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**Research Report**

## Spatial characteristics to explain residential photovoltaic adoption intentions: An exploratory analysis

Beiträge des Instituts für Infrastruktur und Ressourcenmanagement, No. 01/2023

**Provided in Cooperation with:**

Institute for Infrastructure and Resources Management, University of Leipzig

*Suggested Citation:* Schulte, Emily; Bruckner, Thomas; Scheller, Fabian (2023) : Spatial characteristics to explain residential photovoltaic adoption intentions: An exploratory analysis, Beiträge des Instituts für Infrastruktur und Ressourcenmanagement, No. 01/2023, Universität Leipzig, Institut für Infrastruktur und Ressourcenmanagement (IIRM), Leipzig

This Version is available at:

<https://hdl.handle.net/10419/278114>

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# UNIVERSITÄT LEIPZIG

Wirtschaftswissenschaftliche Fakultät  
Faculty of Economics and Management Science

## **Spatial characteristics to explain residential photovoltaic adoption intentions: An exploratory analysis**

Emily Schulte, Thomas Bruckner, Fabian Scheller

**01/2023**



Beiträge des Instituts für Infrastruktur und Ressourcenmanagement  
Contributions of the Institute for Infrastructure and Resources Management

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Nr. 01/2023  
ISSN 2364-4346  
<http://www.econstor.eu/escollectionhome/10419/107939>

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# Spatial characteristics to explain residential photovoltaic adoption intentions: An exploratory analysis

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Despite their relevance for adoption levels in spatial analyses, previous studies on adoption intention excluded measures characterizing the living environment of participants such as population density and previous photovoltaic (PV) installations so far. To fill this gap, this study was designed to investigate relations between residential PV adoption intention and characteristics of the living environment of respondents. A quantitative survey was performed on a representative sample of 1,800 homeowners in Germany and matched with registered spatial characteristics on the zip-code level. The Mann-Whitney U test was used to compare the adoption intention between groups with low and high expressions of the independent variables with the total sample, and with consumer segments using the Sinus-Milieu model. The results for the total sample demonstrated that actual PV diffusion, population density, city-type and share of (semi-) detached houses are not significantly related to the individual adoption intention, whereas perceived diffusion is. Two milieu groups showed higher intentions with lower actual PV diffusion in their spatial environment, and two groups revealed higher intentions along with relatively higher incomes. Perceived diffusion is only weakly related to actual diffusion levels, implying a gap between reality and perceptions. Overall, the results imply that spatial characteristics on the zip-code level are not related to individual adoption intention, whereas the perceived presence of PV systems in the social and spatial environment positively influences adoption intention.

# 1. Introduction

Residential uptake of rooftop PV systems has been researched widely in order to better understand who adopts a PV system for what reason, and to design suitable intervention strategies to push adoption levels. Yet, adoption in the household sector is not meeting ambitious governmental goals (BMWi 2022), despite increasingly positive attitudes toward PV, and continued government incentives (Alipour et al. 2021). In addition, great interest in the future spatial distribution of residential PV systems emerged, resulting in spatial analyses where adoption levels in spatial units such as zip-codes are investigated, see, e.g. (Richter 2013; Groote et al. 2016).

In such analyses, spatial characteristics like population density, share of (semi-) detached houses and previous installations have been proven useful to explain local adoption levels (see, e.g., Schulte et al. 2022a). These explanatory variables deviate greatly from what is used in typical consumer surveys. In consumer surveys, variables like subjective evaluations of the product, perceived social norm, and attitudinal variables of individuals towards the environment and novel goods have been predominantly investigated to explain PV adoption intentions (Schulte et al. 2022b; Schulte et al. 2022c; Vibrans et al. 2022). Unfortunately, the so-called intention behavior gap - stating that intentions are not necessarily translated into behavior, and that factors affecting intention are not necessarily equivalent to factors affecting behavior (Arts et al. 2011; Ajzen 2020) - complicates the transfer of such study results to meaningful policy measures. Do variables that relate to adoption intentions relate to adoption behavior in a similar way and vice versa? To adequately demonstrate the either changing or stable strength of variables and their effect on the evolving intention and finally, the individual behavior, reoccurring studies must be performed. As this endeavour requires time and large financial resources, we propose to explore previously untapped opportunities to bridge the gap between intention and behavior. Characteristics of the spatial environment of individuals are not subject to measurement errors, are typically stable, and are easily accessible. Therefore, it is of great interest to know, whether they are not only related to residential rooftop PV adoption levels and thus the actual behavior, but also to the stated intention to adopt a residential rooftop PV system. To our knowledge, no studies investigating relations between objective measures characterizing the spatial environment and adoption intentions exist until today. Under the umbrella term peer effects, Scheller et al. (2022b) and Mundaca and Samahita (2020) investigate relations between the reported level of diffusion in spatial and social environment and PV adoption intention, revealing positive relations. However, both studies did not assess whether the subjective level of diffusion is related to the actual, objective level of diffusion. Barnes et al. (2022) relate reported values of word of mouth and seeing PV systems to actual diffusion rates

in Las Vegas Valley. Whilst current adopters in regions with relatively high adoption rates report significantly higher values in word of mouth and seeing PV systems, potential adopters in lower diffusion areas report higher values concerning seeing PV systems than potential adopters in higher diffusion areas. As such, we hypothesize that (H1) *spatial characteristics that relate to adoption levels in spatial units are also associated with individual adoption intentions*. We moreover assess whether (H2) *subjective diffusion levels relate to objective diffusion levels*, because as initially indicated by Barnes et al. (2022), it cannot simply be assumed that the subjective perception corresponds to reality.

In addition, recent studies on residential PV adoption demonstrated that consumer segments, represented by Sinus Milieus, provide more robust insights than studies using single or multiple household characteristics as predictors, given that the latter approach neglects the complex, interacting role of background factors such as demographic and socioeconomic characteristics, life values and personality traits (Scheller et al. 2022b; Vibrans et al. 2022; Schulte et al. 2022a). Vibrans et al. (2022) could show that Sinus Milieus not only express different intentions to adopt PV systems, but the strength and effect of explanatory variables differ significantly across the segments. The spatial analysis of Schulte et al. (2022a) revealed associations between PV saturation and the presence of Sinus Milieus overall and in (semi-) detached houses. Interestingly, the milieus with the highest stated intention were not related positively to PV saturation, pointing at the intention behavior gap (Arts et al. 2011; Ajzen 2020). Against this background, we furthermore hypothesize that (H3) *the relations between spatial characteristics and adoption intentions vary across Sinus Milieus*.

This study presents an innovative contribution towards a better understanding of the gap between reported adoption intentions and actual adoption behavior by combining data from a large-scale consumer survey on PV adoption intention (n=1,800) with online registered data on the zip-code level. The results for the total sample show that actual PV diffusion, density, city-type and share of (semi-) detached houses are not related to the individual adoption intention (H1), implying that variables relating to adoption levels in spatial analyses do not correspond to adoption intentions. We demonstrate that the perceived diffusion in social and spatial environment positively relates to adoption intentions, but is hardly related to actual diffusion levels in the zip-code of the respondent (H2). This implies that individuals with a higher adoption intention also subjectively perceive more PV systems in their spatial and social environment, even if they objectively don't generally have more systems in their zip-codes. Lastly, challenging our third hypothesis, only few differences between milieu groups concerning the relations between the assessed explanatory variables and adoption intention could be detected.

## 2. Literature

### 2.1. Spatial variables affecting PV saturation

A central role in PV adoption research plays the influence of peers. In spatial analyses, proximate prior installations have been found to positively affect adoption rates (Bollinger and Gillingham 2010, 2012; Richter 2013; Müller and Rode 2013; Crago and Chernyakhovsky 2014; Graziano and Gillingham 2015; Balta-Ozkan et al. 2015; Rode and Weber 2016; Rode and Müller 2018; Kosugi et al. 2019; Baginski and Weber 2019). Such peer effects appear to decrease with increasing distance (Bollinger and Gillingham 2012; Müller and Rode 2013; Graziano and Gillingham 2015; Rode and Müller 2018; Kosugi et al. 2019). In this context, Wolske et al. (2020) criticize that clustering of behaviors does not necessarily demonstrates peer effects, as the clustered behavior could also appear simply because the individuals "live in a neighbourhood of environmentally-concerned households" and were buying the same product anyway.

In consumer surveys, positive associations between perceived social norm and adoption intention have been identified frequently, see e.g. Wolske et al. (2017), Abreu et al. (2019) and Engelken et al. (2018). However, a perceived social norm is subjective, and must not go along with higher diffusion rates in the neighborhood. It thus appears presumptuous to compare observed peer effects in spatial analyses with effects of social norms in consumer surveys. Results of the study by Mundaca and Samahita (2020) suggest, that in general, hearing about PV systems is more relevant for the adoption likelihood than only seeing PV systems. If the owner of a PV system is known, both hearing about and seeing the system positively affect adoption likelihood. That the active peer effect (interacting with peers about PV systems) has a higher influence on the adoption decision than the passive peer effect (visibility of PV from peers) is also discussed in, e.g., Scheller et al. (2022a), Scheller et al. (2022b) and Scheller et al. (2021). However, the results of the studies rely on self-reported and thus subjective numbers and frequencies, whilst the actual saturation of PV systems in the spatial proximity of respondents is unknown, making it difficult to relate these results to spatial analyses. In our analysis, we include the **perceived diffusion in the social network** and the **perceived diffusion in the spatial environment**, and the actual saturation of residential PV systems in the zip-code of respondents, represented by **registered residential PV systems per 1000 inhabitants** and **registered residential PV systems per km<sup>2</sup>**.

A clear trend concerning the adoption rate of PV systems in spatial studies emerges concerning population density. The denser a region is populated, the lower the adoption rate of PV systems (Bollinger and Gillingham 2012; Crago and Chernyakhovsky 2014; Graziano and Gillingham 2015; Balta-Ozkan et al. 2021; Groote et al. 2016; Kosugi et al. 2019; Baginski and Weber 2019;

Thormeyer et al. 2020; Balta-Ozkan et al. 2015), pointing towards an urban-rural divide. This finding goes along with the results of Schulte et al. (2022a), Balta-Ozkan et al. (2015), Baginski and Weber (2019) and Balta-Ozkan et al. (2021), suggesting that adoption rates in spatial units are fostered by the share of detached and semi-detached houses. To quantify the relation between these variables and adoption intention, we include self-reported **city-type** and **share of (semi-) detached houses**, and the actual **population density** of the zip-code in the analysis.

Spatial analyses deliver mixed results concerning the relation between average household incomes and adoption rates. Focussing on the average income of residents of (semi-) detached houses, presuming that they are the decisive households who have the possibility to adopt a PV system, Schulte et al. (2022a) showed that higher incomes among potential adopters are positively related to PV saturation. We, therefore, investigate the relation between **monthly household income** and PV adoption intention.

## 2.2. The Sinus-milieu model and PV adoption

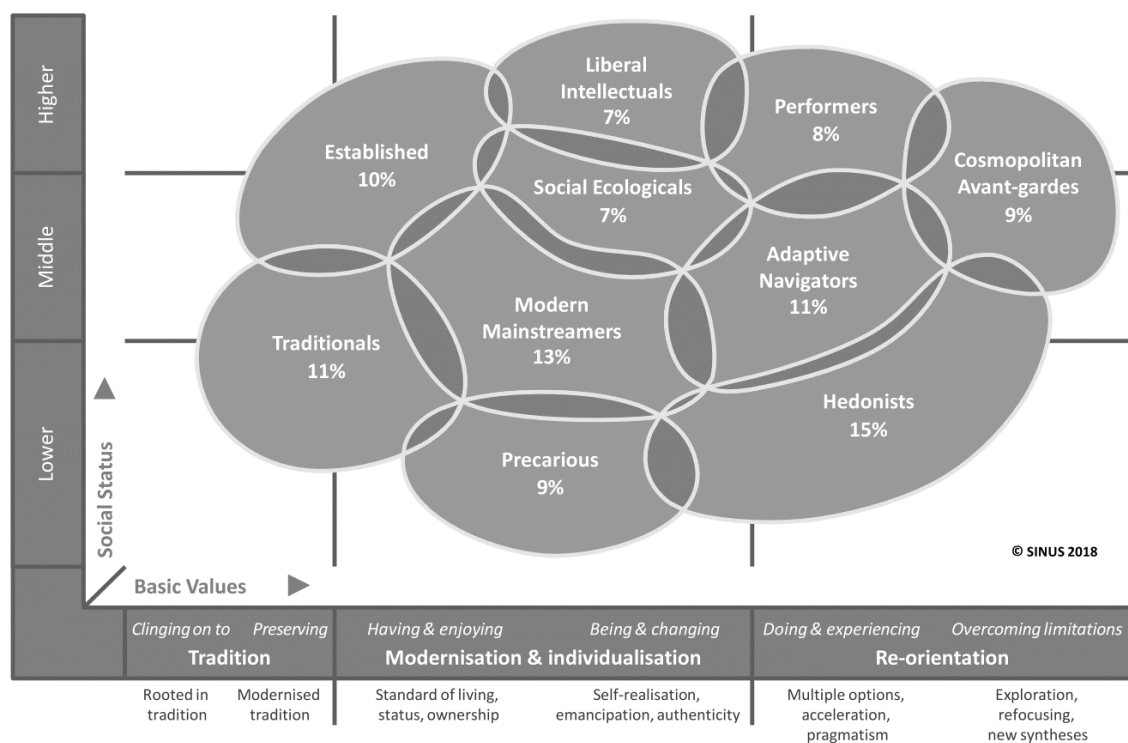
The Sinus-milieu model is one of the most established German market segmentation models (Soyez et al. 2012; VuMa Arbeitsgemeinschaft 2021). Sinus-milieus consist of humans that share a similar lifestyle and outlook on life by considering general value orientation as well as attitudes towards work, family, recreation, money and consumption (Flaig and Bertram Barth 2014). The segmentation is based on two dimensions, social status and value orientation (Balderjahn and Scholderer 2007), and encompasses 10 milieus in the version of 2018 (Tautscher and Flaig 2018) that are shown in Figure 1. Given that the focus group discussions on PV adoption decisions presented in Scheller et al. (2021) revealed influences of decision-maker traits such as risk-aversion and knowledge, and the social environment, the holistic Sinus-milieu model can be a mean to analyze the intentions and behavior of relatively homogeneous groups of people. In addition, a higher influence of like-minded peers on PV decision-making compared to other peers was shown by Scheller et al. (2022b) with a quantitative survey across potential and actual adopters, pointing at the relevance of the presence of members of the own or related milieus in the spatial proximity of potential adopters.

Research on Sinus-milieus could show differences in their intention and behavior towards eco-innovations (Gellrich 2016; Schwarz 2007; Gröger et al. 2011). Concerning PV adoption, Profijt (2010) showed that predominantly the Established, Hedonists and Experimentalists had adopted solar until 2010, whereas Gellrich (2016) reveal highest interest in adopting PV across Post-Materialists and Hedonists. A recent analysis of PV adoption intention demonstrates, that milieus not only differ in their adoption intention, but that the strength and effect size of explanatory variables also differs across milieus, indicating that the behavior of people with



different lifestyles is driven or hindered by different considerations (Vibrans et al. 2022) as has been suggested by, e.g. Schulte et al. (2022b). Whereas the analysis of Vibrans et al. (2022) reveals that leading milieus (Performers and Cosmopolitan avant-gardes) report the highest adoption intention, the spatial analysis of Schulte et al. (2022a) shows a negative relation between the presence of leading milieus and PV saturation, pointing at the intention behavior gap. Further insights into the role of Sinus-milieus for PV adoption are thus required. In this analysis, we assess whether the relations between spatial characteristics and adoption intention vary across milieus.

Figure 1 The Sinus-milieu model of 2018, adapted from (Tautscher and Flaig 2018)



As proposed by Koppelman (2006) and applied by Schwarz (2007), Gröger et al. (2011), Gellrich (2016) and Vibrans et al. (2022), we use milieu groups for further analysis. Based on the prior classifications of the Sinus-milieus of 2018 in (Vibrans et al. 2022) and (Schulte et al. 2022a), we use five milieu groups: The Liberal Intellectuals and Social Ecologicals share attitudes towards the environment and consumption, and are thus defined as “Post-Materialists” (PM). Modern Mainstreamers and Adaptive Navigators aim to balance individual and social needs, thus considering climate change an important topic as long as their freedom is not restricted. They are considered “Mainstreamers” (MAIN). Milieus of the low social class (Traditionals, Precarious and Hedonists) share an orientation towards a status quo and are not particularly interested in climate protection - albeit for different reasons – and are classified “Deprived” (DEP). The milieus of the higher social class are separated in two groups, presuming that the Established are less

innovative than Performers and Cosmopolitan Avant-gardes. We thus classify Performers and Cosmopolitan Avant-gardes as “Leaders” (LEAD) and analyze the “Established” (EST) separately.

### 3. Methodology

#### 3.1. Questionnaire design

A large-scale quantitative survey was performed to quantify individual adoption intentions and self-reported information on the spatial environment of respondents. An English translation of the relevant questions in the questionnaire is provided in Appendix A. A screener ensured, that only individuals who are potential adopters of a PV system (no current ownership of PV, awareness of PV, (partly) responsible for household investment decisions, resides in (semi-) detached house, aged between 18 and 75) participate in the survey. *Adoption intention* was measured with a single indicator using a 7-point Likert scale, with 1 = very weak and 7 = very strong. The *perceived diffusion in the social network* was measured with a single question with an ordinal format, with 1 = none, 6 = 13 or more PV systems and 7 = don’t know. *Perceived diffusion in the spatial environment* was measured with two questions, first asking whether the respondents regularly see rooftop PV systems in their everyday lives (binary format). In case of a positive answer, the respondent was further asked to quantify the number (1 = 1-3 and 5 = 13 or more). Thereafter, respondents were asked to characterize their place of residence by answering ordinal questions about the *city-type* (1 = rural community and 7 = major city) and the *share of (semi-) detached houses* (1 = many and 3 = few). Lastly, socio-demographic variables including *household income* in single choice format were queried. In addition, the *milieu* was measured using the polarizing standardized multi-item scale (4-point Likert scale) developed by SINUS Marktforschung GmbH (c.f Flaig and Bertram Barth 2014).

#### 3.2. Data collection and data merge

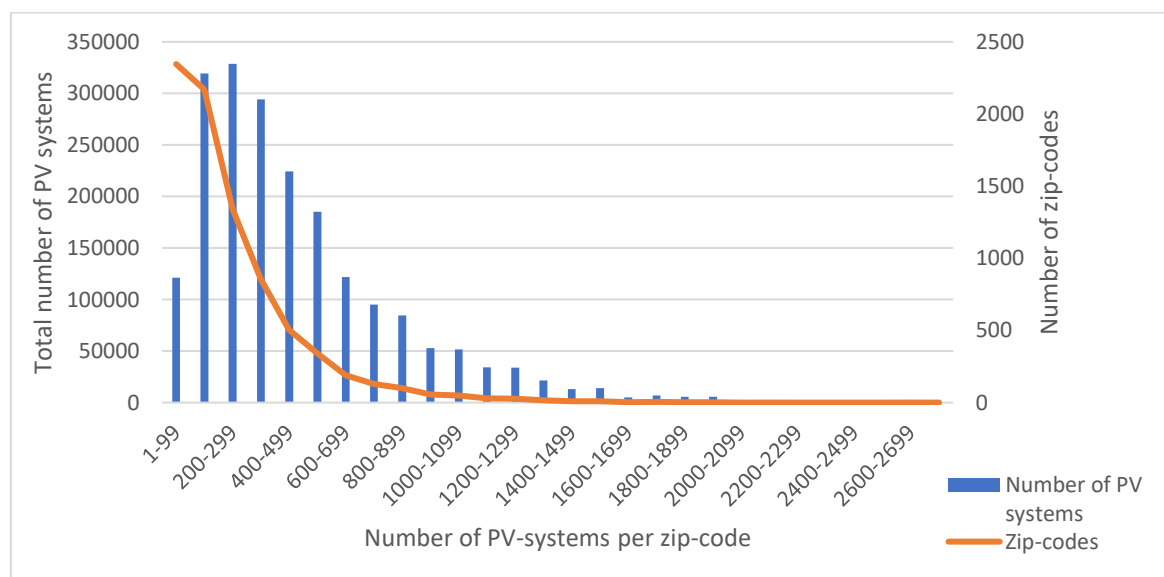
The survey represented a web survey with a sample of German homeowners. The sample was sourced from the respondi Online Access Panel using a specialised sampling tool that makes a random selection of potential participants. The data collection, quality control and testing were overseen by SINUS Markt- und Sozialforschung - a German market research company. A linguistic and cognitive pretest of the questionnaire was performed with 53 participants, resulting in revisions and modifications. Data collection took place in May 2021, and 1,800 questionnaires with full responses were provided. The median time for completing the questionnaire was 16 minutes with a dropout rate of 3.33 %.

To assess associations between spatial characteristics and adoption intentions not only relying on perceptions of the respondents, survey data was also enriched with data on the zip-code level accessible online.

Data on *actual PV adoption* was retrieved from the Marktstammdatenregister (MaStR)<sup>1</sup>, a German nation-wide register of power assets and their location. Before May 2021, 2,098,643 PV systems had been installed in Germany. Of these, 74,504 were not assigned to a zip-code in the database, and thus excluded from the analysis. Using the collapse command in Stata 14.2, the number of PV installations per zip-code was calculated and exported to an Excel file. PV systems are installed in every zip-code in Germany, with the number of the PV installations ranging from 1 – 2,625 per zip-code. 2346 zip-codes with 1-99 installed systems make up the largest group, followed by 2170 zip-codes with 100-199 systems and 1338 zip-codes with 200-299 systems. Higher numbers of PV systems are installed in increasingly fewer zip-codes, as shown by the decreasing orange line in Figure 2. The largest total number of PV systems is installed in zip-codes with between 200 and 299 PV systems (see blue bar in Figure 2).

Data on the *number of inhabitants* and the *size* of the zip-codes was retrieved from a database on German zip-codes<sup>2</sup> in Excel format, providing information on 8170 zip-codes. The average zip-code covers an area of roughly 44 km<sup>2</sup> and is inhabited by 9,800 inhabitants.

Figure 2 Number of zip-codes (orange line) and total number of PV systems (blue bar) per group. Groups relate to the number of PV systems in a zip-code, e.g. 1-99 systems, 100-199 systems.



The survey dataset was combined with the zip-code specific number of PV systems, zip-code size in km<sup>2</sup> and number of inhabitants in Excel, using the zip-code as key. Thereafter, relative

<sup>1</sup> <https://www.marktstammdatenregister.de/MaStR/Einheit/Einheiten/OeffentlicheEinheitenuebersicht>

<sup>2</sup> <https://www.suche-postleitzahl.org/downloads>

measures for *population density* (inhabitants/km<sup>2</sup>) and *PV saturation* (PV systems/km<sup>2</sup> and PV systems/1000 inhabitants) were calculated. Table 1 summarizes the dependent and independent measures.

*Table 1 Description of dependent and independent variables*

Measure	Variable	Range	Source	Note
Adoption intention	INT	1-7	Survey	1 = very weak, 7 = very strong
Perceived diffusion in social network	DSOC	1-6	Survey	1 = None, 6 = 13 or more
Perceived diffusion in spatial environment	DSPA	1-6	Survey	1 = None, 6 = 13 or more
Share of (semi-) detached houses	SDH	1-3	Survey	
City-type	CT	1-7	Survey	
Population density	DENS	18.6-18,880.0	Online	Inhabitants/km <sup>2</sup>
PV system per 1000 inhabitants	PVIN	0.2-232.8	Online	PV systems/1000 inhabitants
PV systems per km <sup>2</sup>	PVKM	0.4-96.7	Online	PV systems/km <sup>2</sup>
Monthly household income	INC	1-13	Survey	

### 3.3. Sample

The proportion of women and men in the sample was almost equal (52.8 % and 47.2 %, respectively) and most of the respondents were married (67.8 %). More than half of the participants were between the ages of 40 and 69 (63.5 %). The other participants were between the ages of 18 and 39 (26.7 %) and 70+ (9.8 %). Most of the respondents had either secondary (29.9 %) or higher education (57.7 %) background and were from western (32.7 %) or southern (30.1 %) Germany. A more detailed description of the sample regarding socio-demographics overall and per milieu group can be found in (Vibrans et al. 2022).

To test for representativeness, the sample was compared with structural data on German homeowners available in the best for planning tool (b4p)<sup>3</sup>. Six one-sample  $\chi^2$ -Tests were performed, showing representativeness in terms of gender ( $\chi^2 = .04$ ;  $p = .850$ ), state ( $\chi^2 = 13.31$ ;  $p = .578$ ) and age group ( $\chi^2 = 8.5$ ;  $p = .131$ ). Significant differences were observed for family status ( $\chi^2 = 284.02$ ;  $p < .001$ ), education ( $\chi^2 = 558.24$ ;  $p < .001$ ) and Sinus-Milieu ( $\chi^2 = 218.02$ ;  $p < .001$ ). Inconsistencies in family status and education can be explained by departing operationalizations of the variables. Deviations in the Sinus-Milieu were in line with the researcher's expectations. Detailed results for the tests are presented in (Vibrans et al. 2022).

An overview of mean, standard deviation, minimum and maximum value and N concerning the variables of concern per milieu group and for the total sample is provided in Table 2. In each column, the highest and lowest values are printed bold. Leaders report the highest, and

<sup>3</sup> <https://mds.mds-mediaplanung.de/>

Deprived the lowest adoption intention, and perceived diffusion in the social and spatial environment. Leaders moreover report the lowest share of (semi-) detached houses, whereas Established report highest shares. Post-Materialists tend to reside in rather urban areas, whereas Mainstreamers predominantly live in rural regions. Post-Materialists have the lowest PV density per 1000 inhabitants in their zip-codes, together with the Deprived, whilst in the zip-codes of Mainstreamers, roughly 4 PV systems are found per 1000 inhabitants. Opposingly, the PV density per km<sup>2</sup> is highest for Post-Materialists, and lowest for the Deprived. Highest monthly income is earned in the milieu group of Leaders, whilst the Deprived earn the least.

*Table 2 Descriptive overview over total sample distribution and milieu groups*

		INT	DSOC	DSPA	SDH	CT	DENS	PVIN	PVKM	INC
Post-Materialists	Mean	3.24	2.03	3.21	1.37	<b>3.27</b>	855.7	<b>28.5</b>	<b>10.6</b>	3780.1
	Sd	1.90	0.95	1.31	0.50	2.07	1283.1	24.6	9.0	1429.3
	Min	1	1	1	1	1	19.5	0.3	0.5	1000
	Max	7	6	6	3	7	12,335.4	165.1	96.7	6500
	N	473	452	473	473	473	473	473	473	473
Mainstreamers	Mean	3.35	1.97	3.16	1.36	<b>2.75</b>	<b>744.0</b>	<b>32.6</b>	9.7	3432.5
	Sd	1.93	0.92	1.35	0.51	1.98	1475.4	28.5	7.7	1427.8
	Min	1	1	1	1	1	22.8	0.4	0.5	1000
	Max	7	6	6	3	7	18,114.7	178.3	49.7	6500
	N	364	340	364	364	364	364	364	364	364
Deprived	Mean	<b>2.98</b>	<b>1.90</b>	<b>2.94</b>	1.38	3.05	876.8	<b>28.5</b>	<b>9.2</b>	<b>3065.1</b>
	Sd	1.89	0.89	1.26	0.56	1.98	1771.7	26.4	7.3	1300.5
	Min	1	1	1	1	1	32.7	0.4	0.4	1000
	max	7	6	6	3	7	18,880.0	152.6	43.8	6500
	N	297	277	297	297	297	297	297	297	297
Established	mean	3.15	2.05	3.05	<b>1.40</b>	3.06	<b>928.7</b>	31.2	10.5	3630.9
	sd	1.75	0.98	1.24	0.52	2.03	1596.2	30.0	8.4	1441.9
	min	1	1	1	1	1	20.5	0.3	0.6	1000
	max	7	6	6	3	7	12,742.4	232.8	79.0	6500
	N	297	276	297	297	297	297	297	297	297
Leader	mean	<b>3.52</b>	<b>2.10</b>	<b>3.24</b>	<b>1.34</b>	3.21	901.0	29.2	9.9	<b>3795.9</b>
	sd	1.86	0.95	1.35	0.51	2.01	1593.8	27.3	7.0	1432.9
	min	1	1	1	1	1	18.6	0.2	0.5	1000
	max	7	6	6	3	7	16,357.7	173.3	50.6	6500
	N	369	357	369	369	369	369	369	369	369
Total	mean	3.26	2.02	3.14	1.37	3.08	857.9	29.9	10.0	3570.4
	sd	1.88	0.94	1.31	0.52	2.03	1526.6	27.2	8.0	1434.0
	min	1	1	1	1	1	18.6	0.2	0.4	1000
	max	7	6	6	3	7	18,880.0	232.8	96.7	6500
	N	1800	1702	1800	1800	1800	1800	1800	1800	1800

### 3.4. Statistical analysis

We initially investigate correlations between the variables of interest. For interpreting correlations, we refer to Cohen's guidelines for Pearson correlation coefficients, stating that correlations between .1 and .3 are small, between .3 and .5 are medium, and above .5 are large (Cohen 1988). Thereafter, tests of hypothesis for hypotheses 1 and 3 were performed in Stata 14.2. The dependent variable is the PV adoption intention. As the hypotheses suggest systematic

differences in adoption intention between respondents with different expressions of spatial characteristics of their living environment (H1), and differences among these relations between milieu groups (H3), a test of difference between two independent groups is required (Bortz and Schuster 2016). Groups are defined through dummy variables, splitting the total sample at the median value of the respective independent variable, and splitting each milieu group at its median value of the respective independent variable. For the variable city-type, we split the sample into rural and urban communities with a binary variable, defining cities with > 100.000 inhabitants as urban communities. An overview over group sizes and ranges is provided in Table 5 in Appendix B. Boxplots and the Shapiro-Wilk test for normality (Stata Corp.) revealed that the dependent variable PV adoption intention is not normally distributed in all groups. In line with this, the two-sided non-parametric Mann-Whitney U (or Wilcoxon rank-sum) test is performed (Bortz and Schuster 2016; Stata Corp.). A variance comparison test (Stata Corp.) revealed inequality of variance in the dependent variable among the groups. Therefore, the Mann-Whitney U test is not suited to compare the equality of medians, but to assess whether there is an equal probability that a randomly selected observation of one group is bigger or smaller than a randomly selected observation of the other group (Bortz and Schuster 2016).

In Stata 14.2, the Mann-Whitney U test provides a z-score and p-value, indicating whether there is a significant effect, and the probability that a draw from the first population is larger than a draw from the second population. To determine whether the effect is small or large, we additionally calculate the effect size statistic  $r$  based on the z-score and the sample size  $n$ :

$$r = \left| \frac{z}{\sqrt{n}} \right|$$

Negative z-scores go along with negative  $r$  values and a drawing probability < .5. In the case of a significant p-value (based on a significance level of 5 %), this indicates that the first group (below and at median of independent variable) is associated with smaller values of the dependent variable than the second group (above median of independent variable). The effect size statistic is interpreted based on Cohen (1988), specifying that  $r > .10$  indicates a small,  $r > .30$  a medium and  $r > .50$  a large effect. For example, the probability that a draw from the subgroup with lower perceived diffusion in the social network (independent variable) has a higher PV adoption intention (dependent variable) than a draw from the subgroup with higher perceived diffusion in the social network is 36 % (see Table 4). The effect size is of medium size, and the p-value indicates significance. Thus, we can conclude that PV adoption intention is higher among respondents who report a higher diffusion in their social network.

#### 4. Results

#### 4.1. Correlation analysis

In our dataset, only three small correlations between investigated variables and adoption intention can be detected (see Table 3). *Perceived diffusion in the spatial environment* (DSPA) ( $r = .258$ ), *perceived diffusion in the social network* (DSOC) ( $r = .232$ ) and *population density* (DENS) ( $r = .101$ ). Interestingly, the *perceived diffusion in the social network* and *spatial environment* are only weakly correlated with *PV installations per 1000 inhabitants* (PVIN) ( $r = .197$  and  $r = .192$ , respectively), and not correlated with *PV installations per km<sup>2</sup>* (PVKM). In the dataset, the *city-type* (CT) is strongly related to *population density* ( $r = .589$ ), has a strong negative correlation with *PV systems per 1000 inhabitants* ( $r = -.510$ ), but a positive correlation of medium size with the number of *PV systems per km<sup>2</sup>* ( $r = .367$ ). In addition, a small correlation between *city-type* and *share of (semi-) detached houses* (SDH) is observed ( $r = .289$ ). This suggests that urban environments are typically more densely populated and have lower shares of (semi-) detached houses, resulting in larger numbers of PV systems per km<sup>2</sup>, but smaller numbers of PV systems per 1000 inhabitants as compared to rural environments. Despite urban residents should consequently see PV systems in their everyday life more often, the perceived diffusion in the spatial environment is not related to the city-type.

Hypothesis 2, stating that subjective diffusion levels relate to objective diffusion levels is partly confirmed. Whilst the subjective diffusion measures *perceived diffusion in the social network* and *perceived diffusion in the spatial environment* are slightly related to the objective number of *PV systems per 1000 inhabitants*, it is uncorrelated to *PV systems per km<sup>2</sup>*. However, the relation is very small, indicating that subjective measures are no reliable proxy for real PV diffusion levels.

Table 3 Correlation matrix displaying Pearson's  $r$  with significance levels. \*\*\* $p < .001$ ; \*\* $p < .01$ ; \* $p < .05$

	INT	DSOC	DSPA	SDH	CT	DENS	PVEW	PVKM
DSOC	<b>0.232***</b>							
DSPA	<b>0.258***</b>	0.427***						
SDH	0.014	-0.010	-0.040					
CT	0.052*	-0.080***	-0.090***	0.289***				
DENS	<b>0.101***</b>	-0.00	-0.050*	0.213***	0.589***			
PVEW	0.009	0.197***	0.192***	-0.180***	-0.510***	-0.370***		
PVKM	0.014	0.031	0.076**	0.153***	0.367***	0.324***	0.011	
INC	0.096***	0.051*	0.094***	-0.010	0.169***	0.122***	-0.060***	0.082***

#### 4.2. Test results

The Mann-Whitney U test revealed a significant positive association between *perceived diffusion in the social network* and the *spatial environment* and adoption intentions, for the total sample

and each milieu group. Thus, adoption intention is higher across all milieus for those individuals who report higher levels of perceived PV diffusion in their social and spatial environment. In the milieu groups Deprived and Established, a higher *PV saturation per 1000 inhabitants* is negatively associated with adoption intentions, suggesting that these milieus have a higher intention if the local diffusion level is lower. Tests for the other milieu groups are insignificant, yet the test result suggest, that they tend to a reversed relation, as shown by the drawing probabilities below 50 % (see column 0>1). A comparable pattern can be observed for the relation between adoption intention and a higher *PV saturation per km<sup>2</sup>*. A higher *income* is positively associated with adoption intentions for the total sample, and the milieu groups Deprived and Post-Materialists. This is interesting, given that the Post-Materialists have noticeable higher financial resources at their disposal than the Deprived (see Table 2). Thus, whilst overall, adoption intention is higher for respondents on the upper level of the income scale, it is also higher among the relatively more affluent member of the Deprived, who on average range on the lower level of the income scale. Tests for the other milieu groups are insignificant but point in a similar direction.

Overall, results do not support the first hypothesis, stating that spatial characteristics that relate to adoption levels in spatial units are also associated with individual adoption intentions. Instead, the share of (semi-) detached houses, city-type, density and PV density per 1000 inhabitants and per km<sup>2</sup> were insignificant for the total sample. Hypothesis 3 is partly supported, as slight differences between single milieus could be detected concerning PV saturation per km<sup>2</sup> and household income.



Table 4 Mean and standard deviation of adoption intention and results of the Mann-Whitney U test including z-score, p-value, effect size r and the probability that a draw from first group is larger than from second group ( $O>1$ ) for the total sample, and the milieu groups

		Total sample						Post Materialists						Mainstreamer					
		$\emptyset$ SD		Mann-Whitney U test				$\emptyset$ SD		Mann-Whitney U test				$\emptyset$ SD		Mann-Whitney U test			
				z	p	r	$O>1$			z	p	r	$O>1$			z	p	r	$O>1$
DSOC	Low	3.094	1.832	-8.153	<b>.000</b>	-.198	36%	3.089	1.856	-3.495	<b>.001</b>	-.164	39%	3.142	1.891	-3.863	<b>.000</b>	-.210	35%
	High	3.992	1.859					3.825	1.927					4.154	1.822				
DSPA	Low	2.992	1.783	-8.999	<b>.000</b>	-.212	37%	2.938	1.812	-5.137	<b>.000</b>	-.236	36%	3.037	1.842	-4.431	<b>.000</b>	-.232	36%
	High	3.877	1.942					3.906	1.908					3.992	1.956				
12	Many	3.247	1.905	-.759	.448	-.018	49%	3.223	1.949	-.589	.556	-.027	48%	3.366	1.956	.067	.947	.004	50%
	Few	3.297	1.828					3.279	1.801					3.333	1.889				
CT	Rural	3.244	1.874	-1.032	.302	-.024	48%	3.290	1.895	1.053	.292	.048	53%	3.338	1.921	-.355	.825	-.019	48%
	Urban	3.360	1.896					3.077	1.894					3.453	2.005				
DENS	Low	3.231	1.874	-.790	.429	-.019	49%	3.186	1.935	-.851	.395	-.039	48%	3.225	1.903	-1.285	.199	-.067	46%
	High	3.298	1.881					3.301	1.856					3.484	1.955				
PVIN	Low	3.302	1.851	1.008	.314	.024	51%	3.139	1.855	-1.122	.262	-.052	47%	3.253	1.839	-.893	.372	-.047	47%
	High	3.227	1.904					3.347	1.932					3.456	2.018				
PVKM	Low	3.238	1.882	-.689	.491	-.016	49%	3.152	1.889	-1.103	.270	-.051	47%	3.308	1.887	-.483	.629	-.025	49%
	High	3.291	1.874					3.335	1.900					3.401	1.977				
INC	Low	3.090	1.845	-4.431	<b>.000</b>	-.104	44%	3.112	1.935	-2.511	<b>.012</b>	-.115	43%	3.198	1.889	-1.774	.076	-.093	45%
	High	3.478	1.897					3.520	1.783					3.561	1.972				

Table 4 Continued

		<i>Deprived</i>						<i>Established</i>						<i>Leader</i>					
		$\emptyset$ SD		Mann-Whitney U test				$\emptyset$ SD		Mann-Whitney U test				$\emptyset$ SD		Mann-Whitney U test			
				<i>z</i>	<i>p</i>	<i>r</i>	<i>O&gt;1</i>			<i>z</i>	<i>p</i>	<i>r</i>	<i>O&gt;1</i>			<i>z</i>	<i>p</i>	<i>r</i>	<i>O&gt;1</i>
DSOC	Low	2.828	1.810	-3.396	<b>.001</b>	-.204	34%	3.023	1.672	-4.269	<b>.000</b>	-.257	32%	3.346	1.859	-2.916	<b>.004</b>	-.154	40%
	High	3.978	2.105					4.067	1.706					4.021	1.802				
DSPA	Low	2.804	1.802	-2.587	<b>.010</b>	-.150	40%	2.934	1.650	-3.288	<b>.001</b>	-.191	38%	3.245	1.761	-3.865	<b>.000</b>	-.201	38%
	High	3.514	2.056					3.714	1.892					4.047	1.931				
SDH	Many	2.959	1.942	-.495	.621	-.029	48%	3.217	1.791	.741	.459	.043	53%	3.410	1.838	-1.589	.112	-.083	45%
	Few	3.010	1.790					3.053	1.695					3.758	1.888				
CT	Rural	2.925	1.871	-1.039	.299	-.060	45%	3.083	1.765	-1.620	.105	-.094	43%	3.487	1.849	-.886	.376	-.046	47%
	Urban	3.279	1.980					3.473	1.687					3.687	1.909				
DENS	Low	2.973	1.899	-.047	.962	-.003	50%	3.094	1.741	-.509	.611	-.030	48%	3.457	1.825	-.678	.497	-.035	48%
	High	2.980	1.882					3.216	1.771					3.590	1.896				
PVIN	Low	3.228	1.918	2.350	<b>.019</b>	.136	58%	3.362	1.721	2.123	<b>.034</b>	.123	57%	3.492	1.851	-.248	.805	-.013	49%
	High	2.723	1.829					2.946	1.768					3.554	1.872				
PVKM	Low	3.020	1.915	.341	.733	.020	51%	3.235	1.734	.809	.418	.047	53%	3.476	1.877	-.438	.661	-.023	49%
	High	2.932	1.865					3.074	1.777					3.571	1.845				
INC	Low	2.688	1.763	-2.759	<b>.006</b>	-.160	41%	3.042	1.726	-1.233	.218	-.072	46%	3.483	1.881	-.663	.507	-.035	48%
	High	3.314	1.977					3.300	1.786					3.597	1.822				

## 5. Discussion

### 5.1. Principal findings

Intending to bridge the gap between explanations for PV adoption *intention* and PV adoption *behavior*, we assessed relations between variables typically included in spatial analyses and residential adoption intentions. We followed an innovative approach by combining data from a representative survey (n=1,800) on PV adoption intention with online register adoption data on the zip-code level. The approach allowed to investigate associations between variables used in spatial analyses to explain observed adoption levels with stated adoption intentions, targeting the intention-behavior gap (Arts et al. 2011; Ajzen 2020). Moreover, picking up on the idea of varying motives and decision-making roads of different population segments (see, e.g., Scheller et al. (2021), Scheller et al. (2022b), Vibrans et al. (2022), Schulte et al. (2022b), Schulte et al. (2022c)), we explore differences in these associations between groups of like-minded people, represented by Sinus-milieus. Lastly, we investigate relations between the self-reported *perceived* diffusion of PV systems in the social and spatial environment and *actual* diffusion levels represented by the number of PV systems per 1000 inhabitants and per km<sup>2</sup>, working towards a better understanding of the role of previous PV installations in the decision-making process, see, e.g. (Scheller et al. 2021; Scheller et al. 2022b).

In spatial analyses, peer effects referring to geographical clustering of PV systems have been reported to influence adoption levels (Bollinger and Gillingham 2010, 2012; Richter 2013; Müller and Rode 2013; Crago and Chernyakhovsky 2014; Graziano and Gillingham 2015; Balta-Ozkan et al. 2015; Rode and Weber 2016; Rode and Müller 2018; Kosugi et al. 2019; Baginski and Weber 2019). Our results do not provide evidence that more PV systems in the spatial environment of respondents, represented as a number of PV systems per 1000 inhabitants (PVIN) and per km<sup>2</sup> (PVKM), are generally related to higher levels of reported adoption *intentions*. The milieu groups Established and Deprived even report higher adoption intentions in regions with lower values of PV systems per 1000 inhabitants. Instead, a higher *perceived* diffusion of PV systems in the social and spatial environment is associated with higher adoption *intentions* across milieu groups. Results moreover suggest, that the perception of individuals concerning the diffusion of PV systems in their social and spatial environment does not necessarily correspond to the real diffusion level in the corresponding zip-code. In this context, it is particularly surprising that there is hardly any correlation between number of PV systems per km<sup>2</sup> (PVKM) and perceived diffusion in the spatial environment (DSPA). We assumed, given that the more PV systems there are per km<sup>2</sup>, the more could also be observed in everyday life of respondents. A comparable result provides the recent study of Barnes et al. (2022) whose dataset indicates higher perceived

visibility of PV systems of potential adopters in neighborhoods with relatively few systems compared to potential adopters in neighborhoods with relatively many systems.

The mismatch furthermore supports Wolske et al. (2020), who criticize that geographical clustering is not providing evidence of positive effects of previous installations on adoption behavior. If individuals are not able to grasp the true level of diffusion in their spatial environment, it is at least questionable whether the true level of diffusion can then be a key driver for adoption. Other explanations for local clustering of PV systems were mentioned in the focus group discussions in Scheller et al. (2021), where participants indicated that their decision-making was influenced by the presence of a local initiative, or that they live in a new development area where the same building contractors advised all households, who now almost all have PV systems on their roofs. Instead, a higher perceived level of diffusion, thus a higher perceived presence of PV systems within the social and spatial environment of respondents is related to adoption intentions. A higher *perceived* diffusion (which is not related to actual diffusion levels) implies a stronger presence of the topic in the respondent's life, presumably evoked by communication with peers. This aligns with recent findings of Mundaca and Samahita (2020), Scheller et al. (2021) and Scheller et al. (2022b), demonstrating that active peer effects are of higher relevance for decision-making than passive exposure to PV systems, and the almost ancient findings on the diffusion of hybrid seed corn by Ryan and Gross (1943), revealing that innovation diffusion is mostly a social process. According to Rogers (2003) and Tautscher and Flaig (2018), individuals tend to communicate mostly with like-minded people, providing one possible explanation why the mere share of (semi-) detached houses in the spatial environment of respondents is not related to adoption intentions: If adoption intentions are predominantly influenced by word of mouth, it is crucial that the decision-maker communicates with the (potential) adopters surrounding him. Therefore, future research could investigate whether living in an environment with high shares of (semi-) detached houses that are inhabited with high shares of households who resemble the decision-maker – as e.g. determined by Sinus-milieu membership – is related to higher adoption intentions.

According to our analysis, higher income households tend to report higher levels of PV adoption intentions than low-income households. This is in line with Trotta (2018), finding that households with lower incomes more often save energy through low or no-cost behavioral changes, whereas high income households tend to invest money in new appliances and retrofit measures that reduce energy consumption. Income does not play a role across all milieus – only among Post-Materialists and Deprived, the individuals with relatively higher incomes tend to report higher adoption intentions. On the other hand, the literature body points towards a subordinate role of socio-demographics like income (Schulte et al. 2022c; Arts et al. 2011). Our

study result only shows that higher income respondents indicated higher adoption intentions – yet, this is not providing evidence of an effect of income explaining adoption intentions. E.g., in the study of Vibrans et al. (2022), the effect of financial considerations on adoption intention was equal across milieus, despite of significant differences in the latent constructs.

We furthermore would like to point out that the number of PV systems per 1000 inhabitants (PVIN) is not related with the number of PV systems per km<sup>2</sup> (PVKM). This finding is relevant in the context of spatial studies, as these analyze different dependent variables (for a recent overview see Schulte et al. (2022a). Attention should be paid when results of studies analyzing the total number (Zhang et al. 2011; Kwan 2012) or capacity (Crago and Chernyakhovsky 2014; Schaffer and Brun 2015) of PV systems per spatial unit, capacity per capita (Dewald and Truffer 2012), PV systems per number of detached houses (Kosugi et al. 2019), PV capacity per household (Baginski and Weber 2019) or number of PV installations per 10000 inhabitants (Thormeyer et al. 2020) are compared.

## 5.2. Study limitations

In this study, we assessed the relation of spatial characteristics and the reported level of adoption intention. Spatial characteristics were on the one hand provided by the participants (city type, share of (semi-) detached house), and assigned on the zip-code level (number of PV systems per 1000 inhabitants and per km<sup>2</sup>, density). Self-reported variables can be subject to misconceptions, and particularly the reported share of (semi-) detached houses is highly subjective. Also, it is questionable if the provided values are representative for the whole zip-code, or if they only relate to the immediate environment, hampering the comparison of these study results with spatial analyses on the zip-code level. Opposingly, zip-code specific variables might not adequately represent the immediate environment of respondents. Despite the survey was conducted with a representative sample of 1,800 participants, a self-selection bias cannot be ruled out as the responsible institute uses a fixed panel (respondi Open Access Panel). Lastly, the presented approach to the intention behavior gap also brings along challenges due to the different temporal associations of intention (snapshot) and behavior (cumulated number of past installations). Changing behavioral drivers and barriers cannot adequately be captured – for this endeavor, systematic, reoccurring studies must be performed, bringing us back to the initial problem of addressing the intention-behavior gap.

## 6. Conclusion

This study was designed to investigate relations between residential PV adoption intention and spatial characteristics of the living environment of respondents. We thereby aimed to bridge

differences between spatial studies, striving to explain adoption levels in spatial units, and consumer surveys, explaining PV adoption decisions mostly based on individual-level variables. A quantitative survey was performed on a representative sample of 1,800 homeowners in Germany and matched with spatial characteristics on the zip-code level. A correlational analysis was performed to initially assess interrelations between the variables of interest. Thereafter, the Mann-Whitney U test was used to compare the adoption intention between groups with low and high expressions of the independent variables with the total sample, and with consumer segments using the Sinus-Milieu model.

Overall, the results for the total sample show that actual PV diffusion, density, city-type and share of (semi-) detached houses are not related to the individual adoption intention. Thus, we have to reject the main hypothesis that spatial characteristics that relate to observed adoption levels in spatial units are also associated with adoption *intentions*. Partly confirming the second hypothesis, perceived diffusion in social and spatial environment show a small correlation with PV saturation per 1000 inhabitants, but not with PV saturation per km<sup>2</sup>. Test results indicate that a higher perceived diffusion in social and spatial environment goes along with higher adoption intentions. Taken together, this implies that individuals are not able to grasp the true level of PV diffusion in their spatial environment, and, consequently, that the true level of diffusion in the spatial environment of respondents does not matter for adoption intentions, challenging the so-called peer effect. Instead, individuals who tend to have higher adoption intentions also tend to perceive a stronger presence of PV systems in their social and spatial environment. Moreover, challenging our third hypothesis, only few differences between milieu groups concerning the relations between the assessed explanatory variables and adoption intention could be detected.

Because this research clearly demonstrates that the spatial characteristics used in spatial analyses to explain *observed* PV adoption levels are not related to PV adoption *intentions*, it is an important contribution to previous research in this area, and in the broader field dealing with the intention behavior gap. We strongly recommend future research to further investigate the changing role of explanatory variables in the decision-making process. Moreover, we pledge for the repeated use of an established and spatially available consumer segmentation tool in consumer surveys and spatial analyses, given that it allows to incorporate a complex and interwoven bundle of individual characteristics, values and lifestyles, and is reproducible. Tools like the Sinus-milieu model also enable a better understanding of social influences on PV decision-making, as they not only allow to assess, whether social norms, previous installations, or perceived diffusion play a different role for different population groups. They also enable the researcher to investigate, whether the discrepancy between reality and perception differs

across milieus and make it possible to determine the spatially close social environment of decision-makers on a large scale.

*Acknowledgement:* Emily Schulte and Fabian Scheller received funding from the project SUSIC (Smart Utilities and Sustainable Infrastructure Change) with the project number 100378087. The project was financed by the Saxon State government out of the State budget approved by the Saxon State Parliament.



## 7. References

Abreu, Joana; Wingartz, Nathalie; Hardy, Natasha (2019): New trends in solar: A comparative study assessing the attitudes towards the adoption of rooftop PV. In *Energy Policy* 128, pp. 347–363. DOI: 10.1016/j.enpol.2018.12.038.

Ajzen, Icek (2020): The theory of planned behavior: Frequently asked questions. In *Human Behav and Emerg Tech* 2 (4), pp. 314–324. DOI: 10.1002/hbe2.195.

Alipour, M.; Salim, H.; Stewart, Rodney A.; Sahin, Oz (2021): Residential solar photovoltaic adoption behaviour: End-to-end review of theories, methods and approaches. In *Renewable Energy* 170, pp. 471–486. DOI: 10.1016/j.renene.2021.01.128.

Arts, Joep W.C.; Frambach, Ruud T.; Bijmolt, Tammo H.A. (2011): Generalizations on consumer innovation adoption: A meta-analysis on drivers of intention and behavior. In *International Journal of Research in Marketing* 28 (2), pp. 134–144. DOI: 10.1016/j.ijresmar.2010.11.002.

Baginski, Paul; Weber, Christoph (2019): Coherent estimations for residential photovoltaic uptake in Germany including spatial spillover effects. Edited by House of Energy Markets & Finance (HEMF Working Paper, 02). Available online at <https://ssrn.com/abstract=3357359>.

Balderjahn, Ingo; Scholderer, Joachim (2007): Benefit- und Lifestyle-Segmentierung. In Sönke Albers (Ed.): *Handbuch Produktmanagement. Strategieentwicklung - Produktplanung - Organisation - Kontrolle*. 3., überarb. und erw. Aufl. Wiesbaden: Gabler.

Balta-Ozkan, Nazmiye; Yildirim, Julide; Connor, Peter M. (2015): Regional distribution of photovoltaic deployment in the UK and its determinants: A spatial econometric approach. In *Energy Economics* 51, pp. 417–429. DOI: 10.1016/j.eneco.2015.08.003.

Balta-Ozkan, Nazmiye; Yildirim, Julide; Connor, Peter M.; Truckell, Ian; Hart, Phil (2021): Energy transition at local level: Analyzing the role of peer effects and socio-economic factors on UK solar photovoltaic deployment. In *Energy Policy* 148, p. 112004. DOI: 10.1016/j.enpol.2020.112004.

Barnes, Jesse L.; Krishen, Anjala S.; Chan, Alexander (2022): Passive and active peer effects in the spatial diffusion of residential solar panels: A case study of the Las Vegas Valley. In *Journal of Cleaner Production* 363, p. 132634. DOI: 10.1016/j.jclepro.2022.132634.

BMWi (2022): Kerninhalte der Referentenentwürfe des BMWK zur Novelle des Erneuerbare-Energien-Gesetzes, zur Novelle des Wind-auf-See-Gesetzes und zum EEG-Entlastungsgesetz. Edited by Bundesministerium für Wirtschaft und Klimaschutz. Available online at

[https://www.bmwi.de/Redaktion/DE/Downloads/E/Kerninhalte\\_EEG\\_WindSeeG.pdf?\\_\\_blob=publicationFile&v=4](https://www.bmwi.de/Redaktion/DE/Downloads/E/Kerninhalte_EEG_WindSeeG.pdf?__blob=publicationFile&v=4), checked on 4/8/2022.

Bollinger, Bryan; Gillingham, Kenneth (2010): Environmental Preferences and Peer Effects in the diffusion of solar PV. Edited by Unpublished Manuscript. Available online at [https://blog.zeit.de/gruenegeschaeft/files/2011/04/BollingerGillingham\\_PeerEffectsSolar.pdf](https://blog.zeit.de/gruenegeschaeft/files/2011/04/BollingerGillingham_PeerEffectsSolar.pdf).

Bollinger, Bryan; Gillingham, Kenneth (2012): Peer Effects in the Diffusion of Solar Photovoltaic Panels. In *Marketing Science* 31 (6), pp. 900–912. DOI: 10.1287/mksc.1120.0727.

Bortz, Jürgen; Schuster, Christof (2016): Statistik für Human- und Sozialwissenschaftler. 7<sup>th</sup> ed.: Springer.

Cohen, Jacob (1988): Statistical Power Analysis for the Behavioral Sciences. 2<sup>nd</sup> ed.: Lawrence Erlbaum Associates.

Crago, C. L.; Chernyakhovsky, I. (2014): Solar PV Technology Adoption in the United States An Empirical Investigation of State Policy Effectiveness. Minneapolis (Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting).

Dewald, Ulrich; Truffer, Bernhard (2012): The Local Sources of Market Formation: Explaining Regional Growth Differentials in German Photovoltaic Markets. In *European Planning Studies* 20 (3), pp. 397–420. DOI: 10.1080/09654313.2012.651803.

Engelken, Maximilian; Römer, Benedikt; Drescher, Marcus; Welp, Isabell (2018): Why homeowners strive for energy self-supply and how policy makers can influence them. In *Energy Policy* 117, pp. 423–433. DOI: 10.1016/j.enpol.2018.02.026.

Flaig, Berthold B.; Bertram Barth (2014): Die Sinus-Milieus 3.0: Hintergründe und Fakten zum aktuellen Sinus-Milieu-Modell. In Marion Halfmann (Ed.): Zielgruppen im Konsumentenmarketing. Wiesbaden: Springer Fachmedien Wiesbaden.

Gellrich, Angelika (2016): Von der Minderheit zur Mehrheit? Psycho-soziale Einflüsse bei der Verbreitung klima-schonender Innovationen. Dissertation. Universität Kassel, Kassel. Humanwissenschaften.

Graziano, M.; Gillingham, K. (2015): Spatial patterns of solar photovoltaic system adoption: The influence of neighbors and the built environment. In *Journal of Economic Geography* 15 (4), pp. 815–839. DOI: 10.1093/jeg/lbu036.

- Gröger, Maria; Schmid, Victoria; Bruckner, Thomas (2011): Lifestyles and their Impact on Energy-related Investment Decisions. In *Low Carbon Economy* 2 (2), pp. 1–9. DOI: 10.4236/lce.2011.22014.
- Groote, Olivier de; Pepermans, Guido; Verboven, Frank (2016): Heterogeneity in the adoption of photovoltaic systems in Flanders. In *Energy Economics* 59, pp. 45–57. DOI: 10.1016/j.eneco.2016.07.008.
- Koppelman, Udo (2006): Marketing: Einführung in Entscheidungsprobleme des Absatzes und der Beschaffung. 8<sup>th</sup> ed.: Lucius & Lucius.
- Kosugi, Takanobu; Shimoda, Yoshiyuki; Tashiro, Takayuki (2019): Neighborhood influences on the diffusion of residential photovoltaic systems in Kyoto City, Japan. In *Environmental Economics and Policy Studies* 21 (4), pp. 477–505. DOI: 10.1007/s10018-019-00239-5.
- Kwan, Calvin Lee (2012): Influence of local environmental, social, economic and political variables on the spatial distribution of residential solar PV arrays across the United States. In *Energy Policy* 47, pp. 332–344. DOI: 10.1016/j.enpol.2012.04.074.
- Müller, Sven; Rode, Johannes (2013): The adoption of photovoltaic systems in Wiesbaden, Germany. In *Economics of Innovation and New Technology* 22 (5), pp. 519–535. DOI: 10.1080/10438599.2013.804333.
- Mundaca, Luis; Samahita, Margaret (2020): What drives home solar PV uptake? Subsidies, peer effects and visibility in Sweden. In *Energy Research & Social Science* 60, p. 101319. DOI: 10.1016/j.erss.2019.101319.
- Profijt, Markus (2010): Milieuspezifische Vorgehensweise für den Einsatz von Smart Metern in deutschen Haushalten: Fraunhofer Verlag.
- Richter, Laura-Lucia (2013): Social Effects in the Diffusion of Solar PV in the UK. Edited by University of Cambridge. Energy Policy Research Group (Cambridge Working Papers in Economics, 1357).
- Rode, Johannes; Müller, Sven (2018): What drives peer effects in household technology adoption - Evidence from solar photovoltaic systems. Edited by Unpublished Manuscript.
- Rode, Johannes; Weber, Alexander (2016): Does localized imitation drive technology adoption? A case study on rooftop photovoltaic systems in Germany. In *Journal of Environmental Economics and Management* 78, pp. 38–48. DOI: 10.1016/j.jeem.2016.02.001.
- Rogers, Everett M. (2003): Diffusion of innovations. 5th ed. New York: Free Press.

Ryan, B.; Gross, N. C. (1943): The Diffusion of Hybrid Seed Corn In Two Iowa Communities. In *Rural Sociological Society* 8 (1).

Schaffer, Axel J.; Brun, Sebastian (2015): Beyond the sun—Socioeconomic drivers of the adoption of small-scale photovoltaic installations in Germany. In *Energy Research & Social Science* 10, pp. 220–227. DOI: 10.1016/j.erss.2015.06.010.

Scheller, Fabian; Doser, Isabel; Schulte, Emily; Johanning, Simon; McKenna, Russell; Bruckner, Thomas (2021): Stakeholder dynamics in residential solar energy adoption: findings from focus group discussions in Germany. In *Energy Research & Social Science* 76, p. 102065. DOI: 10.1016/j.erss.2021.102065.

Scheller, Fabian; Graupner, Sören; Edwards, James; Johanning, Simon; Bergaentzlé, Claire; Bruckner, Thomas (2022a): Social Influence Throughout the Photovoltaic Adoption Process: Exploring the Impact of Stakeholder Perceptions. In *Energy RESEARCH LETTERS* 3 (Early View). DOI: 10.46557/001c.33903.

Scheller, Fabian; Graupner, Sören; Edwards, James; Weinand, Jann; Bruckner, Thomas (2022b): Competent, trustworthy, and likeable? Exploring which peers influence photovoltaic adoption in Germany. In *Energy Research & Social Science* 91, p. 102755. DOI: 10.1016/j.erss.2022.102755.

Schulte, E.; Scheller, F.; Bruckner, T. (2022a): Enhancing understanding of geographical adoption patterns of residential rooftop photovoltaic using a consumer segmentation model – A case study in Saxony, Germany. In *Zeitschrift für Energiewirtschaft*.

Schulte, Emily; Scheller, Fabian; Pasut, Wilmer; Bruckner, Thomas (2022b): Product traits, decision-makers, and household low-carbon technology adoptions: moving beyond single empirical studies. In *Energy Research & Social Science* 83, p. 102313. DOI: 10.1016/j.erss.2021.102313.

Schulte, Emily; Scheller, Fabian; Sloot, Daniel; Bruckner, Thomas (2022c): A meta-analysis of residential PV adoption: the important role of perceived benefits, intentions and antecedents in solar energy acceptance. In *Energy Research & Social Science* 84, p. 102339. DOI: 10.1016/j.erss.2021.102339.

Schwarz, Nina (2007): *Umweltinnovationen und Lebensstile. Eine raumbezogene, empirisch fundierte Multi-Agenten-Simulation*. Marburg: Metropolis.

Soyez, Katja; Thielow, Nadine; Gurtner, Sebastian (2012): Lifestyle of Health and Sustainability: Ein wachsendes Segment gesundheitsbewusster Konsumenten. In Stefan Hoffmann, Uta

- Schwarz, Robert Mai (Eds.): *Angewandtes Gesundheitsmarketing*. Wiesbaden: Springer Fachmedien Wiesbaden, pp. 75–86.
- Stata Corp.: *ranksum* - Equality tests on unmatched data. Available online at <https://www.stata.com/manuals13/ranksum.pdf>.
- Stata Corp.: *sdtest* — Variance-comparison tests. Available online at <https://www.stata.com/manuals13/rsdtest.pdf>.
- Stata Corp.: *swilk* — Shapiro–Wilk and Shapiro–Francia tests for normality. Available online at <https://www.stata.com/manuals/rswilk.pdf>.
- Tautscher, Manfred; Flaig, Berthold B. (2018): Information on Sinus-Milieus 2018. Status 10/2018. Heidelberg. Available online at [https://www.sinus-institut.de/fileadmin/user\\_data/sinus-institut/Bilder/Sinus-Milieus\\_092018/2018-10-31\\_Information\\_on\\_Sinus-Milieus\\_English\\_version.pdf](https://www.sinus-institut.de/fileadmin/user_data/sinus-institut/Bilder/Sinus-Milieus_092018/2018-10-31_Information_on_Sinus-Milieus_English_version.pdf), updated on 2018, checked on 4/1/2022.
- Thormeyer, Christoph; Sasse, Jan-Philipp; Trutnevyte, Evelina (2020): Spatially-explicit models should consider real-world diffusion of renewable electricity: Solar PV example in Switzerland. In *Renewable Energy* 145, pp. 363–374. DOI: 10.1016/j.renene.2019.06.017.
- Trotta, Gianluca (2018): Factors affecting energy-saving behaviours and energy efficiency investments in British households. In *Energy Policy* 114, pp. 529–539. DOI: 10.1016/j.enpol.2017.12.042.
- Vibrans, Luise; Schulte, Emily; Morrissey, Karyn; Bruckner, Thomas; Scheller, Fabian (2022): Same same, but different: explaining heterogeneity among potential photovoltaic adopters in Germany using milieu segmentation. In *Unpublished manuscript*, pp. 1–35.
- VuMa Arbeitsgemeinschaft (2021): Konsumenten im Fokus. Basisinformationen für eine fundierte Mediaentscheidung. Available online at [https://www.vuma.de/fileadmin/user\\_upload/PDF/berichtsbaende/VuMA\\_Berichtsband\\_2021.pdf](https://www.vuma.de/fileadmin/user_upload/PDF/berichtsbaende/VuMA_Berichtsband_2021.pdf), checked on 4/1/2022.
- Wolske, Kimberly S.; Gillingham, Kenneth T.; Schultz, P. Wesley (2020): Peer influence on household energy behaviours. In *Nat Energy* 5 (3), pp. 202–212. DOI: 10.1038/s41560-019-0541-9.
- Wolske, Kimberly S.; Stern, Paul C.; Dietz, Thomas (2017): Explaining interest in adopting residential solar photovoltaic systems in the United States: Toward an integration of behavioral theories. In *Energy Research & Social Science* 25, pp. 134–151. DOI: 10.1016/j.erss.2016.12.023.

Zhang, Yu; Song, Junghyun; Hamori, Shigeyuki (2011): Impact of subsidy policies on diffusion of photovoltaic power generation. In *Energy Policy* 39 (4), pp. 1958–1964. DOI: 10.1016/j.enpol.2011.01.021.

## Appendix A

### SINUS

#### Determinants of PV adoption / intention Questionnaire

ASK ALL.

##### **Q01. Birth Year**

USE STANDARD AGE QUESTION; SCREENOUT U18

**Please enter your date of birth.**

*YEAR/MONTH DROPDOWN*

ASK ALL.

##### **Q02. Gender**

**As what gender do you identify?**

*Single.*

1. Female
2. Male
3. Other

ASK ALL

##### **Q03. State**

USE QMKTSIZE\_DE

**Where do you live?**

GERREGION1 [Hidden]. Hidden recode GERREGION1 from GERZIPCODE and GERTOWNNAME:

1. \_DE1 BADEN-WÜRTTEMBERG
2. \_DE2 BAYERN
3. \_DE3 BERLIN
4. \_DE4 BRANDENBURG
5. \_DE5 BREMEN
6. \_DE6 HAMBURG
7. \_DE7 HESSEN
8. \_DE8 MECKLENBURG-VORPOMMERN
9. \_DE9 NIEDERSACHSEN
10. \_DEA NORDRHEIN-WESTFALEN
11. \_DEB RHEINLAND-PFALZ
12. \_DEC SAARLAND
13. \_DED SACHSEN
14. \_DEE SACHSEN-ANHALT
15. \_DEF SCHLESWIG-HOLSTEIN
16. \_DEG THÜRINGEN

##### **Q12. PV-Intention-General**

**How strong is your current intention to purchase a photovoltaic system?**

*SHOW SLIDER FROM LEFT TO RIGHT. SINGLE.*

1 Very low      2 3 4 5 6      7 Very high

##### **Q16. Diffusion in Social Network**

**How many people that you know own a PV system?**

*Single.*

1. None
2. 1-3

3. 4-6
4. 7-9
5. 10-12
6. 13 or more
7. Don't know

**Q17. Visibility in Spatial Environment**

**Do you see PV systems in your everyday life, i.e. in places where you regularly spend time or pass by?**

*Single.*

1. Yes
2. No

IF Q17 = 1

**Q18. Diffusion in Spatial Environment**

**How many residential PV systems do you regularly see in your everyday life, i.e. in places where you regularly spend time or pass by?**

*Single.*

1. 1-3
2. 4-6
3. 7-9
4. 10-12
5. 13 or more

**Q36. Postal code**

**Q37. Place of residence**

**Which of the following best describes your place of residence?**

*Single*

1. I live in a rural community (up to 5,000 inhabitants)
2. I live in a small town (5,000 - 10,000 inhabitants)
3. I live in a large small town (10,000 - 20,000 inhabitants)
4. I live in a small medium-sized town (20,000-50,000 inhabitants)
5. I live in a large medium-sized city (50,000-100,000 inhabitants)
6. I live in a small big city (100,000-500,000 inhabitants)
7. I live in a large city (500,000 inhabitants and more)

**Q38. Place of residence**

**Which of the following best describes your place of residence?**

*Single*

1. I live in a densely populated residential area
2. I live in a residential area with medium population density
3. I live in a sparsely populated residential area.

**Q39. Place of residence**

**Which of the following best describes your place of residence?**

*Single*

1. I live in an area with a predominance of detached houses
2. I live in an area with a mixed proportion of single-family houses and apartment buildings
3. I live in an area with a high proportion of apartment buildings.

**Q42. Net household income**



**What is your total net monthly household income? This means the total of all wages, salaries, income from self-employment, social benefits, or retirement income received by persons living in your household, after deduction of taxes and social security contributions.**

*Single*

1. Less than 1,100 Euro
2. 1,101 bis 1,300 Euro
3. 1,301 to 1,500 Euro
4. 1,501 to 1,700 Euro
5. 1,701 to 2,150 Euro
6. 2,151 to 2,600 Euro
7. 2,601 to 3,100 Euro
8. 3,101 to 3,600 Euro
9. 3,601 to 4,300 Euro
10. 4,301 to 5,500 Euro
11. 5,501 to 5,700 Euro
12. 5,701 to 6,400 Euro
13. 6,401 Euro or more

ASK ALL.

**Q52. Milieu indicator**

		Doesn't apply at all	Mostly doesn't apply	Doesn't apply complet ely	Applies complete ly
		1	2	3	4
1.	Today, you can no longer secure your professional future through further education.	( )	( )	( )	( )
2.	Religious values play no role in my life.	( )	( )	( )	( )
3.	Whenever I find the time, I always occupy myself with culture and art.	( )	( )	( )	( )
4.	I like to work more in order to be able to afford a few things.	( )	( )	( )	( )
5.	I like to eat exotic dishes (e.g. from India, Japan or Mexico).	( )	( )	( )	( )
6.	It is very important to me that nothing gets out when there are problems in my family.	( )	( )	( )	( )
7.	There is little chance for us to make it big these days.	( )	( )	( )	( )
8.	Things like tarot, crystals or mandalas often help me to make the right decision in difficult life situations.	( )	( )	( )	( )
9.	When I think about it, the old values of thrift, cleanliness and order have quite a lot of significance for my life.	( )	( )	( )	( )
10.	I like to watch films with a lot of violence	( )	( )	( )	( )
11.	It is important to me that food can be kept for as long as possible.	( )	( )	( )	( )
12.	I often buy things without thinking long and hard about whether I can afford it at all.	( )	( )	( )	( )

13.	I am in favour of equal rights for homosexual lifestyles in our society.	( )	( )	( )	( )
14.	Germany is a rich country because we Germans are more industrious and more capable than others.	( )	( )	( )	( )
15.	I feel sufficiently secured for old age.	( )	( )	( )	( )
16.	I don't see anything wrong with someone trying to achieve their goals by force.	( )	( )	( )	( )
17.	I love risky hobbies (e.g. hang gliding, motorcycling, mountain climbing, skydiving).	( )	( )	( )	( )
18.	I regularly inform myself about the current stock market prices.	( )	( )	( )	( )
19.	What I want is fun, variety and entertainment.	( )	( )	( )	( )
20.	In life, I am always open to new opportunities and challenges.	( )	( )	( )	( )
21.	I have the feeling that society is developing in the wrong direction.	( )	( )	( )	( )
22.	I have great understanding for people who only do what they feel like doing at the time.	( )	( )	( )	( )
23.	As far as the future is concerned, I have full confidence in my performance.	( )	( )	( )	( )
24.	I want to be part of what is happening on the internet.	( )	( )	( )	( )
25.	I have the feeling of being excluded from the current changes in our society.	( )	( )	( )	( )
26.	I am looking for stability in my life.	( )	( )	( )	( )
27.	One of the most important things is to achieve a recognised position in society.	( )	( )	( )	( )
28.	Germany without foreigners would be a boring country.	( )	( )	( )	( )
29.	Before you let yourself be ordered around at work, you'd rather live on unemployment benefits.	( )	( )	( )	( )

## Appendix B

*Table 5 Description of group range and size used for Mann-Whitney U test, for total sample and milieugroups*

		<i>Total sample</i>		<i>Post Materialists</i>		<i>Mainstreamer</i>		<i>Deprived</i>		<i>Established</i>		<i>Leader</i>	
		Range	N	Range	N	Range	N	Range	N	Range	N	Range	N
DSOC	Low	1-2	1335	1-2	349	1-2	275	1-2	232	1-2	216	1-2	263
	High	3-7	367	3-7	103	3-7	65	3-7	45	3-7	60	3-7	94
DSPA	Low	1-3	1246	1-3	324	1-3	243	1-3	225	1-3	213	1-3	241
	High	4-6	554	4-6	149	4-6	121	4-6	72	4-6	84	4-6	128
12	Many	1	1166	1	301	1	238	1	194	1	184	1	249
	Few	2-3	634	2-3	172	2-3	126	2-3	103	2-3	113	2-3	120
RC	Rural	1-5	1478	1-5	369	1-5	311	1-5	254	1-5	242	1-5	302
	Urban	6-7	322	6-7	104	6-7	53	6-7	43	6-7	55	6-7	67
DENS	Low		900	19.5-372.4	237	22.8-260.1	182	32.7-314.8	149	2.5-314.3	149	18.6-340.4	186
	High		900	372.8-12335.4	236	264.3-18144.7	182	315.9-18880.0	148	314.7-12742.4	148	434.7-16357.7	183
PVIN	Low	.2-21.9	900	.3-21.5	237	.4-23.3	182	.4-2.8	149	.3-22.8	149	.2-21.4	185
	High	22.0-232.8	900	21.6-165.1	236	23.3-178.3	182	23.9-152.6	148	22.9-232.8	148	21.4-173.3	184
PVKM	Low	.4-8.3	900	.5-8.6	237	.5-8.0	182	.4-7.4	149	.6-8.4	149	.5-8.7	185
	High	8.3-96.7	900	8.6-96.7	236	8.0-49.7	182	7.5-43.8	148	8.5-79.0	148	8.7-50.6	184
INC	Low	1 - 8	990	1 - 9	321	1 - 8	207	1 - 7	160	1 - 8	167	1 - 9	240
	High	9 - 13	810	10 - 13	152	9 - 13	157	8 - 13	137	9 - 13	130	10 - 13	129