes sold per annum (r_s: −0.495). These findings suggest that, whilst certain property attributes are clearly associated with GDA uptake, the degree of association tends to be less than that displayed by the socioeconomic characteristics of the population.

4.4. Regression analysis

The results of the benchmark OLS regression model are presented in Table 8. The highest Variance Inflation Factor (VIF) observed is 7.8,

Table 6
Spearman's correlation analysis between Green Deal Assessments (per 1000 homes) and socioeconomic characteristics.

Variable	Coefficient	Variable	Coefficient
Single under 35	−0.007	No qualification	0.521**
Multi-person under 35	−0.224**	High school (GCSE G-D)	0.280**
Cohabiting under 35 with child	0.408**	High school (GCSE C-A*)	0.176**
Single 35–54	−0.099*	Pre-university (A-levels)	0.137**
Multi-person 35–54	−0.105*	University degree	−0.504**
Cohabiting 35–54 with child	−0.082	Part time employed	0.211**
Single 55–64	0.063	Full time employed	−0.374**
Multi-person 55–64	0.069	Self employed	−0.417**
Cohabiting 55–64 with child	−0.114**	Unemployed	0.338**
Single 65 and over	0.085	Retired	0.139**
Multi-person 65 and over	0.035	Fuel poverty	0.421**
Cohabitating 65 and over with child	0.201**	Mean personal income	−0.544**

* : p-value < 0.05.
** : p-value < 0.01.

Table 7
Spearman's correlation analysis between Green Deal Assessments (per 1000 homes) and property attributes.

Variable	Coefficient	Variable	Coefficient
Detached	0.000	Mean number of rooms	0.080
Semi-detached	0.320**	Mean number of bedrooms	0.090*
Terraced	0.303**	House sales per annum	−0.495**
Flats	−0.363**	No central heating	0.190**
Owned outright	0.033	Gas central heating	0.030
Owned mortgage	0.023	Electric central heating	−0.150**
Rent socially	0.062	Oil central heating	−0.012
Rent privately	−0.123**	EPC A to C rating	−0.103*
Mean number of residents	0.108*	EPC D to G rating	0.103*

* : p-value < 0.05.
** : p-value < 0.01.

Table 8
Ordinary least squares regression model results with Green Deal Assessments (per 1000 homes) as the dependent variable.

Variable	Coeff.	T Stat
Constant	0.054**	5.650
Socioeconomics		
% Cohabiting under 35 with Child (ln)	0.234*	2.013
% University Qualification (ln)	0.223*	2.247
% Self Employed (ln)	−0.328**	−3.650
Mean Personal Income (ln)	−1.139**	−5.307
% Fuel Poverty (ln)	0.069	0.661
Property		
% Detached (ln)	0.263**	7.981
% Terraced (ln)	0.058	1.166
Mean Number of Residents (ln)	0.367	1.132
% House Sales per Annum (ln)	−0.557**	−5.763
% Owned with Mortgage (ln)	0.233	1.895
% No Central Heating (ln)	0.041	1.060
% EPC Grade A - C (ln)	−0.334**	−3.731
Funding		
Pioneer Places[a]	0.017	0.462
Green Deal Communities[a]	0.215**	5.275
Core Cities[a]	0.169**	2.766
Model Fit		
R^2 (adjusted)	0.638	
Log Likelihood	2073.903	
Spatial Diagnostics		
Robust Lagrange-Multiplier (lag)	26.126**	
Robust Lagrange-Multiplier (error)	1.254	

* : p-value < 0.05.
** p-value < 0.01.
[a] : dummy variable for which 1 = WPC received funding and 0 = WPC did not receive funding.

with the mean VIF being 3.1. The Robust Lagrange-Multiplier spatial diagnostic tests (Anselin et al., 1996) indicate that the OLS model could be improved through the introduction of an endogenous spatial interaction effect to account for the continued presence of spatial dependence in the model.

The results of the SDM are reported in Table 9. The fit of the SDM is improved relative to the benchmark OLS model. A number of significant direct, indirect, and total effects are identified. Significant and positive direct effects are found for variables measuring the proportion of the population under the age of 35 and cohabiting with children (β_s: 0.241), the mean number of residents per household (β_p: 1.309), and local funding through the Green Deal Communities (β_f: 0.156) and Core Cities (β_f: 0.157) schemes. Significant and negative direct effects are found for mean personal income (β_s: −0.677) and the proportion of properties classified as EPC grade C or above (β_p: −0.260). This means that variation in these variables within a particular WPC tends to affects GDA uptake within that WPC.

Significant and positive indirect effects are found for variables measuring the proportion of the population that have attained a university degree (Θ: 0.881) and the proportion of properties that are detached (Θ: 0.253). Significant and negative indirect effects are found for the proportion of the population that is self-employed (Θ: −0.858) and mean personal incomes (Θ: −1.220). This means that variation in these variables in neighbouring WPCs tends to affect GDA uptake within a particular WPC. In additional to these direct and indirect effects, a significant and negative total effect is found for the variable measuring the proportion of house sales per annum.

To aid with the interpretation of these findings, consider the positive indirect effect of the variable measuring the proportion of population with university degrees. Areas with relatively high proportions of educated residents may have experienced higher levels of energy-efficiency retrofits in the past, as individuals that fit this profile tend to be more interested in energy efficient technologies and behaviours. As a result, mature supply chains for energy-efficiency retrofits may have developed in these WPCs. With this in mind, the observation of an indirect positive effect between the proportion of the population with university degrees and GDA activity could be the result of these mature supply chains stimulating higher levels of GDA activity in neighbouring areas.

The introduction of the spatial lag of the uptake of GDAs in the SDM evaluates whether GDA activity itself exhibits spatial spillovers. The spatial lag is significant (p: 0.510), indicating that the uptake of GDAs in particular WPCs tend to be affected by the levels of uptake in neighbouring WPCs after accounting for the effect of socioeconomic characteristics, property attributes, and local funding schemes. There are various possible interpretations of this result. Households may be observing the level of GDA activity in their vicinity which affects their own propensity to have a GDA. This is consistent with neighbourhood or proximity effects which is a commonly observed form of social influence. Alternatively, the significance of the spatial lag of GDA uptake could indicate the presence of knowledge spillovers. The experiences of households in one WPC may be communicated to other households in their vicinity and stimulate an increase in GDA uptake in neighbouring WPCs. This is further supported by the the DECC's market research on Green Deal uptake, which found that 9.67% of adopters were motivated by a recommendation from friends and family (reported in Table 1). Additional empirical research with GDA adopters would be needed to determine which if any of these effects is most prevalent.

5. Discussion

The growing awareness of geographic process in low-carbon energy transitions represents a new dimension concerning how innovations in technology and policy spread through society (Coenen and Truffer, 2012; Coenen et al., 2012; Raven et al, 2012; Hansen and Coenen, 2015). The results of the analysis presented in this paper support the view that energy transitions are unlikely to occur consistently across space and that it is important to understand the geographical issues at play which condition how energy technologies are received (Balta-Ozkan et al., 2015). Certain environmental contexts may facilitate the diffusion of energy technologies in particular areas as a result of the coupling that occurs between the conditions of the site and the attributes of the technology. Identifying this inter-dependency allows for innovations to be spatially targeted to locations in which they are most likely to succeed.

The recent expansion in the availability of geographically disaggregated datasets which record the uptake of energy technologies is permitting empirical research which considers the association between adoption and environmental context and charts the spatial diffusion of energy innovations. Much of this empirical research concerns the installation of solar photovoltaic systems (Bollinger and Gilligham, 2012; Kwan, 2012; Davidson et al., 2014; Graziano and Gillingham, 2015; Allan and McIntyre, 2017; Dharshing, 2017). As a result, it has been unclear how transferable a spatial diffusion approach is to other energy innovations. The spatial analysis of GDA uptake reported in this paper

Table 9
Spatial Durbin Model results estimating the direct, indirect and total effects with Green Deal Assessments (per 1000 homes) as the dependent variable.

Variable	Direct		Indirect		Total	
	Mean	T Stat	Mean	T Stat	Mean	T Stat
Socioeconomics						
% Cohabiting under 35 with Child (ln)	0.241**	2.249	0.355	1.010	0.596	1.547
% University Qualification (ln)	−0.035	−0.349	0.881**	3.260	0.846**	3.066
% Self Employed (ln)	0.114	1.139	−0.858**	−3.287	−0.743**	−2.696
Mean Personal Income (ln)	−0.667**	−3.037	−1.220**	−2.381	−1.887**	−3.340
% Fuel Poverty (ln)	0.044	0.329	−0.362	−1.657	−0.318	−1.504
Property						
% Detached (ln)	0.080	1.649	0.253**	2.494	0.333**	3.413
% Terraced (ln)	0.035	0.620	−0.039	−0.27	−0.004	−0.028
Mean Number of Residents (ln)	1.309**	3.445	−1.000	−1.007	0.309**	0.302
% House Sales per Annum (ln)	−0.171	−1.470	−0.383	−1.537	−0.554**	−2.158
% Owned with Mortgage (ln)	−0.121	−0.893	0.343	1.023	0.222	0.608
% No Central Heating (ln)	0.027	0.480	0.080	0.804	0.107	1.266
% EPC Grade A - C (ln)	−0.260**	−3.030	−0.160	−0.703	−0.421	−1.702
Funding						
Pioneer Places[a]	0.0425	1.149	−0.096	−0.875	−0.053	−0.466
Green Deal Communities[a]	0.156**	3.627	0.148	1.456	0.304**	2.945
Core Cities[a]	0.157**	2.260	−0.197	−1.054	−0.040	−0.224
Spatial Interaction						
Spatial lag of GDAs (ln) - *p*	0.510**					
Model Fit						
R^2 (adjusted)	0.733					
Log Likelihood	2414.467					

*: p-value < 0.05.
** p-value < 0.01.
[a] : dummy variable for which 1 = WPC received funding and 0 = WPC did not receive funding.

demonstrates that the factor groups covering the socioeconomic characteristics of the population, the attributes of the properties, and the availability of local support mechanisms can act as valid adoption indicators. These factor groups therefore serve as useful initial starting points for research on the spatial diffusion of energy technologies.

Within these factor groups, an array of characteristics prove significant at explaining the spatial heterogeneity in GDA uptake. The socioeconomic characteristics of the population are linked to the capabilities and motivations of households to pursue energy-efficiency retrofits. From the analysis, the variable measuring the proportion of the population that are under 35 years old and cohabitating with children has a positive direct effect on GDA uptake. This result may imply that the importance of age profiles observed in previous studies (Black et al., 1985; Long, 1993; Brechling and Smith, 1994; Nair et al., 2010) might be masking a more complex set of conditions relating to life-stage and household composition which combine to determine how receptive a household is to energy-efficiency retrofits. As this life-stage is linked to the establishment of a family, this result could indicate a more settled domestic life is associated with a heightened propensity to consider investing in energy efficient technologies (Wilson et al., 2013).

Property attributes shape the opportunity for energy-efficiency options identified by GDAs. From the analysis, the variable measuring the proportion of the housing stock classified EPC grade C or above has a negative direct effect on the uptake of GDAs. Areas with a more energy-efficient housing stock are likely to be less suited to Green Deal activity as they may have fewer cost-effective energy-efficiency opportunities. Walker et al. (2013) demonstrate that the spatial uptake of domestic energy-efficiency retrofits may not naturally coincide with the areas that are most in need of intervention for fuel-poverty or other reasons. However, the analysis in this paper shows that GDAs have been less popular in locations which already have relatively high levels of domestic energy-efficiency, implying that this policy has been moderately successful in gaining interest in areas that could benefit from it.

The availability of local funding schemes supports local agents in marketing, administering, and implementing GDAs. From the analysis, the variables measuring the allocation of funds under the Green Deal Communities and Core Cities schemes have positive direct effects over the uptake of GDAs. With the availability of local financial incentives having been linked to increased rates of adoption for solar photovoltaic systems (Kwan, 2012), the findings presented here imply that the provision of resources to allow local agents to pursue strategies which are tailored to the specific circumstances of the areas (such as conducting street-by-street assessments of the housing stock to identify opportunities) can also promote domestic energy-efficiency activity in homes.

While the analysis presented in this paper focuses on the uptake of domestic energy-efficiency assessments, it is possible for future studies to take a similar approach to investigate spatial heterogeneity in the adoption of other low-carbon energy technologies such as electric vehicles and heat pumps. The growing availability of adoption data which contains a locational component is creating opportunities for future research to consider the relevance of socioeconomic characteristics, environmental features, and local support mechanisms for different energy innovations. A significant step forward could be achieved through the specification of spatial-temporal models which would allow for the sequencing and location of events in the diffusion process to be considered. This in turn should provide novel insights regarding the factors that influence the spread of energy technologies.

Additionally, spatial analyses of energy technology adoption could help identify locations of interest for in-depth case studies of the conditions that support early adoption (e.g. in areas displaying distinctly high levels of uptake). For instance, the results of the analysis indicate that local authorities which received support through the Green Deal Communities and Core Cities funding tend to display higher rates of GDA uptake, while local authorities which were involved with the Pioneer Places scheme do not. Follow up case study research could determine the reasons behind the success of the Green Deal Communities and Core Cities funding and provide insights concerning the seemingly ineffectiveness of the Pioneer Places scheme.

6. Policy implications

At a more general level, this analysis of geographical variation in national energy-efficiency policy uptake shows that different areas have different capacities to adopt low-carbon technologies. Understanding why these capacities are different is a necessary first stage in the development of spatially aware policies. With no apparent successor policy to the Green Deal having been proposed by the UK Government, and considerable remaining potential to upgrade the efficiency of the UK household stock (Rosenow et al., 2017), the insights presented in this paper may be of interest to policy makers in their design of future domestic energy-efficiency initiatives which incorporates such a spatial awareness.

As argued in the works of Walker et al., (2013), considering what areas are likely to benefit the most from the implementation of an energy-efficiency policy can be of use in targeting activity in these areas to boost uptake. For instance, communication and marketing campaigns to raise awareness of such policies could be focused on locations with high occurrences of specific types of household or dwelling which are associated with increased interest in domestic energy-efficiency. Such an approach would allocate resources to local areas which are likely to be the most receptive to the policy so that these locations establish themselves rapidly as lead markets, generating the momentum for the policy to become self-sustaining. This could have further benefits through spatial contagion and spillover, as early adopting households communicate their experiences through local networks and stimulate further activity in neighbouring areas.

An alternative spatially-aware approach framed more strongly by concerns over social equity would recognise that some areas have weaker capacities to respond to the policy yet still have an underlying need for energy-efficiency improvement (Reames, 2016; and Grover and Daniels, 2017). Consequently, resources may be targeted at these areas to ensure they are not marginalised from policy activity. As an example, areas with a high degree of churn in property markets, indicating shorter home tenures and less settled households, tend to have lower rates of GDA uptake, despite the Green Deal having been designed to mitigate this barrier (by linking Green Deal finance repayments to the property, not the household). The allocation of resources to raise the salience of the Green Deal in these areas may help address this persistent issue (Pettifor et al., 2015). Alternatively, the Green Deal may be incentivised through grants to would-be buyers of properties on the market which would benefit from energy-efficiency upgrades (e.g. properties rated EPC D or lower).

Additionally, understanding that transition capacities are unlikely to be spatially uniform can be useful in policy monitoring and evaluation by allowing the setting of targets to account for the particular conditions which may constrain or promote uptake across different spatial contexts. For instance, the expectations for uptake in a region which has a relatively low proportion of cohabiting couples under the age of 35 with children, high levels of personal income, a low proportion of detached homes, a high proportion of household sales, and a high proportion of homes classified as EPC band C or above (all factors which significantly diminish GDA uptake) could be set lower than a region with the opposite conditions for these characteristics. In order for such assessments to occur, governments will need to ensure that accurate spatial data is collected and made publicly available throughout the course of future energy policies.

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