TECHNISCHE UNIVERSITÄT DARMSTADT

Renewable Energy Adoption in Germany

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Drivers, Barriers and Implications

Dissertation

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Summary

This thesis deals with renewable energy adoption in Germany. We exploit a unique dataset which includes the location, date of installation and size of all photovoltaic systems, wind power plants and biomass plants for generating electricity installed in Germany through 2011. Importantly, a strong federal subsidy scheme has fostered the adoption of the three technologies since 2000. Panel data analyses on different levels of geographical aggregation allow us to identify drivers, barriers and implications of renewable energy adoption in Germany.

We start our analysis by motivating the topic. Then, we review literature on technology adoption. Numerous studies confirm that technology diffusion follows an S-shaped, logistic pattern. A description of the institutional context, aggregate trends and regional differences in renewable energy adoption in Germany follows.

The purpose of the subsequent section is to illuminate the spatio-temporal diffusion of photovoltaic installations in Germany quantitatively and to test whether imitation drives photovoltaics adoption. We choose an aggregate approach and employ an epidemic diffusion model which includes a spatial dimension. According to our results, imitative adoption behavior is highly localized and an important factor for the adoption of photovoltaic systems.

In the following section, we change our focus on spatio-temporal variation of peer effects, i.e., imitation, in photovoltaics adoption. We add detailed locational data on potential adopters. This data allows us to construct an individual measure of peer effects for each potential adopter. Based on a discrete choice model, we confirm again that peer effects are mostly localized. They generally occur within a radius of 500 meters. We also find that the peer effect's impact on the decision to adopt decreases over time.

The next section makes use of the well-studied logistic shape of technology diffusion. The common diffusion path allows us to test whether the adoption rate of renewable

energy plants differs between German NUTS-3 regions ('Landkreise und Kreisfreie Städte') in which a successful referendum against a single plant was organized and the remaining regions. We exploit the fact that referenda are mainly organized on the municipal district ('Gemeinde') level against a single plant or building area. Our analysis reveals that the adoption rate (i.e., the first difference in the diffusion level) is indeed lower in NUTS-3 regions where a referendum took place. This finding holds true for wind power and large biomass plants which are both industrial. In contrast, we do not find the same for photovoltaic installations which are mainly private, household installations. We interpret this as evidence that potential investors in wind power and large biomass plants not only avoid the municipal district where a referendum against the specific technology was organized but stay away from the whole NUTS-3 region.

Finally, we turn to implications from renewable energy adoption. We estimate the effect of the diffusion of photovoltaic systems on the fraction of votes obtained by Germany's Green Party in federal elections. We take first differences and instrument adoption rates by lagged diffusion levels. We predict the diffusion levels with a logistic diffusion curve. The existing rationales for non-linearities in diffusion and the ubiquity of logistic curves ensure that our predicted instrument is orthogonal to variables that directly affect voting patterns. We find that the diffusion of domestic photovoltaic systems caused a quarter of the increment in green votes between 1998 and 2009. We confirm our findings with survey data from the German Socio-Economic Panel.

Summary in German – Zusammenfassung

Diese Arbeit beschäftigt sich mit der Verbreitung von erneuerbaren Energietechnologien in Deutschland. Grundlage der Analysen ist ein einmaliger Datensatz, der Aufstellungsort, Netzanbindungsdatum sowie Anlagengröße von allen bis 2011 installierten Photovoltaik-, Windkraft- und Biomasseanlagen zur Stromgewinnung enthält. Die Verbreitung dieser Technologien wird seit dem Jahr 2000 durch das bundesweit gültige Erneuerbare-Energien-Gesetz gefördert. Anhand von Paneldatenschätzungen, die auf unterschiedlichen geographischen Aggregationsleveln zur Anwendung kommen, identifizieren wir sowohl fördernde als auch verbreitungshemmende Faktoren. Zudem decken wir Implikationen der Verbreitung erneuerbarer Energietechnologien auf.

Zunächst motivieren wir das Thema dieser Arbeit. Danach schaffen wir einen Literaturüberblick zum Thema Technologiediffusion. Zahlreiche Studien bestätigen, dass die Verbreitung einem S-förmigen, logistischen Verlauf folgt. Daraufhin beschreiben wir die institutionellen Rahmenbedingungen, aggregierte Trends und regionale Unterschiede in der Verbreitung von erneuerbaren Energietechnologien in Deutschland.

Das Ziel des nächsten Abschnitts dieser Arbeit ist, die Verbreitung von Photovoltaikanlagen in Deutschland quantitativ über Raum und Zeit zu analysieren. Wir überprüfen, ob Imitation die Verbreitung von Photovoltaikanlagen fördert. Wir aggregieren die Nutzungsdaten und verwenden ein epidemisches Diffusionsmodell mit einer räumlichen Komponente. Unsere Ergebnisse deuten darauf hin, dass imitierendes Adoptionsverhalten zwar örtlich stark begrenzt ist, aber dennoch einen wichtigen Faktor für die Verbreitung von Photovoltaikanlagen darstellt.

In dem darauffolgenden Abschnitt analysieren wir die Veränderung des Einflusses von Peer-Effekten (beziehungsweise Imitation) bei der Installation von Photovoltaik-

anlagen über Raum und Zeit. Den zuvor bereits genutzten Datensatz erweitern wir durch detaillierte Ortsinformationen zu potenziellen Nutzern der Technologie. Anhand eines diskreten Entscheidungsmodells bestätigen wir erneut, dass der identifizierte Peer-Effekt örtlich stark begrenzt ist. Zumeist tritt der Effekt innerhalb eines Radius von 500 Metern auf. Unsere Analyse zeigt auch, dass der Einfluss des Peer-Effekts, auf die Entscheidung eine Photovoltaikanlage zu installieren, mit der Zeit abnimmt.

Im nächsten Abschnitt machen wir uns den logistischen Verlauf von Diffusionskurven zunutze. Wir untersuchen, ob sich die Adoptionsrate von erneuerbaren Energietechnologien in deutschen NUTS-3-Regionen (Landkreisen und Kreisfreien Städten), in denen ein erfolgreicher Bürgerentscheid gegen den Bau einer bestimmten Anlage stattgefunden hat, von den restlichen NUTS-3-Regionen unterscheidet. Dabei nutzen wir, dass Bürgerentscheide in erster Linie auf Gemeindeebene gegen eine einzelne Anlage oder ein bestimmtes Baugebiet durchgeführt werden. Unsere Analyse ergibt, dass die Adoptionsrate, das heißt die erste Differenz des Diffusionslevels, tatsächlich in NUTS-3-Regionen niedriger ist, in denen ein erfolgreicher Bürgerentscheid durchgeführt wurde. Unser Ergebnis gilt für Windkraftanlagen und große Biomasseanlagen, folglich nur für industrielle Anlagen. Für Photovoltaikanlagen, die im Wesentlichen private Anlagen sind, gilt der Zusammenhang nicht. Unsere Ergebnisse weisen darauf hin, dass potenzielle Investoren in Windkraft- oder große Biomasseanlagen nicht nur Gemeinden meiden, in denen ein erfolgreicher Bürgerentscheid gegen die jeweilige Technologie durchgeführt wurde. Sie machen sogar einen Bogen um die gesamte NUTS-3-Region der Gemeinde.

Im letzten Abschnitt untersuchen wir Implikationen der Verbreitung von erneuerbaren Energietechnologien. Wir schätzen den Zusammenhang zwischen der Verbreitung von Photovoltaikanlagen und dem Stimmenanteil von Bündnis 90/Die Grünen bei Bundestagswahlen. Wir bilden die erste Differenz und verwenden das Diffusionslevel der Vorperiode als Instrument für die aktuelle Adoptionsrate. Das Diffusionslevel prädizieren wir durch eine logistische Diffusionskurve. Die unterschiedlichen Theorien über Nichtlinearitäten und die Allgegenwärtigkeit der logistischen Kurve hinsichtlich Technologiediffusion stellen sicher, dass sich unser prädiziertes Instrument orthogonal zu Variablen verhält, die Wahlverhalten direkt beeinflussen. Unsere Analyse zeigt, dass die Verbreitung von privaten Photovoltaikanlagen für ein Viertel des Stimmenzuwachses der Grünen zwischen 1998 und 2009 verantwortlich ist. Unsere Ergebnisse stützen wir durch eine abschließende Analyse von Umfragedaten des sozioökonomischen Panels.

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1. Introduction

The finiteness of fossil fuels and their effect on climate change has encouraged the search for sustainable energy technologies. In Germany, the nuclear power phase-out puts additional pressure on creating an energy system based on renewable energy technologies. When the Social Democratic-Green coalition won the 1998 federal elections, it raised the nation-wide feed-in tariffs paid for electricity produced from renewable energy technologies. Since then, many renewable energy plants have been installed across Germany. The objective of this thesis is to identify drivers, barriers and implications of their adoption.

Since Griliches (1957) and Mansfield (1961), economists have studied temporal patterns of technology diffusion. We review models of technology diffusion in Chapter 2. In line with the theory, numerous studies across countries, sectors and periods indicate a common logistic (S-shaped) path of technology diffusion (see Rogers (1983), Geroski (2000), Comin and Hobijn (2009), or Comin and Mestieri (2013a) for examples). Besides this similarity, technology diffuses often more slowly than would be optimal (Rogers, 1983; Geroski, 2000). Dittmar (2011), for instance, gives a historic example by describing the diffusion of the printing press. The diffusion of this technology caused a revolution between 1450 and 1500. Book prices fell by two-thirds, which dramatically changed the way information spread. Still, Dittmar (2011) finds that in the first 50 years after the invention of the printing press only 11% of European cities adopted the technology. There are numerous other examples, e.g., see Griliches's (1957) study of the slow diffusion of hybrid corn, Sommers's (1980) description of the slow adoption of nuclear power, or more recent studies on the slow diffusion of menstrual cups by Oster and Thornton (2012), or agricultural technology by Conley and Udry (2010). Comin and Hobijn (2010) give many further examples in their study on 15 technologies in 166 countries.

In this thesis, we study factors which determine the speed of adoption of renewable energy technologies. Most renewable energy technologies cannot yet compete (or

at least could not compete some years ago) in price with conventionally produced electricity. Since the 1990s a system of financial subsidies has provided significant incentives for installing renewable energy technologies in Germany. The subsidy scheme is the most important factor driving the adoption of renewable energy technologies in Germany. In Chapter 3, we describe the subsidies along with aggregate trends in renewable energy diffusion and regional differences in Germany.

Another factor that drives technology adoption is peer effects (Brock and Durlauf, 2010; Conley and Udry, 2010; Oster and Thornton, 2012). Recently, several studies (Dewald and Truffer, 2011; Dastrup et al., 2012) analyzed the adoption of photovoltaic (PV) systems, i.e., solar cell systems for producing electric power. Many studies found peer effects to be an important driver for PV adoption (Bollinger and Gillingham, 2012; Islam, 2014; Müller and Rode, 2013). We define peers as (potential) adopters nearby. Exact locational data on PV adopters allows us to identify peer effects more precisely than in previous studies, and across a whole country. The country we study is Germany, where the PV capacity installed was by far the highest worldwide in 2013 (IEA-PVPS, 2014).

In their overview of analytical tools for environmental economists studying technological change Jaffe et al. (2002) suggest the epidemic model of technology diffusion when – as in our case – no specific data on the respective decision-makers is available. The model indicates an S-shaped diffusion and builds on the idea that diffusion is primarily driven by the spread of information. Focusing on the latter aspect makes sense as the cost and the revenue opportunities of PV can be considered as having a comparable level across Germany when controlling for certain spatial characteristics such as solar radiation. We therefore employ the epidemic diffusion model to analyze peer effects in PV adoption in Chapter 4. Note that the epidemic diffusion model's terminology refers to imitation which corresponds to peer effects.

In general, the diffusion of new technologies (in space and time) results from a series of individual decisions to adopt (i.e., to begin using the new technology). Since the decision to adopt (in a certain period of time) is a discrete one (Karshenas and Stoneman, 1992), we follow Müller and Rode (2013) and employ a discrete choice model in Chapter 5. Discrete choice analysis is the standard approach to analyzing individual discrete decision-making (McFadden, 2001). Exact locational data on PV adopters and potential adopters allows us to be the first to build a specific measure of the peer effect for each potential decision-maker per time period across a whole

country. By doing so, we can – besides identifying the peer effect – also find out how peer effects in PV adoption vary over time and space.

Understanding the impact of peer effects may help to foster diffusion. That is, installation seeds could be used by (political) decision-makers to raise the diffusion speed by steering adoption to locations where adoption is most intended (Islam, 2014; Müller and Rode, 2013).

After dealing with drivers of renewable energy adoption in Germany, we focus on barriers in this thesis. During recent years we have observed more and more referenda against renewable energy plants (see Datenbank Bürgerbegehren (2014)). In Chapter 6, we want to find out whether local referenda against a single renewable energy plant have a measurable impact on the technology's adoption rate (i.e., the first difference in the diffusion level) nearby. If a local referendum hinders building a plant, investors may search for an alternative spot on which to build a plant in the immediate vicinity of the primary location. Investors may also search for a new site far away or may fully give up their plans. We make use of the well-studied logistic shape of technology diffusion and investigate which effect referenda against renewable energy plants have in Germany.

Finally, we turn to consequences from renewable energy adoption. While PV adoption accelerated strongly in Germany, Germany's Green Party experienced a significant increase in its share of votes in federal elections: from 6.7% in 1998 to 10.7% in 2009. This observation raises a question which has not been studied before. Has the diffusion of green energy technologies helped the Green Party increase its share of votes? We answer this question in Chapter 7.

We face the common identification challenges in all our empirical studies. Failing to control for unobserved heterogeneity may result in biased estimates. We therefore have to account for other barriers, drivers and implications from renewable energy adoption than the ones we study. We take advantage of time fixed effects that capture time-varying factors that have a symmetric effect on the increase in renewable energy diffusion across regions: for example, changes in legislation fostering the adoption of the technologies or changes in their installation costs. We use regional fixed effects to absorb regional-specific trends in the increase in the diffusion of the studied technology. These could be caused by regional characteristics affecting the usability of the technology: e.g., a region's average solar radiation affects the profitability of PV systems, a locations's average wind speed determines

the profitability of wind power plants or local agricultural production can be more or less suitable for biomass plants. Therefore, we control for regional and year fixed effects when studying peer effects in PV adoption in Chapter 4 and 5. We also do so when studying whether a successful referendum against one renewable energy plant is associated with lower adoption rates in the same German region in Chapter 6, and when investigating the impact that the diffusion of PV systems has on the votes obtained by the Green Party in Chapter 7. We give further details on our identification strategies in the following chapters. But before we start our empirical analyses, we review models of technology diffusion in Chapter 2 and describe the institutional context, aggregate trends and regional differences of renewable energy adoption in Germany in Chapter 3.[1]

[1]The notations in the empirical analyses in Chapter 4, 5, 6 and 7 are chapter-specific. The data sets we use in these chapters always build upon the description in Chapter 3. However, depending on when we composed the working papers on which all chapters of this thesis are based, we study different time periods. Although slightly rearranged, this thesis is completely based on the following working papers: Rode and Weber (2012), Rode and Müller (2014), Rode (2014), and Comin and Rode (2013).

2. Models of Technology Diffusion

This chapter contains a review of models of technology diffusion, which is relevant to the empirical analyses at a later stage. Literature relevant to single studies is included in the specific chapters.

Since Griliches' (1957) seminal paper on the diffusion of hybrid corn among farmers, the diffusion of technologies has been frequently studied by economics scholars. Griliches also introduced the idea of an S-shaped pattern of innovation diffusion. In his early work, Mansfield (1961) supplemented this idea by stating that imitation may be important for the spread of innovations among firms. These ideas are enhanced and frequently employed in marketing science. Studies in marketing usually build on the model by Bass (1969) and analyze the diffusion on the aggregate level. Similar models are also common in other disciplines: e.g., Dodds and Watts (2004, 2005) illuminate diffusion models from a biological view.

Roughly speaking, the concept of imitation is based on the idea that the spread of information (more or less directly) leads to adoption decisions. To some extent, this is hard to reject, but due to this very general type of model, many extensions are imaginable (Geroski, 2000). There are numerous models which try to capture the social process behind the diffusion of new technologies more adequately: instead of solely asserting that the knowledge of the novelty is acquired, one can make more sophisticated assumptions on how people behave and why they adopt. Such studies include – inter alia – Karshenas and Stoneman (1993), Conley and Udry (2010) and Levin et al. (2012). The general concept is often referred to as *social learning* (Young, 2009). Social learning means that non-adopters learn the utility of a novelty before they consider adopting.

However, this and other more preconditioning concepts require individual-related data which we cannot access, at least for our Germany-wide aggregate analyses in Chapter 4. In the following, we review other approaches and their rationales for adoption.

2.1. Epidemic diffusion models

The epidemic diffusion model builds on aggregated data and is suggested by Jaffe et al. (2002) for analyzing technological change in environmental economics. This model implies that the decision should mainly depend on the information the potential adopter has.[2] Still, the content, which diffuses, can vary: for instance, it may be information on profitability, the spread of a status effect (Welsch and Kühling, 2009) or of green motives. These aspects support the impact of imitation in our analyses.

Epidemic diffusion models – also called contagion models – explain the diffusion of innovations by the spread of information encouraging adoption (Bass, 1969; Geroski, 2000; Peres et al., 2010). This information may on the one hand be codifiable areas of knowledge, such as information about the existence of the technology itself, or on the other hand tacit areas of knowledge (Polanyi, 1967), such as beliefs, trust or personal experience on how to use the innovation.

An epidemic diffusion model can be described by a population N and the number of users at time t, $y(t)$. The information can be considered as being split into a 'formal', codifiable part, which is being transmitted by a central entity, and into a tacit part, which is borne and sent out by users, who have already adopted the innovation. Following Geroski (2000), we define

$$\Delta y(t) = [\alpha + \beta y(t)] \times [N - y(t)] \,. \tag{2.1}$$

$\Delta y(t)$ denotes the new users between t and $t+1$, i.e., $\Delta y(t) := y(t+1) - y(t)$. The information spread by the central information source is described by the *coefficient of external influence* $\alpha \in [0,1]$: in every period, a share α of non-users adopt the innovation *because* of the central entity. The information borne by current users affects the adoption by non-users through the *coefficient of internal influence* β. Again, in every period, each existing user contacts a share β of current non-users $N - y(t)$ which then leads to $[\beta y(t)] \times [N - y(t)]$ new users.[3] As the number of adopters increases, information flows faster, accelerating the adoption rate. According to the literature, the effect modeled by β refers to imitation related to *word of mouth*. Still,

[2] Certainly, there may also be other motives for not adopting: e.g., potential adopters could mistrust the technology, be financially constrained or expect higher financial attractiveness in future.

[3] It is also possible to model the internal process with a contact rate describing which number of agents of the whole population each user contacts (Bass, 1969).

we do not assert an exclusively personal communication, but rather suggest that the real processes behind this relationship may be more or less institutionalized: the internal source may cover both: just seeing the technology or product in operation and being convinced through being informed by peers. Solving (2.1) for continuous time (see Appendix A) yields the S-shaped curve of innovation diffusion over time plotted in Figure 2.1.

2.2. Probit models of technology diffusion

In addition to epidemic models, other theories also imply S-shaped technology diffusion. Geroski (2000) refers to Probit models. These models rely on exogenous bell-shaped distributions of adoption costs or profits among potential adopters to generate heterogeneity in the timing of adoption. An example is the vintage human capital model of Chari and Hopenhayn (1991).

In general, the diffusion of new technologies (in space and time) results from a series of individual decisions to adopt (i.e., to begin using the new technology). Since the decision to adopt (in a certain period of time) is a discrete one (Karshenas and Stoneman, 1992), technology adoption can be analyzed by probit models. These models explicitly allow modeling the individual decisions. Discrete choice analysis is

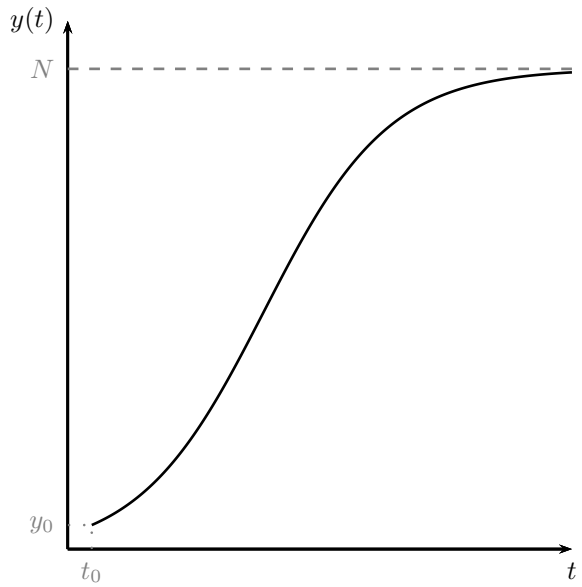

Figure 2.1.: S-shaped technology diffusion $y(t) = \frac{N - \frac{\alpha N(N-y_0)}{\alpha N+\beta y_0} \times \exp\left[-(\alpha+\beta)(t-t_0)\right]}{1+\frac{\beta(N-y_0)}{\alpha N+\beta y_0} \times \exp\left[-(\alpha+\beta)(t-t_0)\right]}$.

the standard approach to analyzing individual discrete decision-making (McFadden, 2001). In particular, Geroski (2000) highlights that when focusing on differences in adopter characteristics the probit model is appropriate. The probit model is a specific discrete choice model. We use a discrete choice model to analyze technology adoption in Chapter 4.

2.3. Further rationales for non-linearities

Besides epidemic and probit models of technology diffusion, the literature has provided two more rationales for the non-linearity of diffusion curves. The tension between the legitimization of the technology in the population and competition for limited resources required to adopt it can generate S-shaped diffusion (Hannan and Freeman, 1977, 1984). Finally, in information cascades models (Arthur, 1989; Banerjee, 1992)) agents initially adopt slowly because they are experimenting with various technological options. Followers, instead, find it optimal to copy their predecessors as in a herd, leading to an acceleration of the speed of diffusion. A survey including all the models mentioned can be found in Geroski (2000).

2.4. Drivers of green technology diffusion

In addition to the standard forces that induce logistic diffusion patterns, a few other drivers have been pointed out as relevant for the adoption of green technologies. These include regulation (Snyder et al., 2003), feed-in tariffs (Dewald and Truffer, 2011; Jacobsson et al., 2004), environmental ideology (Kahn, 2007), consumption patterns of reference persons and habit (Welsch and Kühling, 2009). Further, along with our analyses in Chapters 4 and 5, Bollinger and Gillingham (2012) and Müller and Rode (2013) argue that peer effects deliver logistic dynamics.

3. Institutional Context, Aggregate Trends and Regional Differences

In this chapter, we describe the institutional context of renewable energy adoption, its aggregate trends and regional differences in Germany. We can study regional differences since we exploit a new unique data set. It comes from ÜNB (2013). The data set includes the address, installation date and size of all grid-connected wind power plants, biomass plants, and PV systems for electricity generation across Germany installed between 1992 and 2011.[4] We geocode the address data and can therefore use exact locational data in our analyses.

3.1. PV systems

Several sources (BSW-Solar, 2011; BMU, 2011; Dewald and Truffer, 2011) confirm that most PV systems in Germany ($> 80\%$) are rooftop systems. In consequence, we can take the number of buildings as a proxy for the number of potential PV users. Since the number of buildings on the NUTS-3 level is directly available dating back to 1995 from DESTATIS (2013b), we begin our analysis of PV adoption in 1995. In Figure 3.1 we show the fraction of buildings with new PV system per year according to their capacity. We observe that only few PV systems are larger than $100\,\mathrm{kW_p}$, which are definitely too large to be private household systems. When using other thresholds (e.g., $30\,\mathrm{kW_p}$) the picture does not change dramatically. Our first conclusion from Figure 3.1 is that most PV systems in Germany are small, private household systems.

[4]Since only 1.5% of the wind power plants, 3.5% of the biomass plants and 0.2% of the PV systems were shut down through 2011, we neglect decommissioning in our studies.

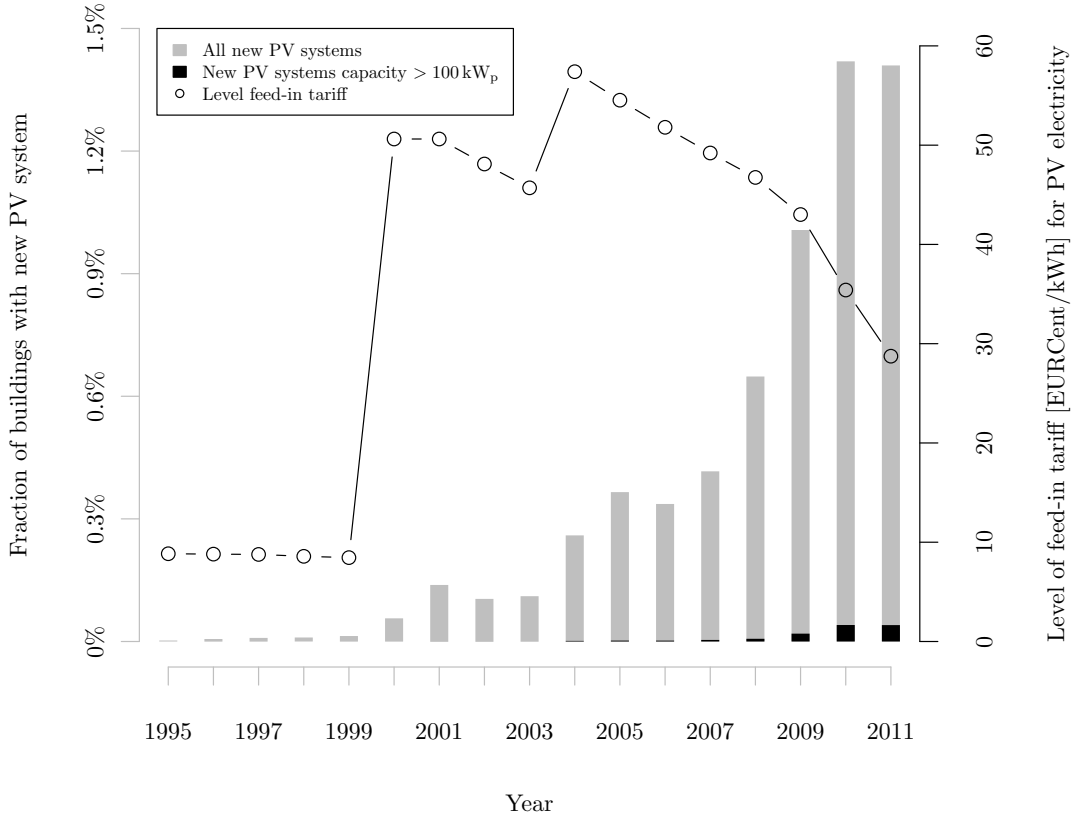

Figure 3.1.: Fraction of buildings with a new PV system and the level of the feed-in tariff for electricity from PV (for systems with a capacity of at most 30 kW_p) in Germany from 1995 through 20011.

Since 1991, the Germany-wide Electricity Feed-in Law ('Stromeinspeisungsgesetz') and its successors have guaranteed that the grid operators have to accept that electricity produced by renewable energy sources is fed into the grid (e.g., see Altrock et al. (2006) for details). The law also guaranteed that the producers of electricity from renewables received a remuneration, which was at the same level (around 9 EURCent/kWh) for all renewable energy technologies.

In 1998, the Social Democratic-Green coalition won the federal elections. Two years later, the government introduced a new feed-in tariff scheme through the 'Erneuerbare-Energien-Gesetz' (EEG), which raised the feed-in tariff for electricity produced from PV. For example, the feed in tariff for systems with a capacity (size) of, at most, 30 kW_p was raised to 50 EURCent/kWh (from 9 EURCent/kWh).[5] The

[5]The capacity (or nominal power) of a PV system is specified in kilowatts-peak [kW_p], i.e., the system's maximum power output under defined conditions. In contrast, produced electricity is measured in kilowatt-hours [kWh].

feed-in tariff was vintage-specific and was guaranteed for twenty years (Agnolucci, 2006; Altrock et al., 2011; Maurer et al., 2012). However, starting in 2002, new installations received a feed-in tariff 5% lower than installations put in place the previous year. See Figure 3.1. The feed-in tariff is financed by apportioning costs to all consumers of electricity; thus the costs are born by all consumers.

Additionally, between 1999 and 2003, the government provided low-interest loans for PV roof installations through the 100,000 roofs program (Jacobsson and Lauber, 2006). By 2003, the fraction of buildings with PV systems was 0.4%, about 10 times larger than in 1999. The 2004 amendment to the EEG further raised the feed-in tariff to 57 EURCent/kWh (see Figure 3.1). By 2011, 6% of buildings had PV systems, which corresponds to more than 1.1 million systems.

In Figure B.1 of Appendix B.1, we show an alternative measure of diffusion: capacity-adjusted adoption per year. Large plants build a higher share with capacity-adjusted measures.

3.2. Wind power

Wind power plants – also called eolic plants – are – in contrast to PV systems – not installed on buildings. In order to normalize their adoption we use forestal and agricultural land area given by CLC (2009). In Figure 3.2, we illustrate the yearly number of new wind power plants per forestal and agricultural land area according to their capacity. We learn from the figure that wind power plants are – in contrast, to PV systems – mainly large systems (above a capacity of 0.5 MW). As investments in wind power plants are large, they are all industrial.

Figure 3.2 also highlights that the adoption of wind plants already accelerated in the 1990s. Whereas the remuneration was not high enough to substantially foster the adoption of PV systems, it was high enough for wind power plants. In 1999, almost 6,000 wind power plants existed in Germany. Their total capacity installed was more than 100 times larger than the capacity installed in PV systems. Also see Figure B.2 of Appendix B.1 which illustrates the capacity-adjusted adoption per year. As for PV, large plants build a higher share with capacity-adjusted measures of eolic adoption.

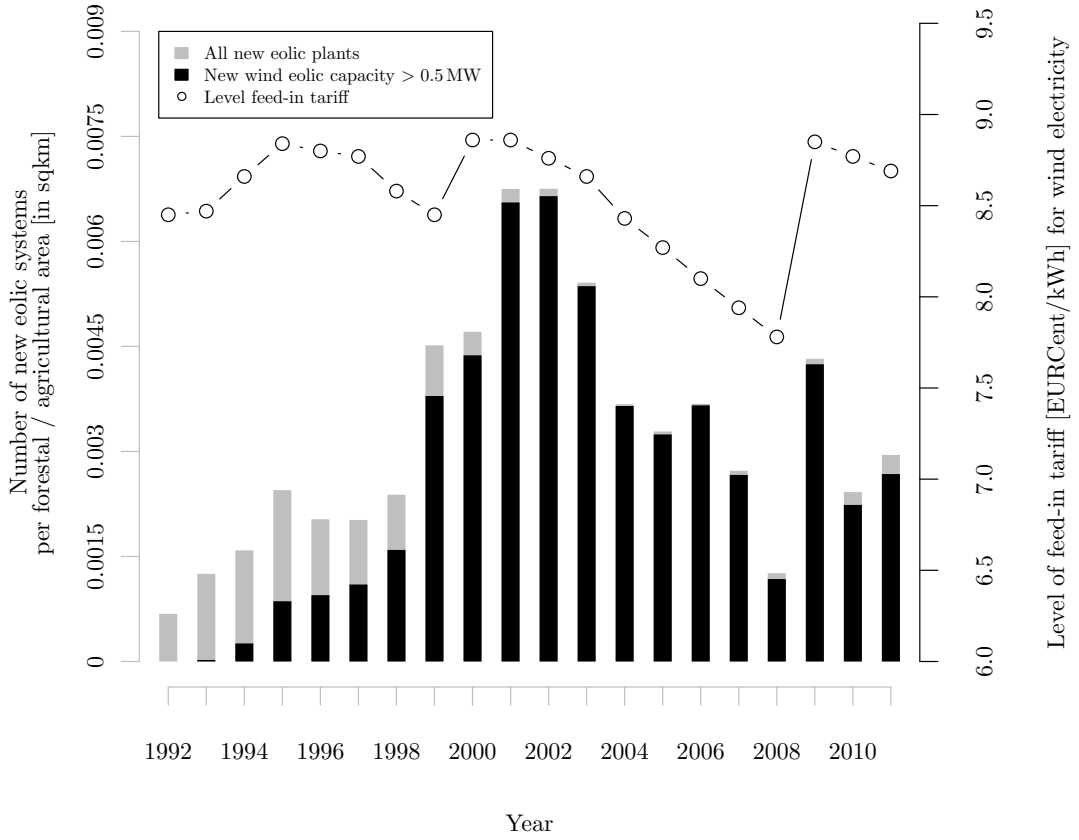

Figure 3.2.: Number of new eolic (onshore) systems per forestal and agricultural area [in sqkm] and the level of the average feed-in tariff for electricity from eolic (onshore) systems (of 90% reference yield without system service or repowering bonus) in Germany from 1991 through 2011.

The 2000 EEG also introduced new feed-in tariff schemes for electricity from eolic plants, though they rose comparatively less than for PV systems (9.1 EURCent/kWh). (See Figure 3.2.) Unlike PV systems, the feed-in tariff for eolic systems was not fixed for 20 years. For the first five years they were fixed at a certain amount and then at some point once the installation was five years old, the feed-in tariff dropped to a new level. The date of reset of the feed-in tariff depended on the efficiency of the installation. In less efficient installations, the high feed-in tariff period was longer. The reset level of the feed-in tariff was 6.19 EURCent/kWh for eolic systems installed in 2000. Since 2000, eolic systems have diffused more slowly than PV systems, and by 2011, the total capacity installed in PV systems almost equaled the capacity installed in eolic plants.

3.3. Biomass plants

As eolic plants, biomass plants are all industrial because of the large investments they require. To build a normalized measure of biomass diffusion, we can use agricultural land area (see left axis in Figure 3.3). As for PV, the number of new biomass plants (see right axis in Figure 3.3) did not grow rapidly during the 1990s. Through 1999 we find less than 300 biomass plants across Germany. Most biomass plants have a capacity below 1 MW_e. MW_e means megawatt electrical to distinguish from MW_{th}, which refers to thermal power produced.

2000's EEG also raised the feed-in tariff for biomass plants: for small biomass plants, e.g., to 10.2 EURCent/kWh. For biomass plants – like PV – the feed-in tariff was guaranteed for 20 years. Since 2002 (2004), new installations have received a feed-in level at 1% (1.5%) lower for biomass plants than those put in place the year before. Further, several bonuses (up to additional 18 EURCent/kWh) exist for

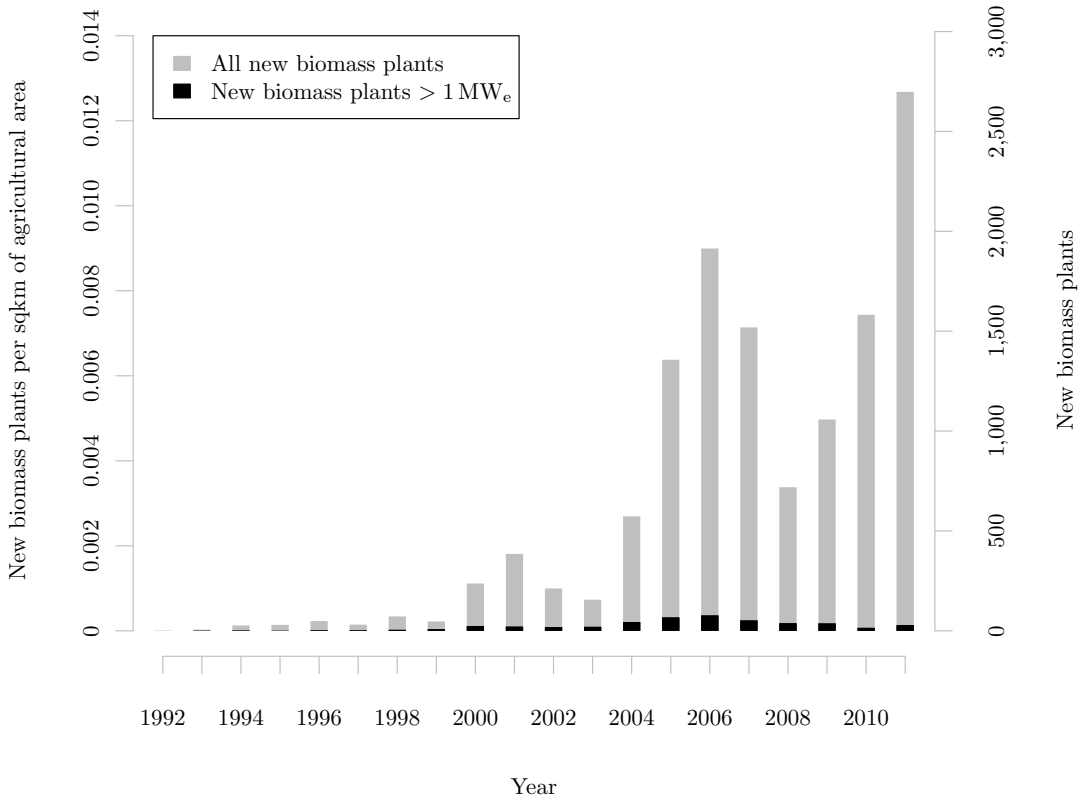

Figure 3.3.: Adoption of biomass plants in Germany per year.

biomass plants if they, e.g., use innovative technologies, certain renewable resources or combine heat and power generation.[6]

With the EEG in place, the adoption of biomass plants accelerated. In 2004 and 2011, amendments to the EEG changed the level of remuneration for biomass in the way that smaller plants receive higher tariffs. By the year 2011, we observe more than 12,500 biomass plants across Germany. This equals 0.06 biomass plants per agricultural sqkm. In total, these biomass plants account for 20% of the capacity all wind power plants have in 2011. Figure B.3 in Appendix B.1 shows capacity-adjusted measures of yearly biomass adoption.

3.4. Regional differences

Beneath these aggregate trends in green energy diffusion there are important regional differences. Figure 3.4 shows the evolution of the fraction of buildings equipped with PV systems for the years 1998, 2002, 2005 and 2009 on the NUTS-3 level in Germany.[7] We choose these years since they are relevant in our analysis at a later stage. In 1998, the diffusion level of PV systems was low in all regions. By 2002, we begin to notice significant regional differences, with higher diffusion rates in the south – Baden-Württemberg and Bavaria – where global solar radiation is higher. Through 2005 and 2009, the highest diffusion rates can be observed in the south, in the north of Hesse and in the east and the north-west of North Rhine-Westphalia. In contrast, relatively few PV systems were installed in the middle of North Rhine-Westphalia, the east of Lower Saxony, the south of Schleswig-Holstein and, in general, the eastern part of Germany.

Figure 3.5 illustrates the diffusion of eolic systems. By 1998, there were already significant regional differences in their diffusion. Some northern regions such as Dithmarschen, Schleswig-Holstein, (0.30 wind mills per sqkm) and Hamburg (0.29) had considerable diffusion of eolic systems. In contrast, 48% of the regions – many of them in Bavaria and Baden-Württemberg – had no eolic system installed. In 2009, these differences prevailed. The regions with highest diffusion levels of eolic systems were Emden, Lower Saxony, (0.88 wind mills per sqkm) and Bremerhaven,

[6]Since the bonuses and their changes over time vary strongly, we cannot easily compare the levels of the feed-in tariff for biomass per year and therefore do not plot them.

[7]Due to the restructuring of districts, we lack data for 2.3% of the NUTS-3 regions for 1998, 2002 and 2005, and for 6.9% for 2009.

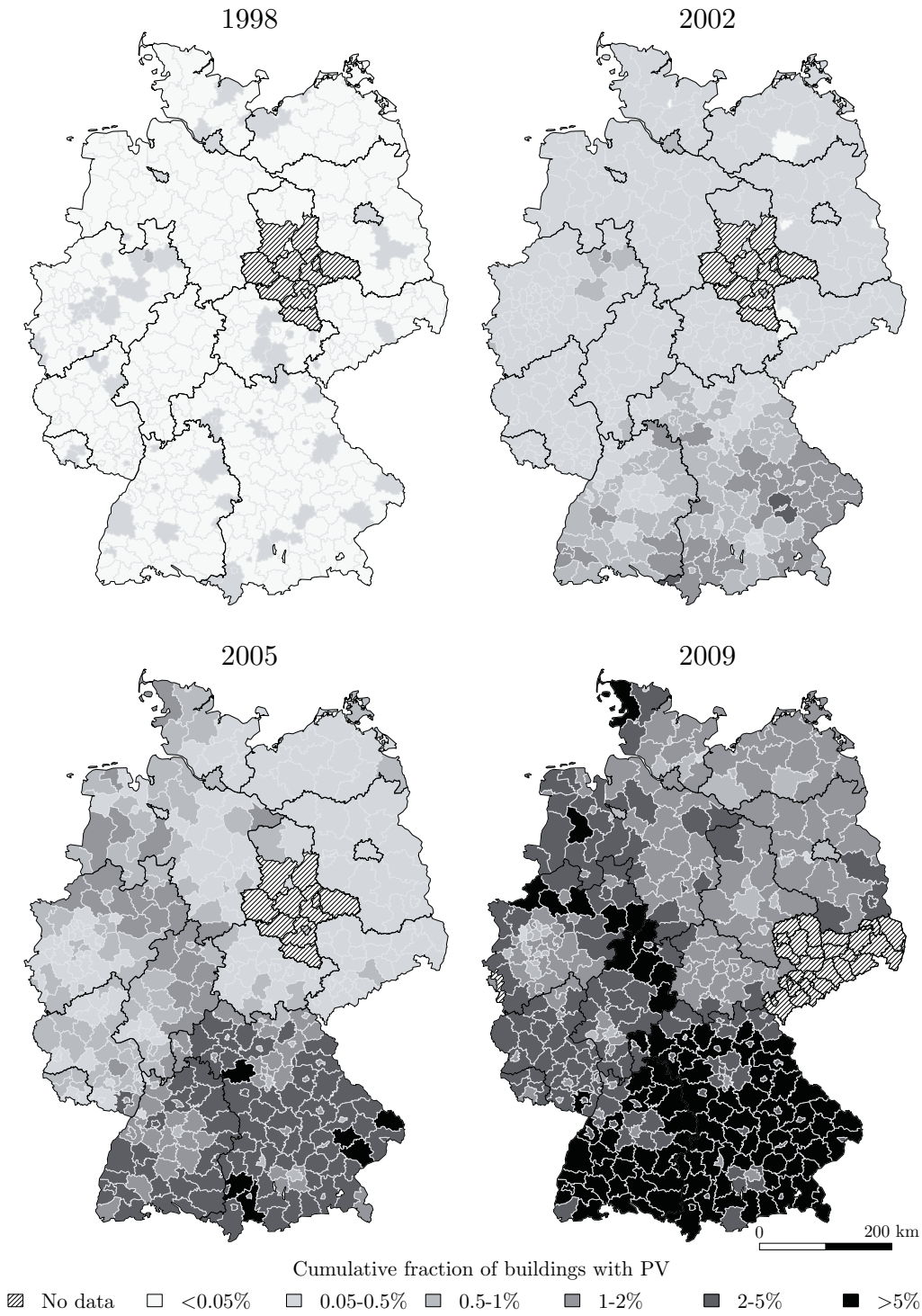

Figure 3.4.: Fraction of buildings with PV at NUTS-3 level for 1998, 2001, 2005 and 2009.

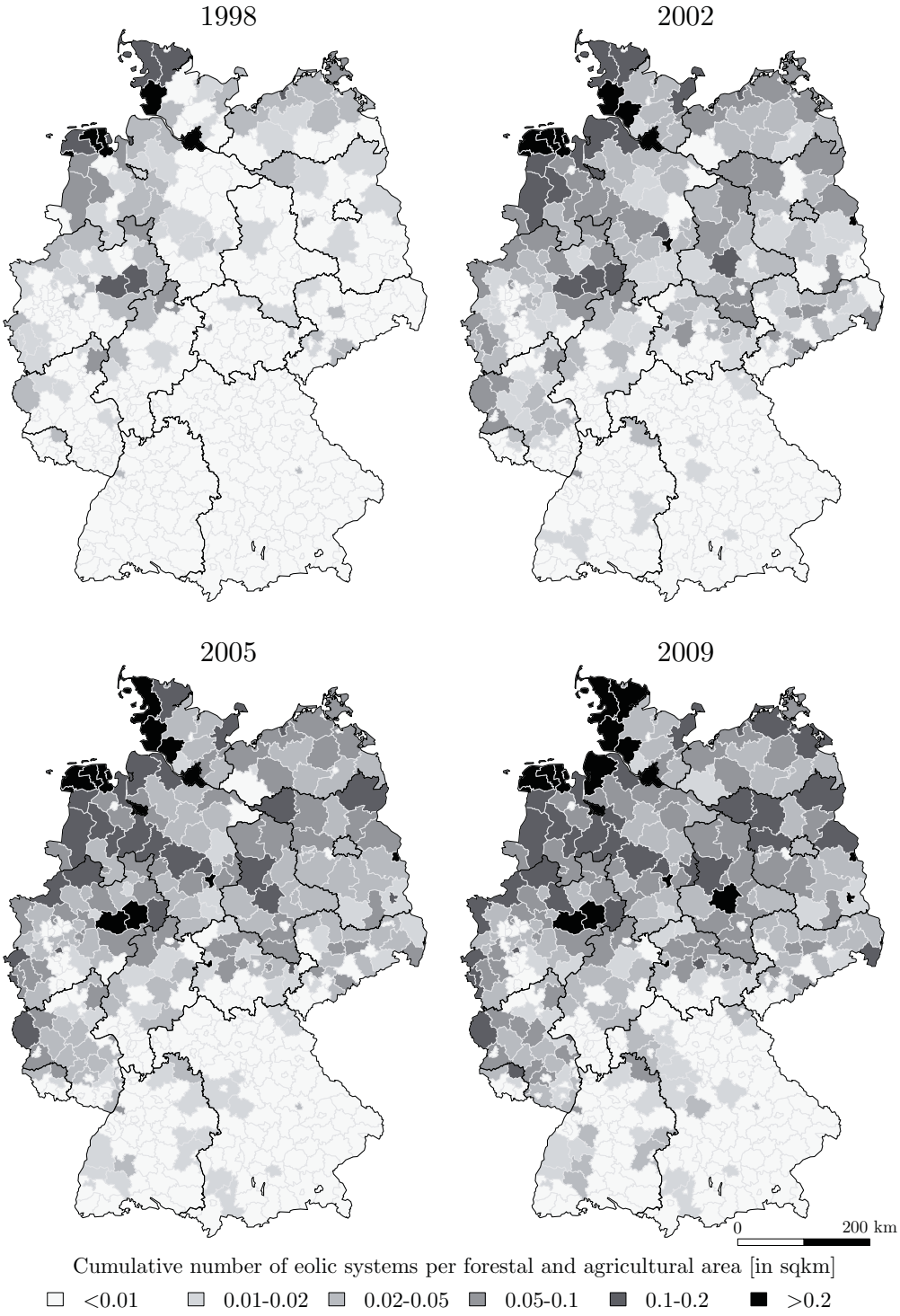

Figure 3.5.: Number of eolic (onshore) systems per forestal and agricultural area [in sqkm] at NUTS-3 level for 1998, 2001, 2005 and 2009.

Bremen, (0.71). The share of regions without eolic systems installed dropped to 24%, and these are concentrated in Bavaria, North Rhine-Westphalia and Baden-Württemberg.

In Figure 3.6 we see the number of biomass plants at the NUTS-3 level in 2011. Most plants are located in the rural areas in the south and the north of Germany.[8] We find only few plants (5.6%) in district-free cities, which is relevant at a later stage.

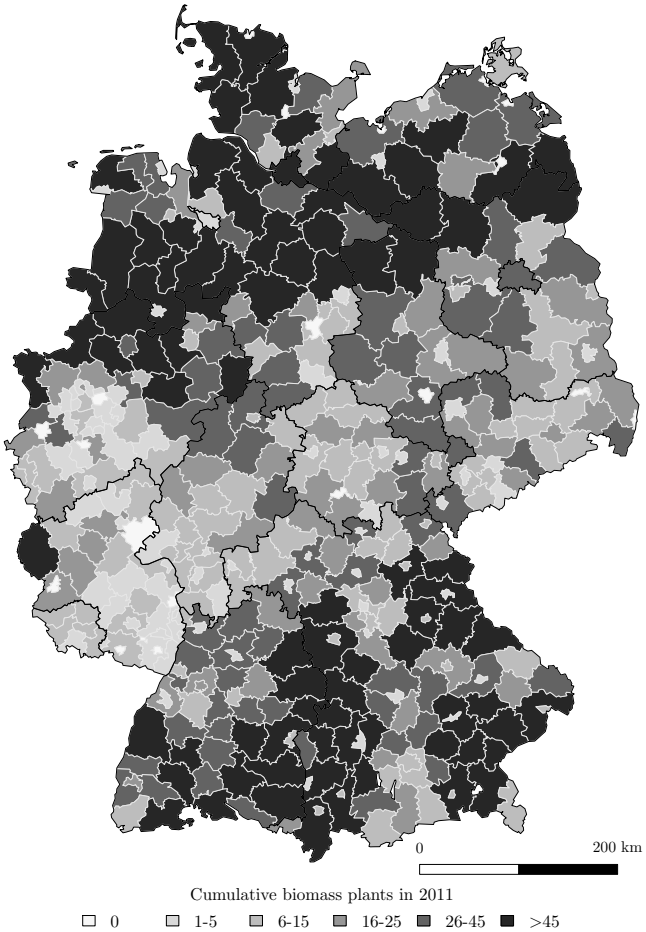

Figure 3.6.: Counts of biomass plants at NUTS-3 level in 2011.

As for biomass, we can illustrate the non-normalized diffusion of PV systems and wind power plants at the NUTS-3 level. Appendix B contains the counts of PV systems (Figure B.4) and wind power plants (Figure B.5) for the year 2011. We observe similar patterns to the normalized diffusion. In Bavaria and Baden-Württemberg (the south of Germany), we even find 46 NUTS-3 regions with no wind power plants

[8]For details, see Mangold (2014), who conducts a solid analysis on biomass diffusion in Bavaria.

at all. As for biomass plants, we see few wind power plants in district-free cities: only 3.3% of all wind power plants are installed in the 113 district-free cities (out of 429 NUTS-3 regions in total), which is relevant at a later stage.

After describing the institutional context of renewable energy adoption, its trends and regional differences in Germany, we turn to the first empirical analysis of this thesis.

4. Does Localized Imitation Drive Adoption[9]

4.1. Motivation

The finiteness of fossil fuels and their effect on climate change has encouraged the search for sustainable energy technologies. One of these technologies is PV, i.e., solar cell systems for producing electric power. Although PV cannot yet compete in price with conventionally produced electricity, since the year 2000 a system of financial subsidies has provided significant incentives for installing PV systems in Germany. In consequence, the PV capacity installed per capita was by far the highest worldwide in 2009 (REN21, 2010), even though the global solar radiation is low when compared to other countries in the south.

Figure 4.1, in which each gray dot marks a PV system, shows that the spatial distribution of PV systems is inhomogeneous in Germany. Our objective is to identify important drivers of this observed distribution. This question is particularly interesting as the impact of a nation-wide policy is studied in time and space. Our analysis may contribute to the understanding of policy-induced diffusion and could therefore be helpful for fostering the diffusion of other distributed energy technologies or subsidized products in general.[10]

To be clear, the purpose of this chapter is to investigate whether localized imitation drives PV adoption. In order to do so, we base our analysis on a data set covering

[9] This chapter is based on a revised version of Rode and Weber (2012).

[10] When referring to a technology, we refer to the artifact, thus, in our case, the PV system as such. In contrast, there are studies which define technology differently, e.g., according to Comin and Hobijn (2010, p. 2032) a technology *"is a group of production methods that is used to produce an intermediate good or service."* Furthermore, adoption – in this chapter – describes the first purchase by an individual whereas diffusion refers to the rate at which something spreads in a group of individuals.

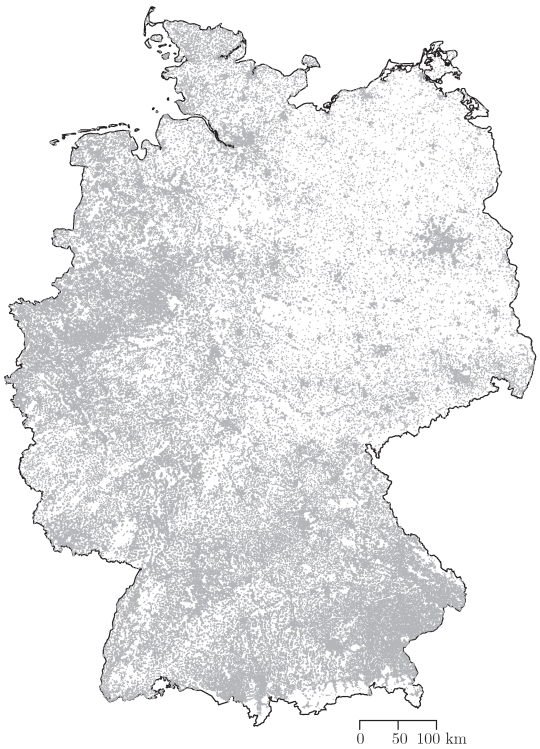

Figure 4.1.: Distribution of PV systems within Germany through 2009; each gray dot represents a PV system.

the PV installations in Germany through 2009. We analyze the data in an epidemic diffusion model, which includes a spatial dimension. The model is discrete in time and space, but its level of geographical aggregation is adjustable in arbitrarily small steps.

In their overview of analytical tools for environmental economists studying technological change Jaffe et al. (2002) suggest the epidemic model of technology diffusion when – as in our case – no specific data on the respective decision makers is available. The model builds on the idea that diffusion is primarily driven by the spread of information. Focusing on this aspect makes sense as the cost and the revenue opportunities of PV can be considered as having a comparable level across Germany when controlling for certain spatial characteristics as solar radiation.

The analysis of PV adoption is different to the general case of purely market driven diffusion since use of the innovation is highly subsidized (Jaffe et al., 2002; Rosendahl, 2004; Davies and Diaz-Rainey, 2011), partly with yearly changes in the subsidy system. Therefore, we complement the epidemic diffusion model by building on approaches from marketing science: as we have data on the installation year for all the PV systems, we can include temporal fixed effects (FE) – in the same way

that Horsky and Simon (1983) extend the model – to cover changes in the subsidy system. Further, we account for aggregate effects by adding control variables – e.g., global solar radiation and household income – as suggested by Boswijk and Franses (2005), allow a time varying number of potential adopters in line with Mahajan and Peterson (1985) and follow Peres et al. (2010) when including space into the epidemic diffusion model. As the epidemic diffusion model requires information on the number of potential adopters in order to capture saturation and most of the PV installations in Germany ($> 80\%$) are rooftop installations (BSW-Solar, 2011), we take the number of buildings as a proxy for the number of potential users.

According to Janssen and Jager (2002), the decision to install solar power can be characterized by a high relevance of social compatibility: *"[c]onsumers frequently feel satisfied when consuming the same as their neighbors (social needs) and often engage in social comparison and imitation when deciding what to consume"* (Ibid., p. 288). Bollinger and Gillingham (2012) and Noll et al. (2013) point in the same direction. They find peer effects in the adoption of PV in the United States (U.S.). In their analysis of individual-level data on the adoption of solar thermal equipment, Welsch and Kühling (2009) confirm this view. They find that the behavior of reference groups is of major importance. In addition, their analysis reveals that environmental awareness is not an important reason for installing solar thermal equipment in Germany since the subsidy system is strong. As the subsidy system is strong for PV systems, environmental awareness may also be of minor importance for PV. To turn the argument on its head, other reasons might prevail: A natural reason to imitate adoption would be if PV systems were highly profitable. However, we show – in Appendix C.1 – that PV systems were sometimes profitable and sometimes not during the time period we study. Still, imitation can be a driving force. Welsch and Kühling (2009, p. 172) suggest that another motive could be status or prestige and refer to a *"Mercedes-Benz on the rooftop"*.

Similarly, numerous simulation studies on innovation diffusion build on the idea that agents are influenced by or learn from social peers or spatial neighbors (Ellison and Fudenberg, 1993; Bala and Goyal, 1998; Chatterjee and Xu, 2004). Related ideas are introduced and partly empirically verified by Hägerstrand (1967), Morrill (1968) and Morrill (1970). These authors highlight the fact that the spatial separation of agents limits the degree of contact. This is based on the assumption that information flows decline with distance. Given that we study the spatial characteristics of PV adoption and if imitation is indeed an important factor for PV adoption, it may also be of interest how far imitation reaches.

In contrast to many studies on technology adoption, we know the exact location and the year of installation for all 552,259 German (PV) technology adopters through the end of 2009.[11] This unique data allows us to estimate characteristics of the diffusion process of a distributed renewable energy technology all over Germany and to explicitly quantify how far imitative adoption behavior reaches for PV. Furthermore, in our analysis we do not assume – e.g., in contrast to Mahajan and Peterson (1979) – a fixed influence of distance, but instead estimate its magnitude empirically.

This chapter is structured as follows. In Section 4.2, we introduce the theoretical background. Subsequently, Section 4.3 describes the model and the data. A discussion of the statistical results follows in Section 4.4. Finally, in Section 4.5 we summarize the chapter and provide an outlook on further research.

4.2. Theoretical background

We use an epidemic diffusion model in this study. Section 2.1 in Chapter 2 contains a general description of the model, which builds on the idea that initial lack of information on the technology prevents potential adopters from adopting technologies. As most PV systems are easily visible to passers-by, learning or imitation is allowed without direct social interaction. Therefore, the assumption of information flows between spatially close neighbors – on which our modeling approach is based – should be appropriate.

Many modifications and complementations of the epidemic diffusion model exist, especially in the marketing literature. The following are of importance for our analysis: firstly, Horsky and Simon (1983) include the effects of advertising by extending the coefficient of external influence. In a similar way, shifts in the external influence – e.g., in the subsidy system – could be covered by allowing α to depend on t. Secondly, Boswijk and Franses (2005) state that the cumulative number of adopters may not be represented by a smooth curve. Shifts could, on the one hand, be caused by individual-specific effects or, on the other hand, come from aggregate effects, e.g.,

[11] E.g., Comin et al. (2012) analyze technology diffusion on the country level and Keller (2002) and Verdolini and Galeotti (2011) study technology spillovers between countries. In contrast, our analysis is conducted on a much lower level of aggregation and we rely, of course, on a different understanding of technology diffusion. In our sense the adoption of PV means installing a PV system on a roof and utilizing it to generate electricity. Other studies, such as Conley and Udry (2010), Bollinger and Gillingham (2012) and Müller and Rode (2013), also analyze diffusion on a low level of aggregation but only consider the diffusion across a small sub-unit of a country.

macroeconomic changes. According to Boswijk and Franses (2005) complementing the model with additional variables can solve this problem. One possibility would be to allow α also to be influenced by control variables: $C(t)$. Thirdly, Mahajan and Peterson (1985) explicitly highlight the fact that the amount of potential adopters may vary over time, which results in $N(t)$. In consequence, the epidemic diffusion model may be represented by:

$$\Delta y(t) = [\alpha\,(t, C) + \beta y(t)] \times [N(t) - y(t)]\,. \tag{4.1}$$

Finally, Mahajan and Peterson (1985) suggest that it might be important to consider space when studying innovation diffusion. A very intuitive insight of spatial analysis – by Tobler (1970, p. 236) – is that

> *"everything is related to everything else, but near things are more related than distant things."*

In terms of statistical analysis, this means that data at spatially close points may exhibit a higher correlation than at more distant points.

Concerning the diffusion of innovations, there is some evidence in literature that adoption of innovations may be localized. This may be especially true for the tacit part of knowledge since it builds on experience, which cannot be transferred easily as codification may not be possible (Breschi and Lissoni, 2001). In contrast, codifiable knowledge is thought to be transmittable over distance as it can easily be written down (Audretsch and Feldman, 1996). Similarly, Jaffe (1989) and Ponds et al. (2007) suppose that face to face contacts are necessary to share tacit forms of knowledge. Geographical proximity is thought to encourage close interaction (Baptista, 1999), which in turn stimulates the exchange of tacit knowledge parts. Taking into account the concept of spatial autocorrelation, one may however not only ask for the 'localization' of imitative behavior but rather for the spatial range of influence the word of mouth has and how it attenuates with distance.

The common methods for incorporating spatial relations in econometric analysis are distance or contiguity matrices (Anselin, 1988). However, we do not want to predefine a certain functional form of spatial relations: often the inverse distance or the squared inverse distance are used in this sense. In contrast, we explicitly estimate the magnitude of spatial influence depending on distance.

4.3. Building the model

To analyze the evolution of PV systems in space and time, we adapt Equation (4.1) by incorporating a localized spatial component.[12] Obviously, Tobler's Law could be valid here in the sense of explaining localized epidemic spread: it is likely that potential adopters become more easily convinced to adopt the innovation the closer the users spreading the tacit knowledge on the innovation are.

In discrete time and space we can localize our population of users within a circle with center point i and radius r_0. We also denote this spatial sample as *inner circle* at point i (alternatively: 'inner circle i'). Let $y_{i,t}$ denote the number of users of the technology within an inner circle at point i and time t. $N_{i,t}$ is the respective population size.[13] By $y_{i,q,t}$, we define the users in a *distance band* with outer radius r_q and inner radius r_{q-1}. q is the integer index of radii starting at 1 for the outer radius of the first distance band. By doing so, we come up with a localized version of the epidemic diffusion model (4.2): still, a share $\alpha\,(t, C)$ of non-users is led to adopt by the central information source and each user contacts a share β_0 of current non-users $N_{i,t} - y_{i,t}$, resulting in $[\beta_0 y_{i,t}] \times [N_{i,t} - y_{i,t}]$ agents to adopt. However, the latter effect (i.e., imitation) also takes place between the population of the distance bands and the inner circle population. To take into account the locational character of the model, we allow C to depend not only on time but also on location: $C = C(i, t)$. The equation takes the following form:

$$\Delta y_{i,t} = [\alpha\,(t, C) + \beta_0 y_{i,t} + \beta_1 y_{i,1,t} + \cdots + \beta_Q y_{i,Q,t}] \times [N_{i,t} - y_{i,t}]. \tag{4.2}$$

The relationship is illustrated in Figure 4.2 for the case of four distance bands, i.e., $Q = 4$. $\alpha\,(t, C)$ and β_q of model (4.2) can be estimated by using a regression technique.

[12] In the functional form of incorporating space into the epidemic diffusion model, we follow Peres et al.'s (2010) description of a cross-country influence model.

[13] We assume the social entity into which PV diffuses – thus our inner circle – to be perfectly connected and homogeneous (Peres et al., 2010).

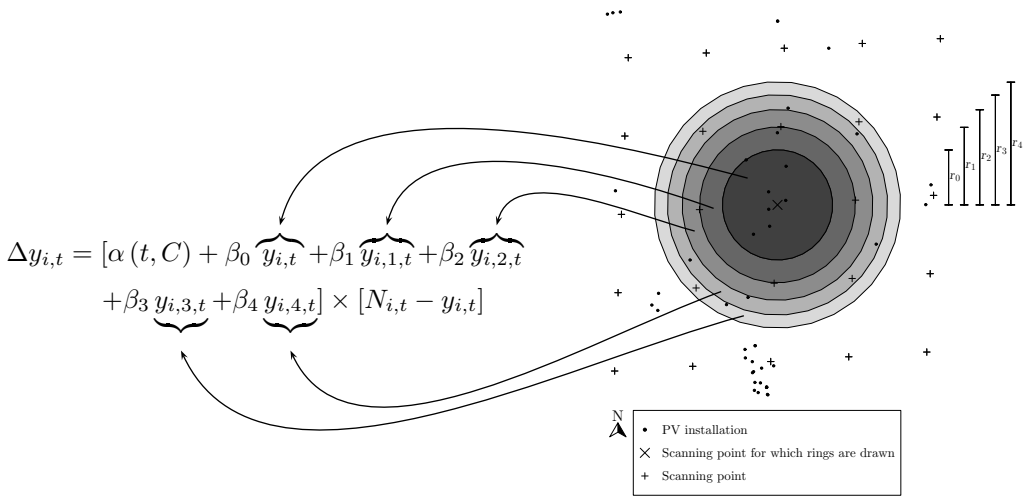

Figure 4.2.: Spatial aggregation of events (PV installations) within the inner circle of radius r_0 (darkest gray) and the surrounding distance bands colored in lightening gray shades for $Q = 4$.

4.3.1. The data

The most central data in the study is that on PV installations. Section 3.1 in Chapter 3 contains details on the subsidy system for PV.[14] See Appendix C.2 for details on the geocoding of the data used in this chapter. The geocoding results in point data on PV installations.[15] Therefore, the model variables $y_{i,t}, y_{i,q,t}, \Delta y_{i,t}$ can be calculated by counting the number of PV installations within the inner circles/distance bands.

Epidemic diffusion models cannot explain why the first users adopt (Geroski, 2000). We refer to the 1,000 roofs program, which was the first *"federal demonstration ... program of small solar cell installations"* in Germany (Jacobsson et al., 2004, p. 16). It was initiated in 1990 and resulted in more than 2,000 grid-connected roof-mounted PV installations. The 1,000 roofs program led to installations across Germany, since a maximum quota of installations was allocated to every German state ('Bundesland') (Hoffmann et al., 1998).

We choose our period of analysis to begin in 1992, since data on our control variables is available dating back to this year. Furthermore, in 1992 the highest number of PV systems funded by the 1,000 roofs program was installed (Hoffmann, 2008).

[14] Although the fraction of buildings equipped with PV is low when looking at Germany as a whole, we come close to saturation at some locations of analysis and therefore consider the epidemic model of technology diffusion, which explicitly allows for saturation, to be appropriate.

[15] A spatial point pattern analysis is not appropriate as we want to model the temporal sequence of events.

In order to be able to control for different environment conditions leading to different propensities to adopt PV, we also employ data on global solar radiation, population density, household income and the share of single/double family homes in all homes. The use of this data should be seen as a possibility to check the robustness of the epidemic mechanism rather than to extend the epidemic model. These controls are incorporated in $\alpha(t, C)$, respectively $C(i, t)$, which besides t can also be specific for inner circle i.

The data on global solar radiation directly affects the income possible with a PV system at a given place: the higher the level of solar radiation is, the higher is the amount of electricity produced and the higher the feed-in remuneration paid to the owner of a PV system will be. The global radiation data, which is provided by the German Weather Service as 1-km raster data (DWD, 2010), is the yearly average from 1981 until 2000 and is hence constant over the whole period of study.[16] We therefore expect the global radiation to have a positive impact on the propensity to install a PV system.

The population density might also play a role: word of mouth might count more in less densely populated areas. The income level may explain possible financial constraints and risk-bearing possibilities. A large share of single/double family homes of all homes within a certain area might also make the process of adoption easier since fewer individuals need to agree on the installation.[17] The three latter data are taken from 2010's INKAR database (INKAR, 2010) and the German Statistical Office (DESTATIS, 2010a,b). These data are available for the whole study period on the NUTS-3 level. We use the 2006 classification with 429 NUTS-3 regions making up Germany as a whole.

Further information on land use is taken from 2006's CORINE Land Cover (CLC) data set, which contains vector data on a scale of $1 : 100,000$ (CLC, 2009).[18] The data enables us to distinguish land use using three different categories: (1) urban areas, (2) field and (3) forest, whereby we neglect forestal areas as very few PV

[16] DWD (2010) combines measures from satellites and local observation stations to build the raster data, i.e., the data accounts for the geographic features of the raster units.

[17] Likewise, Welsch and Kühling (2009) find that agents living in their own house are significantly more likely to have solar thermal equipment than those living in a rented home or in an owned apartment, which also refers to the external agency problem mentioned in Jaffe et al. (2002).

[18] The minimum mapping unit (MMU) for the polygons of 2006's CORINE Land Cover data set is $25\,ha$. In consequence, the CLC data may partly absorb the lack of other control variables on a lower level of geographical aggregation.

systems were installed there. The land use data allows correction for adoption propensities differing between urban and rural areas.

During our period of study – between 1992 and 2009 – the level of the feed-in tariff for electricity produced by PV depended on the year the system was installed. However, only since the year 2000 the Renewable Energy Sources Act has put the subsidy system for PV installations to an interesting level. Nevertheless, prior to this, PV adoption was supported by programs such as the 1,000 roofs program, which fostered PV installations between 1990 and 1995 by bearing 70% of the system and installation costs, and the 100,000 roofs program, which built on subsidized interest rates and fostered PV diffusion between 1999 and 2003.[19] Furthermore, PV installations became cheaper in the time period studied as production costs decreased due to learning effects (Jacobsson et al., 2004; BSW-Solar, 2012). In order to cover the resulting shifts in the incentive to install a PV system, $\alpha(t, C)$ takes into account temporal FE in the form of year dummies. In this manner, we can also allow for saddles in the curve of new PV installations, which, for example, came about in the years 2002/2003 and 2006 in Germany as shown in Figure 3.1 of Section 3.1 in Chapter 3.

The NUTS-3 data, the CLC data and the 1-km raster data required special treatment in order to evaluate them for inner circles. See Appendix C.3 for details.

The number of residential buildings $BUILD_{k,t}$ is also available on the NUTS-3 level for all the years of study. It can be used to calculate the population $N_{i,t}$ of inner circle i for each year t by dividing it equally among all points within a NUTS-3 region k, where k_i is the region in which point i is situated.[20] When $y_{i,2009} = 0$, we set $N_{i,t} = 1$ and ignore this i for the division of buildings within the NUTS-3 region.

The concept of points, inner circles and distance bands can be evaluated in arbitrarily small steps. The most intuitive way to start is to define the scan points i. Our

[19] During the years 1996, 1997 and 1998 the only federal incentive to install PV was a comparatively low feed-in tariff, which was put in place by the Electricity Feed-in Law on the 7th of December 1990. However, at that time some local feed-in tariffs started to foster PV adoption, e.g., in Aachen (Jacobsson et al., 2004).

[20] This approach may lead to a situation where the number of users is extremely close to saturation or even larger than $N_{i,t}$. We require $N_{i,t} \geq y_{i,t}$. In case the $N_{i,t}$ calculated based on $BUILD_{k,t}$ is greater than $y_{i,t}$, we set $N_{i,t}$ to $y_{i,t} + 1$ in order not to assert saturation. This procedure is only necessary for 87 out of 5,824,438 observations for a step width of 1 km. For a step width of 4 km the procedure is needed in 10 out of 333,064 cases. For the step widths of 10 km and 20 km it is not needed.

approach is to define a step width s and to draw latitudinal lines, each having a shortest distance of step width s to its adjacent line. On these lines, we determine points with a step width of s again. Then we remove all scan points outside Germany and those whose circle radii r_q covered areas outside Germany. We take the latter measure to prevent analyzing incomplete areas. Figure 4.3 shows the result for the case of $s = 20\,\text{km}$.

Figure 4.3.: Scanning raster with step width of 20 km; each black dot marks a scanning point.

For defining the radii of the inner circles and respective distance bands, we may choose (in a two-dimensional approximation) $r_0 \geq s/\sqrt{2}$ to ensure that the whole area of Germany is covered by inner circles. This choice implies data resampling to some degree as our inner circles are partly overlapping, which leads to counting some points twice. Therefore, we also resample $N_{i,t}$; the correction procedure is presented in C.4.

The area of the distance bands can be freely chosen, but to ensure comparable sample sizes, we require the distance bands to have the same area as the inner circle. If we set $r_0 = s/\sqrt{2}$, the latter requirement leads to radii $r_q = s \times \sqrt{(q+1)/2}$. Consequently, the scanning raster we use for our study has a step width of $s = 1\,\text{km}$ with an inner circle radius $r_0 = 0.707\,\text{km}$, which results in $342,614$ points. Limits in

computational power prevent us from choosing a lower step width. For comparing different levels of spatial resolution we also compute data on scanning rasters with $s = 4\,\text{km}$, $s = 10\,\text{km}$ and $s = 20\,\text{km}$, respectively. In all three cases we again set $r_0 = s/\sqrt{2}$.

We process the spatial data in a PostgreSQL database with PostGIS extension with self-made C# programs and in R (R, 2013). All distance calculations are done on the WGS 84 coordinate system, except for the algorithm generating the scan points i for which a sphere model of the earth is used. An overview of the data employed is presented in Table 4.1.

Table 4.1.: Overview of the data employed.

Variable	Description	Proxy	Source	Aggregation level
Model Response				
$\Delta y_{i,t}$	New PV installations during t within inner circle i	–	TSOs	Geocoded point data
Explanatory Variables				
$y_{i,t}$	Amount of PV installations through t within inner circle i	Knowledge and experience level regarding PV	TSOs	Geocoded point data
$y_{i,q,t}$	Amount of PV installations through t within distance band q of Q distance bands at i	Knowledge and experience level regarding PV within the distance bands neighborhood of i	TSOs	Geocoded point data
$BUILD_{k,t}$	Number of buildings at k, t	Calculate $N_{i,t}$	DESTATIS (2011)	NUTS-3 level
Variables covered by the external influence $\alpha(t, C)$				
GR_i	Global solar radiation (average of 1981-2000) at i	Earnings from PV	DWD (2010)	1-km raster data
$POP_{i,t}$	Population density at i, t	Correct for sparsely populated areas	DESTATIS (2010a), DESTATIS (2010b)	NUTS-3 level
$INC_{i,t}$	Household income at i, t	Financing and risk-bearing abilities	INKAR (2010)	NUTS-3 level
$SIDO_{i,t}$	Share of single/double family homes at i, t	Ownership structure of roofs	INKAR (2010)	NUTS-3 level
$URBAN_i$, $FIELD_i$	Land use dummy for urban/field areas at i	Cover different propensities to adopt in different areas	CLC (2009)	Scale of 1:100,000, MMU of 25 ha
FE_t	Year dummies for each year between 1993 and 2008	Cover changes in feed-in tariff and cost reduction in PV production	–	–

4.3.2. Setting up the regression model

The regression model is a pooled panel model for the years 1992 to 2009, which results in 17 observable changes from year to year. We denote the value of the control variables with index $j \in \{\text{GR, POP, INC, SIDO, URBAN, FIELD}\}$ as $C_j(i,t)$. We define the external influence as $\alpha(t, C) = \alpha_0 + \sum_{t=1993}^{2008} \alpha_t FE_t + \sum_{\forall j} \alpha_j C_j(i,t)$ which results in

$$\Delta y_{i,t} = \left[\alpha(t, C) + \sum_{q=0}^{Q} \beta_q y_{i,q,t}\right] \times \left[N_{i,t} - y_{i,t}\right]. \tag{4.3}$$

α_0, α_{GR}, α_{POP} , α_{INC}, α_{SIDO}, α_{URBAN}, α_{FIELD}, $\alpha_{1993} \ldots \alpha_{2008}$ and $\beta_0 \ldots \beta_Q$ are the coefficients to be estimated in a generalized linear model (GLM). We choose a negative binomial distribution with an identity link function as the functional relationship is already given through the epidemic model.[21] Standard errors are clustered to be robust against temporal autocorrelation.

4.4. Statistical results and discussion

We study the diffusion of PV on different levels of aggregation. Table C.3, Table C.4, Table C.5 and Table C.6 of C.6 contain the descriptive statistics of our analysis for a step width of 1 km, 4 km, 10 km and 20 km.

Our hypothesis is that localized imitation drives PV adoption. If so, when running regressions with a low step width, we should find significantly positive coefficients for our inner circle and still significantly positive, but smaller coefficients for the close distance bands. Furthermore, the estimated coefficients for the year dummies should be significantly positive for the years when the subsidy system strongly fostered PV adoption. Finally, if localized imitation was important for PV adoption, estimations under a larger step width should have a lower goodness-of-fit than those with small s. On the other hand, if the knowledge triggering adoption in epidemic models disseminated over the whole country without limitations, localized imitation should not matter and we should find zero influence of the distance bands.

Table 4.2 contains estimates for the different levels of aggregation studied. Specification MA and specification MB of Table 4.2 include results for $s = 1$ km. In comparison with specification MA, MB incorporates a distance band, i.e., we add a spatial component. Likewise, MC and MD show the results for $s = 4$ km, specification ME and MF for $s = 10$ km as well as specification MG and MH for $s = 20$ km. The latter of the two specifications on each level of aggregation again contains an added spatial component whereas the former does not. Conducting likelihood ratio tests to compare the respective specifications with and without spatial components shows that adding a spatial component to the epidemic diffusion model significantly improves its goodness-of-fit on all levels of geographical aggregation

[21] Ordinary least squares cannot be applied since the annex is count data. Furthermore, the response is heteroscedastic but variance clearly exceeds the mean. In consequence, a Poisson distribution is not suitable (Hilbe, 2011). See C.5 for details on our estimation procedure.

studied (Table 4.2). Importantly, only for a step width of 1 km do we find significant coefficients. Further, one can easily see that the lowest level – a step width of 1 km – obtains the best results in terms of the goodness-of-fit measure AIC_n.[22] The values of $BIC_{R,n}$ and D_n underpin this finding and support the idea that imitation is highly localized. When comparing the values of the four different levels of aggregation studied, we find the highest estimated value for β_0 on a step width of $s = 1$ km. Similarly, β_1 is highest for a step width of 1 km and on all step widths β_0 is larger than β_1, which again indicates that imitation is highly localized.[23]

Table 4.2.: Estimations for different geographical levels of aggregation.

Specification	MA	MB	MC	MD	ME	MF	MG	MH
Step width	1 km	1 km	4 km	4 km	10 km	10 km	20 km	20 km
α_0	2.16E-05***	2.02E-05***	1.66E-05	1.07E-05	1.26E-05	9.14E-06	1.08E-05	8.63E-06
	(4.50E-08)	(6.23E-08)	(4.69E-05)	(8.20E-05)	(6.83E-03)	(6.21E-03)	(6.83E-03)	(6.21E-03)
β_0	1.32E-03***	1.21E-03***	2.74E-04	2.23E-04	5.31E-05	4.29E-05	1.67E-05	1.39E-05
	(3.75E-04)	(3.64E-04)	(2.03E-02)	(1.95E-02)	(1.86E-01)	(1.80E-01)	(1.86E-01)	(1.80E-01)
β_1		2.66E-04**		2.15E-05		1.11E-05		2.91E-06
		(8.98E-05)		(2.25E-03)		(2.27E-02)		(1.23E-01)
α_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$N_{\text{obs.}}$	5,824,438	5,824,438	333,064	333,064	45,441	45,441	8,738	8,738
LL	-1,370,462	-1,366,887	-410,727	-409,245	-106,524	-106,259	-29,732	-29,699
θ^{-1}	1.973	1.957	1.139	1.139	0.902	0.894	0.782	0.776
AIC	2,740,962	2,733,814	821,492	818,548	213,087	212,559	59,501	59,437
AIC_n	0.471	0.469	2.466	2.458	4.689	4.678	6.809	6.802
$BIC_{R,n}$	-15.398	-15.399	-12.073	-12.081	-9.841	-9.848	-8.037	-8.038
D	1,044,447	1,040,609	213,964	211,036	39,962	39,631	8,913	8,897
D_n	0.179	0.179	0.642	0.634	0.879	0.872	1.020	1.018
Comparing with		MA		MC		ME		MH
LR (Chi)		7,150.0		1,676.4		530.3		66.1
LR $(Pr(> Chisq))$		0***		0***		0***		0***

Robust standard errors in parentheses
‡ significant at $p < .20$; $^{\dagger}p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

More detailed results of our analysis with a step width of $s = 1$ km can be found in Table 4.3. Specification $M1$ contains not only one spatial component but also a second distance band in order to investigate how localized imitative behavior is. Importantly, β_2 of specification $M1$ is smaller than β_1 and β_0. Adding even more distance bands to the epidemic diffusion model – in specification $M2$ we include three, in $M3$ four, in $M4$ nine and in $M5$ ten distance bands – and again performing likelihood ratio tests, reveals that all of the added spatial components significantly improve the goodness-of-fit of the epidemic diffusion model. However, there is a tendency that the more distance bands we include the less they can improve the explanatory power of the model.

Figure 4.4 illustrates the magnitudes of the estimated β-coefficients of specification $M5$. The x-axis shows the inner and outer radius of each distance band and the y-axis pictures each distance bands' β-value. Rectangles in black show coefficients which are significant at $p < .05$. Gray rectangles show coefficients significant

[22] See Hilbe (2011) for definitions of the goodness-of-fit statistics. The measures AIC_n and $BIC_{R,n}$ are relative in the sense that they account for the number of observations.

[23] As the β_qs are relative measures a comparison makes sense across different levels of aggregation.

Table 4.3.: Estimations (step: 1 km, r_0: 0.7 km).

Specification	$M1$	$M2$	$M3$	$M4$	$M5$
Step width	1 km	1 km	1 km	1 km	1 km
α_0	1.94E-05***	1.88E-05***	1.84E-05***	1.72E-05***	1.70E-05***
	(8.88E-08)	(1.17E-07)	(1.42E-07)	(2.22E-07)	(2.34E-07)
β_0	1.20E-03***	1.19E-03***	1.19E-03***	1.18E-03***	1.18E-03**
	(3.64E-04)	(3.65E-04)	(3.66E-04)	(3.68E-04)	(3.68E-04)
β_1	2.32E-04**	2.22E-04**	2.16E-04**	2.07E-04**	2.06E-04**
	(8.40E-05)	(8.26E-05)	(8.18E-05)	(8.14E-05)	(8.14E-05)
β_2	1.04E-04*	8.78E-05*	7.98E-05*	6.68E-05*	6.51E-05*
	(4.54E-05)	(4.16E-05)	(4.03E-05)	(3.91E-05)	(3.89E-05)
β_3		6.72E-05*	5.54E-05*	3.85E-05‡	3.74E-05‡
		(3.55E-05)	(3.30E-05)	(3.07E-05)	(3.07E-05)
β_4			5.73E-05*	3.62E-05‡	3.43E-05‡
			(3.22E-05)	(2.89E-05)	(2.86E-05)
β_5				2.27E-05‡	2.04E-05
				(2.50E-05)	(2.46E-05)
β_6				2.80E-05‡	2.54E-05‡
				(2.83E-05)	(2.77E-05)
β_7				3.20E-05‡	2.80E-05‡
				(2.78E-05)	(2.72E-05)
β_8				2.64E-05‡	2.21E-05‡
				(2.62E-05)	(2.51E-05)
β_9				4.60E-05†	3.85E-05‡
				(3.32E-05)	(3.26E-05)
β_{10}					4.38E-05†
					(3.25E-05)
α_t	YES	YES	YES	YES	YES
$N_{\text{obs.}}$	5,824,438	5,824,438	5,824,438	5,824,438	5,824,438
LL	-1,366,140	-1,365,813	-1,365,577	-1,364,979	-1,364,863
θ^{-1}	1.958	1.960	1.962	1.966	1.967
AIC	2,732,323	2,731,671	2,731,201	2,730,015	2,729,785
AIC_n	0.469	0.469	0.469	0.469	0.469
$BIC_{R,n}$	-15.399	-15.399	-15.399	-15.400	-15.400
D	1,038,811	1,037,789	1,036,982	1,034,838	1,034,482
D_n	0.178	0.178	0.178	0.178	0.178
Comparing with	MB	$M1$	$M2$	$M3$	$M4$
LR (Chi)	1492.7	654.1	471.8	1196.4	231.9
LR $(Pr(>Chisq))$	0***	0***	0***	0***	0***

Robust standard errors in parentheses
‡ significant at $p < .20$; $^{\dagger}p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

to the level of ($.05 < p < .20$) or insignificant. The figure illustrates an attenuating effect of distance. This result encourages the use of an imitation model: the fact that an additional distance band has a positive impact allows the interpretation that information flows over distance, but this flow peters out with distance. Thus, the closer a PV system is located to a potential user, the higher the probability that the potential user also installs such a system. Analyzing the β-values of the distance bands of specification $M5$ in detail shows the β_qs are in fact at first decreasing with distance but from the third distance band onwards stay more or less constant, at least in their order of magnitude: they roughly lie between 2E-05 and 5E-05. Furthermore, the coefficients from the third distance band onwards are only significant to the level of $p < .20$, besides β_9 from specification $M4$ and β_{10} from $M5$ which are significant to the level of $p < .10$ and β_5 of specification $M5$ which is insignificant ($p > .20$).

According to these results, localized imitation can only be quantified up to a range of 1.2 km (for $p < .05$). However, even PV installations which happen to be located further away from a certain decision maker may still have a minor effect on the decision maker's ability to adopt PV.

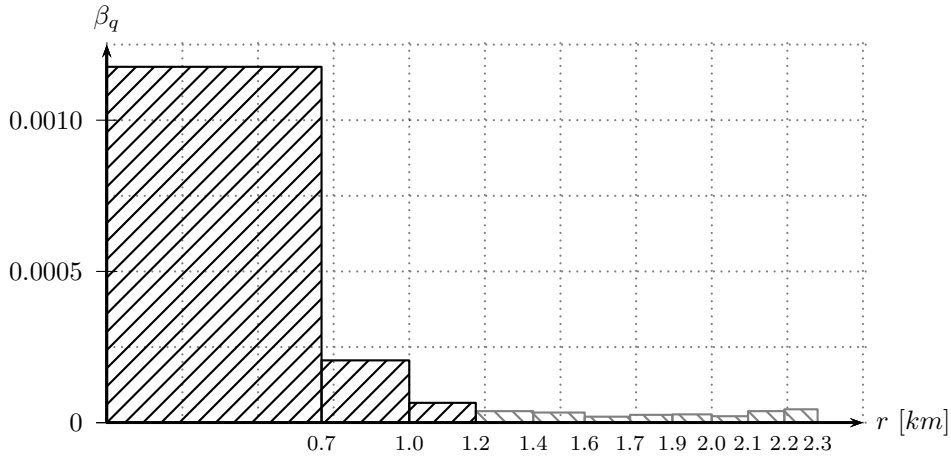

Figure 4.4.: Magnitude of β_q over distance for specification $M5$ (rectangles in gray come from coefficients with a significance level of $p > .05$ or more).

Table 4.3 shows that the more distance bands are added the more α_0 and β_0 decrease while the goodness-of-fit statistics increase. Consequently, epidemic diffusion models which do not consider spatial relations may overestimate values of the constant contact rate α_0 as well as of β_0, covering imitation. In contrast, the influence of neighboring spatial units is underestimated, in that it is neglected.

Since we employ an epidemic diffusion model, the interpretation of the estimated coefficients α_0, β_0, β_1 and the further β_qs is straightforward: Specification $M5$ of Table 4.3 suggests that, in every period, a share of $\alpha_0 = 1.70\text{E-}05$ of non-users adopt PV *because* of a central entity. This means on average a share of 1% of the PV annex can be explained by the central entity. The information borne by current users within the inner circle affects the adoption by non-users through β_0. According to our results, in every period each existing user contacts a share $\beta_0 = 1.18\text{E-}03$ of non-users $[N_{i,t} - y_{i,t}]$ which then in total leads to $[\beta_0 y_{i,t}] \times [N_{i,t} - y_{i,t}]$ new users. I.e., 63% of the PV annex comes from information borne by current users within the inner circle. Further, each existing user of distance band 1 contacts a share $\beta_1 = 2.06\text{E-}04$ agents (this corresponds to 9% of the PV annex), whereas each user of the still highly significant distance band 2 only contacts a share of $\beta_2 = 6.51\text{E-}05$ non-users of the population of the spatial unit of study (3% of PV annex). The β-coefficients of the distance bands located even further away can be interpreted in the same way.

In order to confirm our results, we include several control variables in the external coefficient of the epidemic diffusion model. Due to multicollinearity the controls

are incorporated separately.[24] Table 4.4 shows the results. The α_{SIDO}-coefficient for the number of single/double family homes as well as the coefficient covering spatial units mainly shrouded by fields – α_{FIELD} – do not improve our model. In contrast, global radiation (shown by α_{GR}), population density (α_{POP}), household income (α_{INC}) and urban spatial units (α_{URBAN}) positively increase the annex of PV installations. Again, likelihood ratio tests for the estimation with control variables show a significant improvement of our models' goodness-of-fit for these variables when compared with the reduced specification, which is MA. However, all control variables increase the goodness-of-fit in terms of AIC less than by adding spatial components.

Regarding AIC, the land use information covered by $URBAN_i$ adds the highest amount of explanatory power stemming from the control variables.[25] In contrast, information on the household income, which may cover financial constraints and risk-bearing possibilities, and global radiation, which directly affects the income possible with a PV system at a given place, only slightly improve the goodness-of-fit. We therefore argue that these factors are relatively less important for the diffusion of PV. Further, our results may be interpreted as confirmation that instead of financial aspects other reasons for installing, such as imitation, prevail. In this respect, the findings regarding the influence of the control variables population density, household income and single/double family homes should be treated with caution as they are only available on the NUTS-3 level. Data on a lower level of geographical aggregation may allow more detailed results.

The robustness of the findings regarding our control variables is checked by including ten distance bands in the specification $M6$, $M7$, $M8$, $M9$, $M10$, $M11$, and $M12$. This step results in only minor changes and in any case does not change the significance levels of the distance bands when estimating $M5$. The significance levels and values of the control variables are similar to the ones reported in Table 4.4, which made us decide – for purposes of clarity – not to show the results of this robustness check.

In general, α_t is included and stands for year dummies multiplied by $[N_{i,t} - y_{i,t}]$ as temporal FE. According to our interpretation, these variables cover shifts in the subsidy system for PV and cost reductions in production. The respective coefficients

[24] A test on the joint significance of the control variables shows that multicollinearity is indeed a problem when all controls are added (see $M12$).

[25] Including all control variables at once (see $M12$) confirms that $URBAN_i$ improves the model most.

Table 4.4.: Estimations with control variables (step: 1 km, r_0: 0.7 km).

Specification	$M6$	$M7$	$M8$	$M9$	$M10$	$M11$	$M12$	
Step width	1 km	1 km	1 km	1 km	1 km	1 km	1 km	
α_0	0	1.61E-05***	0	2.02E-05***	4.28E-06***	2.02E-05***	0	
	(6.07E-06)	(3.78E-07)	(2.73E-06)	(2.33E-06)	(1.73E-07)	(7.22E-07)	(5.93E-06)	
β_0	1.21E-03***	1.21E-03***	1.21E-03***	1.21E-03***	1.21E-03***	1.21E-03***	1.21E-03***	
	(3.64E-04)	(3.65E-04)	(3.64E-04)	(3.64E-04)	(3.66E-04)	(3.64E-04)	(3.66E-04)	
β_1	2.66E-04**	2.66E-04**	2.66E-04**	2.66E-04**	2.61E-04**	2.66E-04**	2.61E-04**	
	(8.97E-05)	(9.02E-05)	(8.98E-05)	(8.98E-05)	(9.02E-05)	(8.98E-05)	(9.02E-05)	
α_{GR}	2.03E-08***						0	
	(5.94E-09)						(2.92E-09)	
α_{POP}		6.86E-09***					0	
		(8.54E-10)					(1.35E-09)	
α_{INC}			1.90E-08***				6.23E-10	
			(2.51E-09)				(1.98E-09)	
α_{SIDO}				0			0	
				(2.81E-08)			(4.27E-08)	
α_{URBAN}					1.01E-04***		1.01E-04***	
					(3.73E-06)		(4.12E-06)	
α_{FIELD}						0	0	
						(1.15E-06)	(4.68E-07)	
α_t	YES	YES	YES	YES	YES	YES	YES	
$N_{\text{obs.}}$	5,824,438	5,824,438	5,824,438	5,824,438	5,824,438	5,824,438	5,824,438	
LL	-1,366,861	-1,366,814	-1,366,780	-1,366,887	-1,365,450	-1,366,887	-1,365,432	
θ^{-1}	1.956	1.959	1.957	1.957	1.959	1.957	1.959	
AIC	2,733,764	2,733,671	2,733,603	2,733,816	2,730,942	2,733,816	2,730,917	
AIC_n	0.469	0.469	0.469	0.469	0.469	0.469	0.469	
$BIC_{R,n}$	-15.399	-15.399	-15.399	-15.399	-15.399	-15.399	-15.399	
D	1,040,650	1,040,104	1,040,466	1,040,609	1,037,225	1,040,595	1,037,249	
D_n	0.179	0.179	0.179	0.179	0.178	0.179	0.178	
Comparing with	MA	MA	MA	MA	MA	MA	MA	$M10$
LR (Chi)	51.8	144.8	212.6	0.0	2873.4	0.0	2908.7	35.2
LR $(Pr(>Chisq))$	0***	0***	0***	1	0***	1	0***	0***

Robust standard errors in parentheses
‡ significant at $p < .20$; $^{\dagger}p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

are mainly found to be positive and since the year 1999 have been significantly higher than for the years before. This result is not surprising, as the 100,000 roofs program supported PV installations since the year 1999. A continuous attractiveness on a similar or even higher level was established by the Renewable Energy Sources Act since 2000. However, as the year dummies are only significant on the lowest level of aggregation studied – i.e., on a step width of 1 km – the national subsidy system seems to be very relevant on the local level. We conclude that shifts in the subsidy system should be taken into account when studying the propensity to adopt subsidized technologies with epidemic diffusion models.

In order to test whether imitation is lagged in time, we run regressions under $\Delta y_{i,t,\text{lag}_2} = y_{i,t+2} - y_{i,t+1}$ on the left-hand side, which means that, for example, the PV installations up to the end of the year 2000 are assumed to explain the annex in 2002. This modification results in clearly inferior goodness-of-fit statistics, which are not reported for reasons of clarity. Importantly, the result that imitation decreases with distance is robust for the change in the lag structure. In consequence, we can confidently rule out that the 'reflection problem' described by Manski (1993) biases our results. The reflection problem applies to situations where the adoption decision of an individual depends on others in her reference group and the individuals's adoption also affects other group members. Given that we analyze adoption on a yearly basis, it is reasonable to assume that an individual who adopts at $t + 2$

also decided to adopt at $t + 2$ or at least $t + 1$ and was therefore affected by the behavior of reference group members at t.

The robustness of our results is also checked by only studying the time period between 2000 and 2009, i.e., when the subsidy system fostered the adoption of PV. Slightly lower significance levels (only α_0, β_0 and β_2 are at least significant to the level of $p < .05$), but similar values for the estimated coefficients are found as for specification $M5$. Again, to maintain clarity the results are not shown.

Further robustness tests are performed by including $\alpha_{\text{NUTS-1}}$ or $\alpha_{\text{NUTS-3}}$ – spatial FE on the NUTS-1, respectively NUTS-3 level – into our model. $\alpha_{\text{NUTS-1}}$ and $\alpha_{\text{NUTS-3}}$ could cover idiosyncratic spatial differences as supplementary local incentives: e.g., there are additional government grants in Bavaria ('Programm für rationelle Energiegewinnung und Verwendung') or diffusion patterns may vary between the former East and West Germany. Similar to the year dummies, the NUTS-1 and NUTS-3 dummies are multiplied by $[N_{i,t} - y_{i,t}]$ as they are part of the external influence. Including $\alpha_{\text{NUTS-1}}$, thus 15 dummies for the 16 German states, only slightly changes the magnitude of the estimated coefficients and their significance levels.

Due to limits in computational power, we can only estimate NUTS-3 dummies for parts of Germany. As an example, we show the results for the analysis of Bavaria and Hesse in Table 4.5. We included 95 NUTS-3 dummies for the 96 NUTS-3 regions of Bavaria and 25 dummies for the 26 NUTS-3 regions of Hesse. Table 4.5 compares the estimates for Bavaria and Hesse including and without $\alpha_{\text{NUTS-3}}$. Although the NUTS-3 specific dummies significantly improve the goodness-of-fit of our model as shown by the AIC and a likelihood ratio test comparing specification Ma with Mb, respectively Mc with Md, $\alpha_{\text{NUTS-3}}$ only slightly changes the results of the other estimates. In consequence, the estimations including NUTS-3 dummies also support the hypothesis of localized imitation. Likewise, including $\alpha_{\text{NUTS-3}}$ confirms that imitation attenuates with distance as the internal coefficients β_q are roughly decreasing with distance. Furthermore, the β_qs are insignificant for Bavaria (besides β_0 which is – however – only significant at the level of $p < .20$) suggesting that imitation may be localized to a range of only 0.7 km. Importantly, the significance levels do not change if $\alpha_{\text{NUTS-3}}$ is included in the estimation, indicating that our results are robust to differences at the NUTS-3 level in general. For Hesse, β_q is decreasing in distance and insignificant from the second distance band onwards, whether $\alpha_{\text{NUTS-3}}$ is estimated or not. See C.7 for further results on the NUTS-1 level.

Table 4.5.: Estimations (step: 1 km, r_0: 0.7 km) for Bavaria and Hesse.

	Bavaria		Hesse	
Specification	Ma	Mb	Mc	Md
Step width	1 km	1 km	1 km	1 km
α_0	8.36E-06***	0	2.69E-04***	2.07E-05***
	(5.66E-07)	(6.12E-20)	(3.74E-05)	(1.50E-06)
β_0	2.06E-02‡	2.06E-03‡	1.31E-03*	1.03E-03*
	(2.03E-03)	(2.02E-03)	(9.75E-04)	(5.37E-04)
β_1	1.53E-02	1.51E-04	3.48E-04‡	7.98E-05‡
	(3.13E-04)	(3.16E-04)	(2.63E-04)	(8.07E-05)
β_2	3.93E-05	2.99E-05	1.28E-04	0
	(1.85E-04)	(1.85E-04)	(1.42E-04)	(2.55E-05)
β_3	1.92E-05	1.21E-05	1.15E-04	0
	(1.52E-04)	(1.55E-04)	(1.51E-04)	(2.93E-05)
β_4	1.49E-05	9.24E-06	6.90E-05	0
	(1.44E-04)	(1.49E-04)	(1.26E-04)	(2.71E-05)
β_5	2.86E-06	0	7.40E-05	0
	(1.00E-04)	(6.25E-21)	(1.44E-04)	(3.37E-05)
β_6	0	0	8.27E-05	0
	(5.94E-05)	(2.18E-18)	(1.34E-04)	(2.81E-05)
β_7	6.88E-06	0	1.11E-04	0
	(1.25E-04)	(3.30E-19)	(1.95E-04)	(4.14E-05)
β_8	3.70E-06	0	1.54E-04	0
	(7.16E-05)	(6.78E-20)	(2.31E-04)	(5.61E-05)
β_9	9.92E-06	0	1.57E-04	0
	(1.52E-04)	(1.87E-18)	(1.59E-04)	(2.96E-05)
β_{10}	8.30E-06	0	1.50E-04	0
	(8.59E-05)	(4.55E-19)	(1.69E-04)	(3.13E-05)
α_t	YES	YES	YES	YES
$\alpha_{\text{NUTS-3}}$		YES		YES
$N_{\text{obs.}}$	1146259	1,146,259	357,510	357,510
LL	-420,882	-420,326	-102,862	-95,942
θ^{-1}	1.439	1.432	1.590	1.268
AIC	841,822	840,900	205,751	191,942
AIC_n	0.734	0.734	0.576	0.537
$BIC_{R,n}$	-13.682	-13.682	-12.556	-12.577
D	308,600	308,011	82,395	74,666
D_n	0.269	0.269	0.230	0.209
Comparing with		Ma		Mc
LR (Chi)		95		16
LR ($Pr(> Chisq)$)		0***		0***

Robust standard errors in parentheses
‡ significant at $p < .20$; $^{\dagger}p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Finally, we conduct sensitivity analyses. On the one hand, we run regressions on the richest and the poorest quartiles of German NUTS-3 regions from the year 2008. This analysis again confirms that imitation fades with distance. Interestingly, in the poorer regions imitation could be significantly ($p < .20$) quantified up to a radius of 1.7 km, whereas in the richer regions the significant range is only 1 km. One reason for this finding may be that rich regions are often urban areas where a high population and building density may limit the spatial range that an individual observes intensively. On the other hand, we estimate our model for the most and the least sunny quartiles. Again, the results confirm that imitation attenuates with distance. In less sunny regions the significant range is 1.4 km ($p < .20$), in sunny regions 0.7 km. As fewer PV systems are installed in less sunny regions, the impact of one system on potential users nearby may have a greater distance range.

4.5. Summary

We find that including a spatial dimension in an epidemic diffusion model of PV installations in Germany does significantly increase its explanatory power. In contrast, our control variables contribute less information than a spatial component. Further, the best results are achieved on the lowest level of geographical aggregation. Consequently, epidemic models which do not consider spatial relations may have overestimated values of the constant contact rate α_0 as well as of imitation.

Our analysis reveals a decreasing influence of distance on localized imitation and suggests that from 1.2 km onwards there is actually a roughly constant and only to $p < .20$ significant positive influence on imitation.

Stated more explicitly, our study of PV data indicates that imitative behavior is highly localized, i.e., spatial proximity facilitates imitative behavior. Observing a PV system in operation and talking about it with a person of trust, may increase the likelihood of installing PV.

In his overview of diffusion models, Geroski (2000, p. 621) highlights that, according to the epidemic model, technology diffusion *"happens too slowly, mainly because information does not diffuse fast enough amongst potential users."* By including a spatial component in an epidemic diffusion model and employing it on a low level of geographical aggregation, we conclude that it is not only a case of "too slowly", but also of "not far enough" in geographical terms. This finding may be interpreted in the way that a financial incentive is not the only important factor in fostering adoption, but that the diffusion process may be initiated on the local level in order to boost adoption. This argument is one in favor of locally distributed eye- and attention-catching projects, which could be placed as seeds in key regions. These simply signal that the technology or product works. In the same line of reasoning, schemes on the local level that support spreading of information, such as referral reward programs and impact campaigns, could be promising. For instance, Müller and Rode (2013) refer to Cardwell (2012) who shows that, in the U.S., enthusiastic PV users inform their neighbors about PV. Similar sales strategies are known from Tupperware. To conclude, if fostering technology diffusion is on the agenda, creating incentives for enthusiastic technology users to share their experience with neighbors – i.e., facilitating the spread of information – may be rewarding.

Our analysis leaves room for improvements: a lower level of geographical aggregation for the relevant population and the proxies of economic wealth, population density and the share of single/double family homes should be beneficial. A general drawback of diffusion models on the aggregate level, as with the epidemic model, is their inability to describe different degrees of resistance to adoption caused by heterogeneous user needs and individual preferences. These shortcomings should be a topic for further research on the diffusion of PV and technologies in general.

5. Spatio-Temporal Variation in Peer Effects[26]

In the last chapter, we use an (aggregate) epidemic model of technology diffusion to show that localized imitation drives PV adoption. Now, we focus on the adoption decision of individuals.

5.1. Motivation

The diffusion of new technologies (in space and time) results from a series of individual decisions to adopt (i.e., to begin using the new technology). Understanding factors influencing the choice to adopt is essential both for economists studying the determinants of diffusion and for the creators and producers of such technologies.

Since Griliches (1957) and Mansfield (1961) economists have focused on temporal patterns of technology diffusion, i.e., why diffusion is slow. Hägerstrand (1965, 1967) was the first to concentrate on the spatial aspects of diffusion. Following these early contributions, diffusion might be interpreted as the (cumulative) outcome of individual decisions to adopt. However, it might be rewarding to explicitly study the individual decisions. Since the decision to adopt (in a certain period of time) is a discrete one (Karshenas and Stoneman, 1992), we follow Müller and Rode (2013) and employ a discrete choice model. Discrete choice analysis is the standard approach to analyzing individual discrete decision-making (McFadden, 2001). In particular, Geroski (2000) highlights that when focusing on differences in adopter characteristics a specific discrete choice model, namely the probit model, is appropriate.

[26]This chapter is based on a revised version of Rode and Müller (2014).

PV systems are a sustainable energy technology. In contrast to previous studies on PV adoption, we analyze all potential adopters' individual decisions to adopt PV systems across a whole country, i.e., we study the adoption of PV systems in Germany using individual level panel data. Due to a strong subsidy system, Germany was the country with the highest PV capacity installed per capita in the world through 2012 (IEA-PVPS, 2013). Figure 5.1 illustrates the spatio-temporal dimension of our data. The lighter a given region is colored, the more new PV systems are installed in the corresponding year (while controlling for the number of potential adopters in that region). The figure shows that, e.g., in the east of Bavaria comparatively many PV systems were installed in all years. Besides high global radiation in Bavaria, a localized peer effect may be a reason for the observed clustering.

Peer effects are one factor that drives individual technology adoption (Brock and Durlauf, 2010; Conley and Udry, 2010; Oster and Thornton, 2012). Recently, several studies analyzed the adoption of PV systems (Dewald and Truffer, 2011; Dastrup et al., 2012; Comin and Rode, 2013) and found peer effects to be an important driver (Bollinger and Gillingham, 2012; Rode and Weber, 2012; Islam, 2014; Müller and Rode, 2013). We define peers as (potential) adopters nearby. Exact locational data on PV adopters and potential adopters allows us to be the first who build a specific measure of the peer effect for each adopter per time period across a whole country. By doing so, we can find out how peer effects in PV system adoption vary over time and space.

According to Rogers (1983, 166-167), early adopters are more influential on peers than later adopters, i.e., we hypothesize that the influence of peer effects may decrease over time.[27] Why should it be of interest to know whether the influence of peer effects decreases over time? New technologies often diffuse more slowly than would be optimal (Rogers, 1983; Geroski, 2000; Oster and Thornton, 2012). Understanding the impact of peer effects may help to foster the diffusion. That is, installation seeds could be used by (political) decision-makers to raise the diffusion speed by steering adoption to locations where adoption is most intended (Rode and Weber, 2012; Islam, 2014; Müller and Rode, 2013). Further, we are interested in the characteristics of early adopters. Rogers (1983) describes early adopters as being of high socio-economic status. We hypothesize that early adopters may be associated

[27] At the end of our period of study, in 2010, still less than 5% of the potential users had adopted PV systems. Therefore, we define *early adopters* as those who adopt in the very first periods of diffusion. Following Müller and Rode (2013), *later adopters* are those who adopt in early but not in the very first periods of diffusion.

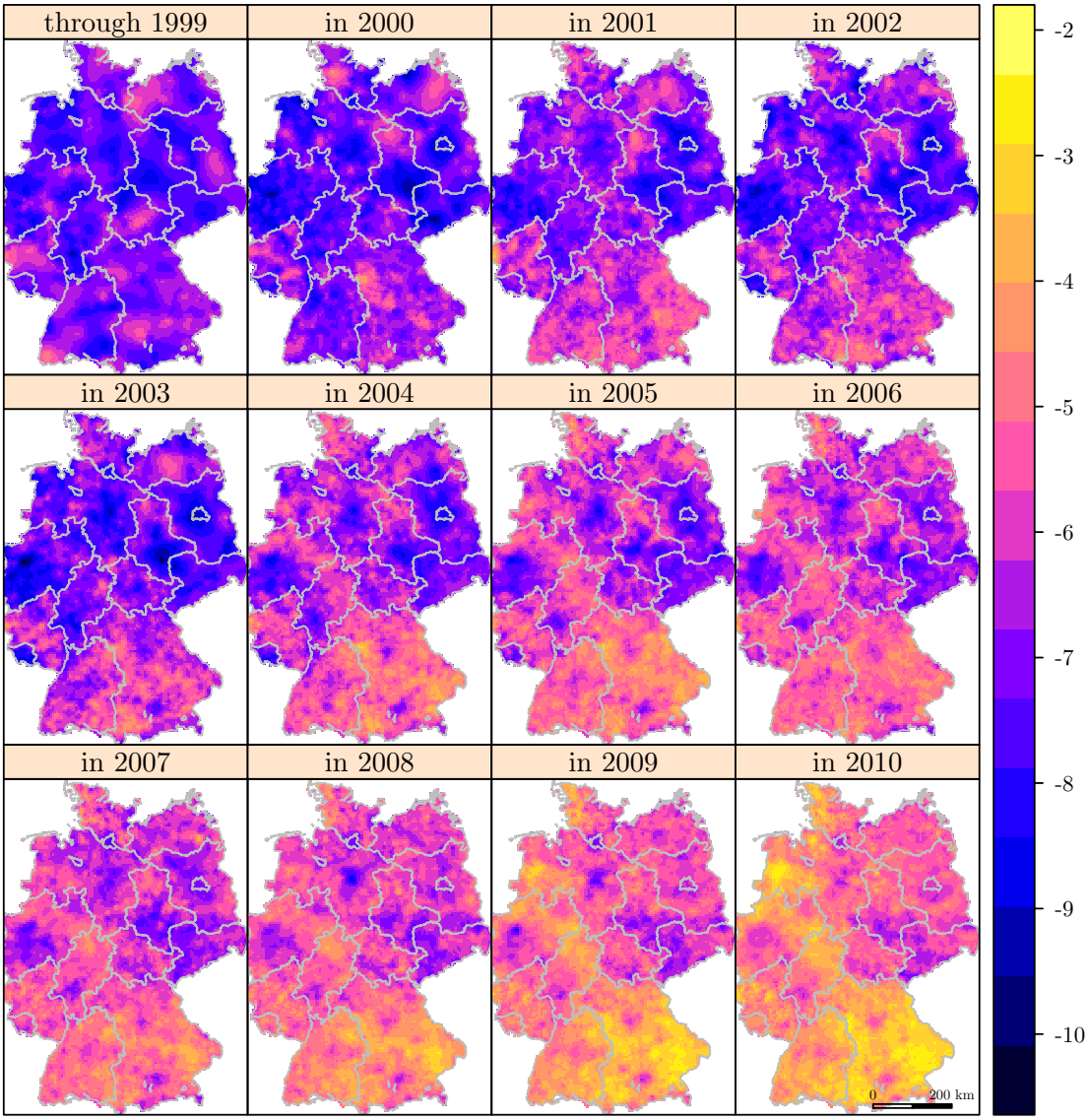

Figure 5.1.: Natural logarithm of yearly annex of PV installations divided by number of potential adopters across Germany. The lighter a region is colored in the figure, the more PV systems are installed in the corresponding year while controlling for the number of addresses.

with measures indicating high income and low population density, i.e., a high share of single- and double-family homes.

Our analysis reveals that peer effects in PV system adoption are largely localized. The peer effect's impact on the decision to adopt decreases over time. This trend is disrupted by changes in the subsidies for PV systems. When comparing early and later adopters, we find that later adopters tend to have lower buying power. They also live in less densely populated areas with lower global radiation. We find different scales of the effects in urban and non-urban areas, and in the east and

west of Germany. Finally, we also show that the number of peers needed to foster adoption at locations with low global radiation increases over time. A case study with building-specific data on global radiation confirms our findings.

In parts, we follow Müller and Rode (2013) when we introduce our discrete choice model with panel data in Section 5.2. We give a description of our empirical study in Section 5.3. The results are shown in Section 5.4, which also contains a case study confirming some of our assumptions. Section 5.5 summarizes the chapter and provides an outlook on further research.

5.2. Discrete choice analysis for binary panel data

This section gives a short description of basics in discrete choice analysis. For further reading, we refer to Ben-Akiva and Lerman (1985), Train (2003), and Koppelman and Bhat (2006).

Consider a decision-maker n (an individual or a household) who faces the decision to adopt or not to adopt the new technology in period t. That is, n chooses in t between two alternatives: first, i.e., $i = 1$, to adopt or second, i.e., $i = 2$, not to adopt. In each period t choice-maker n perceives utility U_{nti} of choosing alternative i. Here, we assume a rational choice behavior, i.e., choice-maker n chooses in period t alternative i that maximizes his utility (Tversky and Kahneman, 1981). Concerning the adoption of new technology, we consider the choice problem

$$U_{nt1} > U_{nt2}. \tag{5.1}$$

Choice-maker n adopts the new technology ($i = 1$) if (5.1) holds. Unfortunately, it is impossible to correctly observe all variables that make up utility U_{nti}. Therefore, in discrete choice analysis the latent construct utility is decomposed into a deterministic (or systematic) part V_{nti} and a stochastic part ε_{nti}:

$$U_{nti} = V_{nti} + \varepsilon_{nti}. \tag{5.2}$$

Usually V_{nti} is linear in parameters:

$$V_{nti} = \sum_{h \in H} \beta_{ith} x_{ntih}. \tag{5.3}$$

The H independent variables x_{ntih} describe alternative i and characteristics of choice-maker n in period t. The exogenous variables x_{ntih} are weighted by coefficients β_{ith}. Obviously, utility of (5.2) is random and hence only probability statements on our behavioral model of (5.1) can be made:

$$\begin{aligned} P_{nt1} &= \text{Prob}\left(U_{nt1} > U_{nt2}\right) \\ &= \text{Prob}\left(\varepsilon_{nt2} - \varepsilon_{nt1} < V_{nt1} - V_{nt2}\right). \end{aligned} \tag{5.4}$$

Equation (5.4) denotes the (choice) probability of choice-maker n adopting the new technology in period t, i.e., n chooses to install a PV system in t. In order to operationalize the choice model of (5.4), we have to make assumptions about the random components of utility ϵ_{nti} in (5.2). We usually assume that each error ε_{nti} is the sum of many random variables. According to the central limit theorem, the sum of many independent and identically distributed random variables approximately follows a normal distribution, i.e., $\varepsilon_{nti} \sim \mathcal{N}(0, \sigma)$. Since the difference of two normally distributed random variables follows a normal distribution as well, we may operationalize the choice probabilities of (5.4) as

$$P_{nt1} = \Phi\left(\frac{V_{nt1} - V_{nt2}}{\sigma}\right). \tag{5.5}$$

Φ is the standardized cumulative normal distribution and σ is the standard deviation that is usually set to one for identification purposes. The choice model of (5.5) is referred to as the binary probability unit model – in short: binary probit model. Although (5.5) is based on simple theoretical assumptions about the stochastic part of utility, it lacks a closed-form probability formula. If we assume that each error ε_{nti} is the maximum of many independent and identically distributed random variables, then, according to the Gumbel theorem, it has been shown that ε_{nti} follows an extreme value distribution (McFadden, 2001). Since the difference of two extreme value distributed random variables follows the logistic distribution, we may operationalize (5.4) as

$$P_{nt1} = \frac{e^{\mu V_{nt1}}}{e^{\mu V_{nt1}} + e^{\mu V_{nt2}}}, \tag{5.6}$$

which is the well-known binary logit model (McFadden, 1974). μ is a scale parameter > 0 that is not identified and has to be set to an arbitrary value (e.g., one) for model identification purposes. In subsequent paragraphs we use BPM for (5.5) and BLM for (5.6).

The unknown coefficients β_{ih} of (5.3) can be provided through maximum likelihood estimation:

$$\max_{\beta \in \mathbb{R}^H} \sum_{n=1}^{N} \sum_{t=1}^{T} \left(o_{nt1} \ln \left(P_{nt1} \right) + \left(1 - o_{nt1} \right) \ln \left(1 - P_{nt1} \right) \right). \tag{5.7}$$

$o_{nt,\mathrm{PV}}$ equals one if we observe that choice-maker n has installed a PV system in period t (zero otherwise). Therefore, $o_{nt,\mathrm{PV}}$ is the dependent variable and hence we are not able to measure U_{nti} directly. Furthermore, we are only able to identify utility differences due to (5.1). Note, N is the set of all considered individuals. As already stated, utility U_{nti} is a latent variable: the observable choices are manifestations of the underlying utilities described by exogenous variables. Nowadays, there are tailored software packages for estimation purposes (see for example StataCorp (2009) and Bierlaire (2003)). The modeling framework is given in Figure 5.2.

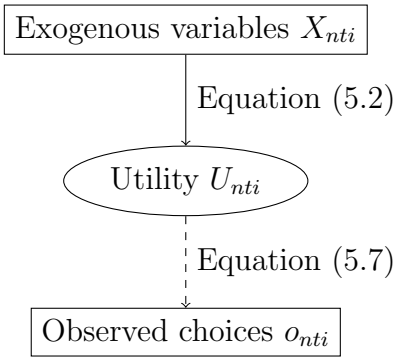

Figure 5.2.: Modeling framework: rectangles represent observed data and the ellipse denotes a latent variable. The solid line represents a structural equation while the dashed line stands for a measurement equation.

Note that BPM (5.5) and BLM (5.6) might exhibit a severe shortcoming depending on the specific choice situation and data to be analyzed: the assumption of independence of the error terms in (5.2). In our case the independence of the error terms over choice alternatives seems to be uncritical because the choice situation is binary and the two alternatives are antipodal. Although the assumption of independence (over periods and choice-makers) might be violated in our case, it is well known from empirical studies that the inferences based on the estimates of (binary) logit and probit models are fairly robust (Hensher and Greene, 2003).

5.3. Empirical study

In this section we discuss the operationalization of peer effects in PV system adoption. We also present details of the data used for model estimation and we specify the utility functions of (5.3).

5.3.1. Data

This study builds on a unique data set including the location (address) and date of installation of the PV systems set up in Germany through 2010. Since 80% of the PV systems in Germany are installed on roofs (BMU (2011) and Dewald and Truffer (2011)), we consider buildings as the predominantly potential places for PV systems. Therefore, we are only interested in PV systems on buildings. Since we obtain adresses, we assume that each address may be equipped with a building that is owned by someone. Eventually, this (artificial) person – the owner or owner group – makes the decision to install in a certain period or not. However, due to data-related issues we do not observe the choice directly. We only observe whether there is a PV system at a given address in a given period or not (see Figure 5.3). Of course, whether the building at the address is owned by a private household or a house cooperation (or a firm) makes a difference. Unfortunately, we do not obtain information on ownership. Still, to the best of our knowledge no other study on PV system adoption, particularly those using aggregate approaches, accounts for ownership (see Bollinger and Gillingham (2012), Müller and Rode (2013) and our analysis in Chapter 5).

Our geocoded data set covers all 882,062 grid-connected PV systems which were installed in Germany through the end of the year 2010 (ÜNB, 2012). We drop solar systems that are obviously solar parks and end up with 879,020 installations. We neglect that a PV system may be uninstalled since – according to our data set – this is only the case for 0.35% of the systems under study. Table D.1 in Appendix D.4 shows the accuracy of the geocoding process. Further, the data set contains 21,808,025 addresses (Infas, 2009a). Each PV system is allocated to its nearest address. 269,752 addresses end up with more than one allocated PV system. This is due to inaccuracy in geocoding, missing address information in the PV system data set and the possibility that more than one building exists at one address and more than one PV system could be installed on one building.

We randomly allocate the PV systems from these observations to another address located in the same spatial unit (statistical district). The 77,847 statistical districts are taken from Infas (2009b).[28] As a consequence, our data set comprises 877,114 PV systems each allocated to a mutually exclusive address.

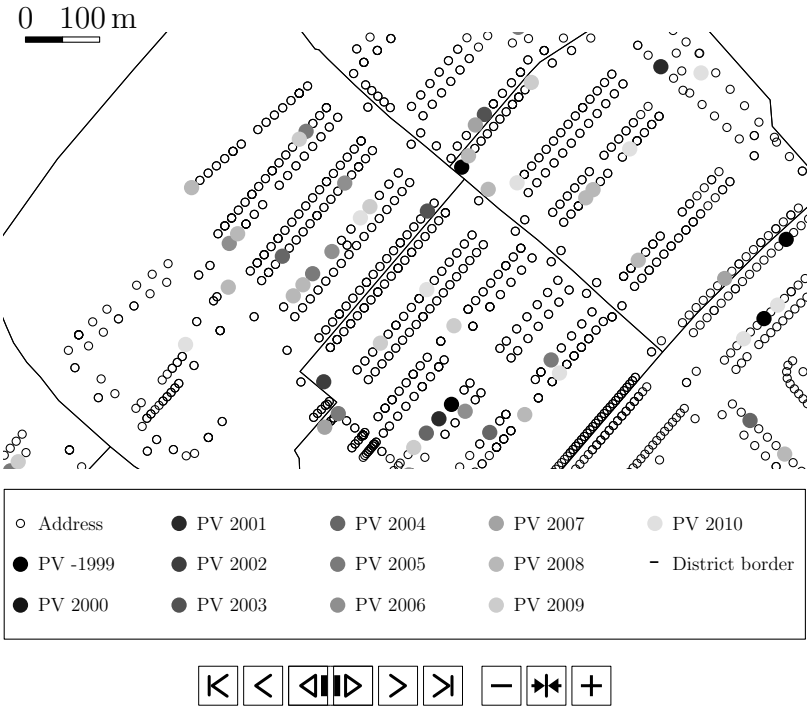

Figure 5.3.: PV installations in detail in space and time. Hollow circles picture potential adopters, i.e., addresses. Filled circles are PV installations. *Animation works with Adobe Reader version ≥7.*

In order to run the estimations in a reasonable amount of time, we randomly choose a 9% sample with 1,982,098 address observations.[29] 78,952 of these are equipped with a PV system. Table D.2 in Appendix D.4 shows the frequencies of each choice alternative per period.

5.3.2. Utility functions and operationalization

The choice problem under consideration is for each n to choose to install a PV system in a given period t or to not install (see Section 5.2). In order to test for peer effects we consider the influence of the choice of $m \in N$ in period $t-1$ on the choice of $n \in N$ in period t, i.e., the dependencies between choice-makers n and m.

[28] The average area of a statistical district is about 4.6 sqkm and the average number of addresses in such a statistical district is 280.

[29] We verify our results for further samples in Section 5.4.1.

We define the peer effect on choice-maker n in period t as

$$\text{IBASE}_{nt} = \sum_{\substack{m \in N, \\ m \neq n \mid \\ d_{nm} \leq D}} o_{m,t-1,1} f\left(d_{nm}\right), \tag{5.8}$$

the installed base (Farrell and Saloner, 1986; Bollinger and Gillingham, 2012). With $d_{nm} > 0$ as the Euclidean distance in meters between the location of n and the location of m. D is a cut-off parameter to be set by the analyst. We may assume that there is no remarkable influence of PV installations farther away from location n than D. Exemplarily, we set $f\left(d_{nm}\right) = 1/\ln\left(d_{nm}\right)$, and $D = 500$ meters.[30] Of course, choice-maker n might also be influenced by peers who have adopted in earlier periods, i.e., $t-2$, $t-3$ etc. We consider the corresponding measure in Appendix D.1. Since the subsidy system for PV systems changes during the period of study, only peers who adopted in the preceding period $(t-1)$ may pass on reliable information regarding, e.g., the reliability, initial costs, and the net present value of PV systems. Note, $o_{m,0,1} = 1$ if m has adopted a PV system in any period preceding period $t = 1$. The spatio-temporal lag variable, (5.8), enables us to test whether preexisting PV systems stimulate further installations nearby.

As we are interested in the adoption of a subsidized environmentally-friendly technology, we incorporate this characteristic into our analysis (Jaffe et al., 2002; Davies and Diaz-Rainey, 2011; Rode and Weber, 2012). We describe the subsidy system for PV in detail in Section 3.1 of Chapter 3. Besides changes in the subsidy system, decreased cost of PV system adoption also caused shifts in the profitability of PV systems. Because the year of installation is known, we can allow for different gains in utility from different installation periods. In order to account for these time-period-specific effects, we consider period dummies.

Before the year 2000 the subsidy level for PV systems was low and only very few systems were installed. Therefore, we define year 2000 to be our first period. Year 2001 is the second period, and finally year 2010 is the eleventh period.

Of course, the utility a decision-maker gains by installing in a certain period or not may also be influenced by factors other than peer effects (IBASE_{nt}) and temporally fixed effects covering shifts in the profitability of PV systems. Unfortunately, we do not have information about the characteristics of the decision-maker itself but

[30] In Section 5.4.1, we relax the specification and show results for further specifications $f\left(d_{nm}\right)$ and D.

we have information on characteristics of the decision-maker's location. We assume that it is very likely that the characteristics of both are comparable and therefore include locational characteristics. In order to account for the problem of modifiable areal units (Openshaw, 1984), these variables (population density, buying power, and global radiation) are of very high spatial resolution. We consider the following variables:

- GR_n denotes the average yearly global radiation in MWh/m^2 according to n's location in 1-km raster cells provided by DWD (2010).[31] A higher level of global radiation indicates a higher potential to produce electricity and therefore a higher remuneration potential to the owner of a PV system at a given location. Hence, we assume the higher GR_n, the higher the utility from installing a PV system. Early adopters may have other motives for installing than to generate income (Rogers, 1983). In contrast, later adopters may install to generate income. Thus, global radiation's contribution to the utility from adoption may rise over time.

- BUYPOW_n is the buying power index of the statistical district according to decision-maker n's location. An index value of 1 corresponds to the median buying power of German households in 2009 (Infas, 2009b). Data is available for 77,847 statistical districts in Germany. Since PV installations are expensive (see Appendix C.1), we might assume that wealthier decision-makers are more likely to install. According to Rogers (1983), early adopters may have a higher socio-economic status than followers, which leads us to the hypothesis that measures indicating high income are associated with early adopters.

- GREEN_n specifies the share of green votes from the casted votes in 2009's federal ("Bundestag") election according to n's location in NUTS-3 districts, i.e., 429 districts across Germany (DESTATIS, 2012). On the one hand, a high share of green votes may be associated with a distinct "green attitude". Therefore, high values of GREEN_n may yield a high propensity of installing a PV system. On the other hand, Welsch and Kühling (2009, p. 172) argue that solar thermal equipment may also be installed due to a status effect and therefore be seen as a "Mercedes-Benz on the rooftop". A similar reasoning may make sense for PV systems. Furthermore, the positive net present value

[31] DWD (2010) combines measures from satellites and local observation stations to build the raster data, i.e., the data accounts for the geographic features of the raster units. Across Germany, the data includes values for 359.586 raster cells, which means on average 61 addresses per raster cell for our data set.

of PV systems – shown in Appendix C.1 in some parts of Germany since 2004 – should result in PV installations no matter how high or low the green attitude of a decision-maker is. If so, we should not observe that the probability to install a PV system increases with the share of green votes. We are therefore unsure what impact to expect from GREEN_n on the propensity to install a PV system.

- POPDEN_n denotes the population density times 100 of the statistical district where n is located in 2009 (Infas, 2009b). Data is available for 77,847 statistical districts in Germany. A low measure of POPDEN_n may refer to places with a high share of single- and double-family homes. For decision-makers located at these places the decision to install a PV system may be easier as fewer parties have to agree upon the installation on a certain building. As a consequence, we expect a negative impact of POPDEN_n on the propensity to install a PV system. In line with Rogers (1983), early adopters may have a higher socio-economic status than later adopters. Therefore, we test whether early adopters are located in districts with a low population density, referring to locations with a high share of single- and double-family homes.

- EAST_n is a dummy variable that equals one, if n is located in the acceded territories of the former German Democratic Republic.

- NUTS-1 ("Länder") dummies cover time-invariant spatial effects. The dummies capture region specific subsidies to install a PV system: e.g., the "Programm für rationelle Energiegewinnung und Verwendung" – a government grant – in the NUTS-1 region "Bavaria".

- PER_t is a dummy variable that equals one for period t, zero otherwise.

- URBAN_n identifies whether n is located in an urban area. According to n's location, we use detailed information on urban areas from 2006's CORINE Land Cover (CLC) data set (CLC, 2009). This data set comprises vector data on a scale of 1:100,000. The minimum mapping unit for the polygons is 25 hectare.

Table D.3 in Appendix D.4 shows the descriptive statistics for the variables. Since we use data from different sources and different spatial scales, Figure 5.4 summarizes the data according to the corresponding spatial resolution.

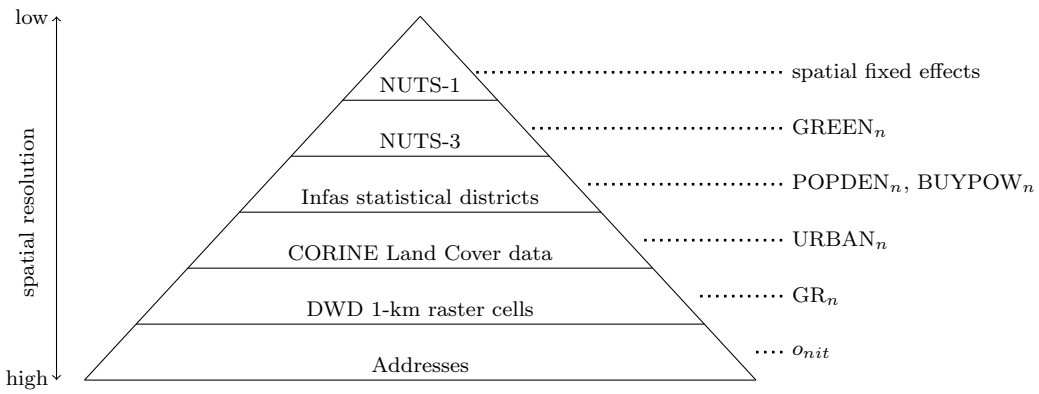

Figure 5.4.: Data and spatial resolution.

Now we specify the deterministic part of utility of observation n to adopt (i.e., $i = 1$) in period t according to (5.3) as

$$\begin{aligned} V_{nt,1} \; =& \beta_0 \\ &+ \beta_1 \text{IBASE}_{n1} + \cdots + \beta_{11}\text{IBASE}_{n11} + \beta_{12}\text{IBASE}_{nt}\text{EAST}_n + \beta_{13}\text{IBASE}_{nt}\text{URBAN}_n \\ &+ \beta_{14}\text{BUYPOW}_n\text{PER}_1 + \cdots \beta_{24}\text{BUYPOW}_n\text{PER}_{11} + \beta_{25}\text{BUYPOW}_n\text{EAST}_n + \beta_{26}\text{BUYPOW}_n\text{URBAN}_n \\ &+ \beta_{27}\text{GR}_n\text{PER}_1 + \cdots + \beta_{37}\text{GR}_n\text{PER}_{11} + \beta_{38}\text{GR}_n\text{EAST}_n + \beta_{39}\text{GR}_n\text{URBAN}_n \\ &+ \beta_{40}\text{GREEN}_n + \beta_{41}\text{GREEN}_n\text{EAST}_n + \beta_{42}\text{GREEN}_n\text{URBAN}_n \\ &+ \beta_{43}\text{POPDEN}_n\text{PER}_1 + \cdots + \beta_{53}\text{POPDEN}_n\text{PER}_{11} + \beta_{54}\text{POPDEN}_n\text{EAST}_n + \beta_{55}\text{POPDEN}_n\text{URBAN}_n \\ &+ \beta_{56}\text{URBAN}_n + \sum_{h=57}^{H} \beta_h W_{nth}, \end{aligned} \tag{5.9}$$

with β_h to be estimated by maximum likelihood of Equation (5.7) and IBASE$_{nt}$ given as (5.8). Spatial and period fixed effects are denoted by dummy variables W_{nth}. According to Section 5.2, only the utility differences are of interest (see Equation 5.4). Therefore, we might normalize the deterministic part of utility of observation n not to adopt (i.e., $i = 2$) in period t as

$$V_{nt,2} \; = \; 0. \tag{5.10}$$

5.4. Results

5.4.1. Germany

Table 5.1 shows the coefficient estimate for the constant-only model, specification M1. If not stated otherwise, we use the BPM model of (5.5). Specification M2 includes a time constant measure of the installed base and the respective control for the east of Germany as well as period dummies and NUTS-1 dummies. A likelihood ratio (LR) test – comparing M1 with M2 – indicates that M2 indeed describes the decision to install a PV system significantly better. Specification M3 of Table 5.1 considers a period-specific measure of the installed base. Again a likelihood ratio test indicates that including the period-specific installed base significantly increases the explanatory power. M4 illustrates the results with a time-constant coefficient for the installed base and BUYPOW_n, GR_n, GREEN_n, POPDEN_n, and the respective control for the east of Germany. These controls improve the model fit significantly but do not largely affect our measure of the installed base. M5 considers the controls and a period-specific measure of the installed base. As shown by $\mathcal{L}(\hat{\beta})$ and a likelihood ratio test, M5 explains the adoption decision process better than M4.

Our *preferred specification* is M6 (see Table D.4 of Appendix D.4 and Equation (5.9)). In comparison to M5, M6 includes interaction terms of URBAN_n, with BUYPOW_n, GR_n, GREEN_n, and POPDEN_n. Furthermore, we estimate period-specific coefficients for BUYPOW_n, GR_n, POPDEN_n. A likelihood ratio test shows that M6 is significantly superior to M5. We also show the robustness of our estimates by using a BLM regression: M6_{Logit} confirms the findings of M6.

We observe that the installed base has a significantly positive influence on the decision to install a PV system. That is, the more proximate PV systems in the preceding period, the higher the propensity of a potential user to obtain a PV system in the current period. Potential users might be influenced by the decisions of their peers. As a consequence, imitation of spatially close precursors might indeed be an explaining factor in PV system adoption; i.e., our results confirm a localized peer effect in the adoption of PV systems. For example, according to M6 in Table D.4, the utility to install a PV system in western, non-urban areas in the year 2000 increases by 0.3 units per PV system installed in previous periods relative to the distance to the previous installations. Imagine a given address and the situation

Table 5.1.: Coefficient estimates of utility functions for sample of Germany.

	M1	M2	M3	M4	M5
$\text{ASC}_{\text{solar}}$	-2.685***	-3.524***	-3.532***	-4.689***	-4.682***
	(-2304.40)	(-288.70)	(-285.35)	(-105.96)	(-105.62)
IBASE_{nt}		0.121***		0.0854***	
		(44.48)		(30.18)	
IBASE_{n1}			0.327***		0.448***
			(8.77)		(12.34)
IBASE_{n2}			0.194***		0.289***
			(4.64)		(7.79)
IBASE_{n3}			0.213***		0.230***
			(12.09)		(12.92)
IBASE_{n4}			0.398***		0.367***
			(14.07)		(12.82)
IBASE_{n5}			0.348***		0.298***
			(17.36)		(14.51)
IBASE_{n6}			0.236***		0.184***
			(19.11)		(14.44)
IBASE_{n7}			0.146***		0.120***
			(15.82)		(11.76)
IBASE_{n8}			0.149***		0.131***
			(12.71)		(11.08)
IBASE_{n9}			0.142***		0.113***
			(16.30)		(12.88)
$\text{IBASE}_{\text{n10}}$			0.0982***		0.0626***
			(16.60)		(10.46)
$\text{IBASE}_{\text{n11}}$			0.103***		0.0616***
			(27.41)		(16.02)
IBASE_{nt}*EAST_n		0.173***	0.171***	0.205***	0.202***
		(11.14)	(10.88)	(13.14)	(12.75)
BUYPOW_n				-0.628***	-0.628***
				(-52.11)	(-52.08)
BUYPOW_n*EAST_n				0.404***	0.404***
				(6.54)	(6.52)
GR_n				2.102***	2.085***
				(46.75)	(46.34)
GR_n*EAST_n				-1.507***	-1.478***
				(-5.90)	(-5.78)
GREEN_n				-2.160***	-2.193***
				(-26.55)	(-26.95)
GREEN_n*EAST_n				0.523	0.541
				(1.24)	(1.28)
POPDEN_n				-0.590***	-0.593***
				(-53.88)	(-54.00)
POPDEN_n*EAST_n				0.412***	0.415***
				(12.23)	(12.29)
NUTS-1 dummies	No	Yes	Yes	Yes	Yes
Period dummies	No	Yes	Yes	Yes	Yes
Observations	21,803,078	21,803,078	21,803,078	21,803,078	21,803,078
DF_{M}	0	27	37	35	45
Final log-likelihood $\mathcal{L}$	-522,595	-477,974	-477,800	-469,093	-468,876
LR: χ^2 (DF)		89,242 (27)	349 (10)	17,763 (8)	433 (10)
LR: p-value		0	5.6e-69	0	8.7e-87
LR test against		M1->M2	M2->M3	M2->M4	M4->M5

VIF below 10 for non-interaction terms
Robust t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

that through 1999 only one PV system was installed 100 meters away. Then, the increase in utility is $0.3/\ln(100) = 0.07$.

Interestingly, we find evidence for spatial non-stationarity: the coefficient for the interaction between IBASE_{nt} and EAST_n is significantly positive, i.e., the peer effect may be more important in the east of Germany. For example, for M6, adding IBASE_{n1}*EAST_n's coefficient to the one of IBASE_{n1} yields the effect of the installed base on the utility to install a PV system in the east in 2000. Since fewer PV installations exist in the east (see Figure 5.1), uncertainty regarding the reliability of a PV system may be higher and therefore information from peers might be more important compared to the west of Germany. Similarly, the interaction between IBASE_{nt} and URBAN_n is significantly positive, i.e., the peer effect may be more important in urban than in non-urban areas.

We see that the coefficients of the installed base decrease over time. However, simply comparing the magnitude of the estimated coefficients yields limited information. Instead, we study their general impact by considering the average marginal effect. Table D.5 of Appendix D.4 shows the respective results for M4, M6 and M6_{Logit}. Obviously, the average marginal effect for the installed base tends to decrease over time (see M6 and M6_{Logit}): i.e., the impact per distance-weighted peer on the utility to install declines (see Figure 5.5). In general, there is the trend that the average marginal effect of prior users on the decision to adopt diminishes. However, we observe three positive shifts. (I), an increase in the year 2003 when the 100,000 roofs program ceased. The shift may be also due to the government's discussion on the amendment of the EEG between 2002 and 2003. In December 2003 the level of the feed-in tariff for PV electricity was indeed modified for 2004.[32] (II), from 2006 to 2007 we find a small increase in the average marginal effect again. This increase may be linked to 2006's slight change in the EEG: an obligation to publish data on location and capacity of all subsidized systems was implemented. (III), in 2010 we also observe a slight increase in the average marginal effect. This increase may be linked to the amendment of the EEG in 2009. In contrast to the yearly changes of the level of the feed-in tariff between 2000 and 2009, the level changed three times in 2010. Having in mind the general trend of a diminishing average marginal effect for IBASE over time, it seems that this trend is interrupted when relevant changes in the subsidy system are implemented.

[32]The amendment of the EEG was implemented in 2004 but the relevant changes in the feed-in tariff for PV electricity were already put in place in December 2003.

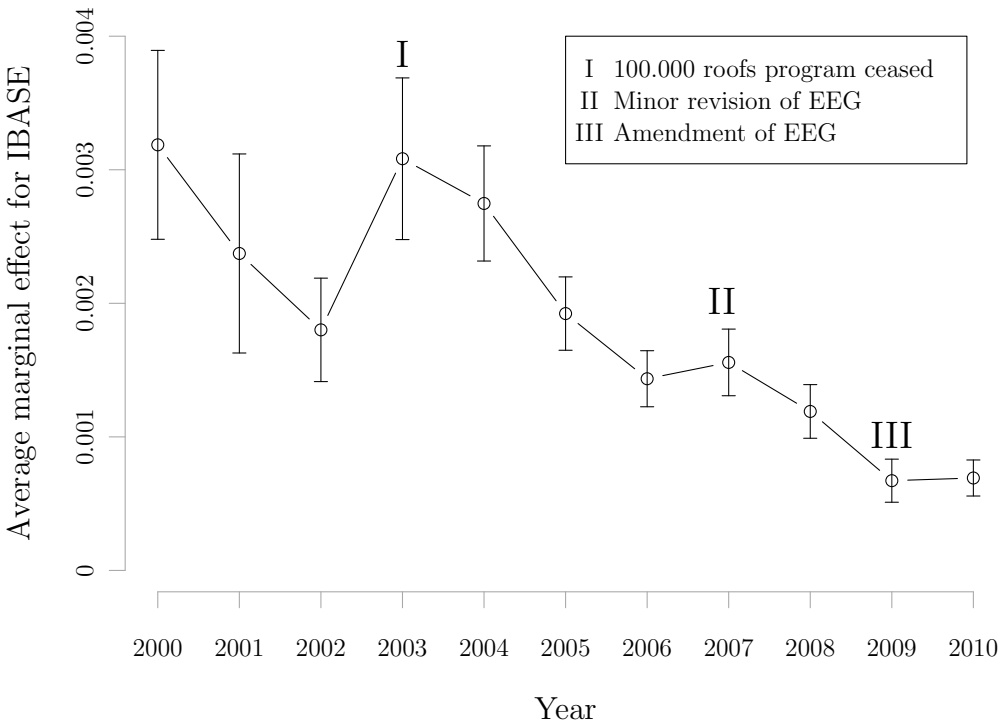

Figure 5.5.: Diminishing average marginal effect for IBASE with time (for M6, non-urban locations in the west). The patterns for urban areas and the east of Germany are very similar.

We are now interested in adopter characteristics. We find that global radiation (GR_n) has a significantly positive effect on PV adoption. This finding is appropriate as a high level of solar radiation indicates a higher potential to produce electricity and confirms a large income potential from a PV system. The average marginal effect of global radiation is also positive. Since 2002 we observe a slightly decreasing trend: in contrast to our expectation, for later adopters global radiation seems to be less relevant than for early adopters. This finding may be evidence for PV adoption due to a status effect. The comparatively low marginal effect of global radiation in 2000 may be associated with the fact that the feed-in tariff was not put in place before April 2000: it may have taken some time until the new subsidy system unfolded its incentive effect. In the east of Germany, global radiation's contribution to the utility of installing a PV system is smaller than in the west. We find a similar pattern for urban areas.

Political decision-makers might influence the diffusion process by systematically establishing seeds, e.g., local or regional incentives (Rode and Weber, 2012; Müller and Rode, 2013). From a planning perspective it is interesting to know to what extend seeding might balance disadvantages of regions in terms of global radiation. There-

fore, we evaluate seeds for promoting diffusion in regions with low global radiation, i.e., we consider the trade-off between peer-effects (IBASE_{nt}) and global radiation (GR_n) in terms of utility. This trade-off is measured as the ratio of the derivative of utility with respect to global radiation and the derivative of utility with respect to the installed base

$$\text{TO}_{\text{GR*PER}_t/\text{IBASE}_t} = \frac{\frac{\partial V_{n1t}}{\partial \text{GR}_n \text{PER}_t}}{\frac{\partial V_{n1t}}{\partial \text{IBASE}_{nt}}} = \frac{\beta_{27,\ldots,39}}{\beta_{1,\ldots,13}}.$$

The units for measuring global radiation are MWh/sqm and the units for measuring the peer-effect (installed base) are number of distance-weighted peers, i.e., peers/ln(m). Therefore, the unit for this measure of utility trade-off is "distance-weighted peers per MWh/sqm", i.e., (peers/ln(m))/(MWh/sqm). Consider exemplarily the corresponding estimates of M6 in Table D.4 for the second period (2001)

$$\text{TO}_{\text{GR*PER}_2/\text{IBASE}_2} = \hat{\beta}_{28}/\hat{\beta}_2 = 2.25/0.24 \approx 9 \frac{\frac{\text{peers}}{\text{ln(m)}}}{\frac{\text{MWh}}{\text{sqm}}}.$$

This means, in terms of utility, 9 distance-weighted peers are equivalent to one MWh/sqm global radiation. Consider exemplarily two locations: location A with a global radiation of 1.05 MWh/sqm and location B with 1 MWh/sqm, all others constant. In order to compensate the disadvantage of 0.05 MWh/sqm (1 standard deviation) of location B by additional peers, one would need to promote additional PV installations such that the measure of installed base IBASE_{B3} increases by $(1.05 - 1) \cdot 9 = 0.45$. For example, this can be achieved by nine additional installations that are located 100 m away from location B (in period 3). As shown in Figure 5.6 this trade-off increases over time. This means that in more recent periods more additional peers are needed to equal one MWh/sqm of global radiation compared to earlier periods. In the east, less peers are needed to equal one MWh/sqm of global radiation. We observe similar shifts in the trade-off between peer-effects and global radiation as in the marginal effect for the peer-effect. Thus, potential adopters' uncertainty caused by shifts in the subsidy system could be balanced through additional seeds.

We go on by discussing further characteristics of PV adopters. For a decision-maker n with an average buying power (i.e., $\text{BUYPOW}_n = 1$), the utility contribution of buying power from installing PV is -0.27 units in 2002 (period 3, M6 in Table D.4). Table D.5 illustrates that the average marginal effect for buying power

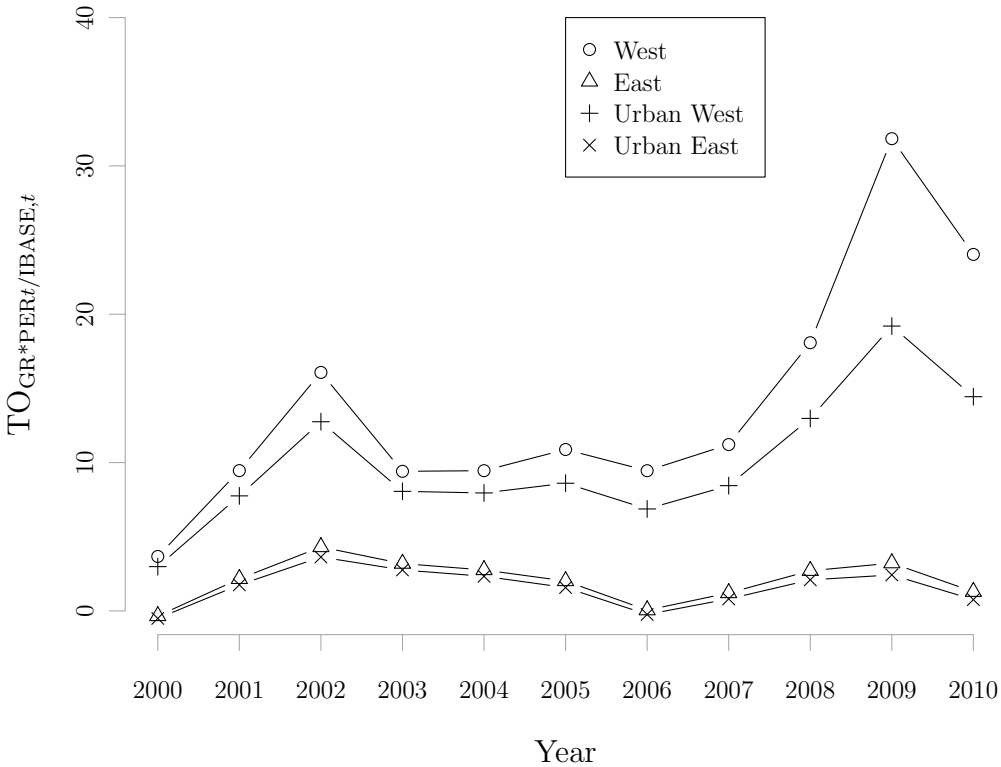

Figure 5.6.: Trade-off between IBASE$_{nt}$ and GR$_n$*PER$_t$ per year for urban and non-urban areas in the east and west of Germany (M5).

decreases over time. As the costs for installing a PV system decreased substantially in our period of study this finding is reasonable. Roughly speaking, early adopters are associated with higher buying power compared to later adopters. This finding is consistent with Rogers' (1983) idea that early adopters are of higher socio-economic status compared to later adopters. Again, there is evidence for spatial non-stationarity: the coefficient for the interaction between BUYPOW$_n$ and EAST$_n$ is significantly positive. For the period 2000-2007, we find positive (or close to zero) coefficients for choice-makers located in the eastern part of Germany. While in the west the utility declines with increasing buying power, we observe the opposite trend for the east during 2000-2007 (excluding 2004). As there are fewer PV installations in the east of Germany, we find early adopter characteristics (i.e., a high buying power) for a longer period of time. Between buying power's impact on the utility to adopt in urban and non-urban areas is no significant difference.

We include the share of green votes in 2009's federal election (GREEN$_n$) as an indicator for environmental attitude. Its influence on the decision to install a PV system is negative. This finding may be seen in line with Welsch and Kühling's (2009) results that – in Germany – environmental awareness is not an important

reason for installing solar thermal equipment, a technology closely related to PV. Regarding the green attitude's impact on the decision to adopt, there is no significant difference between urban and non-urban areas. In the east of Germany the results are similar, although less strong.

The impact of the population density (POPDEN_n) is negative and also decreases over time. This indicates that decision-makers located in less densely populated areas are more likely to install a PV system. We expect that the propensity of decision-makers located in areas with low population density to own a house is high. Once more, there is evidence for spatial non-stationarity: the coefficient for the interaction between POPDEN_n and EAST_n is significantly positive, i.e., on average, PV adopters in the east live in regions with higher population density than those in the west. In urban areas, the impact of population density on the utility to adopt is also less negative.

Comparing the results of M4 shown in Table 5.1 to M6 (Table D.4) indicates that the coefficient estimates are robust. Still, we check the validity of our results by drawing two other 9% samples from our data set. M6_{II} and M6_{III} in Table D.6 of Appendix D.4 confirm the validity of M6's estimates (Table D.4). We also combine the samples of M6 and M6_{II}, respectively M6 and M6_{III}. Then, we estimate our baseline specification and add a dummy variable (set to one for all observations from the second [respectively, third] sample), and interactions with the dummy variable and the explanatory variables of the baseline specification. A joined F-test confirms that the dummy and the interactions with the dummy are not significantly different from zero. As a consequence, our estimates seem to be valid for the whole population. For purposes of clarity we do not show the results here.

In Table D.7 of Appendix D.4, we show that neither a smaller cut-off parameter D of 200 meters (M7) nor a higher cut-off parameter of 1000 meters (M8) changes our findings. The peer effect is highly localized: considering installations further away than 500 meters – i.e., $D > 500\,\text{m}$ – does not significantly increase the explanatory power of the model (see Horowitz test between M6 and M8 in Table D.7 of Appendix D.4).[33] In other words, studies concentrating on peer effects at a higher level of geographical aggregation may fail to represent the peer effect appropriately.

Instead of measuring the installed base by installations from the previous period only, we incorporate all previous installations into specification M9, Table D.8 in Appendix D.4. See Appendix D.1 for a definition of the relevant measure of the

[33] E.g., Ben-Akiva and Lerman (1985) describe the Horowitz non-nested hypothesis test.

installed base: C_IBASE$_{nt}$. Comparing M9 to M6 using a Horowitz test confirms that the adopters of the previous period represent the installed base best.

We also check whether distance-decay functions other than $f = 1/\ln(d_{nm})$ are more appropriate in explaining the decision to adopt a PV system. Table D.9 (Appendix D.4) presents the results. Specification M10 builds on $f = 1/d_{nm}$ and M11 on $f = 1/d_{nm}^2$. A Horowitz test confirms that M6 (with $f = 1/\ln(d_{nm})$) is significantly superior.[34]

5.4.2. Individual-specific effects and local shocks

So far, we have controlled for period fixed effects capturing time-varying factors that have a symmetric effect on the increase in the adoption decision across all regions: for example, changes in legislation fostering PV adoption or changes in their installation costs. We have also included NUTS-1 ('Länder') fixed effects. These absorb NUTS-1-specific trends in the adoption decision and could be caused by 'Länder' characteristics affecting the usability of the technology: e.g., additional time-invariant incentives to install PV. In order to cover local characteristics we have included control variables, e.g. for buying power or population density. However, these are still aggregate controls.

To identify peer effects even more confidently, we should include a time-invariant individual specific fixed effect. We can do so by taking advantage of the conditional (or fixed effects) logit estimator.[35] Note that we cannot then include time-invariant controls. M12 in Table 5.2 reveals the exponentiated coefficients. We can interpret them as odds ratios.[36] The relevant descriptive statistics are shown in Table D.10 of Appendix D.4. When estimating a conditional logit model, groups with all zero outcomes are dropped, i.e., the number of observations is lower compared to the

[34] An estimation with controls for elevation and firm density also confirms our results. Elevation data comes from Jarvis et al. (2008) and data on firm density from Infas (2009b). Both controls are included at very high spatial resolution. For purposes of clarity we do not show these results.

[35] Conditional fixed effects means that the fixed effects are conditioned out of the model estimation through a revised log-likelihood function. In the unconditional case, the standard log-likelihood function is used and indicator variables (covering the fixed effects) included in the estimation. Unfortunately, a conditional probit estimator does not exist.

[36] Since Rural and East are time-invariant, they are absorbed by the individual fixed effects. We therefore do not estimate them separately in specification M12. Note that it does not make a difference that – instead of Urban – we include the antipodal dummy for rural areas (Rural) here. In M12, we also estimate the single period dummies without interaction. We do not show them as they are not relevant to our interpretation.

other estimation approaches although the conditional logit estimator allows us to include the full sample for Germany. Specification M12 in Table 5.2 reveals that for a unit increase in our IBASE measure we expect an increase of (5.8-1)*100%=486% in the odds of installing a PV system (under PV adopters) in period 1. Interpreting the other period-specific exponentiated coefficients is straightforward: e.g., multiplying IBASE_n's exponentiated coefficient with the one of $\text{IBASE}_\text{n} * \text{PER}_2$ reveals that we expect an increase of ((5.8*0.4)-1)*100%=132% in the odds of installing a PV system (under PV adopters) in period 2. Importantly, the analysis with individual-specific (address) fixed effects confirms our previous results: peer effects drive PV adoption but diminish over time. We do not observe a significant difference between peer effects in urban and rural areas. But as observed in our previous estimations, the effect is stronger in the east of Germany. Again, this is evidence for spatial non-stationarity in peer effects.

To identify even more confidently peer effects, we should also put our findings to the test with time-variant effects on the local level. We do so by conducting estimations with district times period fixed effects (i.e., a district fixed effect for every period of study). In these estimations, we control for yearly adoption shocks on the district level (i.e., 77,847 districts across Germany). Such a shock could, for example, be a local advertisement campaign by a PV seller, a new local subsidy fostering PV installations or a housing development in which new local regulations force residents to install PV. M13 in Table 5.2 illustrates the exponentiated coefficients, which we can again interpret as odds ratios. We show the relevant descriptive statistics in Table D.11 of Appendix D.4. The results with district times period fixed effects also confirm our previous results of diminishing peer effects over time and spatial non-stationarity in peer effects.

Note that we choose a cut-off distance of 200 m for the specifications shown in Table 5.2. For these we obtain the best goodness-of-fit measures, which supports the localization of peer-effects even more than the cut-off distance of 500 m, which delivered the best results before.

Our findings for estimations with individual-specific effects and local shocks remain unaffected by lagging our peer effect measure by two periods.[37] We can therefore confidently rule out that the 'reflection problem' described by Manski (1993) biases our results. The reflection problem applies to situations where the adoption decision of an individual i depends on others in i's reference group and i's adoption also affects

[37]For reasons of clarity, we do not show these results.

other group members. Bearing in mind that we study PV adoption on a yearly basis, it is reasonable to assume that an individual who adopts at t also decided to adopt at t or $t-1$. If so, i was affected by the behavior of reference group members at $t-2$. In consequence, the time lag rules out the possibility that the individual could have affected the adoption decision of reference group members, which in turn influenced the individual's adoption.

Table 5.2.: Odds ratio of peer effects for Germany.

	M12	M13
$f(d_{nm})$	$1/\ln(d_{nm})$	$1/\ln(d_{nm})$
Cut-off	200 m	200 m
IBASE_n	5.862^{***}	1.897^{***}
	(19.62)	(4.40)
$\text{IBASE}_\text{n} * \text{PER}_2$	0.407^{***}	0.975
	(-8.55)	(-0.13)
$\text{IBASE}_\text{n} * \text{PER}_3$	0.299^{***}	0.811
	(-12.71)	(-1.36)
$\text{IBASE}_\text{n} * \text{PER}_4$	0.472^{***}	0.726^{*}
	(-7.71)	(-2.01)
$\text{IBASE}_\text{n} * \text{PER}_5$	0.328^{***}	0.674^{**}
	(-11.83)	(-2.60)
$\text{IBASE}_\text{n} * \text{PER}_6$	0.255^{***}	0.650^{**}
	(-14.85)	(-2.90)
$\text{IBASE}_\text{n} * \text{PER}_7$	0.204^{***}	0.651^{**}
	(-17.34)	(-2.90)
$\text{IBASE}_\text{n} * \text{PER}_8$	0.202^{***}	0.624^{**}
	(-17.43)	(-3.19)
$\text{IBASE}_\text{n} * \text{PER}_9$	0.198^{***}	0.608^{***}
	(-17.80)	(-3.39)
$\text{IBASE}_\text{n} * \text{PER}_{10}$	0.157^{***}	0.545^{***}
	(-20.47)	(-4.15)
$\text{IBASE}_\text{n} * \text{PER}_{11}$	0.153^{***}	0.553^{***}
	(-20.81)	(-4.06)
$\text{IBASE}_\text{n} * \text{Rural}_n$	1.017	0.842^{***}
	(1.54)	(-13.28)
$\text{IBASE}_\text{n} * \text{East}_n$	1.203^{***}	1.423^{***}
	(5.68)	(7.86)
$\text{IBASE}_\text{n} * \text{Rural}_n * \text{East}_n$	0.942	1.375^{***}
	(-1.25)	(4.38)
East_n		0.958
		(-0.14)
Rural_n		1.368^{***}
		(81.34)
$\text{Rural}_n * \text{East}_n$		0.805^{***}
		(-16.27)
Observations	9,545,184	109,848,217
DF_M	24	17
Final log-likelihood $\mathcal{L}$	-1,764,494	-4,269,741
District*Period fixed effects	No	Yes
Address fixed effects	Yes	No

Exponentiated coefficients; Robust t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.4.3. Case study

In order to verify the robustness of our results with partially different data, we consider a case study including panel data for the cities of Darmstadt, Karlsruhe, Marburg, and Wiesbaden. We study these cities because building-specific global radiation data (GR BUILDING_n) is accessible. The case study helps us to check some of our assumptions. We test if we can indeed disregard building-specific data on global radiation for our analyses of Germany. Thus we test whether we might neglect roof orientation and shadowing. We also study differences between address and building data. Table 5.3 shows the corresponding data.

Table 5.3.: Characteristics for case study cities.

Characteristic	Darmstadt	Karlsruhe	Marburg	Wiesbaden	Sum
Residents in 2010	144,402	294,761	80,656	275,976	795,795
Number of buildings	100,004	83,819	40,872	113,548	338,243
Number of PV systems through 2010	374	1,058	450	463	2,345
Spatial units	109	302	56	177	644

Data on residents in 2010 is taken from DESTATIS (2013a).

Vermessungsamt Darmstadt (2008), KEK (2010), Stadt Marburg (2011) and Stadt Wiesbaden (2009) provide spatial data of the cities including information on buildings and detailed data on global radiation. Certainly, the level of detail is different for the specific cities. For example in 2010, Karlsruhe had more than twice as many residents than Darmstadt. Nevertheless, in our data set the number of buildings is larger in Darmstadt compared to Karlsruhe. Since we obtain similar results from the following study for each city individually, we neglect the different level of detail.[38]

Table D.12 and Table D.13 in Appendix D.4 present the frequencies of the categories for the case study and the descriptive statistics. Due to the low number of PV systems installed in the four cities through 2010, we can only estimate time-invariant coefficients for buying power, global radiation, installed base and population density. We only have data on GREEN_n at the NUTS-3 level, which does not provide sufficient spatial variation for the case study. Table 5.4 shows the estimates and the average marginal effects. The respective results from BLM are not presented but confirm the shown results from BPM. Both are comparable to the ones found for the whole country. Employing building-specific data on global radiation (GR BUILDING_n), which includes roof orientation and shadowing, does not change our coefficient estimates in terms of algebraic sign and level of significance. Still, a Horowitz test shows that MB, which relies on more accurate data, is significantly superior to MA.

Since also the average marginal effects for MA (Table 5.4) and for M4 (Table D.5) are comparable, we expect that the case study provides insights for our analysis of Germany. Comparing MA to MB (Table D.5) reveals that the average marginal ef-

[38]Taking the four cities together we end up with 338,243 observations (i.e., buildings and therefore potential places for PV installations). As not all PV systems fall inside a building-polygon we allocate 743 out of 2,345 to their nearest building. Due to inaccuracy in geocoding and the possibility that more than one PV system could be installed on one building, 128 buildings have several PV systems installed. As we assume one PV system per building in the case study, we allocate them to a random building in the same spatial unit. Table 5.3 shows that we have all in all 644 spatial units for the four cities under study.

Table 5.4.: Coefficient estimates of utility functions for case study.

	MA		MB	
	Coeff.	Avg. marginal eff.	Coeff.	Avg. marginal eff.
$\text{ASC}_{\text{solar}}$	-5.892***		-3.409***	
	(-22.72)		(-62.44)	
IBASE_{nt}	0.229***	0.000482***	0.251***	0.000523***
	(11.08)	(10.84)	(12.00)	(11.72)
BUYPOW_n	-0.598***	-0.00126***	-0.331***	-0.000689***
	(-12.06)	(-11.77)	(-8.01)	(-7.93)
GR_n	2.912***	0.00614***		
	(11.32)	(11.10)		
GR BUILDING_n			0.393***	0.000819***
			(24.28)	(22.27)
POPDEN_n	-0.170***	-0.000358***	-0.145***	-0.000302***
	(-10.96)	(-10.76)	(-9.71)	(-9.57)
Period dummies	Yes		Yes	
Observations	3,720,662		3,720,662	
DF_{M}	14		14	
Final log-likelihood $\mathcal{L}$	-18,531		-18,196	
Horowitz test statistic (sig. level)			-1.87 (.0307)	
Horowitz test against			MA	

Robust t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

fects for buying power, installed base and population density are not largely affected by more detailed data on global radiation: their algebraic signs stay constant and their absolute values remain at a comparable level. However, the average marginal effect for global radiation decreases if more accurate data is used. This result may be due to the fact that inappropriate roofs are, actually, disregarded for PV installations. Most importantly, the case study confirms the validity of our findings for buying power, installed base, and population density.

In Appendix D.2 we describe a placebo test which uses case study data and confirms our findings. Finally, we use individual level data from the Socio-Economic Panel to verify our results (SOEP, 2013). For details see Appendix D.3.

5.5. Summary

We set out to study the individual adoption decision to install a PV system in Germany. We incorporate the year and location of installation for the PV systems set up in Germany through 2010 and locational data of addresses (at which we assume all PV systems to be installed).

In line with Bollinger and Gillingham (2012), Müller and Rode (2013) and our results in Chapter 5, our discrete choice analysis reveals that the propensity to install

a PV system increases with the number of previously installed systems in spatial proximity; i.e., we confirm a highly localized peer effect. In contrast to the mentioned studies, we measure peer-effects by the installed base using a continuous distance decay function for each (potential) adopter individually across a whole country. Our analysis reveals that the impact of each previously installed PV system on the propensity of a new installation decreases continuously with the distance between the two locations. We find evidence for peer effects within a range of 0-0.5 km. However, within this range the peer effects' impact deflates slowly. Measuring the peer effect by the inverse natural logarithmic distance explains PV system adoption best. Furthermore, a previous year's PV system adopters are – in comparison to all previous adopters – most important for current adopters. Our analysis also shows that the peer effect's impact on the decision to adopt decreases over time. This is not surprising since it is reasonable to expect that the number of prior users reduces uncertainty about the reliable operation of a technology. However, in periods when the subsidy system is revised the peer effect gains importance again since uncertainty about the remuneration potential from a PV system may increase.

When comparing early and later adopters, we find that later adopters tend to have lower buying power. Later adopters also live in less densely populated areas with lower global radiation. We find different scales of the effects in urban and non-urban areas in the east and west of Germany. Finally, we observe that the number of peers that equals the utility contribution of one unit of global radiation increases over time. A case study with building-specific data on global radiation confirms our findings.

The policy implications of our study are straightforward. Our results reveal that it would be efficient to influence the adoption of PV systems using seed installations in the very early periods of diffusion since the importance of peer effects decreases over time. Furthermore, seed installations have the highest impact in the early periods in terms of balancing low levels of global radiation. Seeding is most promising at urban locations with low population density and high global radiation. Finally, policy makers should be careful when implementing changes in the subsidy system for PV. However, potential adopters' uncertainty caused by such changes could be balanced through additional seeding.[39]

[39] Certainly, we study PV adoption after political decision-makers decided to foster PV. We do not evaluate which energy technology or which mix of energy technologies is the best choice for a certain country.

We study PV system adoption in Germany. Certainly, a similar analysis in other countries with different residential structures or climate zones would be of interest. Studying PV adoption at locations where subsidies do not drive their diffusion would be valuable. Further disentangling of the peer effect may also be rewarding. For example, employing data on regional differences in Internet search engine usage may help to find out if the identified effect is driven by communication from face to face or, instead, seeing a PV system in operation is sufficient. Forecasting PV adoption at the local level could also be of interest.

6. Not in My Backyard! Local Resistance to the Adoption of Renewable Energy Technologies[40]

6.1. Motivation

After studying peer effects in PV adoption, we change our focus to resistance against renewable energy adoption. In recent years, we have observed more and more referenda against renewable energy plants (see Datenbank Bürgerbegehren (2014)). We want to investigate whether local referenda against a single renewable energy plant have a measurable impact on the technology's adoption rate (i.e., the first difference in the diffusion level) nearby. If a local referendum hinders building a plant, investors may search for an alternative site on which to build a plant in the immediate vicinity of the primary location. They may also search for a new site far away or may fully give up their plans. The purpose of this chapter is to find out which effect referenda against renewable energy plants have in Germany.

Studies on the diffusion of new technologies in a wide range of countries, sectors and periods confirm a diffusion path following logistic (S-shaped) curves (see Griliches (1957) and Mansfield (1961), or Comin and Mestieri (2013a) for further examples). This diffusion path is characterized by low initial adoption rates that eventually accelerate to reach a technology's long-run penetration rate. The non-linear nature of logistic curves implies that current adoption rates can be forecast by lagged diffusion levels. Epidemic models (Bass, 1969; Rogers, 1983), probit models (Griliches, 1957), legitimization theories (Hannan and Freeman, 1977, 1984), and information cascades models (Arthur, 1989; Banerjee, 1992), all explain the same non-linearity in diffusion. See Chapter 2 for a deeper discussion on the different theories. The common

[40]This chapter is based on Rode (2014).

S-shaped pattern of technology diffusion allows us to test whether the adoption rate of renewable energy plants differs between German NUTS-3 regions ('Landkreise und Kreisfreie Städte') in which a successful referendum against a single plant was organized and the remaining regions.

In this chapter, we exploit our data set regarding the adoption of wind power plants, biomass plants, and PV systems across Germany installed between 1992 and 2011. We add information on local referenda against the three technologies under study and test whether local referenda are associated with lower adoption rates. Our analysis exploits the fact that the referenda are held on the municipal district ('Gemeinde') level against a single plant or building area.

Failing to control for unobserved heterogeneity may result in biased estimates. We therefore have to account for other barriers (and drivers) to renewable energy adoption. Time fixed effects capture time-varying factors that have a symmetric effect on the increase in renewable energy diffusion across regions: for example, changes in legislation fostering the adoption of the technologies or changes in their installation costs. NUTS-3 fixed effects absorb NUTS-3-specific trends in the increase in the diffusion of the studied technology. These could be caused by regional characteristics affecting the usability of the technology: e.g., the average wind speed affects the profitability of wind power plants or local agricultural production can be more or less suitable for biomass plants. Therefore, we control for NUTS-3 and year fixed effects.

To strengthen the robustness of our analysis, we should have potentially omitted variables in mind. Omitted variables are drivers of adoption patterns that are correlated with referenda against renewable energy plants. Besides national time-varying factors and regional time-constant influences that both symmetrically shape renewable energy adoption, we could think of regional time-varying symmetric effects. We absorb these by conducting an analysis with NUTS-2-times-year-fixed effects (i.e., a NUTS-2 fixed effect for every year of study). These control for yearly adoption shocks on one level of aggregation higher than the NUTS-3 level.[41]

We find that adoption is indeed lower in regions where a referendum was conducted. The result is valid for wind power and large biomass plants. In NUTS-3 regions where a referendum against a wind park was organized, we find between 70% and

[41]During our period of study, on average every NUTS-2 region consists of 11 NUTS-3 regions and every NUTS-3 region of 27 municipal districts.

85% fewer new large wind power plants (after the referendum) than in NUTS-3 regions without a referendum. For large biomass plants, our analysis reveals that 99% fewer new plants are located in NUTS-3 regions where a succesful referendum was organized compared to the remaining regions. Our results are robust to using capacity-weighted measures of technology adoption. An analysis with NUTS-2-times-year-fixed effects also confirms our findings. We conclude that local resistance against one plant does not only work as a barrier against adoption in the municipal district where the plant was to be located. Instead, it has a signaling effect and hinders the adoption in the municipals district's NUTS-3 region. We interpret this as evidence that potential investors in wind power and large biomass plants not only avoid the municipal district where a referendum took place but stay away from the municipal district's neighbors.

To better understand the effect of referenda on renewable energy adoption, we conduct a placebo test. We study whether the same effect exists for PV systems, which shape the landscape less than wind power plants and do not come with the same pollution as biomass plants. As expected, we do not find that a referendum against a single PV system hinders PV adoption on the NUTS-3 level. We conclude that referenda only strongly slow down adoption for technologies such as wind power or large biomass plants, which may have – in comparison to PV – a larger effect on the well-being of the local population.

Finally, we analyze data on referenda against renewable energy plants which were announced but not conducted. In these cases, the decision against building the renewable energy plant was taken before the referendum could be organized. For these announced but not organized referenda we cannot confirm the effect found before. This result indicates that only organized referenda prevent potential investors from building renewable energy plants near the primary location.

Our study relates to literature on technology adoption. Many studies find that new technologies often diffuse more slowly than would be optimal (Rogers, 1983; Geroski, 2000; Oster and Thornton, 2012). High adoption costs (Griliches, 1957; Mansfield, 1961) often work as a barrier in the early phase of technology diffusion. Further, a lack of information about the technology's existence – as implied by the epidemic model of technology diffusion (Bass, 1969; Rogers, 1983) – can be responsible for slow diffusion. Similarly, theories on social learning (Young, 2009; Conley and Udry, 2010) imply that a lack of trust in the technology and missing knowledge on how to operate the technology can be a diffusion barrier.

Our analysis is also linked to specific studies on barriers to technology adoption. Comin and Mestieri (2013b) give an overview on active blocking. For example, technologies which improve transportation or communication can reduce the power of certain actors as described by Acemoglu and Robinson (2000). I.e., political or economic incumbents may construct barriers to protect their economic or political rents (Comin and Mestieri, 2013b). Comin and Hobijn (2009) identify lobbies in this context: lobbying efforts of incumbent technology producers which delay technology adoption. This finding is in line with our result in the sense that lobbying (in our context, resistance by the local public through a referendum) can slow down technology adoption.[42]

This chapter is also related to studies on protest movements in Germany. Among others, Marg et al. (2013) describe protest actors against infrastructure, electricity grid or large renewable energy plants and their motives. They find that protests are dominated by well-educated men, often with engineering expertise. In addition, Neukirch (2014) classifies the aims of protest actors and highlights their partly contradicting range of interests.

The remainder of this chapter is structured as follows. Section 6.2 describes implications of green energy adoption in Germany on our estimation strategy and presents details on referenda against renewable energy plants. Section 6.3 includes the empirical analysis, and discusses their interpretation. Section 6.4 concludes.

6.2. Institutional context and referenda

In this chapter, we exploit our data set regarding the adoption of wind power plants, biomass plants, and PV systems across Germany installed between 1992 and 2011. The changes in the feed-in tariff scheme and the shifts in the new installations shown in Figure 3.1, 3.2, and 3.3 of Chapter 3, are important for our econometric analysis. They highlight that we have to account for effects capturing time-varying factors which have a symmetric effect on the increase in renewable energy diffusion across regions, i.e., year fixed effects.

[42] Another stream of literature names country-specific, institutional factors as barriers to technology adoption (e.g., see Parente and Prescott (1994), Parente (1995) or Cunha-e Sá and Reis (2007)). This is less relevant to our study since a country-wide incentive scheme fosters the technologies we analyze. Further, there are many studies identifying factors that foster green technology adoption: see Section 2.4 in Chapter 2 for details.

The regional differences in the diffusion level of the three technologies shown in the maps (Figure 3.4, 3.5, and 3.6 in Section 3.4 of Chapter 3) are also important for our econometric analysis. They illustrate that we have to account for effects capturing time-constant factors that have a symmetric effect on the trend in renewable energy adoption in every region, i.e., NUTS-3 fixed effects. Since we find few wind power plants in district-free cities: only 3.3% of all wind power plants are installed in the 113 district-free cities (out of 429 NUTS-3 regions in total), we neglect district-free cities in our econometric analysis on wind power plants. The same applies to our analysis on biomass plants: we only find few plants (5.6%) in district-free cities and therefore disregard these when studying the adoption of biomass plants.

In this chapter, we want to investigate whether the adoption of renewable energy plants differs between NUTS-3 regions in which a successful referendum against a single plant was organized and the remaining regions. The way referenda are organized is defined in the federal states ('Länder') government codes. E.g., in Bavaria – according to Gemeindeordnung Bayern (1998) – the municipal council can initiate a referendum, or – depending on a municipal district's size – a certain number of citizens have to sign a referendum (e.g., 8% of eligle voters if the municipal district has between 20,001 and 30,000 inhabitants). If this amount of support is reached, the supporters can submit the referendum to the municipal council, including a justification for the referendum and the question to be asked in the referendum. The question must be capable of being answered with yes or no. The municipal council has to decide if the referendum is admissible within one month. If so, the municipal council has to schedule a Sunday (which lies within the coming three months) on which the referendum is organized. The referendum is accepted if a minimum turnout is reached (e.g., 20% for municipal districts below 50,000 inhabitants) and the majority of the votes is in favor of the referendum. Similar rules apply in all German 'Länder'.

The successful referenda shown in Table 6.1 against renewable energy plants are – according to Datenbank Bürgerbegehren (2014) – relevant for our analysis. See Figure 6.1 for a map of the successful referenda.

Table 6.1.: Successful referenda against renewable energy plants.

Technology	Year	Community	NUTS-3 region	'Land'
Wind power plants	1998	Rugendorf	LK Kulmbach	Bavaria
	2010	Büchen	Kreis Herzogtum Lauenburg	Schleswig-Holstein
	2010	Nübbel	Kreis Rendsburg-Eckernförde	Schleswig-Holstein
	2010	Rügge	Kreis Schleswig-Flensburg	Schleswig-Holstein
Biomass plants	2005	Langerringen	LK Augsburg	Bavaria
	2009	Großhabersdorf	LK Fürth	Bavaria
	2010	Großhabersdorf	LK Fürth	Bavaria
	2010	Freilassing	LK Berchtsgadener Land	Bavaria
PV systems	2008	Münster (Lech)	LK Donau-Ries	Bavaria
	2010	Gablingen	LK Augsburg	Bavaria
	2010	Eslarn	LK Neustadt an der Waldnaab	Bavaria

LK stands for 'Landkreis': rural districts

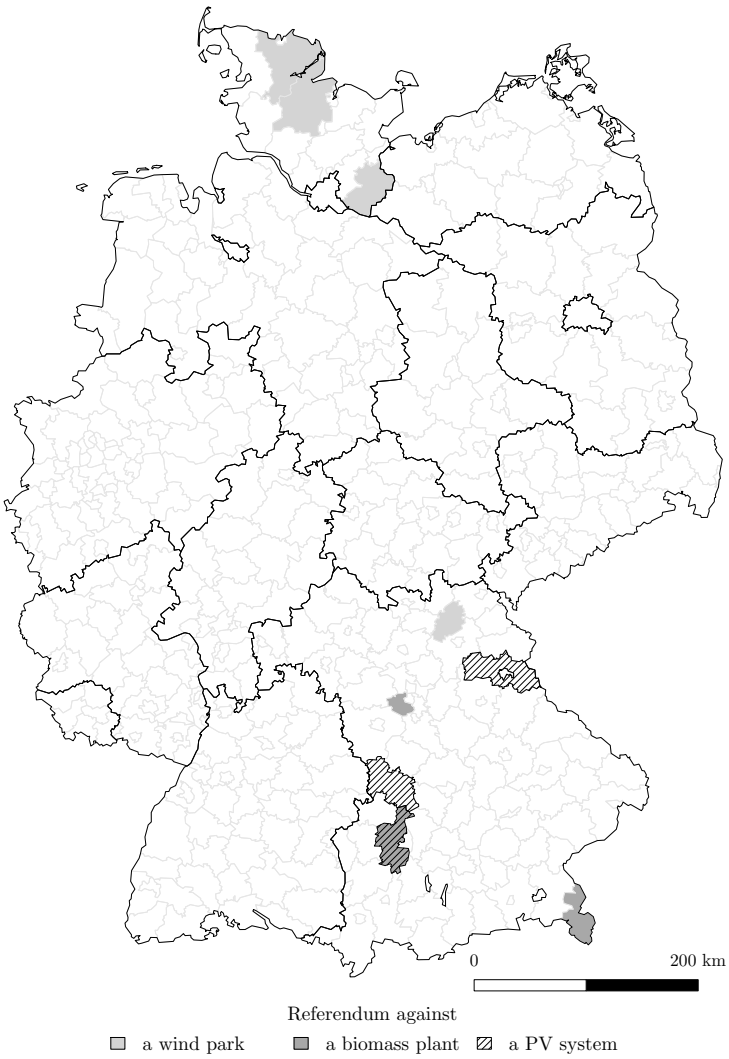

Figure 6.1.: NUTS-3 region with a referendum against a renewable plant.

6.3. Econometric evidence

We consider the following technology-specific econometric model for the adoption rate for NUTS-3 region n in year t (ΔF_{nt}):

$$\Delta F_{nt} = \alpha_n + \alpha_t + \beta F_{nt-1} + \gamma X_{nt} + \rho REF_{nt-1} + \epsilon_{nt}. \tag{6.1}$$

α_n is a region-specific trend, α_t is an aggregate time dummy, F_{nt-1} is the technology-specific (normalized) stock of renewable plants installed in the region at year $t-1$, X_{nt} is a vector of other potential drivers (or barriers) of technology adoption, and ϵ_{nt} is an error term.[43] REF_{nt-1} is a dummy variable which is set to one if a successful referendum against the technology under study was organized at n in $t-1$ or before. We lag REF by one year. If not, a renewable energy plant could be installed before a referendum was organized.[44]

6.3.1. Referenda against wind power plants

Table 6.2 column (1) reports the ordinary least squares (OLS) estimates of Equation (6.1) including NUTS-3 and year fixed effects.[45] The significantly negative coefficient of the referendum dummy indicates that the number of new wind power plants is significantly lower in regions where a successful referendum against wind power was organized in $t-1$. The null that $REF_{\text{Wind},t-1}$ is irrelevant and that $REF_{\text{Wind},t-1}$ and $F_{\text{Wind},t-1}$ are irrelevant predictors for $\Delta F_{\text{Wind},t-1}$ are rejected at any level of significance by a F test. Note that we control – as implied by diffusion theory – for the stock of renewable plants (F_{nt-1}) in this and all coming regressions. The significantly negative coefficient for the level of wind power diffusion in $t-1$ indicates that adoption rates are lower in regions with high diffusion levels.

The descriptive statistics shown in Table E.1 of Appendix E.1 illustrate that our endogenous variable is truncated: only non-negative values, but many zeros exist.

[43] As implied by Figure 3.1, 3.2 and 3.3 in Chapter 3 we normalize the number of wind power plants by the agricultural and forestal area in sqkm, the number of biomass plants by the agricultural area in sqkm, and the number of all PV systems by the amount of buildings and the number of large PV systems (above 100 kW_p) by the agricultural area in sqkm.

[44] Information on the date of installation of the renewable energy plants is only valid on a yearly basis.

[45] Reported standard-errors are, here and in the coming results, robust to heteroscedasticity and clustered for each NUTS-3 region.

Table 6.2.: Estimation of successful referendum on adoption of wind power plants.

	(1)	(2)	(3)
	$\Delta F_{\text{Wind},t}$	$\Delta F_{\text{Wind},t}$	$\Delta\#_{\text{Wind},t}$
Estimator	OLS FE	Cond. Poisson FE	Uncond. Neg. Bin. FE
$REF_{\text{Wind},t-1}$	-0.00185***	-0.576*	-0.723**
	(-6.46)	(-2.12)	(-2.65)
$F_{\text{Wind},t-1}$	-0.0274**	-7.639***	
	(-2.99)	(-4.42)	
$\#_{\text{Wind},t-1}$			-0.00321***
			(-3.59)
θ^{-1}			1.356
NUTS-3 and Year FE	Yes	Yes	Yes
R^2	0.0801		
Adj. R^2	0.0770		
LL		-46.13	-9155.2
F	12.95		
χ^2		362.3	
$F_{REF=0}$ / $\chi^2_{REF=0}$ (p-value)	41.76 (3.93e-10)	4.509 (0.0337)	7.000 (0.00815)
N (DF_M)	6004 (19)	5396 (20)	6004 (128)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

According to Hilbe (2011), a generalized linear model (GLM) with a Poisson distribution and its canonical log link may be appropriate in this case. A conditional fixed effects estimator exists for a GLM with a Poisson distribution (and log link).[46] We report the results in Table 6.2 column (2).[47] Again, the significantly negative coefficient of the referendum dummy indicates that the number of wind power plants is lower in regions where a referendum against wind power was organized in $t-1$. A χ^2 test suggests the validity of the specification.

A GLM with a Poisson distribution may be appropriate but cannot deal with overdispersion. Overdispersion means that the variance of the response exceeds the mean. In this case, Hilbe (2011) recommends a GLM with a negative binomial distribution.[48] Hilbe (2011) further advises employing unconditional fixed effects. Table 6.2 shows the results in column (3). Note that Equation (6.1) is modified for the estimates in column (3): instead of the normalized ΔF_t and F_{t-1}, we have to include the simple counts $\Delta\#_t$ and $\#_{t-1}$. The dispersion parameter (θ^{-1}) is significant to

[46] Such a model is often used for count data but not affected through scaling and therefore a useful option here. Conditional fixed effects means that the fixed effects are conditioned out of the model estimation through a revised log-likelihood function. In the unconditional case, the standard log-likelihood function is used and indicator variables (covering the fixed effects) included in the estimation.

[47] When estimating a conditional fixed effects model for a GLM with a Poisson distribution (and log link), groups with all zero outcomes are dropped. I.e., the number of observations is lower compared to the other estimation approaches.

[48] We parameterize the estimation as NB-2 with a log link. This is standard in Stata 11, which we use (StataCorp, 2009). NB-2 means that the model has a variance $\mathbb{V} = \mu + \theta^{-1}\mu^2$, where μ is the mean and θ^{-1} is the dispersion parameter, also known as alpha.

the 0.1% level, which indicates that overdispersion is present and, therefore, the specification in column (3) most appropriate. Once again, the significantly negative coefficient of the referendum dummy illustrates that the number of wind power plants is significantly lower in regions where a referendum against wind power was organized in $t-1$. Exponentiating the estimated coefficient allows interpreting it as an incidence rate ratio (IRR): in NUTS-3 regions where a referendum against a wind park was organized, we find 50% fewer new wind power plants (after the referendum) compared to NUTS-3 regions with no referendum at all or no successful referendum.

Do our findings change if we only take into account wind power plants of high capacity, i.e., larger systems? Table 6.3 reveals the estimates for wind power plants of capacity higher than 0.5 MW. Figure 3.2 in Section 3.2 of Chapter 3 illustrates that most wind power plants are of this size. Wind power plants with a capacity higher than 0.5 MW have larger rotors and therefore shape the landscape more heavily than small plants.

Table 6.3.: Estimation of successful referendum on adoption of large wind power plants.

	(1)	(2)	(3)
	$\Delta F_{\text{Wind}>0.5\,\text{MW},t}$	$\Delta F_{\text{Wind}>0.5\,\text{MW},t}$	$\Delta\#_{\text{Wind}>0.5\,\text{MW},t}$
Estimator	OLS FE	Cond. Poisson FE	Uncond. Neg. Bin. FE
$REF_{\text{Wind},t-1}$	-0.00253***	-1.252**	-1.890***
	(-8.68)	(-2.70)	(-7.44)
$F_{\text{Wind}>0.5\,\text{MW},t-1}$	-0.00171	-9.362***	
	(-0.20)	(-3.52)	
$\#_{\text{Wind}>0.5\,\text{MW},t-1}$			-0.00271*
			(-2.30)
θ^{-1}			1.525
NUTS-3 and Year FE	Yes	Yes	Yes
R^2	0.0997		
Adj. R^2	0.0967		
LL		-37.45	-7868.7
F	12.50		
χ^2		571.7	
$F_{REF=0}$ / $\chi^2_{REF=0}$ (p-value)	75.37 (2.14e-16)	7.266 (0.00703)	55.41 (9.77e-14)
N (DF_M)	6004 (19)	4940 (20)	6004 (78)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Again we show the estimates for the simple OLS fixed effects regression, the conditional fixed effects estimator for the GLM with Poisson distribution, and the unconditional fixed effects estimator for the GLM with a negative binomial distribution (Table 6.3). The three estimation approaches point in the same direction. They confirm that the number of new wind power plants is significantly lower in regions where a referendum against wind power was organized in $t-1$. The effect is stronger for

larger wind plants. The exponentiated point estimate shown in column (3) reveals that (after a successful referendum) 85% less new wind power plants are located in NUTS-3 region with a successful referendum compared to the rest of the NUTS-3 regions.

6.3.2. Referenda against biomass plants

Let us turn to the adoption of biomass plants. Can we confirm the same effect as for wind power plants? Table E.2 of Appendix E.1 reports the descriptive statistics. In Table 6.4, we see the point estimates for new biomass plants while, of course, always including NUTS-3 and year fixed effects. We cannot confirm any effect when including all biomass plants. No matter which estimation approach we choose, the point estimate for the referendum dummy at $t-1$ does not significantly vary from zero. F and χ^2 tests confirm this result.

Table 6.4.: Estimation of successful referendum on adoption of biomass plants.

	(1)	(2)	(3)
	$\Delta F_{\text{Biomass},t}$	$\Delta F_{\text{Biomass},t}$	$\Delta\#_{\text{Biomass},t}$
Estimator	OLS FE	Cond. Poisson FE	Uncond. Neg. Bin. FE
$REF_{\text{Biomass},t-1}$	-0.000853	-0.253	-0.227
	(-0.24)	(-0.73)	(-0.69)
$F_{\text{Biomass},t-1}$	0.110**	-10.17	
	(3.06)	(-1.45)	
$\#_{\text{Biomass},t-1}$			-0.00557*
			(-2.32)
θ^{-1}			0.237
NUTS-3 and Year FE	Yes	Yes	Yes
R^2	0.311		
Adj. R^2	0.308		
LL		-40.75	-6942.9
F	113.2		
χ^2		2283.5	
$F_{REF=0}$ / $\chi^2_{REF=0}$ (p-value)	0.0565 (0.812)	0.537 (0.464)	0.470 (0.493)
N (DF_M)	6004 (19)	5928 (20)	6004 (24)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The picture changes if we study the effect of referenda on the adoption of biomass plants with high capacity. Figure 3.3 in Section 3.3 of Chapter 3 illustrates the adoption of large biomass systems (above 1 MW_e). In comparison to small systems, they have higher pollution. Although there are relatively few large biomass plants, we observe more than 500 plants installed across Germany through 2011, 86 of these located in Bavaria, where referenda against biomass plants were organized. Further, more than half of the large biomass plants in Bavaria were installed later

than 2005, which is the year when the first referendum against a biomass plant was organized in the municipal district Langerringen (NUTS-3 region Landkreis Augsburg, Bavaria).

Table 6.5 shows our estimates for large biomass plants. We again control for NUTS-3 and year fixed effects. No matter which estimation strategy we use, we find that the number of new large biomass plants is significantly lower in regions where a referendum against a biomass plant was organized in $t-1$. As the dispersion parameter does not significantly differ from zero, the estimates in column (2), i.e., the ones from the conditional fixed effects estimator for the GLM with Poisson distribution, seem to be most appropriate. Exponentiating the point estimate reveals that 99% fewer new plants are located in NUTS-3 regions where a successful referendum against biomass plants was organized compared to the remaining regions.

Table 6.5.: Estimation of successful referendum on adoption of large biomass plants.

	(1)	(2)	(3)
	$\Delta F_{\text{Biomass}>1\,\text{MW}_\text{e},t}$	$\Delta F_{\text{Biomass}>1\,\text{MW}_\text{e},t}$	$\Delta\#_{\text{Biomass}>1\,\text{MW}_\text{e},t}$
Estimator	OLS FE	Cond. Poisson FE	Uncond. Neg. Bin. FE
$REF_{\text{Biomass},t-1}$	-0.000205***	-13.26***	-18.91***
	(-3.99)	(-12.78)	(-18.91)
$F_{\text{Biomass}>1\,\text{MW}_\text{e},t-1}$	-0.0853***	-853.0***	
	(-7.22)	(-3.91)	
$\#_{\text{Biomass}>1\,\text{MW}_\text{e},t-1}$			-0.922***
			(-5.15)
θ^{-1}			0
NUTS-3 and Year FE	Yes	Yes	Yes
R^2	0.0388		
Adj. R^2	0.0356		
LL		-1.382	-946.7
F	15.79		
χ^2		383.8	
$F_{REF=0}$ / $\chi^2_{REF=0}$ (p-value)	15.93 (0.0000820)	163.2 (2.22e-37)	357.6 (9.34e-80)
N (DF_M)	6004 (19)	3382 (20)	6004 (315)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.3.3. Shocks on the NUTS-2 level

The negative association between referenda and the adoption rates could also result from omitting relevant variables from the vector of controls, X_{nt}. So far, we control for federal time-varying factors, regional time-constant influences and the lagged adoption level. Any regional time-varying effect could be an omitted variable which biases our estimates. However, we can absorb regional time-varying symmetric ef-

fects by conducting an analysis with NUTS-2-times-year-fixed effects. These control for yearly adoption shocks on one level of aggregation higher than the NUTS-3 level. Such a shock may, for example, be the result of a 'Länder' government, which tries to locate renewable energy plants in a certain NUTS-2 region through additional subsidies, a regional change in agricultural production which makes a NUTS-2 region more attractive for biomass plants, or even relevant changes in per capita income or the population density.

In the following analysis, we only study renewable energy plants of the size for which we find the strongest effect of referenda in the previous exercise. Table 6.6 reports the estimates for wind power plants with capacity higher than 0.5 MW. As before, the stock of adoption serves as a control.[49] The three different estimation approaches again point in the same direction: the number of new wind power plants (above 0.5 MW) is significantly lower in regions where a referendum against wind power was organized in $t-1$. F and χ^2 tests confirm this result. Since θ^{-1} is significant at any level of significance, we find the results given in column (3) most appropriate. They reveal that 70% fewer new wind power plants (above 0.5 MW) are located in NUTS-3 regions where a referendum against wind power plants was organized compared to the remaining regions.

Table 6.6.: Estimation of successful referendum on adoption of large wind power plants (controlling for yearly NUTS-2 shocks).

	(1)	(2)	(3)
	$\Delta F_{\text{Wind}>0.5\,\text{MW},t}$	$\Delta F_{\text{Wind}>0.5\,\text{MW},t}$	$\Delta\#_{\text{Wind}>0.5\,\text{MW},t}$
Estimator	OLS FE	Cond. Poisson FE	Uncond. Neg. Bin. FE
$REF_{\text{Wind},t-1}$	-0.00119^{+}	-0.844**	-1.204*
	(-1.75)	(-2.99)	(-2.30)
$F_{\text{Wind}>0.5\,\text{MW},t-1}$	0.0641***	10.94***	
	(10.99)	(10.69)	
$\#_{\text{Wind}>0.5\,\text{MW},t-1}$			0.0141***
			(9.31)
θ^{-1}			1.870
NUTS-2xYear FE	Yes	Yes	Yes
R^2	0.0977		
Adj. R^2	0.0974		
LL		-30.98	-8127.4
F	60.57		
χ^2		161.6	
$F_{REF=0}$ / $\chi^2_{REF=0}$ (p-value)	3.061 (0.0806)	8.935 (0.00280)	5.273 (0.0217)
N (DF_M)	6004 (1)	4728 (2)	6004 (277)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[49] Reported standard-errors for the regressions with NUTS-2-times-year-fixed are still robust to heteroscedasticity but clustered on the NUTS-2-times-year level.

Turning back to the adoption of large biomass plants, Table 6.7 confirms our previous findings for referenda against biomass plants. Again F and χ^2 tests approve this result. Our preferred estimation is shown in column (3) since θ^{-1} is significant to the 5% level. According to this estimation, again 99% fewer new large biomass plants are located in NUTS-3 regions where a referendum against biomass plants was organized (compared to the remaining regions).

Table 6.7.: Estimation of successful referendum on adoption of large biomass plants (controlling for yearly NUTS-2 shocks).

	(1)	(2)	(3)
	$\Delta F_{\text{Biomass}>1\,\text{MW}_\text{e},t}$	$\Delta F_{\text{Biomass}>1\,\text{MW}_\text{e},t}$	$\Delta\#_{\text{Biomass}>1\,\text{MW}_\text{e},t}$
Estimator	OLS FE	Cond. Poisson FE	Uncond. Neg. Bin. FE
$REF_{\text{Biomass},t-1}$	-0.000237**	-12.82***	-18.89***
	(-2.86)	(-26.36)	(-18.48)
$F_{\text{Biomass}>1\,\text{MW}_\text{e},t-1}$	0.00521	27.15	
	(0.94)	(1.01)	
$\#_{\text{Biomass}>1\,\text{MW}_\text{e},t-1}$			0.249***
			(7.97)
θ^{-1}			0.155
NUTS-2xYear FE	Yes	Yes	Yes
R^2	0.000299		
Adj. R^2	-0.0000343		
LL		-1.514	-1023.6
F	4.286		
χ^2		697.1	
$F_{REF=0}$ / $\chi^2_{REF=0}$ (p-value)	8.170 (0.00439)	695.0 (3.68e-153)	341.5 (3.08e-76)
N (DF_M)	6004 (1)	2229 (2)	6004 (2)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In estimations not shown, we confirm our findings. Our results hold true if we only study the parts of Germany in which most plants are located. For wind power we only study the north (Schleswig-Holstein, Lower-Saxony, and Mecklenburg-West Pomerania) and for large biomass plants we only study the south (Baden-Württemberg and Bavaria). Our results also remain unaffected from including cities and from neglecting the lagged diffusion level (which is correlated with current adoption rates) in our estimations.

We also put the robustness of our findings to the test with alternative measures of adoption. Instead of simply counting the renewable energy plants, we calculate the capacity-adjusted adoption rates

$$\Delta F_{\text{Wi.Cap}>0.5\,\text{MW},nt} = \frac{\Delta\text{Total wind capacity installed } > 0.5\,\text{MW}_{nt}}{\text{Sqkm of agricultural/forestal area}_n} \tag{6.2}$$

and

$$\Delta F_{\text{Bio.Cap} > 1\,\text{MW}_\text{e},nt} = \frac{\Delta\text{Total biomass capacity installed } > 1\,\text{MW}_{\text{e},nt}}{\text{Sqkm of agricultural area}_n}, \tag{6.3}$$

as well as the respective levels with time lag. Figure B.2 and Figure B.3 in Appendix B.1 illustrate the adoption of wind power plants using capacity-adjusted adoption rates. Large plants build a higher share with capacity-adjusted measures. As capacity-adjusted adoption measures are not count data, we only rely on OLS fixed effects regression and the conditional fixed effects estimator for the GLM with Poisson distribution. Tables E.4 and E.5 illustrate the results with NUTS-3 and year fixed effects in column (1) and (2), and NUTS-2-times-year-fixed effects in column (3) and (4). The capacity-adjusted analyses confirm our previous findings.

6.3.4. Neighborhood effects of referenda on the NUTS-3 level

So far, we have shown that referenda against wind power and large biomass plants on the municipal district level work as a barrier to the adoption of both technologies on the NUTS-3 level. We may expect that this effect also spills over to neighboring NUTS-3 regions. We therefore include a spatially-lagged version of our referendum dummy in our estimations: $W\,REF_{t-1}$. W is a row-normalized contiguity matrix of the NUTS-3 regions. Note that we also control for the spatially lagged diffusion level in the previous period: $W\,F_{t-1}$ and accordingly $W\,\#_{t-1}$. The following analysis again includes NUTS-3 and year fixed effects.

Referenda against wind power plants

Table 6.8 reports the neighborhood effect of referenda (against wind power plants) on new wind power plants (above 0.5 MW). Note that the estimate for the non-spatially lagged referendum dummy is very similar to the one in Table 6.3 and therefore confirms our previous results. The spatially-lagged referendum dummy shows a significantly negative impact in column (1) and (2), i.e., for the simple OLS fixed effects regression and the conditional fixed effects estimator for the GLM with Poisson distribution. The dispersion parameter of the regression shown in column (3) is positive to any level of significance. We therefore regard the estimates in column (3) as most reliable. The unconditional fixed effects estimator for the

GLM with a negative binomial distribution does not reveal a significant impact of the spatially lagged referendum dummy. Therefore, we cannot confirm that the negative effect from a referendum spills over to neighboring NUTS-3 regions for wind power plants.

Table 6.8.: Estimation of successful referendum nearby on adoption of large wind power plants.

	(1)	(2)	(3)
	$\Delta F_{\text{Wind}>0.5\,\text{MW},t}$	$\Delta F_{\text{Wind}>0.5\,\text{MW},t}$	$\Delta\#_{\text{Wind}>0.5\,\text{MW},t}$
Estimator	OLS FE	Cond. Poisson FE	Uncond. Neg. Bin. FE
$REF_{\text{Wind},t-1}$	-0.00251***	-1.184*	-1.877***
	(-8.94)	(-2.38)	(-6.66)
$W\,REF_{\text{Wind},t-1}$	-0.00935*	-4.605**	-4.326
	(-2.51)	(-3.17)	(-1.11)
$F_{\text{Wind}>0.5\,\text{MW},t-1}$	-0.00184	-9.282***	
	(-0.22)	(-3.49)	
$W\,F_{\text{Wind}>0.5\,\text{MW},t-1}$	0.00429	3.481	
	(0.97)	(1.18)	
$\#_{\text{Wind}>0.5\,\text{MW},t-1}$			-0.00250*
			(-2.13)
$W\,\#_{\text{Wind}>0.5\,\text{MW},t-1}$			0.00634^{+}
			(1.94)
θ^{-1}			1.511
NUTS-3 and Year FE	Yes	Yes	Yes
R^2	0.100		
Adj. R^2	0.0970		
LL		-37.42	-7861.6
F	11.77		
χ^2		581.2	
$F_{W\,REF=0}$ / $\chi^2_{W\,REF=0}$ (p-value)	6.296 (0.0126)	10.06 (0.00152)	1.230 (0.267)
N (DF_M)	6004 (21)	4940 (22)	6004 (78)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Referenda against biomass plants

Is there a spill-over effect for large biomass plants? Independent of the estimation strategy we choose, the estimates in Table 6.9 report that less large biomass plants are found in NUTS-3 regions which share a border with a NUTS-3 region where a referendum against biomass plants was organized (in a previous period).[50] F and χ^2 tests confirm this result.

We find evidence that a referendum against large biomass plants in a NUTS-3 region is associated with lower adoption in neighboring NUTS-3 regions. We conclude that

[50]Due to convergence problems, we can only estimate the GLM with a negative binomial distribution (Table 6.9 column (3)) for the panel between 1994 and 2011.

Table 6.9.: Estimation of successful referendum nearby on adoption of large biomass plants.

	(1)	(2)	(3)
	$\Delta F_{\text{Biomass}>1\,\text{MW}_\text{e},t}$	$\Delta F_{\text{Biomass}>1\,\text{MW}_\text{e},t}$	$\Delta\#_{\text{Biomass}>1\,\text{MW}_\text{e},t}$
Estimator	OLS FE	Cond. Poisson FE	Uncond. Neg. Bin. FE
$REF_{\text{Biomass},t-1}$	-0.000200***	-15.35***	-19.31***
	(-3.94)	(-14.72)	(-19.29)
$W\,REF_{\text{Biomass},t-1}$	-0.000369**	-92.69***	-104.4***
	(-2.64)	(-13.45)	(-15.73)
$F_{\text{Biomass}>1\,\text{MW}_\text{e},t-1}$	-0.0857***	-856.6***	
	(-7.27)	(-3.95)	
$W\,F_{\text{Biomass}>1\,\text{MW}_\text{e},t-1}$	-0.00239	-24.67	
	(-0.97)	(-0.72)	
$\#_{\text{Biomass}>1\,\text{MW}_\text{e},t-1}$			-0.921***
			(-5.23)
$W\,\#_{\text{Biomass}>1\,\text{MW}_\text{e},t-1}$			0.201
			(0.77)
θ^{-1}			1.57e-49
NUTS-3 and Year FE	Yes	Yes	Yes
R^2	0.0391		
Adj. R^2	0.0356		
LL		-1.379	-928.4
F	14.42		
χ^2		631.4	
$F_{W\,REF=0}$ / $\chi^2_{W\,REF=0}$ (p-value)	6.963 (0.00874)	180.8 (3.18e-41)	247.6 (8.72e-56)
N (DF_M)	6004 (21)	3382 (22)	5372 (315)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

local resistance against one plant may not only work as a barrier against adoption in the municipal district where the plant should be located; instead it may hinder the adoption in the municipal district's NUTS-3 region (and for the case of large biomass plants also in neighboring NUTS-3 regions). We interpret this as evidence that potential investors in wind power and large biomass plants not only avoid the municipal district where a referendum took place but stay away from the municipal district's NUTS-3 region.[51]

6.3.5. A placebo test – Referenda against PV systems

To better understand the effect of referenda on renewable energy adoption, we conduct a placebo test. We study whether the same effect exists for PV systems, which

[51] An alternative explanation would be that in NUTS-3 regions where referenda were organized small instead of large plants are built. In estimations not shown, we find evidence against this idea. We estimate the effect of referenda against biomass plants on the adoption of small biomass plants. For all estimation approaches, there is a negative (but only sometimes significant) point estimate for the referendum dummy.

shape the landscape less than wind power plants and do not come with pollution as biomass plants.

PV systems are mainly small, private household systems (see Figure 3.1, BMU (2011) and Dewald and Truffer (2011)). A referendum will only be organized against a large system recognized by the public. If we analyze the adoption of all PV systems, there is no reason to expect that a referendum against a large industrial PV plant should be associated with low adoption (of all systems).

Table E.3 of Appendix E.1 reports the descriptive statistics. As expected, Table 6.10 indicates that a referendum against a single PV system does not hinder PV adoption on the NUTS-3 level. Instead, we see that the referendum dummy is significantly positive for PV systems. Referenda against PV were organized in Bavaria where most (small household) PV systems exist. Therefore, it makes sense to see that we find 16% more (small household) PV systems in regions where a referendum against a (large) PV plant was organized than in the remaining regions (column (3) in Table 6.10).

Table 6.10.: Estimation of successful referendum on adoption of PV systems.

	(1)	(2)	(3)
	$\Delta F_{\mathrm{PV},t}$	$\Delta F_{\mathrm{PV},t}$	$\Delta \#_{\mathrm{PV},t}$
Estimator	OLS FE	Cond. Poisson FE	Uncond. Neg. Bin. FE
$REF_{\mathrm{PV},t-1}$	0.00629*	0.207**	0.149+
	(2.39)	(2.79)	(1.73)
$F_{\mathrm{PV},t-1}$	0.260***	-3.203***	
	(46.48)	(-8.00)	
$\#_{\mathrm{PV},t-1}$			-0.0000150
			(-0.99)
θ^{-1}			0.297
NUTS-3 and Year FE	Yes	Yes	Yes
R^2	0.865		
Adj. R^2	0.865		
LL		-57.73	-29646.8
F	978.2		
χ^2		8377.7	
$F_{REF=0}$ / $\chi^2_{REF=0}$ (p-value)	5.702 (0.0174)	7.765 (0.00533)	3.008 (0.0828)
N (DF_M)	6435 (15)	6420 (16)	6435 (17)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

But, is there evidence for a negative effect of referenda on large, industrial PV systems (above 100 $\mathrm{kW_p}$ capacity)? Table 6.11 contains the results. We see that for large PV systems, there is no significant effect from referenda at all. F and χ^2 tests approve this finding.

Table 6.11.: Estimation of successful referendum on adoption of large PV systems.

	(1)	(2)	(3)
	$\Delta F_{\mathrm{PV>100\,kW_p},t}$	$\Delta F_{\mathrm{PV>100\,kW_p},t}$	$\Delta \#_{\mathrm{PV>100\,kW_p},t}$
Estimator	OLS FE	Cond. Poisson FE	Uncond. Neg. Bin. FE
$REF_{\mathrm{PV},t-1}$	0.000305	-0.113	0.222
	(0.05)	(-0.67)	(1.18)
$F_{\mathrm{PV>100\,kW_p},t-1}$	0.400***	-1.556**	
	(9.42)	(-3.06)	
$\#_{\mathrm{PV>100\,kW_p},t-1}$			-0.00400***
			(-3.40)
θ^{-1}			0.0905
NUTS-3 and Year FE	Yes	Yes	Yes
R^2	0.571		
Adj. R^2	0.570		
LL		-113.9	-6644.0
F	152.2		
χ^2		41443.9	
$F_{REF=0}$ / $\chi^2_{REF=0}$ (p-value)	0.00218 (0.963)	0.449 (0.503)	1.386 (0.239)
N (DF_M)	6435 (15)	6420 (16)	6435 (17)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Does the picture change if we control for shocks on the NUTS-2 level? Table 6.12 illustrates that – across the three estimation approaches – there is still no significant effect of referenda against PV systems on the adoption of large PV systems when controlling for NUTS-2-times-year-fixed effects.[52] In Table E.6 of Appendix E.3, we show that neither a spill-over effect from referenda against PV systems exists in neighboring NUTS-3 regions. Referenda seem to slow down adoption strongly for technologies as wind power or large biomass plants, which may have – in comparison to PV – a larger effect on the well-being of the local population. Initiators of referenda for instance argue that biomass plants come with odour emissions and traffic from the supply of wood chips or other combustibles (Bernstein and Knoll, 2011).

6.3.6. Announced but not conducted referenda

In order to improve our understanding of the effect of referenda on renewable energy adoption, we analyze data on referenda against renewable energy plants which were announced but not conducted. In these cases, the decision against building the renewable energy plant was taken before the referendum could be organized. Figure 6.2 illustrates where referenda against wind power plants or biomass plants were announced but not conducted.

[52] Due to convergence problems, we can only estimate the GLM with a negative binomial distribution (Table 6.12 column (3)) for the panel between 2003 and 2011.

Table 6.12.: Estimation of successful referendum on adoption of large PV systems (controlling for yearly NUTS-2 shocks).

	(1)	(2)	(3)
	$\Delta F_{\mathrm{PV>100\,kW_p},t}$	$\Delta F_{\mathrm{PV>100\,kW_p},t}$	$\Delta \#_{\mathrm{PV>100\,kW_p},t}$
Estimator	OLS FE	Cond. Poisson FE	Uncond. Neg. Bin. FE
$REF_{\mathrm{PV},t-1}$	0.00680	0.0893	0.159
	(0.71)	(0.90)	(0.51)
$F_{\mathrm{PV>100\,kW_p},t-1}$	0.425***	3.595***	
	(11.34)	(11.02)	
$\#_{\mathrm{PV>100\,kW_p},t-1}$			0.0293***
			(12.59)
θ^{-1}			0.433
NUTS-2xYear FE	Yes	Yes	Yes
R^2	0.414		
Adj. R^2	0.414		
LL		-162.4	-7081.3
F	68.16		
χ^2		166.4	
$\mathrm{F}_{REF=0}$ / $\chi^2_{REF=0}$ (p-value)	0.503 (0.478)	0.806 (0.369)	0.256 (0.613)
N ($\mathrm{DF_M}$)	6435 (1)	4036 (2)	3432 (296)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.13 and 6.14 report the estimates. No matter which estimation strategy we use, we cannot confirm the effect found before: neither for wind power plants nor for large biomass plants. This result indicates that only organized referenda prevent potential investors from renewable energy plants nearby the primary location.

Table 6.13.: Estimation of announced but not organized referendum on adoption of large wind power plants.

	(1)	(2)	(3)
	$\Delta F_{\mathrm{Wind>0.5\,MW},t}$	$\Delta F_{\mathrm{Wind>0.5\,MW},t}$	$\Delta \#_{\mathrm{Wind>0.5\,MW},t}$
Estimator	OLS FE	Cond. Poisson FE	Uncond. Neg. Bin. FE
$REF_{\mathrm{Wind,n.o.},t-1}$	0.000991	0.0406	0.276
	(0.79)	(0.12)	(0.62)
$F_{\mathrm{Wind>0.5\,MW},t-1}$	-0.00164	-9.368***	
	(-0.20)	(-3.51)	
$\#_{\mathrm{Wind>0.5\,MW},t-1}$			-0.00272*
			(-2.27)
θ^{-1}			1.527
NUTS-3 and Year FE	Yes	Yes	Yes
R^2	0.0998		
Adj. R^2	0.0968		
LL		-37.41	-7857.5
F	11.62		
χ^2		540.7	
$\mathrm{F}_{REF=0}$ / $\chi^2_{REF=0}$ (p-value)	0.625 (0.430)	0.0136 (0.907)	0.386 (0.534)
N ($\mathrm{DF_M}$)	5988 (19)	4924 (20)	5988 (76)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

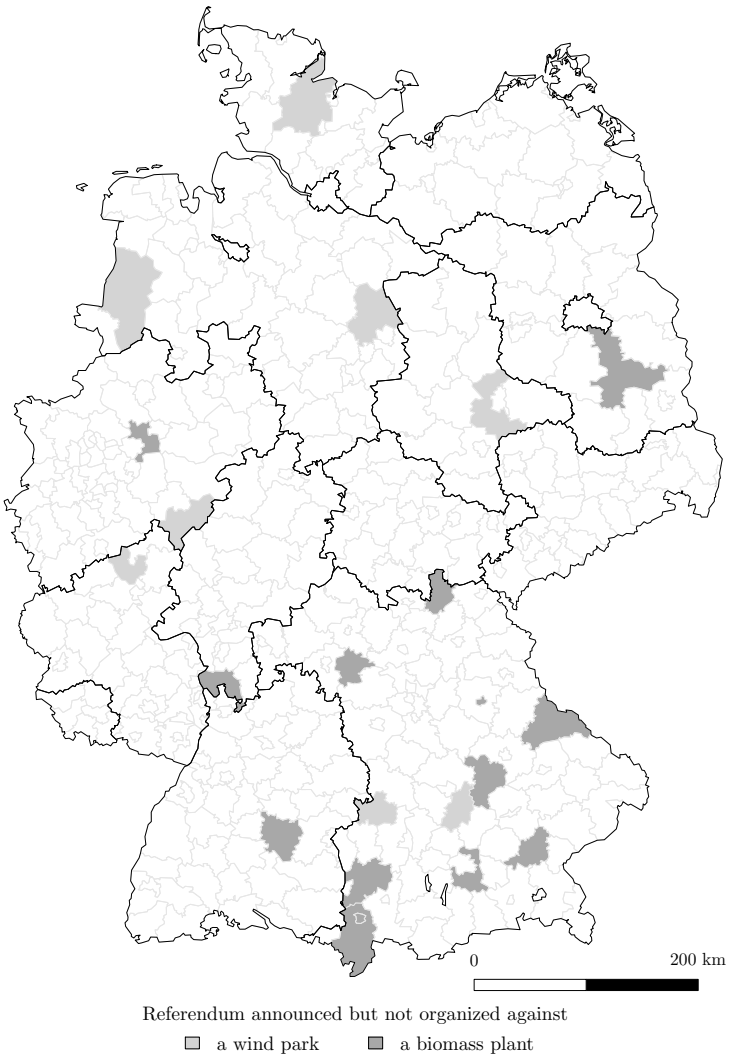

Figure 6.2.: NUTS-3 regions where a referendum was announced but not organized against a renewable plant.

6.4. Summary

We set out to study whether a successful referendum against one renewable energy plant is associated with lower adoption rates in the same German NUTS-3 region at a later stage. Importantly, the technologies of study are fostered by a strong federal subsidy scheme, which has already been in place since 2000. The fact that the subsidy system existed for over a decade signals public support. In other words, the public supports the adoption of the technologies in general but there is resistance to the adoption at the local level through referenda. While controlling for regional and time fixed effects, we find that the adoption of wind power plants and of large biomass plants is indeed lower in regions where a successful referendum against a

Table 6.14.: Estimation of announced but not organized referendum on adoption of large biomass plants.

	(1)	(2)	(3)
	$\Delta F_{\text{Biomass}>1\,\text{MW}_\text{e},t}$	$\Delta F_{\text{Biomass}>1\,\text{MW}_\text{e},t}$	$\Delta\#_{\text{Biomass}>1\,\text{MW}_\text{e},t}$
Estimator	OLS FE	Cond. Poisson FE	Uncond. Neg. Bin. FE
$REF_{\text{Biomass,n.o.},t-1}$	0.000192	0.759	0.494
	(1.34)	(0.95)	(0.81)
$F_{\text{Biomass}>1\,\text{MW}_\text{e},t-1}$	-0.0858***	-857.3***	
	(-7.34)	(-3.86)	
$\#_{\text{Biomass}>1\,\text{MW}_\text{e},t-1}$			-0.923***
			(-5.15)
θ^{-1}			2.84e-14
NUTS-3 and Year FE	Yes	Yes	Yes
R^2	0.0392		
Adj. R^2	0.0360		
LL		-1.381	-946.5
F	15.03		
χ^2		247.2	
$F_{REF=0}$ / $\chi^2_{REF=0}$ (p-value)	1.785 (0.182)	0.910 (0.340)	0.658 (0.417)
N (DF_M)	5995 (19)	3375 (20)	5995 (315)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

renewable plant of the same technology was organized. We do not observe the same for PV systems.

Our findings are good news to those who protest against renewable energy plants in their backyard. Referenda have their intended effect on renewable energy technology adoption in Germany. Local resistance against one plant does not only work as a barrier against adoption in the municipal district where the plant was to be located. It also has a signaling effect and hinders the adoption in the municipal district's NUTS-3 region. We interpret this as evidence that potential investors in wind power or large biomass plants not only avoid the municipal district where a referendum took place but stay away from the municipal district's NUTS-3 region. Our findings imply that a federal incentive system has limited effects without local support.

This analysis also contributes to the discussion on the effect of democratic political institutions on technology diffusion. According to the literature, there is a positive link (Acemoglu et al., 2001; Comin and Hobijn, 2004). If, however, the local public participates in the decision whether a wind park or more general infrastructure projects such as large power lines or railway tracks should be built, their adoption may be slowed down. Still, potential investors in wind power or large biomass plants can convince the local public of the benefits of their plans which may prohibit resistance. For instance, in the municipal district Sauerlach (NUTS-3 region Landkreis

München, Bavaria), the local public was involved early on when a biomass plant was built. In Sauerlach no organized resistance occurred (Bernstein and Knoll, 2011).

During recent years we have observed more and more referenda against renewable energy plants (see Datenbank Bürgerbegehren (2014)). It would be interesting to study whether our findings hold true when we can employ updated data sets on renewable energy adoption in Germany. To investigate why local resistance did not occur in the cases in which wind parks and large biomass plants were actually built would also be promising.

Our findings raise many new questions. Firstly, does the adoption barrier from a referendum only persist for a certain time period? Secondly, do we see similar barriers to the adoption of renewable energy systems in other countries? Thirdly, do we observe similar effects for other technologies and what do they have in common?

7. From Green Users to Green Voters[53]

In the last chapter, we discussed the effect of referenda on renewable energy adoption in Germany. Now, we turn to implications from their adoption.

7.1. Motivation

Can the diffusion of technologies affect voting patterns? Do political parties reap political benefits from the diffusion of certain technologies? Technology is usually not aligned with a specific ideology or political party. Indeed, to the extent that technology raises living standards, all parties tend to favor technology diffusion. However, in some cases, voters may associate a political party with a specific technology. This may be the case because the technology is important for the fulfillment of the party's aspirations or because the party has actively supported policies that affect the diffusion of the technology. One example where both of these nexes are present is environmentally-friendly technologies. Green parties advocate the diffusion of green energy technologies and pursue policies that foster the diffusion of green energies. In Germany, for example, when the Social Democratic-Green coalition won the 1998 federal elections, it raised the feed-in tariffs paid for electricity produced from wind and solar power.[54]

Coinciding with the diffusion of PV systems, Germany's Green Party experienced a significant increase in its share of votes, from 6.7% in 1998 to 10.7% in the 2009 elections. This observation raises a question that the literature has not contemplated

[53]This chapter is based on a revised version of Comin and Rode (2013).

[54]Indeed, these measures may have accelerated the diffusion of PV systems (Dewald and Truffer (2011), Jacobsson et al. (2004) and Jacobsson and Bergek (2004)).

yet. Has the diffusion of green energy technologies helped the Green Party increase its share of votes?[55]

Identifying the effects of diffusion on green votes presents well-known identification challenges. An increase in the political power of the Green Party may enable the approval of subsidies to green energy that accelerate its diffusion. Such reverse causality logic may result in biased estimates of the effect of PV systems diffusion on green votes. Similarly, failing to control for unobserved heterogeneity may result in biased estimates if omitted drivers of Green Party votes are correlated with diffusion patterns.

We avoid these potential biases by exploiting variation in adoption rates (i.e., the increment in diffusion) exogenous to the political process. To find a valid instrument for adoption rates, we build on the key finding of over 50 years of economic and marketing research on diffusion curves. Namely, that new technologies in a wide range of sectors, countries and periods diffuse approximately following logistic curves (e.g., Griliches (1957) and Mansfield (1961)).[56] Logistic curves are characterized by low initial adoption rates that eventually accelerate to reach a technology's long-run penetration rate. One implication of the non-linear nature of logistic curves is that current adoption rates can be forecasted by lagged diffusion levels. In Chapter 2, we outline the four distinct rationales for the non-linearity of diffusion curves.

It is important to note that (i) all the sources of non-linear dynamics proposed in the literature are orthogonal to voting patterns and more generally to politics; and (ii) non-linear dynamics have been documented in the diffusion of a large number of technologies, most of which are orthogonal to the political process. These two observations allow us to confidently claim that variation in adoption rates that comes from the non-linearity of technology diffusion is orthogonal to voting patterns. Under this premise, we can use lagged diffusion levels to instrument for current adoption rates of PV systems.

Further, we make direct use of the fact that technology diffusion across sectors, countries and periods approximately follows logistic curves. A non-linear least squares (NLS) estimation allows us to predict diffusion levels and conduct our analysis with a predicted instrument (as, e.g., Czernich et al. (2011) do).

[55] In Section 7.4.7, we provide two possible rationales for why adopting PV systems may affect voting patterns. One is based on Bayesian updating and the other based on cognitive dissonance (Akerlof and Dickens, 1982).

[56] See Comin and Mestieri (2013a) for some examples.

We implement this identification strategy by constructing a panel at the NUTS-3 level that covers both the diffusion of PV systems and the fraction of total votes that went to the Green Party in all the federal elections between 1998 and 2009. Our baseline regression includes year dummies and region-specific trends in green voting. We find a significant effect of PV adoption on the increase in the share of votes for the Green Party. In particular, the increase in the diffusion rate of PV systems between 1998 and 2009 led to an increase in the fraction of green votes of 0.9%, which represents about 25% of the actual increase in the voting rate experienced by the Green Party between 1998 and 2009.

To better understand the mechanism by which green-technology adoption affects voting patterns, we investigate several hypotheses. First, we explore whether voters compensate the Green Party for a windfall gained by adopting PV systems at a higher feed-in tariff. We deem this hypothesis as unlikely to drive our findings because (i) our estimates are robust to controlling for proxies of the profitability of adopting PV systems and (ii) we show that installing a PV system did not significantly contribute to household income. A second hypothesis is that observing the diffusion of green technologies is sufficient to affect voters propensity to vote for the Green Party. We evaluate this hypothesis by exploring whether the diffusion of industrial green technologies (PV and eolic, i.e., wind) has a similar effect on green voting to what we have observed for household PV systems. In contrast to our findings for household PV systems, we find no effect of the adoption of industrial PV systems and eolic systems on green voting.

We interpret these results as evidence that seeing more green energy installations in the neighborhood is not sufficient to induce voting for the Green Party. Instead, individuals that use green technologies are more likely to become Green Party voters.

We put our findings to the test at the individual level. Survey data from the German Socio-Economic Panel confirms our results. We find that the odds that a home owner, who has previously installed a PV system, becomes greener is 1.7 times higher than for a home owner who has not installed PV. We define becoming greener as stating a change in support from another party to green or stating a change from a weaker to a stronger level of Green Party support. We do not find evidence for reverse causality.

This analysis is related to various literatures that have explored the drivers of voting behavior. Deacon and Shapiro (1975) and Fischel (1979) use survey data from voters in referenda on environmental issues to study which factors affect the probability of voting in support of the environment. They find that occupation, political affiliation, education, income and location are important drivers of green voting.[57] A number of studies have explored the role of monetary incentives in voting both from the perspective of voters and of politicians. The existing evidence suggests that monetary rewards are relatively ineffective in driving votes both when trying to affect the position taken by elected representatives (Ansolabehere et al., 2003) and the votes of the electorate (Cornelius (2004), Wang and Kurzman (2007), Schaffer and Schedler (2007)).

Falck et al. (2014) reveal that the availability of Internet technology impacts voter turnout negatively in Germany. The specific driver of voting patterns we explore is the diffusion of PV systems. To the best of our knowledge, our paper is the first to explore positive effects of technology diffusion on specific party votes.[58]

As mentioned above, our identification strategy exploits the logistic diffusion pattern observed for many technologies. In addition to the standard forces that induce logistic diffusion patterns, a few other drivers have been pointed out as relevant for the adoption of green technologies. See Section 2.4 in Chapter 2 for details.

The rest of the chapter is organized as follows. Section 7.2 presents the aggregate trends and regional differences in green voting. Section 7.3 develops a model of technology adoption to explore the drivers of diffusion and motivate the instrumentation strategy. Section 7.4 presents the empirical findings, and discusses their robustness and interpretation. Section 7.5 concludes.

[57] A related literature (e.g., Tjernström and Tietenberg (2008), Torgler and García-Valiñas (2007), Whitehead (1991), Nord et al. (1998) Zelezny et al. (2000)) has used survey data to explore drivers (mostly socio-economic and demographic) of attitudes towards green issues.

[58] Our analysis is also related to the literature on policy feedback (Schattschneider, 1935; Pierson, 1993; Soss and Schram, 2007). These authors argue that new policies can create their own support through a range of mechanisms. However, the effects we identify are orthogonal to potential policy feedbacks since (i) we control for policy changes and (ii) we exploit exogenous variation in adoption rates which, by definition, is not driven by new policies.

7.2. Aggregate trends and regional differences in green voting

In Chapter 3 of this thesis, we describe the institutional context of green energy diffusion, its aggregate trends and regional differences. Coinciding with the diffusion of green energies, the Green Party experienced a significant increase in votes. (See Figure 7.1.)[59] In the 1998 elections, the Green Party received 6.7% of valid votes. This share increased to 8.6% in 2002, declined to 8.1% in 2005 and reached 10.7% in 2009.

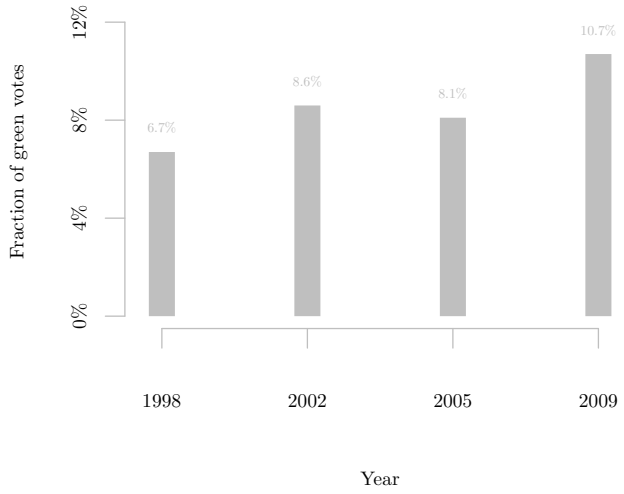

Figure 7.1.: Fraction of green votes in federal elections in Germany from 1998 through 2009.

Beneath these aggregate trends in votes there are important regional differences. The cross-sections of the share of green votes are plotted in Figure 7.2.[60] In 1998, the Green Party obtained large voting shares in Freiburg, Baden-Württemberg, in Heidelberg, Baden-Württemberg, in Tübingen, Baden-Württemberg, and in Darmstadt, Hesse. On the contrary, the Green Party did poorly in the eastern part of Germany. In the next decade, we observe an increase in green votes in most regions. The highest increases in the share of green votes between 1998 and 2009 took place in Lüneburg, Lower-Saxony, in Flensburg, Schleswig-Holstein, and in Würzburg, Bavaria.

[59] Voting data comes from DESTATIS (2012). We consider second votes (*'Zweitstimmen'*).

[60] Due to the restructuring of districts, we lack data for some 3% of the NUTS-3 regions for 1998 and 2002, 0.7% for 2005 and 7.5% for 2009.

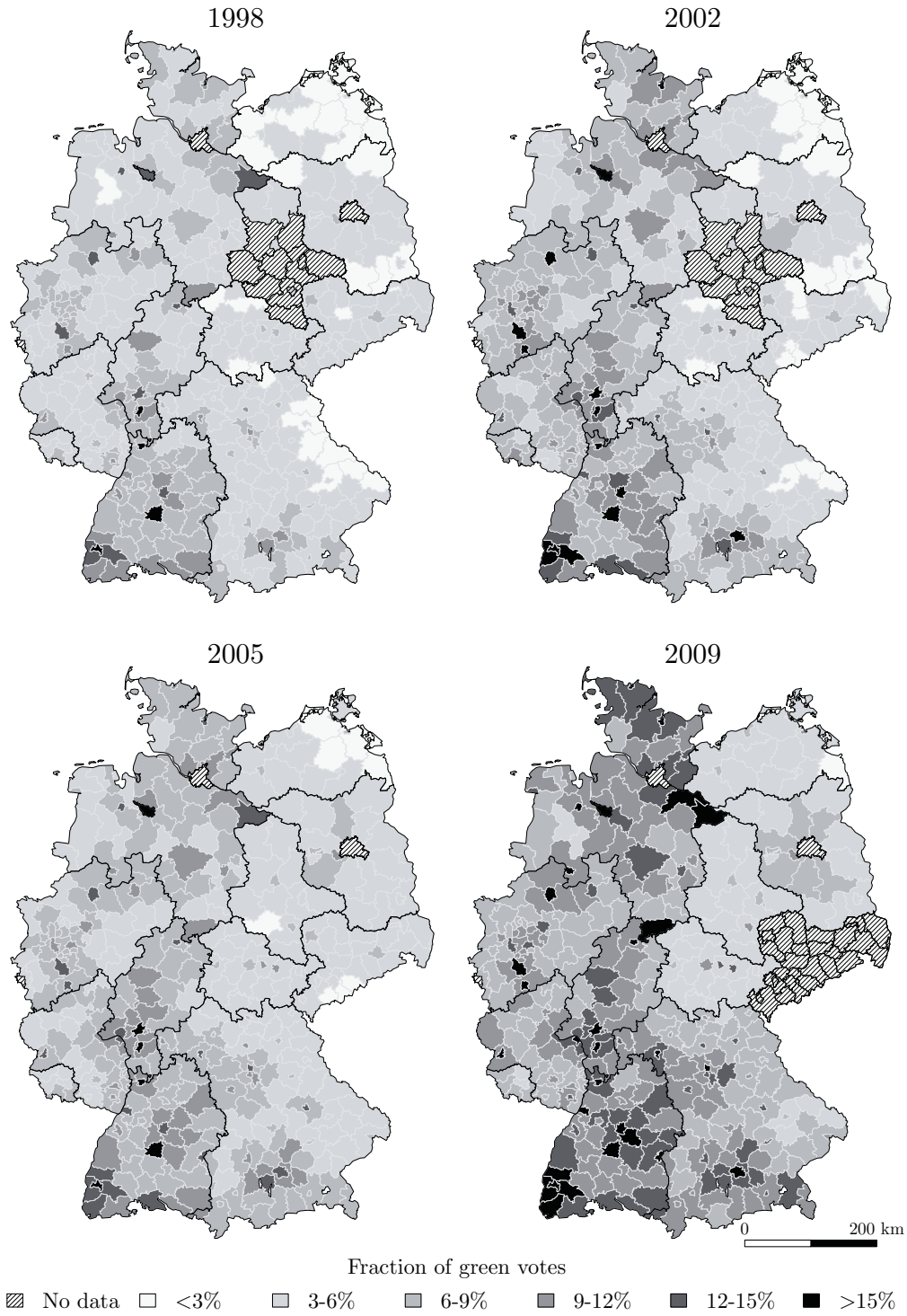

Figure 7.2.: Fraction of green votes at NUTS-3 level for 1998, 2001, 2005 and 2009.

7.3. A simple model of diffusion

To illustrate the drivers of the adoption decisions, we develop a simple model. After characterizing the individual adoption decision, we study the diffusion dynamics of PV systems at the regional level. Though our model belongs to the so-called probit models, it shares with other diffusion models the prediction that diffusion follows an S-shaped pattern. In our empirical analysis, we take no particular stand on which of the theories proposed in the literature drives the non-linear diffusion dynamics.

In each location (NUTS-3 region), there is a continuum of potential adopters, j, that differ in the potential electricity production, e_j^l, (due to differences in solar radiation, alignment potential...) and in the sunk cost of setting up the PV system, c_{jt}. The sunk cost of installation declines over time deterministically as follows:

$$c_{jt} = c_{j0}e^{-\alpha t}.$$

Without loss of generality, we index the potential adopters, j, in each region n so that the ratio c_{j0}/e_j is increasing. Furthermore, we assume that, in each region, $\log(c_{j0}/e_j)$ is distributed according to the following logistic cumulative density function:

$$F_n(x) = \frac{1}{1 + e^{-b_n x}}$$

where b_n is a region-specific parameter that determines how concentrated the density function is.

The instant t in which a PV system is installed defines its vintage. For simplicity, we assume that adopters of vintage-τ PV systems obtain a constant feed-in tariff of P_τ forever.[61] P_t evolves stochastically according to the following Poisson process:

$$dP_t = \begin{cases} \phi P_t, & \text{with probability } \lambda dt, \\ 0, & \text{with probability } 1 - \lambda dt. \end{cases} \tag{7.1}$$

This formulation captures the possibility that the feed-in tariff increases discretely, as occurred in Germany in 2000.

Given a constant discount rate of r, the expected value of a PV system of vintage τ is defined by:

[61] In reality, it is for a 20 year period.

$$rV_\tau dt = P_\tau e_j dt \tag{7.2}$$

which yields

$$V_\tau = \frac{P_\tau e_j}{r}. \tag{7.3}$$

Conditional on not having installed a PV system at time t, when the feed-in tariff is P_t, the option value of installing a PV system, W_t, is defined by

$$W\left(t, P_t\right) = \max\left\{E_t \frac{W(t+dt, P_{t+\mathrm{d}t})}{1+rdt}, V_t - c_{jt}\right\}, \tag{7.4}$$

where E_t is the expectation operator. The following proposition characterizes both the optimal adoption rule and the diffusion of PV systems.

Proposition 1 *(i) A potential producer j has adopted a PV system at time t if her ratio*

$$c_{j0}/e_j \leqslant \frac{(1-\lambda(\phi-1)/r)P_t}{e^{-\alpha t}(r+\alpha)},$$

where P_t is the prevailing feed-in tariff at time t. (ii) The fraction of potential adopters that have installed a PV system at t when the prevailing feed-in tariff is P_t is given by

$$\begin{aligned} & F_n\left(\log\left[(1-\lambda(\phi-1)/r)P_t\right] - \log(r+\alpha) + \alpha t\right) \\ = \; & \left[1+\exp\left(-b_n\left(\log\left[(1-\lambda(\phi-1)/r)P_t\right] - \log(r+\alpha) + \alpha t\right)\right)\right]^{-1}. \end{aligned} \tag{7.5}$$

Proof: See Appendix F.1.□

Taking a first order Taylor expansion of (7.5), it follows that the fraction of newly installed PV systems, f_n, is approximately equal to

$$\begin{aligned} dF_{nt} &\equiv f_{nt}\left(\log\left[(1-\lambda(\phi-1)/r)P_t\right] - \log(r+\alpha) + \alpha t\right) \\ &\simeq F_{nt} * (1-F_{nt}) * b_n * \underbrace{\left[\frac{dP_t}{P_t} + \alpha * dt\right]}_{\text{revision in return}}. \end{aligned} \tag{7.6}$$

Equation (7.6) characterizes the determinants of the adoption rate. Adoption rates are increasing in the revisions of the return to adopting PV systems. In particular,

the return to adopting PV systems increase with the growth rate of the feed-in tariff (dP_t/P_t), and with the rate of decline of installation costs, α. Adoption rates also increase with the concentration of the ratio c_{j0}/e_j (b_n), and, in the initial stages of adoption (i.e., when $(1 - F_{nt}) \simeq 1$), it is also increasing in the diffusion level, F_{nt}. Note that, the diffusion level is a driver of adoption rates that varies both over time and across regions. Therefore, we can exploit exogenous variation in diffusion levels to instrument for adoption rates in the presence of both time and region-specific fixed effects.

7.4. Econometric evidence

We consider the following reduced form for the fraction of votes received by the Green Party in region n in the federal elections that take place in year t (V_{nt}) :

$$V_{nt} = \alpha_n + g_n * t + \alpha_t + \beta F_{nt} + \rho X_{nt} + \epsilon_{nt}. \tag{7.7}$$

α_n is a region (NUTS-3) level effect, g_n is a region-specific trend, α_t is an aggregate time dummy, F_{nt} is the stock of PV systems installed normalized by the number of potential adopters in the region, X_{nt} is a vector of other potential drivers of green votes, and ϵ_{nt} is an error term. Taking differences between consecutive election years (t and $t - k$), (7.7) can be expressed as:

$$\triangle V_{nt} = g_n + \gamma_t + \beta \triangle F_{nt} + \rho \triangle X_{nt} + u_{nt} \tag{7.8}$$

where $\triangle V_{nt} \equiv V_{nt} - V_{nt-k}$ is the increment in the share of green votes, $\gamma_t \equiv \alpha_t - \alpha_{t-k}$ is a time dummy, $u_{nt} \equiv \epsilon_{nt} - \epsilon_{nt-k}$ is an error term and $\triangle F_{nt} \equiv F_{nt} - F_{nt-k}$ is the adoption rate defined as the increase in the ratio of the stock of PV systems adopted over the number of potential adopters.

As elections took place in fall and technology adoption could occur in the same year but after the election, we have to adjust our lag structure. Table 7.1 illustrates the situation. In case 2, the change in green votes could have occurred before PV adoption. In case 1, this is not possible. We therefore lag PV adoption by one year: $\Delta \mathrm{F}_{\mathrm{PV},t-1}$.

Table 7.1.: Contrasting lag structure.

	Case 1			Case 2		
	$t-2$	$t-1$	t	$t-2$	$t-1$	t
$\Delta \mathrm{v}_t$		0	1		0	1
$\Delta \mathrm{F}_{\mathrm{PV},t}$	0	1	0	0	0	1

Table 7.2 reports the ordinary least squares estimates of Equation (7.8) including the lag structure.[62] We consider four specifications which differ according to whether time and NUTS-3 fixed effects are included. Time fixed effects capture time-varying factors that have a symmetric effect in voting patterns across regions. For example, nation-wide changes in green sentiment or political changes in the Green Party and how these are perceived by voters. Regional fixed effects capture region-specific trends in attitudes towards the Green Party, education and values, which may lead to regional trends in green votes. Because the specification that includes both time and NUTS-3 fixed effects controls for these trends, we consider it to provide a cleaner identification than the other three alternatives. In addition, all specifications control for the logarithm of per capita income in the region.

Table 7.2.: OLS estimation of increase in PV diffusion on increase in share of green votes.

	(1) Δv_t	(2) Δv_t	(3) Δv_t	(4) Δv_t
$\Delta F_{\mathrm{PV},t-1}$	0.402***	0.638***	0.120***	0.241***
	(13.60)	(13.48)	(4.75)	(5.84)
$\ln(\mathrm{GDP}_{\mathrm{cap},t})$	0.00674***	0.00853	0.00597***	-0.0000851
	(6.61)	(1.13)	(6.84)	(-0.01)
α	-0.0591***		-0.0384***	
	(-5.79)		(-4.30)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.147	0.215	0.582	0.642
Adj. R^2	0.146	-0.182	0.581	0.459
F	131.5	177.5	427.1	311.4
N	1160	1160	1160	1160

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Turning back to Table 7.2, we find that increments in the share of green votes are positively associated with adoption rates in all four specifications. These associations are statistically and economically significant. Based on the estimates in our preferred specification (column 4), an increase in the adoption rate by one standard deviation is associated with an increase in the fraction of green votes by .24 standard deviations (see Table F.1 in Appendix F.2 for the relevant descriptive statistics). Similarly, the

[62] Reported standard errors (SE) are always robust to both arbitrary heteroskedasticity and arbitrary autocorrelation. They have a bandwidth of 2.

diffusion of PV systems between 1998 and 2009 is associated with an increase in the fraction of green votes of 0.9%, which is approximately 25% of the actual increase in the voting rate experienced by the Green Party between 1998 and 2009.

At this point, we do not interpret the estimates in Table 7.2 as a causal effect of PV adoption on green votes. The correlation between adoption rates and the increment in the fraction of green votes could also result from omitting relevant variables from the vector of controls, $\triangle X_{nt}$. To confidently argue that the estimates reflect the causal effect of PV adoption on green voting, we need some exogenous source of variation in the adoption of PV systems. That is, variation in PV adoption that is driven by factors that do not affect directly voting patterns or that are not correlated with factors other than adoption that may drive voting patterns.

Finding valid instruments is, in general, a difficult task. However, in our context, the non-linear diffusion patterns of new technologies provide us with a natural instrumental variable. As shown in Section 7.3, a property of logistic diffusion curves is that current adoption rates are a function of the lagged diffusion level. Indeed, in the early stages of diffusion, current adoption is (approximately) a linear function of the lagged diffusion level. But, what is the nature of this relationship? Is it orthogonal to voting patterns?

The literature has proposed several hypotheses on the source of the non-linearities of diffusion patterns. These theories include epidemic models (Bass, 1969; Rogers, 1983) where information diffuses slowly, probit models where the exogenous distribution of adoption costs and profits in the population is bell-shaped (Griliches, 1957), legitimization theories where the population accepts slowly the validity of the technology (Hannan and Freeman, 1989) and information cascades models where agents initially experiment with multiple forms of the technology until a dominant form emerges (Arthur (1989) and Banerjee (1992)). Importantly, in none of these theories is the non-linear nature of diffusion dynamics related to politics or voting dynamics.

Furthermore, S-shape diffusion patterns have been documented for a wide range of technologies, periods and countries with very diverse political and contextual factors. The ubiquity of S-shaped diffusion patterns strongly supports the premise that variation in the adoption of PV systems driven by the non-linearities of diffusion are exogenous to changes in voting patterns. In particular, we find it difficult to

make the argument that factors that drive changes in green votes between $t-k$ and t are correlated in any way with the stock of adoption until one year before the previous election year $(t-k-1)$; especially, after controlling for time and regional fixed effects that capture cross-regional differences in attitudes towards the Green Party, and in their trends, as well as any pattern of aggregate time-variation in green vote drivers.

Table 7.3 reports the estimates of the first stage regression where we use the PV diffusion level in the previous election year $(t-k)$ to forecast the adoption rate over the electoral cycle (i.e., from $t-k$ to t). The findings are quite similar for all four specifications, including our preferred one with both region and time fixed effects. Lagged diffusion levels are a very strong predictor of current adoption rates. The t-statistics of this coefficient are close to 20 or above. The null that the instrument is irrelevant is rejected at any level of significance. Furthermore, the high R^2 (over 0.8 in all four specification) shows that the logistic curve provides a very good approximation for the diffusion process of PV systems at the NUTS-3 level.

Table 7.3.: First stage estimation of increase in PV diffusion on increase in share of green votes.

	(1)	(2)	(3)	(4)
	$\Delta F_{\mathrm{PV},t-1}$	$\Delta F_{\mathrm{PV},t-1}$	$\Delta F_{\mathrm{PV},t-1}$	$\Delta F_{\mathrm{PV},t-1}$
$F_{\mathrm{PV},t-k-1}$	1.827***	1.519***	1.679***	1.318***
	(28.78)	(20.60)	(23.03)	(15.94)
$\ln(\mathrm{GDP}_{\mathrm{cap},t})$	-0.00139**	0.0276***	-0.00170***	0.00199
	(-3.26)	(8.85)	(-4.13)	(0.58)
α	0.0163***		0.0227***	
	(3.81)		(5.42)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.802	0.806	0.822	0.840
Adj. R^2	0.802	0.708	0.821	0.759
F	419.7	708.7	444.2	535.2
$\mathrm{F}_{\mathrm{Instrument}=0}$	828.3	424.4	530.2	254.2
$\text{p-value}_{\mathrm{Instrument}=0}$	8.07e-138	1.83e-75	7.43e-97	1.17e-49
N	1160	1160	1160	1160

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7.4 shows the estimates from the second stage regression. In all specifications we find a positive and significant effect of instrumented adoption rates on the increment in Green Party votes. The point estimates vary from 0.16 to 0.5 depending on the specification. In our preferred specification with region and time fixed effects the point estimate is 0.26 which implies that one standard deviation increase in the adoption rate of PV systems over one electoral period induces an increase in the share of votes for the Green Party by 0.31 percentage points. Cumulating that over

the three elections that took place after 1998 until 2009 implies that the diffusion of PV systems accounts for a cumulative increase in the fraction of green votes of 0.9 percentage points. This increment represents approximately a quarter of the actual increase in votes experienced by the Green Party over this period.

Table 7.4.: Two-stage least squares estimation of increase in PV diffusion on increase in share of green votes.

	(1) Δv_t	(2) Δv_t	(3) Δv_t	(4) Δv_t
$\Delta \hat{F}_{\text{PV},t-1}$	0.375***	0.499***	0.159***	0.259***
	(12.88)	(10.15)	(4.99)	(5.06)
$\ln(\text{GDP}_{\text{cap},t})$	0.00684***	0.0212**	0.00595***	0.0000469
	(6.71)	(2.73)	(6.85)	(0.01)
α	-0.0599***		-0.0389***	
	(-5.87)		(-4.37)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.147	0.209	0.581	0.641
Adj. R^2	0.145	-0.191	0.580	0.459
F	120.9	139.7	420.5	297.2
N	1160	1160	1160	1160

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Although we believe it to be unlikely, one may question whether factors that drive changes in green voting between $t-k$ and t are correlated with the stock of adoption one year before the previous election year. To further strengthen our instrumentation strategy, we can directly make use of the fact that technology diffusion follows a logistic pattern. A NLS estimation allows us to estimate the non-linear diffusion curve. We specify Equation (7.9) in such a way that only region n's average amount of solar radiation (sun_n), its share of single and double family houses (share si-do houses_{nt}) and an east dummy (east_n) affect the diffusion level in region n and year t:

$$F_{\text{PV},nt} = \frac{a + a_{\text{sun}} * \frac{\text{sun}_n}{10^4} + a_{\text{share si-do houses}} * \frac{\text{share si-do houses}_{nt}}{10^3} + a_{\text{east}} * \text{east}_n}{1 + e^{-b(t-c)}} + \zeta_{nt}. \quad (7.9)$$

ζ_{nt} is an error term. The numerator determines the level of saturation, b the diffusion speed and c the diffusion process' inflexion point (Czernich et al., 2011). Table 7.5 reports the estimates for the NLS estimation. All coefficients are highly significant. The high R^2 confirms the very good fit of the specification. As we would expect, global radiation and the share of single and double family houses shape the saturation level positively and the east dummy negatively. A positive diffusion speed b makes sense as well as an inflexion point between the year 2001 and 2004 (having in mind the relevant descriptive statistics in Table F.2 of Appendix F.2 and the time lag).

Table 7.5.: First stage NLS estimation of logistic PV diffusion.

	(1)
	$F_{\mathrm{PV},t-k-1}$
a	-0.126***
	(-4.11)
a_{sun}	1.198***
	(4.21)
$a_{\mathrm{share\ si\text{-}do\ houses}}$	0.178***
	(3.30)
a_{east}	-0.00623***
	(-4.24)
b	2.244***
	(4.57)
c	4.585***
	(17.09)
NUTS-3 fixed effects	No
Time fixed effects	No
R^2	0.751
Adj. R^2	0.749
N	1157

t statistics in parentheses, robust SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Now, we can use the predicted values of $\hat{F}_{\mathrm{PV},t-k-1}$ to instrument the adoption rate ($\Delta F_{\mathrm{PV},t-1}$). Table 7.6 reports the results. Across the specifications, the findings are quite similar. Column (4) contains our preferred specification with NUTS-3 and time fixed effects. The predicted lagged adoption levels are a very strong instrument for the current adoption rate. In all specifications, the goodness-of-fit measure R^2 is still very high and a F test rejects the null that the instrument is irrelevant at any level of significance. Note that we control for the logarithm of per capita income and the time-variant predictor, which we use in the NLS estimation, share si-do houses$_{nt}$. In columns (2) and (4) of Table 7.6, the time-invariant predictors of the NLS estimation are covered by the NUTS-3 fixed effects.

Let us turn to the third stage in Table 7.7. Across specifications we find a strong positive effect from the instrumented adoption rate on the increase in Green Party votes. The point estimates vary from 0.17 to 0.64 depending on the specification. In our preferred specification with region and time fixed effects – shown in column (4) – the point estimate is 0.17, which implies that one standard deviation increase in the adoption rate of PV systems over one electoral period induces an increase in the share of votes for the Green Party by 0.2 percentage points. Cumulating this over the three elections that took place after 1998 until 2009 implies that the diffusion of PV systems accounts for a cumulative increase in the fraction of green votes of 0.6 percentage points. This increment represents approximately 15% of the actual increase in votes experienced by the Green Party over this period.

Next, we conduct a series of robustness checks to gain further assurance that the estimated effect of PV adoption on green voting reflects a causal relationship.

Table 7.6.: Second stage estimation of increase in PV diffusion on increase in share of green votes.

	(1)	(2)	(3)	(4)
	$\Delta F_{\mathrm{PV},t-1}$	$\Delta F_{\mathrm{PV},t-1}$	$\Delta F_{\mathrm{PV},t-1}$	$\Delta F_{\mathrm{PV},t-1}$
$\hat{F}_{\mathrm{PV},t-k-1}$	1.977***	1.816***	1.817***	1.644***
	(23.61)	(22.74)	(16.09)	(14.22)
$\ln(\mathrm{GDP}_{\mathrm{cap},t})$	0.000296	0.0194***	0.000626	0.0133**
	(0.34)	(5.19)	(0.71)	(2.84)
share si-do hous_t	0.000110***	-0.000363	0.000128***	-0.000801
	(4.59)	(-0.94)	(5.33)	(-1.68)
α	-0.0103		-0.0129	
	(-1.01)		(-1.27)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.671	0.760	0.678	0.769
Adj. R^2	0.671	0.638	0.677	0.650
F	196.9	355.9	181.3	271.7
$\mathrm{F}_{\mathrm{Instrument}=0}$	557.7	516.9	258.9	202.2
$\text{p-value}_{\mathrm{Instrument}=0}$	6.90e-101	6.78e-88	1.09e-52	6.69e-41
N	1157	1157	1157	1157

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7.7.: Third stage estimation of increase in PV diffusion on increase in share of green votes.

	(1)	(2)	(3)	(4)
	Δv_t	Δv_t	Δv_t	Δv_t
$\Delta\hat{F}_{\mathrm{PV},t-1}$	0.552***	0.635***	0.180***	0.171*
	(14.73)	(10.72)	(3.54)	(2.13)
$\ln(\mathrm{GDP}_{\mathrm{cap},t})$	0.00303*	0.00958	0.00523***	-0.000168
	(2.51)	(0.99)	(5.41)	(-0.02)
share si-do hous_t	-0.000173***	-0.000241	-0.0000372	-0.000422
	(-4.46)	(-0.29)	(-1.08)	(-0.40)
α	-0.00859		-0.0289**	
	(-0.61)		(-2.62)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.145	0.215	0.580	0.640
Adj. R^2	0.143	-0.183	0.579	0.456
F	98.14	95.96	347.4	257.7
N	1157	1157	1157	1157

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7.4.1. The profitability of PV systems

The first check consists of exploring the role played by the profitability of PV adoption in our results. We do this in two different ways. Firstly, we control for the profitability of PV systems in the region and year. Secondly, we calculate the ratio of net profits from PV systems to household income to assess the possible significance of the income from PV system installations in households' decisions.

Controlling for profitability

Controlling for the profitability of adopting a PV system allows us to study the importance of omitted variables (OV) for our estimates of the effect of PV adoption on voting patterns. OV are drivers of voting patterns that are correlated with adoption rates. The most natural source of co-movement between OV and adoption rates is a potential correlation between the OV and the profitability of PV adoption. Hence, by controlling for profitability we test the relevance of this channel.

As implied by Section 7.3, we proxy changes in profitability by the growth rate of the feed-in tariff interacted by the average solar radiation of the NUTS-3 region. Note that this measure captures the asymmetric effect that the feed-in tariff has on the return to PV systems. Therefore, it has variation even after including time and regional fixed effects.

The first stage NLS estimation which we use to predict the lagged adoption level is the same we used before (see Table 7.5). Table 7.8 presents the second stage estimates after controlling for profitability. Consistent with the literature (Dewald and Truffer (2011), Jacobsson et al. (2004) and Jacobsson and Bergek (2004)), we find that changes in profitability have a positive effect on adoption rates if we include time fixed effects (column (3)). However, once NUTS-3 fixed effects are also considered (column (4)), changes in profitability do not affect adoption rates. This observation suggests that the potential for omitted variables to drive the relationship between PV adoption and voting patterns is very limited.[63] Also note that the strength of the predicted instrument is not affected by controlling for profitability. In particular, the coefficient of the lagged (predicted) diffusion level in the second stage regression, its significance or the R^2 of this regression are not affected by the additional control. All this suggests that although changes in profitability may have some effects on adoption rates, the variation we use to identify the effect of adoption on voting patterns is orthogonal to changes in profitability.

Table 7.9 explores the third stage. Columns (1) and (2) show a positive and significant association between changes in profitability and the increment in green votes. We interpret this coefficient as reflecting the larger increase in green votes in the southern regions of Germany during the 2002 election, the first after the EEG raised

[63] Indeed, in the OLS regressions (not shown) the coefficient of adoption on the increment in green votes does not change at all after controlling for profitability.

Table 7.8.: Second stage estimation of increase in PV diffusion on increase in share of green votes (controlling for profitability).

	(1)	(2)	(3)	(4)
	$\Delta F_{\mathrm{PV},t-1}$	$\Delta F_{\mathrm{PV},t-1}$	$\Delta F_{\mathrm{PV},t-1}$	$\Delta F_{\mathrm{PV},t-1}$
$\hat{F}_{\mathrm{PV},t-k-1}$	1.990***	1.898***	1.831***	1.678***
	(20.63)	(21.65)	(16.22)	(11.88)
$\Delta p_{\mathrm{PV},t-1}/p_{\mathrm{PV},t-k-1} * \mathrm{sun}$	0.000482	0.00367***	0.0321***	0.00837
	(0.63)	(4.04)	(5.33)	(0.52)
$\ln(\mathrm{GDP}_{\mathrm{cap},t})$	0.000276	0.0236***	0.000161	0.0133**
	(0.31)	(5.98)	(0.17)	(2.84)
share si-do hous_t	0.000108***	0.000162	0.000117***	-0.000756
	(4.52)	(0.43)	(4.70)	(-1.55)
α	-0.0101		-0.00667	
	(-0.99)		(-0.62)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.671	0.763	0.680	0.769
Adj. R^2	0.670	0.643	0.678	0.650
F	207.5	285.7	178.4	226.6
$\mathrm{F}_{\mathrm{Instrument}=0}$	425.6	468.6	263.1	141.2
$\text{p-value}_{\mathrm{Instrument}=0}$	9.98e-81	1.80e-81	1.95e-53	5.21e-30
N	1157	1157	1157	1157

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the feed-in tariff. The main finding from Table 7.9 is that the effect of PV adoption rates on voting patterns is unaffected by the profitability control. This further confirms that our estimates are not driven by omitted variable biases.

Table 7.9.: Third stage estimation of increase in PV diffusion on increase in share of green votes (controlling for profitability).

	(1)	(2)	(3)	(4)
	Δv_t	Δv_t	Δv_t	Δv_t
$\Delta \hat{F}_{\mathrm{PV},t-1}$	0.867***	1.218***	0.179***	0.282*
	(15.80)	(16.88)	(3.53)	(2.08)
$\Delta p_{\mathrm{PV},t-1}/p_{\mathrm{PV},t-k-1} * \mathrm{sun}$	0.0240***	0.0468***	-0.00740	0.0445
	(13.46)	(18.95)	(-0.38)	(1.09)
$\ln(\mathrm{GDP}_{\mathrm{cap},t})$	0.00195	0.0524***	0.00534***	-0.00135
	(1.47)	(5.32)	(5.37)	(-0.15)
share si-do hous_t	-0.000274***	0.00668***	-0.0000344	-0.0000953
	(-6.29)	(5.62)	(-0.99)	(-0.09)
α	0.00399		-0.0304**	
	(0.25)		(-2.63)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.184	0.442	0.580	0.642
Adj. R^2	0.181	0.158	0.578	0.459
F	87.56	128.1	289.7	220.1
N	1157	1157	1157	1157

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Money for votes?

The hypothesis we test in this chapter is whether the adoption of PV increases the propensity to vote for the Green Party. An alternative hypothesis to explain the correlation between PV diffusion and green votes is that voters reward the Green Party for the monetary transfers that may come with the installation of PV systems. The robustness of our estimates to controlling for the changes in profitability of PV systems seems hard to reconcile with this hypothesis. However, to further explore its plausibility, we next calculate the monetary return from adopting PV systems.

We compute the income from installing a PV system relative to household income as follows:

$$\begin{aligned}\text{Profit Income Ratio} = \text{Capacity} * \Bigg[\sum_{t=0}^{T=19} \left(\frac{1-v}{1+r}\right)^t [\ \text{Feed-in Tariff} \\ * \#\ \text{Full-load Hours}\ ] - \text{Investment per kW}_\text{p} \\ * \left(1 + \sum_{t=0}^{T=19} \frac{b}{(1+r)^t}\right)\Bigg] / (\text{Household Income} * 20).\end{aligned} \tag{7.10}$$

In this formula, both the costs and revenues from PV systems are proportional to the capacity of the PV system. The first term in the numerator is the present discounted value of revenues per unit of capacity installed,[64] while the second term is the cost of installing and operating the PV system per unit of capacity. Because we want to evaluate the economic significance of the net revenues from PV systems, we scale them by the annual average household income (DESTATIS, 2013a).

Revenues from PV systems are calculated by multiplying the level of the feed-in tariff times the number of full-load hours the system operates per year. The feed-in tariff varies with the year of installation of the system. The number of full-load hours depends on the location and alignment of the installation. The average for the number of full-load hours in Germany is 900 hours (Klaus et al., 2010; Wirth, 2013). To assess the sensitivity of our calculations to variation in solar radiation, we also compute the profit to income ratio when calibrating the number of full-load

[64] We use a standard value for the annual discount rate, 5% per year (e.g., Cooley and Prescott (1995)).

hours to 1,110 hours which is at the 90th percentile of the full-load hours for all the systems installed in Germany through 2009.[65] The depreciation of the PV systems reduces its efficiency at a rate (v) of 0.5% per year (BMU, 2011; Wirth, 2013). (See Table 7.10 for a definition of the parameters, their value and their source.)

Table 7.10.: Details on the calculation of PV profits.

Definition	Parameter	Value	Source
Household Income	Disposable income per household [EUR]	Yearly	DESTATIS (2013a)
Feed-in Tariff	Level feed in tariff [EUR]	Yearly	EEG (2000, 2004, 2011)
Investment per kW_p	Investment costs [EUR]	Yearly	2000-05: Janzing (2010); 2006-09: BSW-Solar (2012), pvX (2012)
r	Weighted average cost of capital	5.0%	Cooley and Prescott (1995), BMU (2011),Wirth (2013)
b	Yearly operating costs	1.0%	BMU (2011), Wirth (2013)
$T+1$	Life span [years]	20	EEG (2000, 2004, 2011), BMU (2011),Wirth (2013)
v	Yearly decrease in revenue	0.5%	BMU (2011), Wirth (2013)
Capacity	Median capacity $[kW_p]$	4	KEK (2010), DESTATIS (2013b)
	90th percentile capacity $[kW_p]$	6.4	KEK (2010), DESTATIS (2013b)
Full-load Hours	Average [hours/year]	900	BMU (2011), Wirth (2013)
	90th percentile [hours/year]	1110	DWD (2010), BMU (2011), Wirth (2013)

The costs of installing PV systems dropped very significantly between 2000 and 2009 (Janzing (2010) and BSW-Solar (2012)). In 2000, the cost of installing one kW_p was 8,000 EUR while in 2009 it was approximately 4,000 EUR. In addition to the installation costs, there is an annual cost of operation and maintenance (b) which amounts to 1% of the cost of installation (BMU, 2011; Wirth, 2013).

Because we use household income as the benchmark for net PV income, we should calibrate the capacity level to that of systems installed in single household residences. Unfortunately, this information is not directly available. However, we can make some back of the envelope calculations by using information collected in 2010 by the Karlsruher Energie- und Klimaschutzagentur (KEK) for Karlsruhe, Baden-Württemberg.[66] KEK is a government agency which authorized SUN-AREA (a private company) to use information on the roof inclination, area, orientation and solar radiation to calculate the potential capacity of PV systems on each roof. Combining

[65]These values come from combining data on solar global radiation (DWD, 2010) with an optimistic performance ratio of 85%. KEK (2010), BMU (2011) and Wirth (2013) confirm our calculations.

[66]Karlsruhe is a 300,000 city (among the 25 largest in Germany) with a global solar radiation similar to the average in Baden-Württemberg and Bavaria (DWD, 2010), two of the regions with highest solar radiation in Germany and where most German PV systems are installed.

this data with information on the fraction of single-family residences in Karlsruhe,[67] it follows that the median potential area for PV installation in single household residences is 37 sqm, and the 90th percentile is 58 sqm.[68] Given this potential roof area, we estimate that the capacity supported by the median single-family residence is approximately 4 kW_p, while for the residence at the 90th percentile it is 6.4 kW_p.

Table 7.11 reports the value of (7.10) for four combinations of full-load hours and capacity, that represent the average/median and 90th percentile values in each dimension. Given the time series variation in the feed-in tariff and installation costs, we report the ratios for four years over the period 2000-2009. The profit to income ratio ranges from -2.7% to 0.8% with lower values for earlier years and for systems with lower capacity and full-load hours.

Table 7.11.: Yearly profits from investment in PV as share of yearly average household income according to yearly full load hours and time of installation.

Year of installation	PV system with 4 kW_p		PV system with 6.4 kW_p	
	Full load hours [h/a]		Full load hours [h/a]	
	900	1110	900	1110
2000	-1.7%	-1.0%	-2.7%	-1.6%
2004	-0.5%	0.2%	-0.9%	0.3%
2006	-0.3%	0.3%	-0.5%	0.5%
2009	0.0%	0.5%	0.0%	0.8%

Beyond this variation, the main conclusion we extract from the table is that, even for systems with high capacity and installed in areas with high global solar radiation, the net revenues from PV electricity production are negligible for households. Therefore, we do not consider plausible that current and future PV adopters compensate the Green Party with their votes *in exchange for* the net income from PV systems.[69] This observation implies that the effects of adoption on green votes are general and not just driven by the southern regions.

[67] According to DESTATIS (2013b) there were 39,607 residential buildings in Karlsruhe in 2010; 17,631 of these were single-family homes. Assuming that, out of all the residential buildings, single-family houses are those with smaller roofs, we can use KEK (2010) data to measure the potential roof area of single family residences. In particular, according to KEK (2010) there were 40,043 residential buildings in the city of Karlsruhe in 2010.

[68] It is necessary to install between 8 and 10 sqm of solar modules to reach a capacity of 1 kW_p (KEK, 2010). We use a value of 9 sqm per kW_p in our calculations.

[69] In results not reported here, we have shown that the effect of adoption on Green Party votes is robust to eliminating the regions from the south of Germany (where solar radiation is highest) from the third stage (in Appendix F.2.1, see Table F.3 for the estimates and Table F.4 for the descriptive statistics).

7.4.2. Lagged diffusion

As we have shown in Section 7.3, the non-linearity that characterizes logistic curves implies that lagged diffusion is a good predictor of adoption rates. So far, we have used the predicted diffusion level one year before the previous election year to instrument for the adoption rate between the previous and current election years. But, in principle, we could also use earlier predicted diffusion levels to instrument for current adoption rates. This alternative strategy would provide even greater assurance for the exogeneity of the instruments since it seems unreasonable that drivers of changes in attitudes between $t-k$ and t are correlated with the predicted PV diffusion level at $t-2*k-1$ (after including time and fixed effects).

Tables 7.12, 7.13 and 7.14 report the results from the first, second and third stage, respectively. The NLS estimation for the first stage again has a very good fit. Global solar radiation is only significant at the 10% level, the share of single and double family houses and the east dummy are not significant. Still, they have their expected sign. They may not be significant, as the two-period lag implies dealing with the adotion levels in 1993, 1997 and 2001, i.e., an early phase of PV adoption.[70] The main finding from the second stage regression is that, as implied by the theory, the predicted diffusion level at $t-2*k-1$ is a good predictor of the adoption rate between $t-k-1$ and $t-1$. When comparing Tables 7.13 and 7.6, we see only small reductions in the R^2. The third stage estimates in Table 7.14 are also very similar to those in Table 7.7. There is no significant difference in the estimated effects of adoption rates on voting patterns or in the R^2 of this relationship under both instrumentation strategies. I.e., the analysis with a two-period lag in the predicted diffusion level supports the validity of our results.

7.4.3. Synthetic instrument

Can we provide further assurance that $\hat{F}_{\text{PV},t-k-1}$ is indeed exogenous to Δv_t? We put our results to the test with a synthetic instrument: $F_{\text{PV, synthetic},t-k-1}$.

[70] E.g., at the beginning of the 1990s, the feed-in tariff for PV was very low and the 1,000 roofs program (precurser of the 100,000 roofs program) fostered PV adoption. Importantly, the 1,000 roofs program led to installations across Germany since a maximum quota of installations was allocated to every federal state (Hoffmann et al., 1998). The homogeneous distribution of PV systems in Germany in the early diffusion phase may be the reason for less strong predictors of the logistic curve's ceiling (in comparison to Table 7.5).

Table 7.12.: First stage NLS estimation of logistic PV diffusion (two-period lag).

	(1)
	F_{t-2k-1}
a	-0.337+
	(-1.77)
a_{sun}	0.375+
	(1.72)
$a_{\text{share si-do houses}}$	0.000953
	(0.24)
a_{east}	-0.0241
	(-1.62)
b	3.253***
	(4.26)
c	4.932***
	(12.25)
NUTS-3 fixed effects	No
Time fixed effects	No
R^2	0.717
Adj. R^2	0.716
N	1156

t statistics in parentheses, robust SE
+ p¡0.10, * p¡0.05, ** p¡0.01, *** p¡0.001

Table 7.13.: Second stage estimation of increase in PV diffusion on increase in share of green votes (two-period lag).

	(1)	(2)	(3)	(4)
	$\Delta F_{\text{PV},t-1}$	$\Delta F_{\text{PV},t-1}$	$\Delta F_{\text{PV},t-1}$	$\Delta F_{\text{PV},t-1}$
$\hat{F}_{\text{PV},t-2k-1}$	6.280***	5.487***	6.942***	5.069***
	(23.86)	(21.24)	(14.55)	(11.81)
$\ln(\text{GDP}_{\text{cap},t})$	0.00263**	0.0243***	0.00216*	0.0146**
	(2.90)	(6.05)	(2.39)	(2.87)
share si-do hous_t	0.000275***	-0.00240***	0.000264***	-0.00311***
	(10.26)	(-4.93)	(10.09)	(-5.06)
α	-0.0462***		-0.0429***	
	(-4.32)		(-4.04)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.629	0.726	0.634	0.732
Adj. R^2	0.628	0.588	0.633	0.595
F	203.0	311.0	167.1	241.7
$F_{\text{Instrument}=0}$	569.5	451.1	211.8	139.6
p-$\text{value}_{\text{Instrument}=0}$	1.27e-102	4.07e-79	3.68e-44	1.04e-29
N	1157	1157	1157	1157

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Certainly, the average level of solar radiation is exogenous to Δv_t.[71] We rank the regions under study according to their average level of solar radiation. Then, we generate $F_{\text{PV, synthetic},t-k-1}$ to be the average value of $F_{\text{PV},t-k-1}$'s four nearest (rank) neighbors.

[71] Table F.5 in Appendix F.2.2 shows the insignificant estimate of average solar radiation on the increase in green votes regardless of whether we control for the level of green votes one year before the previous election. We include year fixed effects and – as always – control for the logarithm of per capita income in Table F.5. Note that there is neither a significant association between average solar radiation and increase in Green Party votes before the time period in which we observe a positive impact of PV adoption on Green Party votes, i.e., there is no significant association before 1998.

Table 7.14.: Third stage estimation of increase in PV diffusion on increase in share of green votes (two-period lag).

	(1) Δv_t	(2) Δv_t	(3) Δv_t	(4) Δv_t
$\Delta \hat{F}_{\text{PV},t-1}$	0.810***	1.051***	0.211***	0.212*
	(17.50)	(14.99)	(3.51)	(2.09)
$\ln(\text{GDP}_{\text{cap},t})$	-0.000153	-0.0319**	0.00499***	-0.000113
	(-0.12)	(-3.02)	(5.04)	(-0.01)
share si-do hous_t	-0.000294***	0.000960	-0.0000495	-0.000179
	(-7.03)	(1.10)	(-1.33)	(-0.16)
α	0.0313*		-0.0260*	
	(2.01)		(-2.29)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.0697	0.163	0.579	0.641
Adj. R^2	0.0673	-0.261	0.577	0.457
F	124.9	111.8	352.3	265.5
N	1157	1157	1157	1157

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7.15 and 7.16 show the results for the first and second stage regression. Comparing the results using the synthetic instrument with Table 7.3 and 7.4 reveals that the R^2 values are lower when using the synthetic approach. Still, the estimated coefficients and their significance levels are similar, regardless of whether NUTS-3 and time fixed effects are included. The synthetic instrumentation strategy confirms the positive effect of adoption rates on green voting patterns.

Table 7.15.: First stage estimation of increase in PV diffusion on increase in share of green votes using synthetic instrument.

	(1) $\Delta F_{\text{PV},t-1}$	(2) $\Delta F_{\text{PV},t-1}$	(3) $\Delta F_{\text{PV},t-1}$	(4) $\Delta F_{\text{PV},t-1}$
$F_{\text{PV, synthetic},t-k-1}$	5.341***	4.203***	4.378***	2.971***
	(17.19)	(14.80)	(9.94)	(8.72)
$\ln(\text{GDP}_{\text{cap},t})$	-0.00157*	0.0317***	-0.00164*	-0.000806
	(-2.16)	(7.20)	(-2.24)	(-0.15)
α	0.0196**		0.0242**	
	(2.66)		(3.20)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.471	0.630	0.488	0.661
Adj. R^2	0.471	0.444	0.487	0.489
F	148.8	301.6	144.6	220.1
$\text{F}_{\text{Instrument}=0}$	295.5	218.9	98.78	76.10
$\text{p-value}_{\text{Instrument}=0}$	3.73e-59	8.82e-44	2.17e-22	1.66e-17
N	1159	1158	1159	1158

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7.16.: Two-stage least squares estimation of increase in PV diffusion on increase in share of green votes using synthetic instrument.

	(1) Δv_t	(2) Δv_t	(3) Δv_t	(4) Δv_t
$\Delta \hat{F}_{\mathrm{PV},t-1}$	0.756***	1.090***	0.193**	0.225*
	(15.96)	(13.85)	(3.16)	(2.25)
$\ln(\mathrm{GDP}_{\mathrm{cap},t})$	0.00539***	-0.0330***	0.00592***	-0.00307
	(5.05)	(-3.35)	(6.85)	(-0.36)
α	-0.0488***		-0.0393***	
	(-4.56)		(-4.37)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.0600	0.153	0.581	0.644
Adj. R^2	0.0584	-0.274	0.579	0.463
F	150.8	151.8	422.2	317.5
N	1159	1158	1159	1158
$\mathrm{DF_M}$	2	388	4	390

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7.4.4. Green voting dynamics before 1998

Could a general trend which makes people more prone to vote for the Green Party be the reason for our finding? We study this possibility by analyzing Green Party voting in the time before our main period of study. We estimate the lagged level of the share of Green Party votes (v_{t-k}) on the increase in the share of Green party votes (Δv_t) for the time before 1998. Then, we use the point estimate of v_{t-k} before 1998 to filter away the pre-1998 voting dynamics from the increase in Green votes since 1998.

The Green Party participated in the federal elections for the first time in 1980. Table 7.17 reports that the lagged level of the Green Party share of votes has a mainly negative association with the increase in Green Party votes before 1998. See Table F.6 in Appendix F.2.3 for the relevant descriptives statistics. Our preferred specification in column (4) – with NUTS-3 and time fixed effects – has an especially good fit in terms of R^2.

We employ the instrumentation strategy used before. The estimates from the non-linear first stage estimation and the ones from the second stage are still those given in Table 7.5 and Table 7.6. Table 7.18 reports the third stage, which are similar to the ones from the OLS regression (see Table F.7 in Appendix F.2.3). Our results are unaffected by filtering away the pre-1998 voting dynamics from the increase in Green Party voting during our main period of study (1998-2009). Column (4) of Table 7.18 suggests that an increase in the PV adoption rate of one standard deviation causes

Table 7.17.: OLS estimation of level of share of green votes on increase in share of green votes (1980-1998).

	(1)	(2)	(3)	(4)
	Δv_t	Δv_t	Δv_t	Δv_t
v_{t-k}	-0.590***	-1.004***	0.00242	-0.822***
	(-19.44)	(-53.87)	(0.13)	(-19.77)
α	0.0391***		-0.00543***	
	(28.16)		(-4.55)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.361	0.740	0.843	0.934
Adj. R^2	0.361	0.674	0.842	0.918
F	377.5	2899.5	1036.9	3356.9
N	1713	1621	1713	1621

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

an increase of 0.4% in Green Party votes. Accumulating this over the three elections we study, we see that the increase in PV adoption is responsible for more than one quarter of the actual increase in Green Party votes.

Table 7.18.: Third stage estimation of increase in PV diffusion on increase in share of green votes (pre-1998 voting dynamics filtered away).

	(1)	(2)	(3)	(4)
	$\Delta v_t - \hat{\beta_{v_{t-k}}} v_{t-k}$	$\Delta v_t - \hat{\beta_{v_{t-k}}} v_{t-k}$	$\Delta v_t - \hat{\beta_{v_{t-k}}} v_{t-k}$	$\Delta v_t - \hat{\beta_{v_{t-k}}} v_{t-k}$
$\Delta \hat{F}_{\mathrm{PV},t}$	0.893***	0.988***	0.178***	0.317***
	(11.84)	(15.35)	(3.60)	(4.19)
$\ln(\mathrm{GDP}_{\mathrm{cap},t})$	0.0228***	0.0220**	0.00515***	-0.00810
	(7.20)	(2.65)	(5.52)	(-1.05)
share si-do hous_t	-0.000575***	0.00519***	-0.0000354	0.00114
	(-5.79)	(4.82)	(-1.07)	(1.36)
α	-0.137***		-0.0284**	
	(-3.72)		(-2.64)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.273	0.556	0.581	0.749
Adj. R^2	0.271	0.330	0.579	0.622
F	117.9	227.6	344.7	339.1
N	1157	1157	1157	1157

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7.4.5. Placebo tests

The hypothesis we are testing in this chapter is that using green technology makes voters more prone to vote for the Green Party. If this is the case, the effect of green adoption on green voting should be entirely driven by the adoption of household systems. By the same token, we should observe no effect for the adoption of industrial

green energy systems on voting patterns. Next, we implement this placebo test in two exercises. Firstly, we differentiate between large PV systems which are feasible only in industrial installations and small PV systems that are typically installed by households. Secondly, we also explore the relationship between the adoption of eolic systems and voting patterns, since the investments required to install eolic systems are too large to be financed by households.

Industrial vs. household PV systems

To assess whether the relationship between PV adoption and green voting is driven by the adoption of household or industrial systems we construct series for the adoption of low and high capacity systems. We use two thresholds for the maximum capacity of household systems, 30 kW_p and 100 kW_p. In addition we study the effects of the diffusion of very large PV systems (1,000 kW_p or more) which definitely are industrial. To save space, we focus on our preferred specification with regional and time fixed effects and only report the three-stage estimates which are consistent with the OLS estimates. Table F.8 and Table F.9 in Appendix F.2 presents the first and second stage regressions for the adoption of PV systems of various capacities. For the industrial installations, we have to adjust the non-linear first stage estimation since both, the share of single and double family houses and their location in the east or west, are less relevant for their adoption level. Instead we add a squared global radiation term and a dummy for urban areas. For household installations the goodness-of-fit measures are higher than for industrial installations. For all capacity groupings besides very large systems, the lagged predicted diffusion level is a strong and very significant predictor of current adoption rates. The R^2 of the second stage regressions are very high for household and sufficient for industrial systems suggesting that the logistic provides a good characterization of the diffusion for both.

Table 7.19 reports the estimates of the instrumented adoption rates and changes in green voting rates for industrial and household systems. For household systems we basically estimate the same effects as in the full sample (Table 7.7). The estimated effect is slightly higher for systems with a capacity of at most 30 kW_p than for systems of at most 100 kW_p. In both cases, the effect of PV adoption on green voting is significant with p-values smaller than 0.05. The estimates change dramatically

for industrial systems. When we focus on systems with capacity above 100 kW_p, we find a significantly negative association between instrumented adoption rates and changes in green votes. For very large PV systems (over 1 MW_p capacity), the relationship between instrumented adoption rates and voting patterns disappears completely. These findings are consistent with the view that using (rather than seeing) green technologies is what induces voters to vote for the Green Party.

Table 7.19.: Third stage estimation of increase in PV diffusion on increase in share of green votes (industrial vs. household systems).

	Household installations		Industrial installations	
	(1)	(2)	(3)	(4)
	Δv_t	Δv_t	Δv_t	Δv_t
$\Delta\hat{F}_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t-1}$	0.193*			
	(2.17)			
$\Delta\hat{F}_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t-1}$		0.175*		
		(2.20)		
$\Delta\hat{F}_{\mathrm{PV}>100\,\mathrm{kW_p},t-1}$			-26.82***	
			(-3.77)	
$\Delta\hat{F}_{\mathrm{PV}>1\,\mathrm{MW_p},t-1}$				-30.69
				(-1.43)
$\ln(\mathrm{GDP}_{\mathrm{cap},t})$	-0.000132	-0.0000744	0.0122	0.00532
	(-0.01)	(-0.01)	(1.10)	(0.27)
share si-do hous_t	-0.000400	-0.000407		
	(-0.38)	(-0.39)		
R^2	0.640	0.640	0.389	0.150
Adj. R^2	0.456	0.457	0.0792	-0.285
F	255.3	255.8	185.9	72.27
N	1157	1157	1134	747

t statistics in parentheses, built with Newey-West SE
NUTS-3 and time fixed effects included
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Capacity-adjusted measures of diffusion

The measures of PV system diffusion used so far make no adjustment for the capacity of the system. To explore the robustness of our findings to alternative measures of diffusion, we consider the following measure of the capacity-adjusted adoption rate:

$$\triangle F_{\mathrm{PVCapac.},nt} = \frac{\triangle \text{ Total solar capacity installed}_{nt}}{\#\text{ Buildings}_{nt} * \text{Avg. capacity}} \tag{7.11}$$

where "Avg. capacity" is the average capacity of all PV systems installed across all regions in all periods.

Column (1) of Table 7.20 presents the OLS estimates of the effect of the increase in capacity on the increase in the share of green votes in our preferred specification with

both year and region fixed effects. The main finding is that now the relationship between the two is negative (and significant at the 5% level).

Table 7.20.: OLS estimation of increase in PV diffusion (capacity-adjusted measure) on increase in share of green votes.

	All inst.	Household installations		Industrial installations	
	(1) Δv_t	(2) Δv_t	(3) Δv_t	(4) Δv_t	(5) Δv_t
$\Delta F_{\text{PVCapac.},t-1}$	-0.0247*				
	(-2.08)				
$\Delta F_{\text{PVCapac.}\leq 30\,\text{kW}_\text{p},t-1}$		0.196***			
		(5.92)			
$\Delta F_{\text{PVCapac.}\leq 100\,\text{kW}_\text{p},t-1}$			0.191***		
			(5.73)		
$\Delta F_{\text{PVCapac.}>100\,\text{kW}_\text{p},t-1}$				-1.683*	
				(-2.14)	
$\Delta F_{\text{PVCapac.}>1\,\text{MW}_\text{p},t-1}$					-1.687*
					(-2.14)
$\ln(\text{GDP}_{\text{cap},t})$	-0.000677	-0.000484	-0.000112	-0.000623	-0.000619
	(-0.07)	(-0.05)	(-0.01)	(-0.07)	(-0.07)
R^2	0.632	0.642	0.642	0.633	0.633
Adj. R^2	0.445	0.460	0.461	0.446	0.446
F	280.9	299.6	292.7	281.3	281.4
N	1160	1160	1160	1160	1160

t statistics in parentheses, built with Newey-West SE
NUTS-3 and time fixed effects included
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As one could expect from the previous analysis, this change in the sign is entirely driven by the fact that capacity-weighted adoption measures, such as $\Delta F_{\text{PVCapac.}}$, are dominated by industrial installations which have much larger capacity than household installations. To make this clear, columns (2) and (3) of Table 7.20 use the capacity-weighted measure of adoption but consider only installations with a capacity of at most 30 kW_p in column (2) and of at most 100 kW_p in column (3). After excluding industrial installations, the sign of the relationship between capacity-weighted adoption rates of PV systems and changes in the Green Party share of votes is again positive and significant as we found in the previous section. In contrast, when we only consider installations with a capacity larger than 100 kW_p (column 4) or 1,000 kW_p (column 5) we find a negative relationship between adoption rates and green votes, again.

The conclusions from the OLS estimates remain after instrumenting capacity-weighted adoption rates with lagged predicted capacity-weighted diffusion levels. In results not shown here, we find that the non-linear first stage estimations have a very good fit for household systems and are also sufficient for industrial systems. The

predicted instrument is strong, especially for household systems. As before, instrumenting does not change the magnitude or sign of the OLS estimates. In particular, Table 7.21 shows the third stage coefficients. We only find positive and significant effects of capacity-weighted measures of adoption on the increase in the Green Party share of votes in the small capacity systems. Therefore, we conclude that our findings are robust to using capacity-weighted measures of diffusion.

Table 7.21.: Third stage estimation of increase in PV diffusion (capacity-adjusted measure) on increase in share of green votes.

	All inst.	Household installations		Industrial installations	
	(1)	(2)	(3)	(4)	(5)
	Δv_t	Δv_t	Δv_t	Δv_t	Δv_t
$\Delta\hat{F}_{\text{PVCapac.},t-1}$	-0.168*				
	(-2.24)				
$\Delta\hat{F}_{\text{PVCapac.}\leq 30\,\text{kW}_\text{p},t-1}$		0.151*			
		(2.29)			
$\Delta\hat{F}_{\text{PVCapac.}\leq 100\,\text{kW}_\text{p},t-1}$			0.167**		
			(2.78)		
$\Delta\hat{F}_{\text{PVCapac.}>100\,\text{kW}_\text{p},t-1}$				-13.63*	
				(-2.45)	
$\Delta\hat{F}_{\text{PVCapac.}>1\,\text{MW}_\text{p},t-1}$					-11.15
					(-1.05)
$\ln(\text{GDP}_{\text{cap},t})$	0.00615	-0.000401	-0.00144	0.00811	-0.00437
	(0.67)	(-0.04)	(-0.16)	(0.88)	(-0.29)
share si-do hous$_t$		-0.000383	-0.000113		
		(-0.37)	(-0.11)		
R^2	0.560	0.641	0.643	0.516	0.466
Adj. R^2	0.337	0.457	0.461	0.270	0.193
F	237.4	268.5	262.2	216.1	105.3
N	1160	1157	1131	1160	747

t statistics in parentheses, built with Newey-West SE
NUTS-3 and time fixed effects included
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The diffusion of eolic systems

A similar investigation can be conducted with eolic installations which, because of the large investments they require, are all industrial. Table 7.22 column (1) and (2) report the OLS estimates of the relationship between eolic adoption rates and increase in green share of votes.[72] In particular, column (1) focuses on the number of new eolic installations over the electoral period normalized by the forestal and agricultural land area in the region. Note that this normalization reflects the fact

[72]See Table F.10 in Appendix F.2 for the descriptive statistics.

that, unlike most PV systems, eolic plants are not installed on buildings. Column (2) uses a capacity-weighted measure of adoption given by this formula

$$\triangle F_{\text{EolicCapac.},nt} = \frac{\triangle \text{ Total eolic capacity installed}_{nt}}{\text{Agricultural \& forestal area}_n \text{ * Avg. capacity}} \tag{7.12}$$

where "Avg. capacity" is the average capacity of all eolic installations across all regions in all periods.

Table 7.22.: Estimation of increase in eolic diffusion on increase in share of green votes.

	OLS		Third stage estimation	
	(1) Δv_t	(2) Δv_t	(3) Δv_t	(4) Δv_t
$\Delta F_{\text{Eolic},t-1}$	-0.0367*			
	(-2.21)			
$\Delta F_{\text{EolicCapac.},t-1}$		-0.0128		
		(-1.38)		
$\Delta \hat{F}_{\text{Eolic},t-1}$			-0.335**	
			(-2.70)	
$\Delta \hat{F}_{\text{EolicCapac.},t-1}$				-2.616
				(-0.38)
$\ln(\text{GDP}_{\text{cap},t})$	-0.00114	-0.00193	0.0123	0.176
	(-0.13)	(-0.22)	(0.87)	(0.31)
R^2	0.632	0.631	0.496	-27.14
Adj. R^2	0.445	0.443	0.240	-41.44
F	275.0	274.9	205.4	5.179
N	1161	1161	1161	1161

t statistics in parentheses, built with Newey-West SE
NUTS-3 and time fixed effects included
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For both measures of adoption, the OLS estimates are not significantly positive. Table F.11 and F.12 in Appendix F.2 and Table 7.22 column (3) and (4) present the estimates in the first, second and third stage. After instrumenting adoption rates for eolic systems, we still find no positive effect on the increase in the share of Green Party votes. This result confirms our hypothesis that observing the diffusion of green technologies is not sufficient for voters to vote for the Green Party. Our findings suggest that voters need to actually adopt/use green technologies to become more prone to vote for the Green Party.

7.4.6. Evidence on the individual level

So far, we have studied the effect of the diffusion of PV systems on the fraction of votes obtained by Germany's Green Party on the NUTS-3 level. Certainly, an

analysis on the aggregate level does not reveal whether PV adopters are indeed more likely to vote for the Green Party. We use German survey data from 2013's Socio-Economic Panel (SOEP) to put our findings to the test at the individual level. We employ the SOEP's cross-sections from 2007 through 2012 since these include information on PV adoption.

See Table F.13 in Appendix F.2.6 for the descriptive statistics. We define ΔGreen_{it} to be one if individual i states a change in support from another party to green or if i states a change from a weaker to a stronger level of Green Party support between consecutive years, zero otherwise. We set PV_{it-1} to one if individual i states that her dwelling has a PV system in $t-1$.

Table 7.23 reports the odds ratios obtained through logit estimation. Column (1) shows that the odds that a person who has installed a PV system becomes greener is 1.4 times higher than for a person without PV. The estimate is significant at the 1% level.[73] Note that we control for the natural logarithm of real household income, year times NUTS-1 fixed effects (i.e., a NUTS-1 fixed effect interacted with every year of study) and a set of individual characteristics by including fixed effects for the level of education and the labor force status. See Appendix F.2.6 for details regarding the controls.

Table 7.23.: Odds ratio of PV level on change in green attitude.

	All	Home owners	Non-home owners
	(1)	(2)	(3)
	ΔGreen_t	ΔGreen_t	ΔGreen_t
PV_{t-1}	1.438**	1.728***	0.521
	(2.76)	(3.84)	(-1.38)
$\ln \text{RHHINC}_t$	1.093	1.167	1.169
	(1.31)	(1.51)	(1.56)
Time∗NUTS-1 dummies	Yes	Yes	Yes
College and vocational degree dummy_t	Yes	Yes	Yes
Labor status dummy_t	Yes	Yes	Yes
Observations	45455	25062	19268
DF_M	67	64	61
Final log-likelihood $\mathcal{L}$	-5144.0	-2853.3	-2240.9

Exponentiated coefficients; Robust t statistics in parentheses clustered on households
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In contrast to the effect from the adoption of household PV systems, we find no effect from the adoption of industrial PV systems and eolic systems on voting patterns at the NUTS-3 level. We conclude that voters have to be involved in the adoption

[73] We only contemplate at respondents who do not claim to have removed their PV system. There is strong evidence that this group best illustrates the effect under study. Comparing the SOEP data set with reported data from the German transmission system operators, shows that disproportionately many PV systems were removed according to the SOEP data, see Figure F.1 in Appendix F.2.6.

and operation of the technology to affect their voting patterns. Only the owner of a house will actually use a PV system. The owner is usually the one who decides if a PV system is adopted. We should therefore only contemplate people living in their own house or flat. Column (2) of Table 7.23 shows that the odss that a home owner who has installed a PV system becomes greener is 1.7 times higher than for a home owner who has not installed PV. This estimated coefficient is significant at the 0.1% level and confirms that direct involvement in the technology may increase the odss to affect voting patterns. Note that we do not find a positive association between PV adoption and becoming greener for non-home owners (see column (3)).

So far, we cannot confirm a causal effect for our analysis of the SOEP data. To deal with causality, we could only include newly installed PV systems on the right hand-side, i.e., ΔPV_{t-1}. However, we do not know when an increase in green attitude occurs due to PV adoption. For this reason, we introduce $\Delta\text{PV}_{t-1,t-2,t-3}$, which captures a newly installed PV system in t causing an increase in green attitude not only in $t+1$, but also in $t+2$, and $t+3$.

Table 7.24 column (1) shows that new PV adopters are more, but not significantly more, likely to become greener. However, as discussed earlier, we should focus on home owners. Column (2) reveals that under home owners, the odds of becoming greener is 1.4 times higher for new PV adopters. The respective coefficient is significant at the 10% level. Note that we control for changes in the natural logarithm of real household income and – as before – year times NUTS-1 fixed effects and individual characteristics. Appendix F.2.6 contains further robustness checks.

Table 7.24.: Odds ratio of PV change on change in green attitude.

	All	Home owners	Non-home owners
	(1)	(2)	(3)
	ΔGreen_t	ΔGreen_t	ΔGreen_t
$\Delta\text{PV}_{t-1,t-2,t-3}$	1.270	1.441^{+}	0.432
	(1.15)	(1.72)	(-1.18)
$\Delta \ln \text{RHHINC}_t$	0.971	0.751^{+}	1.281
	(-0.23)	(-1.76)	(1.60)
Time∗NUTS-1 dummies	Yes	Yes	Yes
College and vocational degree dummy$_t$	Yes	Yes	Yes
Labor status dummy$_t$	Yes	Yes	Yes
Observations	45044	24831	19100
DF_M	67	64	61
Final log-likelihood $\mathcal{L}$	-5281.5	-2925.7	-2317.2

Exponentiated coefficients; Robust t statistics in parentheses clustered on households
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To deal even more confidently with causality, we can instrument the lagged level of PV adoption (PV_{it-1}) by using natural instruments: the adoption of other (not

related) technologies. We define Internet_{it-1} to one if individual i has an Internet connection in her household $t-1$, zero otherwise. The same applies to PC_{it-1} regarding a personal computer (PC) in the household. Simply speaking, there are neither theories nor empirical studies claiming that computer or Internet usage are endogenous to becoming greener. Therefore, we consider our instruments to be valid ex-ante. Table 7.25 reports the probit and bi-probit results for home owners. Note that we again control for the natural logarithm of real household income, year times NUTS-1 fixed effects and a set of individual characteristics. The probit and bi-probit estimates confirm the logit estimates presented earlier. We cannot interpret the former as odds ratios (we show the coefficients) and – for reasons of clarity – only use them to confirm the effect found before. Column (2) illustrates that Internet usage and PC usage are strong predictors for PV adoption. A χ^2 test confirms that the instruments are not irrelevant to any level of significance. ρ is the correlation between the error terms of the first and the second stage regression and does not significantly differ from zero. This indicates ex-post that our instruments are indeed not endogenous to changes in green voting (for details see Wooldridge (2002, p. 477)). A Wald test on $\rho = 0$ points in the same direction as the p-value is greater 0.05. In Table F.17 of Appendix F.2.6 we report that a two-stage least squares estimation further supports the previous results. As we include two instruments, we can make use of an overidentification restriction test which also confirms the validity of our instruments.[74]

A critical reader may still question if our analysis on the individual level allows us to speak about a causal effect of PV adoption on becoming greener. Could it also be the other way around? In order to check, we set Green2_{it} to one if respondent i claims to support the Green Party at t. Table 7.26 and 7.27 report odds ratios. In Table 7.26 we see that Green Party supporters are not more likely to adopt PV than those who do not support the Green Party. This finding holds true no matter if we include all individuals or only home owners into the analysis. Table 7.27 illustrates

[74] In Appendix F.2.6, we show that – when analyzing all individuals in comparison to only including home-owners – the effect is significant for the two-stage least squares estimation (Table F.18) but not for bi-probit (Table F.19). Further, there is no effect for non-home owners (see Appendix F.2.6, Table F.20 for the bi-probit estimation and Table F.21 for the two-stage least squares estimation). Appendix F.2.6 contains further robustness checks.

Table 7.25.: Estimation of PV level on change in green attitude (for home owners).

	Probit	Bi-Probit
	(1)	(2)
	ΔGreen$_t$	ΔGreen$_t$
PV$_{t-1}$	0.241***	0.652*
	(3.71)	(2.10)
ln RHHINC$_t$	0.0808$^+$	0.0630
	(1.86)	(1.41)
First stage		
Internet$_{t-1}$		0.124*
		(2.54)
PC$_{t-1}$		0.236***
		(3.74)
ln RHHINC$_t$		0.226***
		(4.35)
Time∗NUTS-1 dummies	Yes	Yes
College and vocational degree dummy$_t$	Yes	Yes
Labor status dummy$_t$	Yes	Yes
ρ		-0.214
$\chi^2_{\rho=0}$ (p-value)		1.855 (0.173)
$\chi^2_{\text{Instruments}=0}$ (p-value)		25.87 (0.00000241)
Observations	25062	25706
DF$_{\text{M}}$	64	133
Final log-likelihood $\mathcal{L}$	-2851.0	-11009.2

Robust t statistics in parentheses clustered on households
$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

that individuals who became greener are also not more likely to adopt PV than those who did not become greener in a previous period.[75]

Table 7.26.: Odds ratio of green attitude level on PV change.

	All	Home owners	Non-home owners
	(1)	(2)	(3)
	ΔPV$_{t-1}$	ΔPV$_{t-1}$	ΔPV$_{t-1}$
Green2$_{t-1}$	0.778	0.692	0.977
	(-1.08)	(-1.21)	(-0.06)
ln RHHINC$_t$	1.768***	1.554**	1.641*
	(4.83)	(2.80)	(2.54)
Time∗NUTS-1 dummies	Yes	Yes	Yes
College and vocational degree dummy$_t$	Yes	Yes	Yes
Labor status dummy$_t$	Yes	Yes	Yes
Observations	42755	23045	15121
DF$_{\text{M}}$	54	47	44
Final log-likelihood $\mathcal{L}$	-2566.7	-1781.5	-718.3

Exponentiated coefficients; Robust t statistics in parentheses clustered on households
$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To sum up, the SOEP analysis confirms our hypothesis, i.e., PV adopters are more likely to become greener than non-adopters. Further, there is evidence for a causal effect of PV adoption on becoming greener. We also rule out reverse causality.

[75] We define becoming greener as switching from supporting another (or no) party to supporting the Green Party or as increasing the intensity of Green Party support. Appendix F.2.6 contains further robustness checks.

Table 7.27.: Odds ratio of change in green attitude on PV change.

	All	Home owners	Non-home owners
	(1)	(2)	(3)
	ΔPV_{t-1}	ΔPV_{t-1}	ΔPV_{t-1}
$\Delta\text{Green}_{t-1,t-2,t-3}$	0.677	0.461*	1.140
	(-1.60)	(-2.08)	(0.39)
$\Delta \ln \text{RHHINC}_t$	0.836	0.885	0.799
	(-0.82)	(-0.43)	(-0.64)
Time∗NUTS-1 dummies	Yes	Yes	Yes
College and vocational degree dummy$_t$	Yes	Yes	Yes
Labor status dummy$_t$	Yes	Yes	Yes
Observations	42534	22917	15052
DF_M	54	47	44
Final log-likelihood $\mathcal{L}$	-2569.5	-1772.4	-721.1

Exponentiated coefficients; Robust t statistics in parentheses clustered on households
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7.4.7. Discussion

So far, we have uncovered the impact that the diffusion of PV systems has on the votes obtained by the Green Party. However, we have not explored the mechanisms that may lead PV adopters to vote green. Answering this question is beyond the scope of this study. However, we would like to point to some mechanisms that may cause this effect. Broadly speaking, we can think of two mechanisms. One is Bayesian learning about the Green Party. As potential voters adopt PV systems they learn about values and technologies supported by the Green Party. They update upwards their prior on the political value of the Green Party raising the odss of voting green. An alternative channel by which green adoption may affect voting behavior is based on the notion that voters suffer from cognitive dissonance (e.g., Akerlof and Dickens (1982)). That is, the choice to adopt green technologies may trigger a change in voters preferences towards green values which may ultimately induce them to vote for the Green Party.

Both of these hypotheses are consistent with the new findings uncovered in this study. To fully discern between the two hypothesis would require the use of adequate survey data. However, we may learn about their plausibility by studying how the effect of PV adoption on green votes varies between federal states ('Länder') where the Green Party was in power and those where it was not. One feature of Bayesian learning is that the marginal effect on the posterior of a given signal diminishes with the information the agent has (i.e., with the precision of the prior). We consider it safe to assume that voters in NUTS-1 regions ruled by the Green Party have more precise priors about the Green Party and green values than those in NUTS-1 regions

where the Green Party had not ruled before 1998 (i.e., our first data point in our main analysis). Therefore, if our findings are the result of Bayesian learning, we should expect a smaller effect of PV system adoption on green voting in NUTS-1 regions where the Green Party had ruled.

Table 7.28 evaluates this prediction by introducing an additional regressor in our baseline specification which is an interaction between the adoption rate of PV systems and a dummy that equals one if the Green Party was in a governing coalition in the NUTS-1 regions before 1998. The first column reports the OLS estimates and the second the three-stage estimates. In both cases, the differential effect of adoption on green voting is, if anything, positive in regions where the Green Party was in power through 1998. This is precisely the opposite of what we would expect from a Bayesian learner. Therefore, we interpret this result as suggestive that voters' cognitive dissonance is likely to be the mechanism driving our findings. However, as emphasized above, much more work needs to be undertaken to establish that.

Table 7.28.: Estimation of increase in PV diffusion on increase in share of green votes (Bayesian learning).

	OLS	Third stage estimation
	(1)	(2)
	Δv_t	Δv_t
$\Delta F_{\text{PV},t-1}$	0.242***	
	(5.86)	
$\Delta F_{\text{PV},t-1} * Green_{\text{Land}}$	0.162+	
	(1.75)	
$\Delta \hat{F}_{\text{PV},t-1}$		0.193+
		(1.80)
$\Delta F_{\text{PV},t-1} * \hat{Green}_{\text{Land}}$		0.0663
		(0.39)
$\ln(\text{GDP}_{\text{cap},t})$	-0.000396	-0.000322
	(-0.04)	(-0.04)
share si-do hous_t		-0.000236
		(-0.20)
R^2	0.643	0.641
Adj. R^2	0.461	0.458
F	257.4	214.2
N	1160	1157

t statistics in parentheses, built with Newey-West SE
NUTS-3 and time fixed effects included
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7.5. Summary

In this chapter we have posed a new research question: Does the diffusion of technology affect voting patterns? To start understanding the political consequences of technology diffusion, we have explored two specific technologies (PV and eolic systems) in one country (Germany). Our identification strategy has exploited the (widely documented) non-linearities in the diffusion of new technologies to obtain exogenous variation in adoption rates. Our analysis implies that approximately a quarter of the increase in the share of votes experienced by the Green Party between 1998 and 2009 is driven by the diffusion of PV systems. These estimates are robust to controlling for measures of profitability of solar energy, income and a set of regional and time fixed effects. In contrast, we find no such effects from the diffusion of industrial PV systems and eolic systems. This contrast confirms the importance of voters' direct involvement with the adoption and/or operation of the technology for this to affect their voting patterns. Survey data from the German Socio-Economic Panel confirms our results. The survey analysis even allows us to disprove reverse causality.

Our findings raise many new questions. First, more work is needed to uncover the mechanism by which adoption of PV systems leads to vote for the Green Party. Second, do we see similar effects of the diffusion of PV systems in other countries? In Spain, for example, green parties continued to be irrelevant despite the large diffusion of PV systems. However, unlike Germany, in Spain most of the systems installed were industrial and households have not yet adopted them in any significant way. Third, are there political consequences of the diffusion of other technologies? Do they also affect voting patterns?[76] Fourth, in addition to voting patterns, does the diffusion of technology affect other political phenomena such as campaign contributions, party affiliation, voter turnout, civic involvement in politics, etc. Finally, for which technologies do we observe these effects and what do they have in common?

[76] E.g., without the diffusion of Internet technology the Pirate Party may not have been founded in Sweden in 2006 (and in many other countries at a later stage).

8. Conclusions

We set out to study drivers, barriers and implications of renewable energy adoption in Germany. In order to do so, we exploit a new unique dataset which includes the location, date of installation and size of all PV systems, wind power plants and biomass plants for generating electricity installed in Germany through 2011. Importantly, a strong federal subsidy scheme has fostered the adoption of the three technologies since 2000.

We start our analysis by delineating the topic. Then, we review models of technology diffusion. Along with the theory, numerous studies confirm that technology diffusion follows an S-shaped, logistic pattern. A description of the institutional context, aggregate trends and regional differences in renewable energy adoption in Germany follows.

In Chapter 4, we test whether peer effects drive PV adoption. We aggregate the data to different levels and employ an epidemic diffusion model which includes a spatial dimension. According to our results, peer effects are highly localized and an important factor for the adoption of PV systems. Observing a PV system in operation and talking about it with a person of trust may increase the likelihood of installing PV. This finding is in line with Bollinger and Gillingham (2012) and Müller and Rode (2013), who also study peer effects in PV adoption. Peer effects imply that locally distributed eye- and attention-catching projects could be placed as PV seeds in key regions. These simply signal that the technology or product works. In the same line of reasoning, schemes on the local level that support spreading of information, such as referral reward programs and impact campaigns, could be promising. For instance, Müller and Rode (2013) refer to Cardwell (2012) who shows that, in the U.S., enthusiastic PV users inform their neighbors about PV. To conclude, if fostering technology diffusion is on the agenda, creating incentives for enthusiastic technology users to share their experience with neighbors – i.e., facilitating the spread of information – may be rewarding.

In the following Chapter 5, we change our focus to spatio-temporal variation of peer effects in PV adoption. We add detailed locational data on potential adopters. This data allows us to construct an individual measure of peer effects for each potential adopter. Based on a discrete choice model and the more accurate data, we confirm again that peer effects are mostly localized. They generally occur within a radius of 500 meters around a decision-maker's residence. We also find that the peer effect's impact on the decision to adopt decreases over time. The policy implications of the latter result are straightforward. It would be efficient to influence the adoption of PV systems using seed installations or schemes supporting the spread of information in the very early periods of diffusion.

In the first part of this thesis, we study PV adoption in Germany. Certainly, a similar analysis in other countries with different residential structures or climate zones would be of interest. Studying PV adoption at locations where subsidies do not drive their diffusion and further disentangling of the peer effect may be rewarding. For example, employing data on regional differences in Internet search engine usage may help to find out if the identified effect is driven by communication from face to face or, instead, seeing a PV system in operation is sufficient. Our models could also be used to forecast PV adoption at the local level.

In Chapter 6 of this thesis, we turn to barriers to renewable energy adoption. We make use of the well-studied logistic shape of technology diffusion. The common diffusion path allows us to test whether the adoption rate of renewable energy plants differs between German NUTS-3 regions in which a successful referendum against a single plant was organized and the remaining regions. We exploit the fact that referenda are mainly organized on the municipal district level against a single plant or building area. Our analysis reveals that the adoption rate (i.e., the first difference in the diffusion level) is indeed lower in NUTS-3 regions where a referendum took place. This finding holds true for wind power and large biomass plants, which are both industrial. In contrast, we do not find the same for PV installations which are mainly private, household installations. We interpret this as evidence that potential investors in wind power and large biomass plants not only avoid the municipal district where a referendum against the specific technology was organized but stay away from the municipal district's NUTS-3 region.

Our results are good news to those who protest against renewable energy plants. Referenda have their intended effect on renewable energy adoption in Germany. This finding is relevant to the discussion on the effect of democratic political in-

stitutions on technology diffusion. According to the literature there is a positive link (Acemoglu et al., 2001; Comin and Hobijn, 2004). If, however, the local public participates in the decision whether, e.g., a wind park, or more general infrastructure projects should be built, their adoption may be slowed down. Still, potential investors in wind power or large biomass plants may be able to convince the local public of the benefits of their plans, which may prohibit resistance. For instance, in the municipal district Sauerlach (NUTS-3 region Landkreis München, Bavaria), the local public was involved early on when a biomass plant was built. In Sauerlach no organized resistance occurred (Bernstein and Knoll, 2011).

In recent years we have observed more and more referenda against renewable energy plants (see Datenbank Bürgerbegehren (2014)). It would be interesting to study whether our findings hold true when we can employ updated data sets on renewable energy adoption in Germany and in other countries. To investigate why local resistance did not occur in the cases in which wind parks and large biomass plants were actually built is also promising. Another topic for future research is the persistence of the adoption barrier from a referendum.

In Chapter 7, we turn to implications from renewable energy adoption. We estimate the effect of the diffusion of PV systems on the fraction of votes obtained by Germany's Green Party in federal elections. We take first differences and instrument adoption rates by lagged diffusion levels. We predict the diffusion levels with a logistic diffusion curve. The existing rationales for non-linearities in diffusion, and ubiquity of logistic curves ensure that our predicted instrument is orthogonal to variables that directly affect voting patterns. We find that the diffusion of domestic PV systems caused a quarter of the increment in green votes between 1998 and 2009. In contrast, we find no such effects from the diffusion of industrial PV systems and eolic systems. This contrast confirms the importance of voters' direct involvement with the adoption and/or operation of the technology for this to affect their voting patterns. We confirm our findings with survey data from the German Socio-Economic Panel.

Certainly, the mechanism by which adoption of PV systems leads to vote for the Green Party needs more scrutiny. Whether we see similar effects from the diffusion of PV systems in other countries and investigating political consequences of the diffusion from other technologies would be of interest.

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A. Appendix to Chapter 2 – Models of Technology Diffusion

In the following, we derive the mixed information source epidemic model. The mixed information source model can be written as

$$\Delta y(t) = [\alpha + \beta y(t)] \times [N - y(t)]. \tag{A.1}$$

Letting $t \to 0$, the differential equation is

$$y' = [\alpha + \beta y] \times [N - y],$$

which is a Riccati differential equation (Merziger et al., 2001, p. 157):

$$y' + (\alpha - \beta N)y = (\alpha N) + (-\beta)\, y^2. \tag{A.2}$$

To solve the differential given above, one needs a particular solution v. One can see that $v = N$ is a particular solution of (A.2). By applying the substitution

$$y = v + \frac{1}{u} \tag{A.3}$$

we obtain the first order linear differential equation

$$u' + (-2N\beta - \alpha + \beta N)u = \beta N. \tag{A.4}$$

We may then solve (A.4) by finding a solution of the homogeneous and inhomogeneous differential equation separately. The solution of the homogeneous differential equation is a general solution u_H, whereas the solution of the inhomogeneous differential equation is a particular solution u_P. The general solution of the homogeneous differential equation is then

$$u = u_H + u_P.$$

Homogeneous Solution. We find a solution to be

$$u_H = C \times \exp\left[(\alpha + \beta N)t\right], \quad C \in \mathbb{R}. \tag{A.5}$$

We solve for the constant C later in order to have $y(0) = y_0$.

Inhomogeneous Solution. It is easily seen, that

$$u_P = \frac{-\beta}{\alpha + \beta N} \tag{A.6}$$

is a particular solution to the inhomogeneous equation. We therefore obtain:

$$\begin{aligned} y &= N + \frac{1}{u_H + u_P} \\ &= N + \frac{1}{C \times \exp\left[(\alpha + \beta N)t\right] + \frac{-\beta}{\alpha+\beta N}}. \end{aligned} \tag{A.7}$$

To solve for C, we set $y(0) = y_0$. This yields:

$$C = \frac{1}{y_0 - N} + \frac{\beta}{\alpha + \beta N}. \tag{A.8}$$

Replacing (A.8) into (A.7) results in:

$$y(t) = N + \left[\left(\frac{1}{y_0 - N} + \frac{\beta}{\alpha + \beta N}\right) \times \exp[(\alpha + \beta N)t] - \frac{\beta}{\alpha + \beta N}\right]^{-1},$$

which is equivalent to

$$
\begin{aligned}
y(t) &= N + \frac{1}{\left(\frac{\alpha+\beta N+\beta y_0-\beta N}{(y_0-N)\times(\alpha+\beta N)}\right) \times \exp[(\alpha+\beta N)t] - \frac{\beta}{\alpha+\beta N}} \\
&= N + \frac{1}{\frac{(\alpha+\beta y_0)\exp[(\alpha+\beta)t]-\beta y_0+\beta N}{(y_0-N)(\alpha+\beta N)}} \\
&= N + \frac{(y_0-N)(\alpha+\beta N)}{(\alpha+\beta y_0)\exp[(\alpha+\beta N)t]-\beta y_0+\beta N} \\
&= \frac{N[(\alpha+\beta y_0)\exp[(\alpha+\beta N)t]-\beta y_0+\beta N]+(y_0-N)(\alpha+\beta N)}{(\alpha+\beta y_0)\exp[(\alpha+\beta N)t]-\beta y_0+\beta N} \\
&= \frac{N+\frac{N(\beta N-\beta y_0)+(y_0-N)(\alpha+\beta N)}{\alpha N+\beta y_0}\exp[-(\alpha+\beta N)t]}{1-\frac{\beta(y_0-N)}{\alpha+\beta y_0}\exp[-(\alpha+\beta N)t]} \\
&= \frac{N-\frac{\alpha(N-y_0)}{\alpha+\beta y_0}\exp[-(\alpha+\beta N)t]}{1+\frac{\beta(N-y0)}{\alpha+\beta y_0}\exp[-(\alpha+\beta N)t]}. \qquad \text{(A.9)}
\end{aligned}
$$

This is equivalent to the solution given by Mahajan and Peterson (1985):

$$
y(t) = \frac{N-\frac{\alpha(N-y_0)}{\alpha+\beta y_0}\exp[-(\alpha+\beta N)t]}{1+\frac{\beta(N-y_0)}{\alpha+\beta y_0}\exp[-(\alpha+\beta N)t]}.
$$

B. Appendix to Chapter 3 – Institutional Context, Aggregate Trends and Regional Differences

B.1. Capacity-adjusted measures

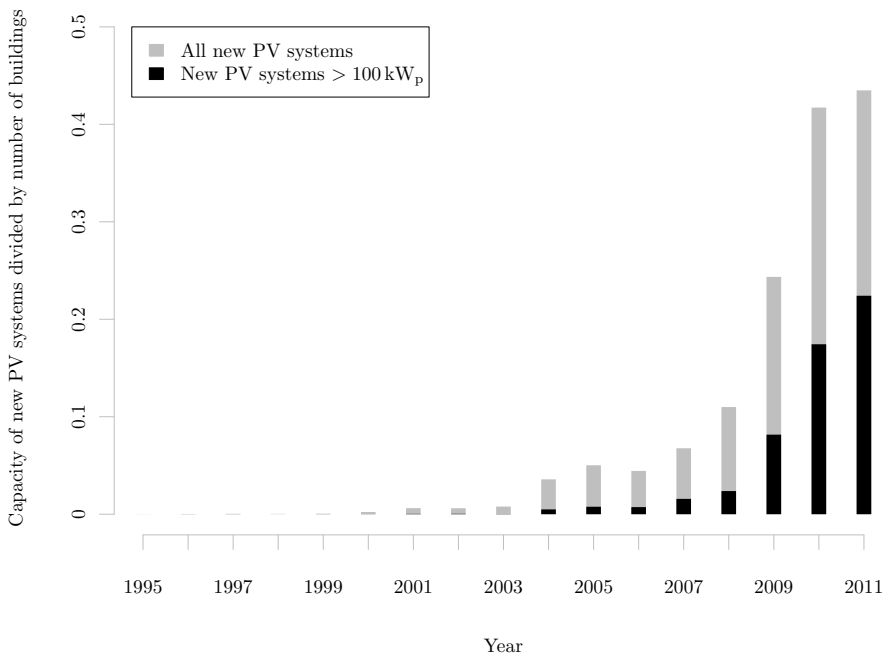

Figure B.1.: Adoption of PV systems in Germany per year (capacity-adjusted measures).

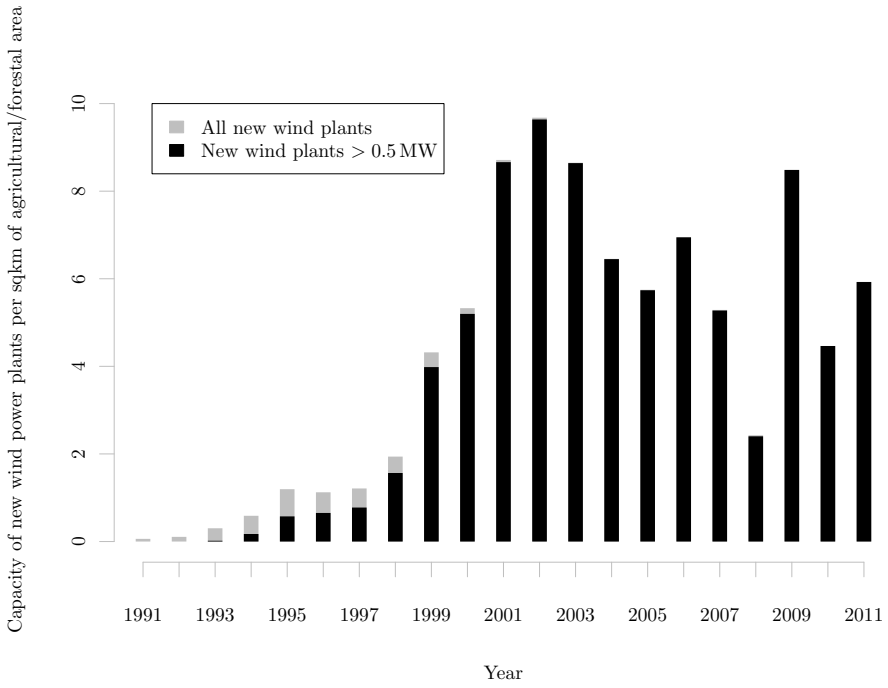

Figure B.2.: Adoption of wind power plants in Germany per year (capacity-adjusted measures).

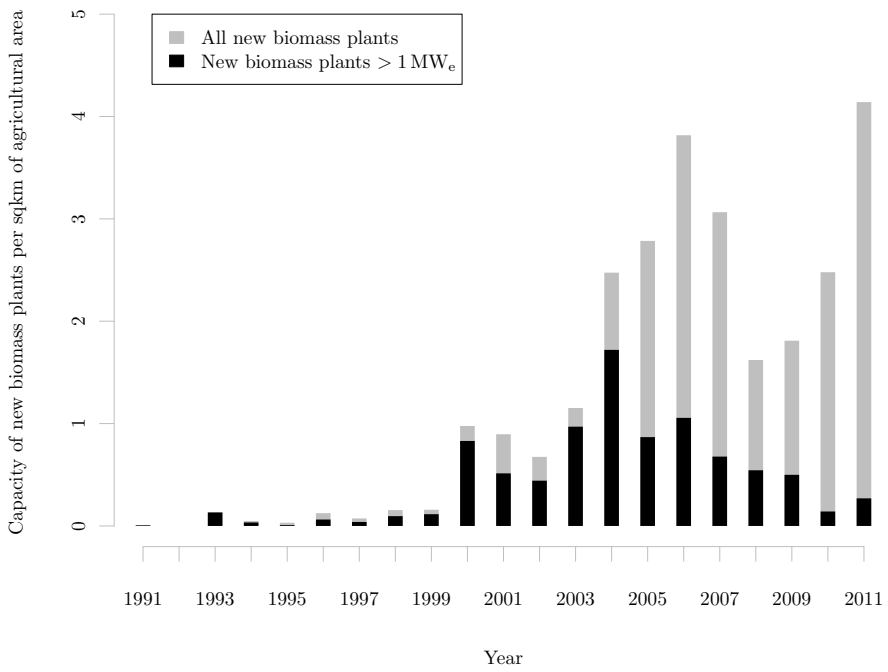

Figure B.3.: Adoption of biomass plants in Germany per year (capacity-adjusted measures).

B.2. Maps with counts

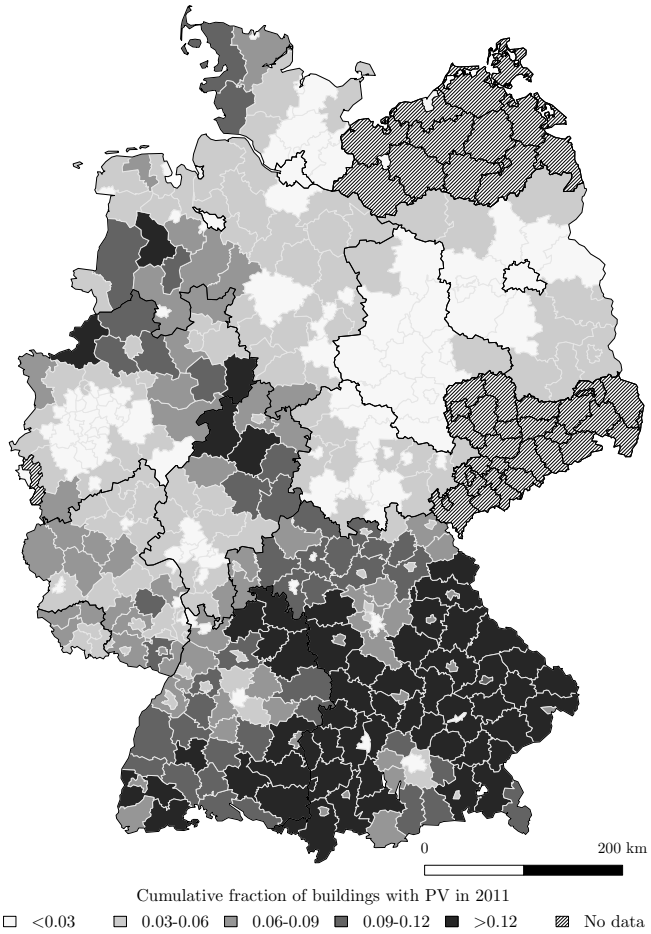

Figure B.4.: Fraction of buildings with PV system at NUTS-3 level in 2011.

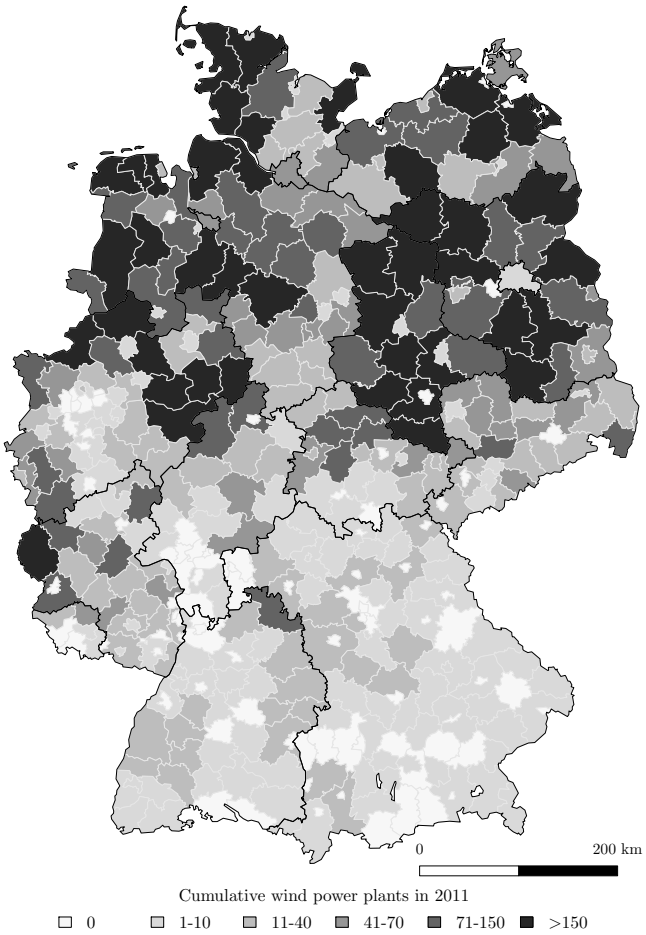

Figure B.5.: Counts of wind power plants at NUTS-3 level in 2011.

C. Appendix to Chapter 4 – Does Localized Imitation Drive Adoption

C.1. The profitability of PV in Germany since 2000

In order to find out whether PV systems have been an interesting investment in Germany since the year 2000, we conduct calculations on their net present value (NPV). In a rather conservative scenario, we assume a weighted average cost of capital w of 5.0%, yearly operating costs b of 1%, an operating time of $T + 1 = 20$ years and a yearly decrease in revenue v of 0.5%. Furthermore, f_{year} specifies the rate of the feed-in tariff with respect to the installation year, *cap* the assumed system capacity of $4,000\,W_p$ and $full$ the full load hours. In addition, I_{year} denotes the year specific investment costs, including value added tax (VAT). Finally, we calculate the net present value as

$$NPV_{\text{year,cap}} = \sum_{t=0}^{T=19} \left(\frac{f_{\text{year}} \times cap \times full \times (1-v)^t}{(1+w)^t} \right) - \left(I_{\text{year}} \times cap + \sum_{t=0}^{T=19} \left(\frac{I_{\text{year}} \times cap \times b}{(1+w)^t} \right) \right). \tag{C.1}$$

I_{year} was available for the years 2006 through 2009 from BSW-Solar (2012). For this period, the reliability of I_{year} was confirmed by data from pvX (2012). Data on I_{year} from 2000 through 2005 comes from Janzing (2010). When assuming $full = 900\,h/a$, which is commonly seen as the average for Germany (Klaus et al., 2010), we can

only find a positive net present value for the fourth quarter in 2009 (see Table C.1). However, in the southern part of Germany, $full = 1000\,h/a$ is realistic. There, we find a slightly positive NPV for quarter 4 in 2006, 2007, 2008 and 2009. Further, if a reduced weighted average cost of capital is assumed (e.g., 3%), which makes sense from 2000 through 2003 when the 100,000 roofs program offered subsidized interest rates, we find a slightly positive NPV for $full = 1000\,h/a$ in the year 2002.

Table C.1.: NPV according to full load hours.

			NPV according to average full load hours			
t	I_{year}	I_{year} without VAT	850 h/a	900 h/a	1000 h/a	1100 h/a
2000	8.00 EUR/W_p	6.90 EUR/W_p	-14,551 EUR	-13,277 EUR	-10,729 EUR	-8,182 EUR
2001	6.96 EUR/W_p	6.00 EUR/W_p	-9,828 EUR	-8,554 EUR	-6,007 EUR	-3,459 EUR
2002	6.03 EUR/W_p	5.20 EUR/W_p	-6,708 EUR	-5,498 EUR	-3,077 EUR	-656 EUR
2003	6.44 EUR/W_p	5.55 EUR/W_p	-9,572 EUR	-8,422 EUR	-6,122 EUR	-3,822 EUR
2004	6.73 EUR/W_p	5.80 EUR/W_p	-5,878 EUR	-4,434 EUR	-1,545 EUR	1,344 EUR
2005	6.21 EUR/W_p	5.35 EUR/W_p	-4,788 EUR	-3,418 EUR	-679 EUR	2,061 EUR
Q4 2006	5.69 EUR/W_p	4.91 EUR/W_p	-3,583 EUR	-2,279 EUR	328 EUR	2,935 EUR
Q4 2007	5.31 EUR/W_p	4.46 EUR/W_p	-2,945 EUR	-1,707 EUR	70 EUR	3,246 EUR
Q4 2008	5.19 EUR/W_p	4.36 EUR/W_p	-3,465 EUR	-2,288 EUR	65 EUR	2,417 EUR
Q4 2009	3.87 EUR/W_p	3.26 EUR/W_p	878 EUR	1,960 EUR	4,125 EUR	6,290 EUR

As most PV systems were installed at the end of a year, we only show the last quarter if quarterly data is available. VAT changed from 16% to 19% on 1.1.2007.

C.2. Geocoding

The data on PV installations used in Chapter 4 was downloaded in September 2010 which ensures that most installations having received their remuneration for 2009 are included as the annual statement of feed-in subsidies is completed by July/August. The files include a total of 572,379 PV installations until the end of the year 2009. According to our data less than 0.5% of the PV systems are decomissioned during our period of analysis.[77] We therefore neglect this very small share. In order to perform our analysis, we have to geocode the data. The accuracy of the geocoding is shown in Table C.2. For nearly 88% of the PV systems we reach an address or street level accuracy.

Table C.2.: Geocoding accuracy of PV data.

Accuracy	Amount	Fraction
Address level	262,090	45.79%
Street level	239,845	41.90%
Town (city, village) level	40,048	7.00%
Ambiguous	13,365	2.33%
Post code level	10827	1.89%
No result / ambiguous	4,656	0.81%
No result	1,157	0.20%
Premise (building name, property name, shopping center, etc.) level	356	0.06%
Unknown location	31	0.01%
Region (state, province, prefecture, etc.) level accuracy	3	0.00%
Country level accuracy	1	0.00%
Sum	572,379	100 %

[77] As PV systems are designed for a life span of more than 20 years such a small fraction makes sense.

When we test if the geocoded data results in positions within Germany, we have to drop some of the observations and finally end up with 552, 259 PV systems for our analysis. The location test is performed with a SHP-file containing information on 2006's NUTS-3 level on a map scale of 1:3 million obtained from Eurostat (2010).

C.3. Spatial aggregation

In the following, we outline how we handle the NUTS-3 data, the CLC data and the 1-km raster data with inner circles. For the case of NUTS-3 and CLC data, our approach is illustrated in Figure C.1: the intersection area between the circle of the spatial aggregation function and the spatial shapes A, B and C – e.g., representing three administrative regions – is taken to weight the values.

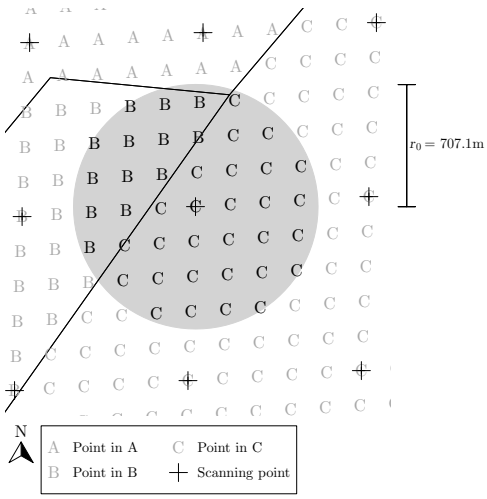

Figure C.1.: Spatial aggregation of point data defined for arbitrary areas.

To optimize the time needed for computation, we do not use the spatial shapes directly to calculate the weights. Instead, we create a 200 m scanning raster all over Germany. Then, we match the values of the control variables to each point of the scanning raster according to their location related to the spatial shapes. Finally, we use the intersection area between the inner circle and the relevant points of the 200 m scanning raster to calculate the weighted averages. In Figure C.1 these intersecting points are black whereas the others are gray.

The 1-km raster data is converted to the center points of the polygons. Then, the mean of the values associated with all points being covered by a certain inner circle

is calculated. In general, applying our modeling approach enables us to reach more detailed results in comparison to ordinary spatial models with a weights matrix since disaggregated point data can be analyzed on an arbitrary level of geographical aggregation and the usual boundary problems are avoided.

C.4. Correcting $N_{i,t}$ for resampling

y_t is the amount of PV installations within Germany in year t and S_t is the correcting factor denoting the year specific sum over the number of PV systems of the scanning points divided by the actual amount of installations in year t: thus $S_t = \sum_{\forall i} (y_{i,t}/y_t)$. We denote the number of points i within region k with $POINTS_k$ and the number of points within k which have a $y_{i,2009}$ of 0 with $NOPV_k$. Furthermore, we multiply $(BUILD_{k_i,t} - NOPV_{k_i}) / (POINTS_{k_i} - NOPV_{k_i})$ by S_t if our $y_{i,t} < (BUILD_{k_i,t} - NOPV_{k_i}) \times S_t / (POINTS_{k_i} - NOPV_{k_i})$. Finally, we determine the population by:

$$N_{i,t} = \begin{cases} 1 & \text{if } y_{i,2009} = 0, \\ \frac{(BUILD_{k_i,t} - NOPV_{k_i}) \times S_t}{POINTS_{k_i} - NOPV_{k_i}} & \text{if } y_{i,t} < \frac{(BUILD_{k_i,t} - NOPV_{k_i}) \times S_t}{POINTS_{k_i} - NOPV_{k_i}}, \\ y_{i,t} + 1 & \text{else.} \end{cases} \tag{C.2}$$

C.5. Estimation procedure

The estimation is parameterized as NB-2 since this suites the data best. NB-2 means that the model has a variance $\mathbb{V} = \mu + \theta^{-1}\mu^2$, where μ is the mean and $\theta^{-1} \in \mathbb{R}^+$ is the NB-2 dispersion parameter, also known as alpha. We use the former notation to avoid confusion with the coefficient of internal influence. However, as an identity link does not inherently exclude negative predictions (which are undefined for the negative binomial distribution), we have to constrain the estimation procedure to non-negative coefficients. Therefore, we allow the iteratively re-weighted least-squares algorithm of the GLM procedure to update only one coefficient estimate at a time. The estimation algorithm consists of an iteratively re-weighted least squares (IRLS) loop, which ends when the model deviance improvement is less than 1E-6, and a surrounding Nelder-Mead Simplex Algorithm (Nelder and Mead, 1965) for the estimation of θ^{-1}, which stops when the absolute difference between

the worst and the best values of the current simplex (measured in log-likelihood) is below 1E-4. When estimating the epidemic diffusion model with NUTS-3 controls for Bavaria, Saarland and Sachsen, we had to end the IRLS algorithm after 200 iterations, because it did not converge within reasonable time. For performance reasons, we implemented the modified negative binomial estimation program in C++ with openMP multi-processor support.

Although the left-hand side of our observations is often zero, using a zero-inflated negative binomial model is not necessary. We can explain the vast part of zero appendices with the fact that none of the distance bands shows any installations (92.9%).

C.6. Descriptive statistics and correlation matrix

Table C.3.: Descriptive statistics (step: 1 km, r_0: 0.7 km).

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Missing Values
$\Delta y_{i,t}$	0	0	0	0.1437	0	680	0
$y_{i,t}$	0	0	0	0.3981	0	789	0
$y_{i,1,t}$	0	0	0	0.3973	0	789	0
$y_{i,2,t}$	0	0	0	0.3994	0	789	0
$y_{i,3,t}$	0	0	0	0.3977	0	792	0
$y_{i,4,t}$	0	0	0	0.3978	0	209	0
$y_{i,5,t}$	0	0	0	0.3983	0	790	0
$y_{i,6,t}$	0	0	0	0.3989	0	789	0
$y_{i,7,t}$	0	0	0	0.397	0	794	0
$y_{i,8,t}$	0	0	0	0.3999	0	794	0
$y_{i,9,t}$	0	0	0	0.3981	0	789	0
$y_{i,10,t}$	0	0	0	0.3986	0	792	0
$INC_{i,t}$	633.4	1135	1252	1267	1409	2443	0
GR_i	928	989	1016	1031	1067	1259	0
$PD_{i,t}$	38.15	90.5	128	232.2	209.7	4275	0
$HOUS_{i,t}$	33.9	84.4	88.7	87.09	92.1	97.5	0
$URBAN_i$	0	0	0	0.07757	0.05405	1	0
$FIELD_i$	0	0.3243	0.6829	0.6087	0.9268	1	0
$N_{i,t}$	1	1	1	73.41	118.9	909.9	0
$y_{i,t}(N_{i,t} - y_{i,t})$	0	0	0	76.75	0	73660	0
$y_{i,1,t}(N_{i,t} - y_{i,t})$	0	0	0	64.65	0	54950	0
$y_{i,2,t}(N_{i,t} - y_{i,t})$	0	0	0	58.98	0	39860	0
$y_{i,3,t}(N_{i,t} - y_{i,t})$	0	0	0	55.28	0	36060	0
$y_{i,4,t}(N_{i,t} - y_{i,t})$	0	0	0	53.29	0	44160	0
$y_{i,5,t}(N_{i,t} - y_{i,t})$	0	0	0	52.13	0	47630	0
$y_{i,6,t}(N_{i,t} - y_{i,t})$	0	0	0	51.73	0	114800	0
$y_{i,7,t}(N_{i,t} - y_{i,t})$	0	0	0	50.55	0	38670	0
$y_{i,8,t}(N_{i,t} - y_{i,t})$	0	0	0	50.75	0	116000	0
$y_{i,9,t}(N_{i,t} - y_{i,t})$	0	0	0	49.89	0	32950	0
$y_{i,10,t}(N_{i,t} - y_{i,t})$	0	0	0	49.75	0	115200	0
$GR_i(N_{i,t} - y_{i,t})$	929	1009	1075	75060	122200	881600	0
$PD_{i,t}(N_{i,t} - y_{i,t})$	38.15	105.6	224.5	45250	14740	3174000	0
$INC_{i,t}(N_{i,t} - y_{i,t})$	633.4	1184	1440	98490	152800	1626000	0
$HOUS_{i,t}(N_{i,t} - y_{i,t})$	33.9	86.9	92.7	6018	10650	76740	0
$URBAN_i(N_{i,t} - y_{i,t})$	0	0	0	18.12	0.1707	908.9	0
$FIELD_i(N_{i,t} - y_{i,t})$	0	0.4634	1	43.15	72.01	909.9	0

Table C.4.: Descriptive statistics (step: 4 km, r_0: 2.8 km).

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Missing Values
$\Delta PV_{i,t}$	0	0	0	2.305	2	686	0
$y_{i,t}$	0	0	0	6.384	4	808	0
$y_{i,1,t}$	0	0	0	6.357	4	367	0
$y_{i,2,t}$	0	0	0	6.402	4	813	0
$y_{i,3,t}$	0	0	0	6.348	4	353	0
$y_{i,4,t}$	0	0	0	6.366	5	832	0
$y_{i,5,t}$	0	0	0	6.391	5	835	0
$y_{i,6,t}$	0	0	0	6.419	5	817	0
$y_{i,7,t}$	0	0	0	6.311	5	800	0
$y_{i,8,t}$	0	0	0	6.397	5	836	0
$y_{i,9,t}$	0	0	0	6.344	5	803	0
$y_{i,10,t}$	0	0	0	6.372	5	333	0
$N_{i,t}$	1	590.5	809.4	1158	1224	17750	0
$y_{i,t}(N_{i,t} - y_{i,t})$	0	0	0	11780	4149	1919000	0
$y_{i,1,t}(N_{i,t} - y_{i,t})$	0	0	0	11610	4387	2041000	0
$y_{i,2,t}(N_{i,t} - y_{i,t})$	0	0	0	11510	4531	2073000	0
$y_{i,3,t}(N_{i,t} - y_{i,t})$	0	0	0	11310	4632	1669000	0
$y_{i,4,t}(N_{i,t} - y_{i,t})$	0	0	0	11320	4766	2267000	0
$y_{i,5,t}(N_{i,t} - y_{i,t})$	0	0	0	11200	4816	1571000	0
$y_{i,6,t}(N_{i,t} - y_{i,t})$	0	0	0	11160	4928	2461000	0
$y_{i,7,t}(N_{i,t} - y_{i,t})$	0	0	0	10940	4860	1864000	0
$y_{i,8,t}(N_{i,t} - y_{i,t})$	0	0	0	11060	5002	2017000	0
$y_{i,9,t}(N_{i,t} - y_{i,t})$	0	0	0	10860	5009	1258000	0
$y_{i,10,t}(N_{i,t} - y_{i,t})$	0	0	0	10870	5120	1640000	0

Table C.5.: Descriptive statistics (step: 10 km, r_0: 7 km).

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Missing Values
$\Delta PV_{i,t}$	0	0	1	14.16	14	707	0
$y_{i,t}$	0	0	3	39.22	30	1240	0
$y_{i,1,t}$	0	0	3	39.08	32	1101	0
$y_{i,2,t}$	0	0	3	39.15	32	1086	0
$y_{i,3,t}$	0	0	3	39.43	33	1035	0
$y_{i,4,t}$	0	0	3	39.72	34	1093	0
$y_{i,5,t}$	0	0	3	39.34	34	1137	0
$y_{i,6,t}$	0	0	3	39.98	35	1014	0
$y_{i,7,t}$	0	0	3	39.32	34	996	0
$y_{i,8,t}$	0	0	3	39.68	35	929	0
$y_{i,9,t}$	0	0	3	39.64	35	994	0
$y_{i,10,t}$	0	0	4	39.85	35	904	0
$N_{i,t}$	936	3355	4627	6802	7238	130100	0
$y_{i,t}(N_{i,t} - y_{i,t})$	0	0	12490	401500	181400	81820000	0
$y_{i,1,t}(N_{i,t} - y_{i,t})$	0	0	14300	388000	190700	71720000	0
$y_{i,2,t}(N_{i,t} - y_{i,t})$	0	0	14470	373600	194100	61880000	0
$y_{i,3,t}(N_{i,t} - y_{i,t})$	0	0	15550	372000	203000	53340000	0
$y_{i,4,t}(N_{i,t} - y_{i,t})$	0	0	16340	375300	202200	48030000	0
$y_{i,5,t}(N_{i,t} - y_{i,t})$	0	0	17000	369300	205100	48810000	0
$y_{i,6,t}(N_{i,t} - y_{i,t})$	0	0	17460	366800	210300	40600000	0
$y_{i,7,t}(N_{i,t} - y_{i,t})$	0	0	17430	361900	206100	52610000	0
$y_{i,8,t}(N_{i,t} - y_{i,t})$	0	0	17640	359700	210800	37340000	0
$y_{i,9,t}(N_{i,t} - y_{i,t})$	0	0	17980	360900	214000	46130000	0
$y_{i,10,t}(N_{i,t} - y_{i,t})$	0	0	18580	359300	213200	45820000	0

Table C.6.: Descriptive statistics (step: 20 km, r_0: 14 km).

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Missing Values
$\Delta PV_{i,t}$	0	0	7	56.11	60	1064	0
$y_{i,t}$	0	1	12	156.2	127	3630	0
$y_{i,1,t}$	0	2	13	156.6	136	2794	0
$y_{i,2,t}$	0	2	14	154.9	137	3235	0
$y_{i,3,t}$	0	2	15	155.6	138	3187	0
$y_{i,4,t}$	0	2	14	154.1	138	3379	0
$y_{i,5,t}$	0	2	15	153.9	141	2690	0
$y_{i,6,t}$	0	2	16	155.7	143	2654	0
$y_{i,7,t}$	0	2	16	154.7	141	2513	0
$y_{i,8,t}$	0	2	16	155.1	142	2739	0
$y_{i,9,t}$	0	2	16	154.9	143	2453	0
$y_{i,10,t}$	0	3	16	155.4	144	2622	0
$N_{i,t}$	3289	10650	15460	22070	24290	202800	0
$y_{i,t}(N_{i,t} - y_{i,t})$	0	16150	207100	4909000	2553000	457100000	0
$y_{i,1,t}(N_{i,t} - y_{i,t})$	0	21840	225100	4707000	2665000	345000000	0
$y_{i,2,t}(N_{i,t} - y_{i,t})$	0	27020	253000	4561000	2697000	406600000	0
$y_{i,3,t}(N_{i,t} - y_{i,t})$	0	28490	255700	4448000	2757000	311200000	0
$y_{i,4,t}(N_{i,t} - y_{i,t})$	0	26600	240700	4343000	2677000	351000000	0
$y_{i,5,t}(N_{i,t} - y_{i,t})$	0	32030	253900	4275000	2715000	361100000	0
$y_{i,6,t}(N_{i,t} - y_{i,t})$	0	32290	274100	4241000	2765000	344600000	0
$y_{i,7,t}(N_{i,t} - y_{i,t})$	0	35910	264900	4209000	2725000	337400000	0
$y_{i,8,t}(N_{i,t} - y_{i,t})$	0	36480	271200	4230000	2814000	363300000	0
$y_{i,9,t}(N_{i,t} - y_{i,t})$	0	37700	276200	4156000	2821000	284600000	0
$y_{i,10,t}(N_{i,t} - y_{i,t})$	0	37080	271600	4161000	2809000	319000000	0

Table C.7.: Correlation (step: 1 km, r_0: 0.7 km).

	X	$y_{i,t}$	$y_{i,1,t}$	$y_{i,2,t}$	$y_{i,3,t}$	$y_{i,4,t}$	$y_{i,5,t}$	$y_{i,6,t}$	$y_{i,7,t}$	$y_{i,8,t}$	$y_{i,9,t}$	$y_{i,10,t}$	GR_i	$POP_{i,t}$	$INC_{i,t}$	$HOUS_{i,t}$	$URBAN_i$	$FIELD_i$
X	1.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
$y_{i,t}$	0.35	1.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
$y_{i,1,t}$	0.35	0.62	1.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
$y_{i,2,t}$	0.36	0.55	0.65	1.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–
$y_{i,3,t}$	0.36	0.52	0.60	0.68	1.00	–	–	–	–	–	–	–	–	–	–	–	–	–
$y_{i,4,t}$	0.35	0.49	0.55	0.61	0.67	1.00	–	–	–	–	–	–	–	–	–	–	–	–
$y_{i,5,t}$	0.35	0.47	0.52	0.58	0.61	0.65	1.00	–	–	–	–	–	–	–	–	–	–	–
$y_{i,6,t}$	0.34	0.46	0.50	0.54	0.57	0.59	0.63	1.00	–	–	–	–	–	–	–	–	–	–
$y_{i,7,t}$	0.36	0.48	0.51	0.55	0.57	0.58	0.61	0.62	1.00	–	–	–	–	–	–	–	–	–
$y_{i,8,t}$	0.35	0.46	0.50	0.53	0.55	0.56	0.57	0.59	0.65	1.00	–	–	–	–	–	–	–	–
$y_{i,9,t}$	0.36	0.48	0.52	0.54	0.55	0.55	0.57	0.57	0.62	0.63	1.00	–	–	–	–	–	–	–
$y_{i,10,t}$	0.33	0.44	0.47	0.49	0.50	0.50	0.51	0.52	0.56	0.56	0.61	1.00	–	–	–	–	–	–
GR_i	1.00	0.36	0.36	0.36	0.36	0.36	0.36	0.35	0.36	0.36	0.36	0.34	1.00	–	–	–	–	–
$POP_{i,t}$	0.73	0.32	0.33	0.34	0.35	0.35	0.35	0.34	0.35	0.35	0.36	0.33	0.72	1.00	–	–	–	–
$INC_{i,t}$	0.98	0.41	0.40	0.41	0.41	0.40	0.40	0.39	0.41	0.40	0.41	0.38	0.98	0.73	1.00	–	–	–
$HOUS_{i,t}$	0.98	0.34	0.33	0.34	0.33	0.33	0.33	0.32	0.33	0.33	0.33	0.31	0.98	0.59	0.96	1.00	–	–
$URBAN_i$	0.73	0.38	0.36	0.35	0.35	0.34	0.33	0.32	0.33	0.33	0.33	0.30	0.72	0.80	0.72	0.64	1.00	–
$FIELD_i$	0.76	0.19	0.19	0.21	0.21	0.21	0.21	0.20	0.21	0.21	0.21	0.20	0.76	0.33	0.74	0.80	0.20	1.00

All variables are multiplied by $X = (N_{i,t} - y_{i,t})$, except X in the second row, respectively second column

C.7. Results on NUTS-1 level

In order to check the robustness of our results, we also estimate the epidemic diffusion model including $\alpha_{\text{NUTS-3}}$ for the remaining NUTS-1 regions, see Table C.8. Baden-Württemberg and Nordrhein-Westphalia are missing since our estimation algorithm does not converge for these within reasonable time.

The estimations shown in Table C.8 confirm that including $\alpha_{\text{NUTS-3}}$ only slightly changes the results and nearly all estimations indicate that β_q is decreasing (and then roughly staying constant) with distance.[78] The results without $\alpha_{\text{NUTS-3}}$ are not shown to maintain clarity.

[78] Only in the case of Brandenburg β_1 is estimated to be larger than β_0. This result may be caused by installations close to Brandenburg's border but situated in another NUTS-1 region, e.g., Berlin. For the regressions on the NUTS-1 level, we include all scanning points located within the NUTS-1 region of study no matter if their inner circle or distance bands cover areas outside of the specific NUTS-1 region.

Table C.8.: Estimations (step: 1 km, r_0: 0.7 km) for the remaining NUTS-1 regions.

	Berlin	Branden-burg	Bremen	Hamburg	Mecklenburg-Vorpommern	Rhineland-Palatinate	Saarland	Sachsen	Sachsen-Anhalt	Lower Saxony	Schleswig-Holstein	Thüringen
Specification	Me	Mf	Mg	Mh	Mi	Mj	Mk	Ml	Mm	Mn	Mo	Mp
Step width	1 km	1 km	1 km	1 km	1 km	1 km	1 km	1 km	1 km	1 km	1 km	1 km
α_0	4.09E-05***	1.43E-61	6.61E-11†	2.73E-05***	0	8.47E-07***	6.40E-13***	3.79E-06***	6.06E-07***	1.40E-06†	5.59E-06**	0
	(1.23E-06)	(3.15E-61)	(4.16E-11)	(6.37E-07)	(2.88E-09)	(7.72E-08)	(1.22E-13)	(6.63E-07)	(3.99E-08)	(9.81E-07)	(2.10E-06)	(6.10E-07)
β_0	7.08E-05***	7.87E-05***	3.40E-05***	2.97E-05***	3.27E-04***	8.09E-04**	4.71E-04*	1.74E-04***	1.63E-04***	6.09E-04***	5.49E-04***	3.00E-04**
	(1.03E-05)	(1.48E-05)	(4.48E-06)	(2.22E-06)	(6.65E-05)	(3.13E-04)	(2.03E-04)	(3.10E-05)	(4.24E-05)	(8.16E-05)	(1.46E-04)	(1.15E-04)
β_1	3.34E-05***	1.08E-04***	2.12E-05***	1.77E-05***	2.71E-04***	8.62E-05*	6.98E-05†	8.22E-05***	1.23E-04***	2.00E-04***	1.99E-04**	1.30E-04***
	(7.09E-06)	(2.02E-05)	(4.79E-06)	(2.05E-06)	(5.02E-05)	(5.03E-05)	(4.69E-05)	(1.93E-05)	(2.03E-05)	(4.88E-05)	(7.16E-05)	(3.17E-05)
β_2	1.37E-05**	5.52E-05***	5.55E-06†	5.99E-06**	1.48E-04***	0	2.58E-06	6.36E-05**	6.72E-05***	1.20E-04**	5.52E-05†	6.42E-05**
	(5.08E-06)	(1.56E-05)	(4.14E-06)	(2.00E-06)	(3.25E-05)	(7.87E-06)	(1.07E-05)	(2.15E-05)	(1.32E-05)	(3.95E-05)	(3.75E-05)	(2.16E-05)
β_3	1.08E-05**	1.38E-05‡	1.86E-05***	3.48E-06*	7.07E-05**	0	0	3.60E-05**	5.09E-05***	3.38E-05†	5.51E-05†	1.17E-05‡
	(4.31E-06)	(1.18E-05)	(5.72E-06)	(1.81E-06)	(2.55E-05)	(1.25E-05)	(9.48E-12)	(1.39E-05)	(1.22E-05)	(2.31E-05)	(4.30E-05)	(1.14E-05)
β_4	8.90E-06*	7.54E-07	2.02E-06	2.78E-06†	7.44E-05**	0	9.95E-06	1.82E-06	4.91E-05**	2.25E-05‡	4.71E-05†	0
	(4.15E-06)	(3.31E-06)	(3.35E-06)	(1.98E-06)	(2.70E-05)	(8.72E-06)	(1.84E-05)	(5.93E-06)	(1.83E-05)	(2.50E-05)	(3.02E-05)	(1.10E-07)
β_5	1.01E-06	3.21E-05*	0	7.15E-06***	8.57E-05**	0	2.22E-11	4.21E-05**	2.06E-05*	3.04E-05‡	1.66E-05	0
	(4.56E-06)	(1.57E-05)	(3.02E-06)	(1.99E-06)	(3.33E-05)	(8.34E-06)	(1.65E-10)	(1.77E-05)	(1.10E-05)	(2.54E-05)	(2.72E-05)	(3.76E-08)
β_6	0	4.07E-05*	0	4.99E-06**	6.01E-05**	0	0	6.44E-05**	2.90E-05**	2.86E-06	3.64E-05‡	7.29E-06
	(4.52E-06)	(2.00E-05)	(2.90E-06)	(2.00E-06)	(2.30E-05)	(9.28E-06)	(9.65E-12)	(2.22E-05)	(1.11E-05)	(1.51E-05)	(3.39E-05)	(1.61E-05)
β_7	9.44E-06**	0	0	3.25E-06*	7.08E-05**	0	0	1.39E-05‡	1.88E-05*	6.98E-06	3.25E-05‡	2.68E-05†
	(3.82E-06)	(1.27E-05)	(3.08E-06)	(1.74E-06)	(2.41E-05)	(5.41E-06)	(1.12E-11)	(1.13E-05)	(9.45E-06)	(1.61E-05)	(2.99E-05)	(1.84E-05)
β_8	0	5.79E-05**	0	6.12E-06***	2.97E-05*	0	0	2.38E-05*	3.10E-05**	0	0	1.46E-05‡
	(3.72E-06)	(2.24E-05)	(9.50E-10)	(1.49E-06)	(1.62E-05)	(7.71E-06)	(9.24E-12)	(1.32E-05)	(1.24E-05)	(1.19E-05)	(1.35E-05)	(1.26E-05)
β_9	7.46E-06*	0	0	0	6.14E-06	0	1.99E-11	1.52E-05‡	2.79E-05**	0	1.74E-05	4.61E-05
	(3.59E-06)	(9.78E-61)	(3.91E-06)	(1.47E-06)	(1.20E-05)	(8.69E-06)	(2.98E-10)	(1.45E-05)	(1.10E-05)	(1.19E-05)	(2.39E-05)	(8.00E-05)
β_{10}	0	0	8.17E-07	3.36E-06*	2.98E-05†	0	0	0	0	7.07E-06	2.60E-06	3.19E-05*
	(3.35E-06)	(1.58E-60)	(3.94E-06)	(1.72E-06)	(2.00E-05)	(1.02E-05)	(1.05E-11)	(6.60E-06)	(2.55E-06)	(1.51E-05)	(1.42E-05)	(1.91E-05)
α_t	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
$\alpha_{\text{NUTS-3}}$	–	YES	YES	–	YES	YES	YES	YES	YES	YES	YES	YES
$N_{\text{obs.}}$	15,113	353,515	5,967	11,798	492,303	327,284	38,267	348,007	294,304	782,986	229,534	274,091
LL	-6,432	-12,510	-2,109	-4,246	-24,099	-71,044	-14,580	-16,808	-26,312	-130,072	-34,926	-24,594
θ^{-1}	0.757	1.013	0.646	0.872	0.808	0.879	0.819	0.946	1.041	1.172	1.734	1.291
AIC	12,921	25,111	4,279	8,550	48,289	142,215	29,228	33,699	52,736	260,293	69,939	49,291
AIC_n	0.855	0.071	0.717	0.725	0.098	0.435	0.764	0.097	0.179	0.332	0.305	0.180
$BIC_{R,n}$	-9.182	-12.737	-8.285	-8.979	-13.057	-12.512	-10.232	-12.709	-12.502	-13.419	-12.208	-12.433
D	6,406	13,016	2,191	4,414	23,890	60,131	11,926	17,166	25,829	117,597	30,580	23,500
D_n	0.424	0.037	0.367	0.374	0.049	0.184	0.312	0.049	0.088	0.150	0.133	0.086

Robust standard errors in parentheses

‡ significant at $p < .20$; $^{\dagger}p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

D. Appendix to Chapter 5 – Spatio-Temporal Variation in Peer Effects

D.1. Cumulative peer effects

As outlined in Section 5.3.2 of Chapter 5 adoption decisions of peers in periods preceding $t-1$ might impact the decision of choice-maker n in period t as well. Therefore, we consider the cumulative installed base as

$$\text{C\_IBASE}_{nt} = \sum_{\substack{m \in N, \\ m \neq n \mid \\ d_{nm} \leq D}} \sum_{l=0}^{t-1} o_{ml1} f\left(d_{nm}\right). \tag{D.1}$$

D.2. Placebo test

We use the case study data to verify that our model indeed describes PV system adoption appropriately. We randomly allocate the same number of PV installations, which were in fact installed in the four cities per period, to the cities' buildings. Estimations with the resulting data set do not reveal any significant effect of the variables under study on the utility to adopt a PV system. I.e., the placebo test confirms the validity of our findings.

D.3. SOEP

The Socio-Economic Panel (SOEP) includes yearly data on PV adoption for the time period 2007-2012 (SOEP, 2013). There is no low level locational information included in the data, i.e., SOEP does not allow to study peer effects. However, analyzing the individual level data confirms that the impact of measures of income – in the SOEP case real household income – on PV adoption decreases over time. Further, we find no positive impact of green party support on PV adoption. We also find a negative effect of population density, e.g., measured by a significantly negative coefficient on PV adoption for households having no garden. For reasons of clarity we do not show the SOEP results.

Although our data set's level of detail is extraordinary high for our analysis of Germany, we rely on the assumption that spatial differences in buying power, global radiation, green votes, population density and urban districts stay constant across Germany. The SOEP results justify this assumption. They also illustrate that the characteristics of the decision-maker itself are indeed comparable to information on characteristics of the decision-maker's location.

D.4. Tables

For only 28,862 – thus, 3.28% – of the installations the entity type of the geocoding accuracy is unknown and the confidence less than medium, see Table D.1. However, 86.59% of the installations have a high geocoding confidence, and 86.54% have a high geocoding confidence and are allocated to addresses or road block entities.

Table D.1.: Geocoding accuracy.

Entity type	Confidence	Frequency in category
Address	High	599,746
Address	Medium	25,786
Neighborhood	Medium	62
PopulatedPlace	High	8
PopulatedPlace	Medium	3,201
Postcode1	High	18
Postcode1	Medium	19,092
RoadBlock	High	160,929
RoadBlock	Medium	40,524
RoadIntersection	High	402
RoadIntersection	Medium	390
Unknown		28,862
	Sum	879,020

Table D.2.: Frequency of choice alternatives for sample of Germany.

Period t	Year	Alternative	Frequency in category
1	2000	0: No PV system installed	1,981,222
		1: PV system installed	876
2	2001	0: No PV system installed	1,979,742
		1: PV system installed	2,356
3	2002	0: No PV system installed	1,980,330
		1: PV system installed	1,768
4	2003	0: No PV system installed	1,980,277
		1: PV system installed	1,821
5	2004	0: No PV system installed	1,977,780
		1: PV system installed	4,318
6	2005	0: No PV system installed	1,976,105
		1: PV system installed	5,993
7	2006	0: No PV system installed	1,976,306
		1: PV system installed	5,792
8	2007	0: No PV system installed	1,975,136
		1: PV system installed	6,962
9	2008	0: No PV system installed	1,971,649
		1: PV system installed	10,449
10	2009	0: No PV system installed	1,965,726
		1: PV system installed	1,6372
11	2010	0: No PV system installed	1,959,853
		1: PV system installed	22,245
		Sum of PV installations	78,952

Table D.3.: Descriptive statistics, Germany.

	Mean	Std. Dev.	Min.	Max.
choice	.0036	.06	0	1
IBASE_{nt}	.15	.31	0	13
IBASE_{n1}	.0035	.042	0	9.2
IBASE_{n2}	.0028	.033	0	5
IBASE_{n3}	.0068	.056	0	10
IBASE_{n4}	.0049	.044	0	4.7
IBASE_{n5}	.0049	.046	0	4.7
IBASE_{n6}	.011	.076	0	6.5
IBASE_{n7}	.015	.1	0	9.5
IBASE_{n8}	.016	.098	0	5.8
IBASE_{n9}	.019	.11	0	5.9
$\text{IBASE}_{\text{n10}}$	.028	.15	0	7.7
$\text{IBASE}_{\text{n11}}$	.04	.21	0	13
IBASE_{nt}*EAST_n	.0091	.064	0	7.4
IBASE_{nt}*URBAN_n	.13	.3	0	13
BUYPOW_n	1	.16	0	3.2
BUYPOW*PER_i	.09	.29	0	3.2
BUYPOW_n*EAST_n	.16	.33	0	1.5
BUYPOW_n*URBAN_n	.8	.43	0	3.2
GR_n	1	.056	.93	1.2
GR*PER_i	.093	.3	0	1.2
GREEN_n	.071	.028	.017	.19
GREEN_n*EAST_n	.0081	.021	0	.12
GREEN_n*URBAN_n	.058	.039	0	.19
POPDEN_n	.19	.34	0	13
POPDEN*PER_i	.017	.12	0	13
URBAN_n	.79	.4	0	1
N	21803078			

Table D.4.: Coefficient estimates of utility functions for sample of Germany.

		M6		$M6_{Logit}$	
0	ASC_{solar}	-4.323***	(-25.09)	-11.71***	(-19.48)
1	$IBASE_{n1}$	0.320***	(8.84)	0.809***	(8.13)
2	$IBASE_{n2}$	0.238***	(6.24)	0.624***	(6.92)
3	$IBASE_{n3}$	0.181***	(9.12)	0.436***	(9.43)
4	$IBASE_{n4}$	0.310***	(9.99)	0.831***	(10.09)
5	$IBASE_{n5}$	0.276***	(12.51)	0.689***	(12.31)
6	$IBASE_{n6}$	0.193***	(13.74)	0.465***	(13.24)
7	$IBASE_{n7}$	0.144***	(13.42)	0.324***	(13.29)
8	$IBASE_{n8}$	0.156***	(12.25)	0.390***	(11.68)
9	$IBASE_{n9}$	0.120***	(11.62)	0.274***	(10.75)
10	$IBASE_{n10}$	0.0675***	(8.16)	0.117***	(5.85)
11	$IBASE_{n11}$	0.0695***	(10.06)	0.102***	(6.17)
12	$IBASE_{nt}$*$EAST_n$	0.182***	(11.73)	0.574***	(15.46)
13	$IBASE_{nt}$*$URBAN_n$	0.0390***	(5.89)	0.154***	(9.61)
14	$BUYPOW_n$*PER_1	0.0391	(0.60)	0.234	(1.04)
15	$BUYPOW_n$*PER_2	-0.107*	(-2.18)	-0.272	(-1.73)
16	$BUYPOW_n$*PER_3	-0.273***	(-4.78)	-0.860***	(-4.61)
17	$BUYPOW_n$*PER_4	-0.200***	(-3.79)	-0.610***	(-3.60)
18	$BUYPOW_n$*PER_5	-0.483***	(-11.37)	-1.385***	(-10.91)
19	$BUYPOW_n$*PER_6	-0.467***	(-12.27)	-1.257***	(-11.34)
20	$BUYPOW_n$*PER_7	-0.335***	(-8.95)	-0.867***	(-7.95)
21	$BUYPOW_n$*PER_8	-0.463***	(-12.82)	-1.215***	(-11.67)
22	$BUYPOW_n$*PER_9	-0.501***	(-15.31)	-1.276***	(-14.14)
23	$BUYPOW_n$*PER_{10}	-0.663***	(-22.37)	-1.668***	(-21.23)
24	$BUYPOW_n$*PER_{11}	-0.685***	(-24.58)	-1.686***	(-23.43)
25	$BUYPOW_n$*$EAST_n$	0.477***	(7.79)	1.250***	(6.54)
26	$BUYPOW_n$*$URBAN_n$	-0.0257	(-1.07)	-0.203**	(-3.08)
27	GR_n*PER_1	1.175***	(7.00)	4.388***	(7.45)
28	GR_n*PER_2	2.254***	(18.23)	7.525***	(19.07)
29	GR_n*PER_3	2.908***	(20.41)	10.10***	(21.63)
30	GR_n*PER_4	2.913***	(20.04)	9.984***	(20.99)
31	GR_n*PER_5	2.608***	(24.73)	8.030***	(25.68)
32	GR_n*PER_6	2.101***	(22.65)	6.054***	(22.84)
33	GR_n*PER_7	1.362***	(15.05)	3.947***	(15.26)
34	GR_n*PER_8	1.754***	(20.01)	4.935***	(19.82)
35	GR_n*PER_9	2.161***	(27.31)	5.736***	(26.67)
36	GR_n*PER_{10}	2.148***	(28.60)	5.328***	(26.88)
37	GR_n*PER_{11}	1.671***	(23.35)	3.826***	(20.61)
38	GR_n*$EAST_n$	-1.346***	(-5.22)	-3.581***	(-4.52)
39	GR_n*$URBAN_n$	-0.104*	(-2.15)	0.164	(1.23)
40	$GREEN_n$	-1.972***	(-15.95)	-5.984***	(-17.80)
41	$GREEN_n$*$EAST_n$	0.877*	(2.13)	2.248	(1.70)
42	$GREEN_n$*$URBAN_n$	-0.233	(-1.71)	-0.462	(-1.22)
43	$POPDEN_n$*PER_1	-0.799***	(-11.35)	-2.471***	(-11.32)
44	$POPDEN_n$*PER_2	-0.871***	(-12.63)	-2.687***	(-12.54)
45	$POPDEN_n$*PER_3	-0.951***	(-13.15)	-3.010***	(-12.97)
46	$POPDEN_n$*PER_4	-0.958***	(-12.66)	-3.057***	(-12.37)
47	$POPDEN_n$*PER_5	-1.115***	(-15.33)	-3.530***	(-15.40)
48	$POPDEN_n$*PER_6	-1.146***	(-16.19)	-3.565***	(-16.20)
49	$POPDEN_n$*PER_7	-1.089***	(-15.59)	-3.359***	(-15.55)
50	$POPDEN_n$*PER_8	-1.031***	(-14.85)	-3.135***	(-14.51)
51	$POPDEN_n$*PER_9	-1.126***	(-16.65)	-3.397***	(-16.39)
52	$POPDEN_n$*PER_{10}	-1.271***	(-18.76)	-3.799***	(-18.38)
53	$POPDEN_n$*PER_{11}	-1.380***	(-20.57)	-4.053***	(-19.88)
54	$POPDEN_n$*$EAST_n$	0.327***	(15.08)	0.975***	(12.87)
55	$POPDEN_n$*$URBAN_n$	0.690***	(10.57)	2.055***	(10.29)
56	$URBAN_n$	-0.0464	(-0.93)	-0.499***	(-3.59)
	NUTS-1 dummies	Yes		Yes	
	Period dummies	Yes		Yes	
	Observations	21,803,078		21,803,078	
	DF_M	81		81	
	Final log-likelihood $\mathcal{L}$	-466,538		-466,337	
	LR: χ^2 (DF)	4,676 (36)			
	LR: p-value	0			
	Horowitz test statistic (signific. level)			-3.11 (9.4e-04)	
	LR/Horowitz test against	M5->M6		M6->$M6_{Logit}$	

Robust t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.5.: Average marginal effects of utility functions for sample of Germany.

	M4		M6		$M6_{Logit}$	
$IBASE_{nt}$	0.000854***	(30.05)				
$IBASE_{n1}$			0.00319***	(8.83)	0.00289***	(8.13)
$IBASE_{n2}$			0.00237***	(6.24)	0.00223***	(6.92)
$IBASE_{n3}$			0.00180***	(9.12)	0.00156***	(9.43)
$IBASE_{n4}$			0.00308***	(9.98)	0.00297***	(10.09)
$IBASE_{n5}$			0.00275***	(12.50)	0.00247***	(12.30)
$IBASE_{n6}$			0.00192***	(13.73)	0.00166***	(13.23)
$IBASE_{n7}$			0.00144***	(13.41)	0.00116***	(13.28)
$IBASE_{n8}$			0.00156***	(12.24)	0.00140***	(11.67)
$IBASE_{n9}$			0.00119***	(11.62)	0.000979***	(10.74)
$IBASE_{n10}$			0.000672***	(8.16)	0.000418***	(5.85)
$IBASE_{n11}$			0.000692***	(10.06)	0.000365***	(6.17)
$IBASE_{nt}$*$EAST_n$	0.00205***	(13.13)	0.00181***	(11.72)	0.00205***	(15.44)
$IBASE_{nt}$*$URBAN_n$			0.000388***	(5.89)	0.000552***	(9.61)
$BUYPOW_n$	-0.00628***	(-51.67)				
$BUYPOW_n$*PER_1			0.000389	(0.60)	0.000837	(1.04)
$BUYPOW_n$*PER_2			-0.00107*	(-2.18)	-0.000972	(-1.73)
$BUYPOW_n$*PER_3			-0.00272***	(-4.78)	-0.00308***	(-4.61)
$BUYPOW_n$*PER_4			-0.00199***	(-3.79)	-0.00218***	(-3.60)
$BUYPOW_n$*PER_5			-0.00481***	(-11.36)	-0.00495***	(-10.91)
$BUYPOW_n$*PER_6			-0.00465***	(-12.26)	-0.00450***	(-11.33)
$BUYPOW_n$*PER_7			-0.00333***	(-8.95)	-0.00310***	(-7.95)
$BUYPOW_n$*PER_8			-0.00461***	(-12.81)	-0.00435***	(-11.66)
$BUYPOW_n$*PER_9			-0.00499***	(-15.30)	-0.00457***	(-14.13)
$BUYPOW_n$*PER_{10}			-0.00660***	(-22.33)	-0.00597***	(-21.19)
$BUYPOW_n$*PER_{11}			-0.00682***	(-24.53)	-0.00603***	(-23.37)
$BUYPOW_n$*$EAST_n$	0.00404***	(6.54)	0.00475***	(7.79)	0.00447***	(6.54)
$BUYPOW_n$*$URBAN_n$			-0.000256	(-1.07)	-0.000727**	(-3.08)
GR_n	0.0210***	(46.44)				
GR_n*PER_1			0.0117***	(7.00)	0.0157***	(7.45)
GR_n*PER_2			0.0224***	(18.22)	0.0269***	(19.04)
GR_n*PER_3			0.0290***	(20.39)	0.0361***	(21.58)
GR_n*PER_4			0.0290***	(20.01)	0.0357***	(20.94)
GR_n*PER_5			0.0260***	(24.68)	0.0287***	(25.60)
GR_n*PER_6			0.0209***	(22.62)	0.0217***	(22.79)
GR_n*PER_7			0.0136***	(15.05)	0.0141***	(15.25)
GR_n*PER_8			0.0175***	(19.99)	0.0177***	(19.79)
GR_n*PER_9			0.0215***	(27.26)	0.0205***	(26.60)
GR_n*PER_{10}			0.0214***	(28.55)	0.0191***	(26.82)
GR_n*PER_{11}			0.0166***	(23.32)	0.0137***	(20.59)
GR_n*$EAST_n$	-0.0151***	(-5.90)	-0.0134***	(-5.22)	-0.0128***	(-4.52)
GR_n*$URBAN_n$			-0.00103*	(-2.15)	0.000587	(1.23)
$GREEN_n$	-0.0216***	(-26.50)	-0.0196***	(-15.94)	-0.0214***	(-17.78)
$GREEN_n$*$EAST_n$	0.00523	(1.24)	0.00873*	(2.13)	0.00804	(1.70)
$GREEN_n$*$URBAN_n$			-0.00232	(-1.71)	-0.00165	(-1.22)
$POPDEN_n$	-0.00590***	(-53.51)				
$POPDEN_n$*PER_1			-0.00796***	(-11.34)	-0.00884***	(-11.31)
$POPDEN_n$*PER_2			-0.00867***	(-12.63)	-0.00961***	(-12.54)
$POPDEN_n$*PER_3			-0.00947***	(-13.15)	-0.0108***	(-12.96)
$POPDEN_n$*PER_4			-0.00954***	(-12.66)	-0.0109***	(-12.36)
$POPDEN_n$*PER_5			-0.0111***	(-15.32)	-0.0126***	(-15.38)
$POPDEN_n$*PER_6			-0.0114***	(-16.18)	-0.0128***	(-16.18)
$POPDEN_n$*PER_7			-0.0108***	(-15.58)	-0.0120***	(-15.53)
$POPDEN_n$*PER_8			-0.0103***	(-14.84)	-0.0112***	(-14.50)
$POPDEN_n$*PER_9			-0.0112***	(-16.64)	-0.0122***	(-16.37)
$POPDEN_n$*PER_{10}			-0.0127***	(-18.74)	-0.0136***	(-18.35)
$POPDEN_n$*PER_{11}			-0.0137***	(-20.55)	-0.0145***	(-19.84)
$POPDEN_n$*$EAST_n$	0.00412***	(12.22)	0.00325***	(15.07)	0.00349***	(12.86)
$POPDEN_n$*$URBAN_n$			0.00687***	(10.57)	0.00735***	(10.29)
$URBAN_n$			-0.000462	(-0.93)	-0.00179***	(-3.59)
Observations	21803078		21803078		21803078	

Marginal effects; Robust t statistics in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.6.: Coefficient estimates of utility functions for further samples of Germany.

	$M6_{II}$		$M6_{III}$	
ASC_{solar}	-4.190***	(-25.21)	-4.462***	(-26.46)
$IBASE_{n1}$	0.249***	(5.89)	0.232***	(4.84)
$IBASE_{n2}$	0.253***	(7.10)	0.187***	(4.63)
$IBASE_{n3}$	0.187***	(9.44)	0.153***	(6.15)
$IBASE_{n4}$	0.324***	(11.06)	0.266***	(8.66)
$IBASE_{n5}$	0.301***	(13.74)	0.265***	(12.10)
$IBASE_{n6}$	0.222***	(16.33)	0.207***	(14.96)
$IBASE_{n7}$	0.159***	(15.08)	0.131***	(12.12)
$IBASE_{n8}$	0.158***	(12.41)	0.152***	(11.64)
$IBASE_{n9}$	0.147***	(14.38)	0.150***	(14.73)
$IBASE_{n10}$	0.0744***	(9.06)	0.0797***	(9.81)
$IBASE_{n11}$	0.0735***	(10.73)	0.0741***	(10.90)
$IBASE_{nt}$*$EAST_n$	0.171***	(11.51)	0.173***	(11.15)
$IBASE_{nt}$*$URBAN_n$	0.0285***	(4.35)	0.0339***	(5.18)
$BUYPOW_n$*PER_1	0.0980	(1.57)	0.136*	(2.28)
$BUYPOW_n$*PER_2	-0.104*	(-2.24)	-0.133**	(-2.93)
$BUYPOW_n$*PER_3	-0.296***	(-5.45)	-0.249***	(-4.77)
$BUYPOW_n$*PER_4	-0.264***	(-4.91)	-0.398***	(-7.30)
$BUYPOW_n$*PER_5	-0.571***	(-13.33)	-0.561***	(-12.99)
$BUYPOW_n$*PER_6	-0.534***	(-13.83)	-0.543***	(-14.05)
$BUYPOW_n$*PER_7	-0.400***	(-10.69)	-0.387***	(-10.49)
$BUYPOW_n$*PER_8	-0.439***	(-12.57)	-0.445***	(-12.10)
$BUYPOW_n$*PER_9	-0.539***	(-16.34)	-0.595***	(-18.00)
$BUYPOW_n$*PER_{10}	-0.712***	(-23.94)	-0.690***	(-23.08)
$BUYPOW_n$*PER_{11}	-0.733***	(-25.78)	-0.753***	(-26.48)
$BUYPOW_n$*$EAST_n$	0.484***	(7.86)	0.476***	(7.74)
$BUYPOW_n$*$URBAN_n$	0.00242	(0.10)	0.0174	(0.72)
GR_n*PER_1	0.981***	(6.01)	1.212***	(7.31)
GR_n*PER_2	2.060***	(16.58)	2.331***	(18.78)
GR_n*PER_3	2.824***	(19.08)	2.701***	(18.75)
GR_n*PER_4	3.225***	(21.98)	3.412***	(23.17)
GR_n*PER_5	2.366***	(22.03)	2.424***	(22.97)
GR_n*PER_6	1.989***	(21.40)	2.209***	(23.51)
GR_n*PER_7	1.325***	(14.53)	1.405***	(15.52)
GR_n*PER_8	1.655***	(19.08)	1.728***	(19.60)
GR_n*PER_9	1.954***	(24.57)	1.982***	(24.88)
GR_n*PER_{10}	2.093***	(27.80)	2.070***	(27.63)
GR_n*PER_{11}	1.706***	(23.75)	1.563***	(21.80)
GR_n*$EAST_n$	-1.658***	(-6.50)	-1.452***	(-5.60)
GR_n*$URBAN_n$	-0.107*	(-2.20)	-0.129**	(-2.66)
$GREEN_n$	-1.746***	(-14.07)	-1.781***	(-14.28)
$GREEN_n$*$EAST_n$	-0.0473	(-0.11)	0.946*	(2.32)
$GREEN_n$*$URBAN_n$	-0.311*	(-2.28)	-0.363**	(-2.65)
$POPDEN_n$*PER_1	-0.834***	(-11.31)	-0.771***	(-10.47)
$POPDEN_n$*PER_2	-0.906***	(-12.33)	-0.848***	(-11.86)
$POPDEN_n$*PER_3	-0.914***	(-12.13)	-0.901***	(-12.10)
$POPDEN_n$*PER_4	-1.020***	(-12.41)	-0.927***	(-11.83)
$POPDEN_n$*PER_5	-1.116***	(-14.67)	-1.040***	(-13.82)
$POPDEN_n$*PER_6	-1.197***	(-15.83)	-1.122***	(-15.19)
$POPDEN_n$*PER_7	-1.119***	(-15.27)	-1.043***	(-14.48)
$POPDEN_n$*PER_8	-1.136***	(-15.62)	-1.116***	(-15.61)
$POPDEN_n$*PER_9	-1.174***	(-16.23)	-1.167***	(-16.40)
$POPDEN_n$*PER_{10}	-1.325***	(-18.42)	-1.277***	(-18.17)
$POPDEN_n$*PER_{11}	-1.376***	(-19.26)	-1.320***	(-18.98)
$POPDEN_n$*$EAST_n$	0.351***	(15.99)	0.346***	(16.49)
$POPDEN_n$*$URBAN_n$	0.711***	(10.22)	0.663***	(9.77)
$URBAN_n$	-0.0574	(-1.14)	-0.0485	(-0.97)
NUTS-1 dummies	Yes		Yes	
Period dummies	Yes		Yes	
Observations	21,795,334		21,799,327	
DF_M	81		81	
Final log-likelihood $\mathcal{L}$	-464,214		-465,947	

Robust t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.7.: Coefficient estimates of utility functions for further cut-off distances for Germany.

	M7		M8	
Cut-off	200 m		1000 m	
ASC_{solar}	-4.102***	(-23.61)	-4.324***	(-25.18)
$IBASE_{n1}$	0.218***	(3.32)	0.221***	(10.47)
$IBASE_{n2}$	0.303***	(3.44)	0.166***	(7.04)
$IBASE_{n3}$	0.169***	(3.47)	0.166***	(12.98)
$IBASE_{n4}$	0.320***	(5.79)	0.222***	(12.77)
$IBASE_{n5}$	0.249***	(5.91)	0.208***	(14.60)
$IBASE_{n6}$	0.127***	(4.33)	0.151***	(17.55)
$IBASE_{n7}$	0.105***	(4.19)	0.0949***	(16.90)
$IBASE_{n8}$	0.132***	(4.91)	0.110***	(14.26)
$IBASE_{n9}$	0.0952***	(4.62)	0.0934***	(15.01)
$IBASE_{n10}$	0.0328	(1.85)	0.0574***	(11.82)
$IBASE_{n11}$	0.0584***	(4.64)	0.0615***	(15.13)
$IBASE_{nt}$*$EAST_n$	0.154***	(5.95)	0.127***	(12.95)
$IBASE_{nt}$*$URBAN_n$	0.144***	(10.94)	-0.00622	(-1.59)
$BUYPOW_n$*PER_1	0.0891	(1.38)	-0.00823	(-0.12)
$BUYPOW_n$*PER_2	-0.0950	(-1.91)	-0.122*	(-2.46)
$BUYPOW_n$*PER_3	-0.263***	(-4.62)	-0.297***	(-5.10)
$BUYPOW_n$*PER_4	-0.204***	(-3.86)	-0.217***	(-4.05)
$BUYPOW_n$*PER_5	-0.487***	(-11.49)	-0.504***	(-11.70)
$BUYPOW_n$*PER_6	-0.479***	(-12.67)	-0.483***	(-12.54)
$BUYPOW_n$*PER_7	-0.337***	(-9.12)	-0.348***	(-9.25)
$BUYPOW_n$*PER_8	-0.450***	(-12.61)	-0.476***	(-13.08)
$BUYPOW_n$*PER_9	-0.497***	(-15.32)	-0.513***	(-15.53)
$BUYPOW_n$*PER_{10}	-0.670***	(-22.71)	-0.667***	(-22.43)
$BUYPOW_n$*PER_{11}	-0.710***	(-25.69)	-0.687***	(-24.54)
$BUYPOW_n$*$EAST_n$	0.525***	(8.66)	0.430***	(6.95)
$BUYPOW_n$*$URBAN_n$	-0.0420	(-1.76)	-0.0236	(-0.98)
GR_n*PER_1	0.914***	(5.40)	1.209***	(7.19)
GR_n*PER_2	2.118***	(17.16)	2.206***	(17.78)
GR_n*PER_3	2.895***	(20.35)	2.751***	(19.11)
GR_n*PER_4	3.004***	(21.19)	2.784***	(18.94)
GR_n*PER_5	2.699***	(26.34)	2.482***	(23.08)
GR_n*PER_6	2.229***	(24.87)	1.973***	(20.90)
GR_n*PER_7	1.453***	(16.47)	1.325***	(14.66)
GR_n*PER_8	1.779***	(20.88)	1.695***	(19.15)
GR_n*PER_9	2.183***	(28.34)	2.084***	(26.06)
GR_n*PER_{10}	2.168***	(29.86)	2.103***	(27.78)
GR_n*PER_{11}	1.814***	(26.42)	1.600***	(22.19)
GR_n*$EAST_n$	-1.469***	(-5.73)	-1.336***	(-5.16)
GR_n*$URBAN_n$	0.112*	(2.40)	-0.0648	(-1.33)
$GREEN_n$	-2.139***	(-17.26)	-1.921***	(-15.50)
$GREEN_n$*$EAST_n$	0.886*	(2.14)	0.890*	(2.16)
$GREEN_n$*$URBAN_n$	-0.333*	(-2.44)	-0.199	(-1.46)
$POPDEN_n$*PER_1	-0.729***	(-10.59)	-0.922***	(-12.24)
$POPDEN_n$*PER_2	-0.815***	(-12.05)	-0.982***	(-13.37)
$POPDEN_n$*PER_3	-0.892***	(-12.60)	-1.082***	(-13.95)
$POPDEN_n$*PER_4	-0.900***	(-12.15)	-1.083***	(-13.39)
$POPDEN_n$*PER_5	-1.063***	(-14.88)	-1.240***	(-16.00)
$POPDEN_n$*PER_6	-1.095***	(-15.78)	-1.277***	(-16.90)
$POPDEN_n$*PER_7	-1.036***	(-15.16)	-1.209***	(-16.26)
$POPDEN_n$*PER_8	-0.975***	(-14.37)	-1.154***	(-15.57)
$POPDEN_n$*PER_9	-1.069***	(-16.16)	-1.255***	(-17.39)
$POPDEN_n$*PER_{10}	-1.214***	(-18.30)	-1.395***	(-19.32)
$POPDEN_n$*PER_{11}	-1.319***	(-20.10)	-1.520***	(-21.28)
$POPDEN_n$*$EAST_n$	0.329***	(15.54)	0.340***	(14.69)
$POPDEN_n$*$URBAN_n$	0.633***	(9.92)	0.785***	(11.27)
$URBAN_n$	-0.218***	(-4.47)	-0.0863	(-1.71)
NUTS-1 dummies	Yes		Yes	
Period dummies	Yes		Yes	
Observations	21,803,078		21,803,078	
DF_M	81		81	
Final log-likelihood $\mathcal{L}$	-467,368		-466,538	
Horowitz test statistic (signific. level)	-6.31 (1.4e-10)		-.0326 (.487)	
Horowitz test against	M7->M6		M6->M8	

Robust t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.8.: Coefficient estimates of utility functions using a cumulative peer effects measure for Germany.

	M9	
ASC_{solar}	-4.376***	(-25.36)
C_IBASE_{n1}	0.349***	(9.74)
C_IBASE_{n2}	0.209***	(7.56)
C_IBASE_{n3}	0.160***	(10.50)
C_IBASE_{n4}	0.128***	(9.56)
C_IBASE_{n5}	0.108***	(11.71)
C_IBASE_{n6}	0.0851***	(13.06)
C_IBASE_{n7}	0.0597***	(11.52)
C_IBASE_{n8}	0.0369***	(8.54)
C_IBASE_{n9}	0.0239***	(6.86)
C_IBASE_{n10}	0.0151***	(5.22)
C_IBASE_{n11}	0.0137***	(5.34)
C_IBASE_{nt}*$EAST_n$	0.0992***	(13.92)
C_IBASE_{nt}*$URBAN_n$	0.0165***	(6.89)
$BUYPOW_n$*PER_1	0.0503	(0.77)
$BUYPOW_n$*PER_2	-0.117*	(-2.35)
$BUYPOW_n$*PER_3	-0.284***	(-4.97)
$BUYPOW_n$*PER_4	-0.220***	(-4.14)
$BUYPOW_n$*PER_5	-0.502***	(-11.72)
$BUYPOW_n$*PER_6	-0.487***	(-12.73)
$BUYPOW_n$*PER_7	-0.341***	(-9.09)
$BUYPOW_n$*PER_8	-0.448***	(-12.44)
$BUYPOW_n$*PER_9	-0.491***	(-15.02)
$BUYPOW_n$*PER_{10}	-0.657***	(-22.12)
$BUYPOW_n$*PER_{11}	-0.690***	(-24.70)
$BUYPOW_n$*$EAST_n$	0.441***	(7.14)
$BUYPOW_n$*$URBAN_n$	-0.0274	(-1.14)
GR_n*PER_1	1.232***	(7.34)
GR_n*PER_2	2.364***	(19.24)
GR_n*PER_3	2.997***	(21.09)
GR_n*PER_4	3.037***	(21.12)
GR_n*PER_5	2.652***	(24.96)
GR_n*PER_6	2.099***	(22.27)
GR_n*PER_7	1.313***	(14.01)
GR_n*PER_8	1.707***	(18.83)
GR_n*PER_9	2.153***	(26.36)
GR_n*PER_{10}	2.154***	(27.92)
GR_n*PER_{11}	1.752***	(23.86)
GR_n*$EAST_n$	-1.272***	(-4.93)
GR_n*$URBAN_n$	-0.168***	(-3.42)
$GREEN_n$	-2.085***	(-16.84)
$GREEN_n$*$EAST_n$	1.074**	(2.61)
$GREEN_n$*$URBAN_n$	-0.281*	(-2.06)
$POPDEN_n$*PER_1	-0.792***	(-11.20)
$POPDEN_n$*PER_2	-0.876***	(-12.61)
$POPDEN_n$*PER_3	-0.959***	(-13.14)
$POPDEN_n$*PER_4	-0.970***	(-12.65)
$POPDEN_n$*PER_5	-1.133***	(-15.38)
$POPDEN_n$*PER_6	-1.165***	(-16.34)
$POPDEN_n$*PER_7	-1.099***	(-15.64)
$POPDEN_n$*PER_8	-1.034***	(-14.82)
$POPDEN_n$*PER_9	-1.128***	(-16.60)
$POPDEN_n$*PER_{10}	-1.277***	(-18.75)
$POPDEN_n$*PER_{11}	-1.394***	(-20.68)
$POPDEN_n$*$EAST_n$	0.332***	(15.08)
$POPDEN_n$*$URBAN_n$	0.688***	(10.50)
$URBAN_n$	0.0186	(0.37)
NUTS-1 dummies	Yes	
Period dummies	Yes	
Observations	21,803,078	
DF_M	81	
Final log-likelihood $\mathcal{L}$	-466,815	
Horowitz test statistic (signific. level)	-3.64 (1.4e-04)	
Horowitz test against	M9->M6	

Robust t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.9.: Coefficient estimates of utility functions for sample of Germany using different functional forms for peer effects.

	M10		M11	
$f(d_{nm})$	$1/d_{nm}$		$1/d_{nm}^2$	
$\text{ASC}_{\text{solar}}$	-4.100***	(-23.60)	-4.054***	(-23.32)
IBASE_{n1}	0.420*	(1.98)	0.736	(1.35)
IBASE_{n2}	0.910***	(3.60)	1.732**	(2.74)
IBASE_{n3}	0.476**	(2.66)	0.525	(0.94)
IBASE_{n4}	0.963***	(5.88)	1.880***	(4.85)
IBASE_{n5}	0.625***	(4.74)	0.826*	(2.14)
IBASE_{n6}	0.289**	(3.19)	0.122	(0.43)
IBASE_{n7}	0.227**	(2.94)	0.148	(0.64)
IBASE_{n8}	0.322***	(3.82)	0.349	(1.48)
IBASE_{n9}	0.151*	(2.23)	-0.0498	(-0.26)
$\text{IBASE}_{\text{n10}}$	0.0218	(0.36)	-0.0648	(-0.43)
$\text{IBASE}_{\text{n11}}$	0.146***	(3.59)	0.151	(1.57)
IBASE_{nt}*EAST_n	0.457***	(5.88)	1.119***	(6.29)
IBASE_{nt}*URBAN_n	0.607***	(14.00)	0.616***	(5.55)
BUYPOW_n*PER_1	0.0911	(1.41)	0.0942	(1.46)
BUYPOW_n*PER_2	-0.0945	(-1.90)	-0.0939	(-1.89)
BUYPOW_n*PER_3	-0.263***	(-4.63)	-0.264***	(-4.63)
BUYPOW_n*PER_4	-0.204***	(-3.87)	-0.206***	(-3.90)
BUYPOW_n*PER_5	-0.488***	(-11.52)	-0.491***	(-11.55)
BUYPOW_n*PER_6	-0.480***	(-12.71)	-0.484***	(-12.79)
BUYPOW_n*PER_7	-0.339***	(-9.16)	-0.342***	(-9.24)
BUYPOW_n*PER_8	-0.451***	(-12.64)	-0.451***	(-12.64)
BUYPOW_n*PER_9	-0.498***	(-15.36)	-0.499***	(-15.39)
BUYPOW_n*PER_{10}	-0.672***	(-22.76)	-0.673***	(-22.80)
BUYPOW_n*PER_{11}	-0.713***	(-25.79)	-0.716***	(-25.99)
BUYPOW_n*EAST_n	0.527***	(8.68)	0.531***	(8.75)
BUYPOW_n*URBAN_n	-0.0424	(-1.78)	-0.0461	(-1.93)
GR_n*PER_1	0.911***	(5.38)	0.863***	(5.09)
GR_n*PER_2	2.118***	(17.16)	2.086***	(16.89)
GR_n*PER_3	2.901***	(20.41)	2.891***	(20.34)
GR_n*PER_4	3.011***	(21.30)	3.011***	(21.31)
GR_n*PER_5	2.712***	(26.51)	2.710***	(26.50)
GR_n*PER_6	2.240***	(25.05)	2.240***	(25.09)
GR_n*PER_7	1.461***	(16.60)	1.462***	(16.65)
GR_n*PER_8	1.784***	(20.97)	1.778***	(20.95)
GR_n*PER_9	2.193***	(28.51)	2.187***	(28.49)
GR_n*PER_{10}	2.172***	(29.95)	2.174***	(30.10)
GR_n*PER_{11}	1.819***	(26.56)	1.860***	(27.29)
GR_n*EAST_n	-1.470***	(-5.74)	-1.504***	(-5.87)
GR_n*URBAN_n	0.109*	(2.33)	0.164***	(3.52)
GREEN_n	-2.140***	(-17.27)	-2.171***	(-17.50)
GREEN_n*EAST_n	0.887*	(2.14)	0.893*	(2.16)
GREEN_n*URBAN_n	-0.331*	(-2.42)	-0.343*	(-2.51)
POPDEN_n*PER_1	-0.730***	(-10.59)	-0.728***	(-10.54)
POPDEN_n*PER_2	-0.816***	(-12.05)	-0.814***	(-12.01)
POPDEN_n*PER_3	-0.892***	(-12.60)	-0.891***	(-12.57)
POPDEN_n*PER_4	-0.901***	(-12.15)	-0.900***	(-12.12)
POPDEN_n*PER_5	-1.064***	(-14.89)	-1.065***	(-14.87)
POPDEN_n*PER_6	-1.096***	(-15.79)	-1.097***	(-15.78)
POPDEN_n*PER_7	-1.038***	(-15.18)	-1.038***	(-15.17)
POPDEN_n*PER_8	-0.978***	(-14.39)	-0.977***	(-14.37)
POPDEN_n*PER_9	-1.072***	(-16.18)	-1.071***	(-16.16)
POPDEN_n*PER_{10}	-1.217***	(-18.33)	-1.215***	(-18.30)
POPDEN_n*PER_{11}	-1.324***	(-20.15)	-1.323***	(-20.14)
POPDEN_n*EAST_n	0.330***	(15.60)	0.332***	(15.63)
POPDEN_n*URBAN_n	0.633***	(9.92)	0.630***	(9.85)
URBAN_n	-0.215***	(-4.41)	-0.260***	(-5.35)
NUTS-1 dummies	Yes		Yes	
Period dummies	Yes		Yes	
Observations	21,803,078		21,803,078	
DF_M	81		81	
Final log-likelihood $\mathcal{L}$	-467,425		-467,634	
Horowitz test statistic (signific. level)	-6.52 (3.6e-11)		-7.25 (2.1e-13)	
Horowitz test against	M10->M6		M11->M6	

Robust t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.10.: Descriptive statistics for M12 (Address fixed effects, cut-off 200 m).

	Mean	Std. Dev.	Min.	Max.
choice	.091	.29	0	1
PER	6	3.2	1	11
IBASE_{nt}	.079	.21	0	13
Urban_n	.65	.48	0	1
Rural_n	.35	.48	0	1
East_n	.069	.25	0	1
N	9545184			

Table D.11.: Descriptive statistics for M13 (District*Period fixed effects, cut-off 200 m).

	Mean	Std. Dev.	Min.	Max.
choice	.0079	.089	0	1
PER	7.4	2.9	1	11
IBASE_{nt}	.079	.19	0	13
Urban_n	.77	.42	0	1
Rural_n	.23	.42	0	1
East_n	.13	.34	0	1
N	109848218			

Table D.12.: Frequency of choice alternatives for case study of four cities.

Period t	Year	Alternative	Frequency in category
1	2000	0: No PV system installed	338,172
		1: PV system installed	70
2	2001	0: No PV system installed	338,128
		1: PV system installed	114
3	2002	0: No PV system installed	338,196
		1: PV system installed	46
4	2003	0: No PV system installed	338,195
		1: PV system installed	47
5	2004	0: No PV system installed	338,169
		1: PV system installed	73
6	2005	0: No PV system installed	338,055
		1: PV system installed	187
7	2006	0: No PV system installed	338,043
		1: PV system installed	199
8	2007	0: No PV system installed	337,983
		1: PV system installed	259
9	2008	0: No PV system installed	337,943
		1: PV system installed	299
10	2009	0: No PV system installed	337,784
		1: PV system installed	458
11	2010	0: No PV system installed	337,674
		1: PV system installed	568
		Sum of PV installations	2,320

Table D.13.: Descriptive statistics case study.

	Mean	Std. Dev.	Min.	Max.
choice	.00062	.025	0	1
IBASE_{nt}	.1	.2	0	3.7
BUYPOW_n	1.1	.16	.73	1.6
GR_n	1.1	.027	.99	1.1
GR BUILDING_n	.6	.5	0	1.3
POPDEN_n	.39	.5	.0027	3.3
N	3720662			

E. Appendix to Chapter 6 – Not in My Backyard! Local Resistance

E.1. Descriptive statistics

Table E.1.: Descriptive statistics, wind.

	Mean	Std. Dev.	Min.	Max.
$\Delta F_{\text{Wind},t}$	.0028	.0064	0	.092
$\Delta F_{\text{Wind}>0.5\,\text{MW},t}$	.0024	.0058	0	.092
$\Delta F_{\text{Wi.Cap}>0.5\,\text{MW},t}$	3.7	9.5	0	146
$\Delta\#_{\text{Wind}>1\,\text{MW},t}$	2.9	7.6	0	86
$F_{\text{Wind},t-1}$	.026	.048	0	.49
$F_{\text{Wind}>0.5\,\text{MW},t-1}$	.018	.036	0	.34
$F_{\text{Wi.Cap}>0.5\,\text{MW},t-1}$	25	51	0	461
$\#_{\text{Wind}>1\,\text{MW},t-1}$	22	49	0	476
$W\,F_{\text{Wind}>1\,\text{MW},t-1}$	.027	.039	0	.45
$W\,\#_{\text{Wind}>1\,\text{MW},t-1}$	15	25	0	281
$REF_{\text{Wind},t-1}$	.0027	.052	0	1
$REF_{\text{Wind,n.o.},t-1}$	.0065	.08	0	1
$W\,REF_{\text{Wind},t-1}$	.0018	.016	0	.25
N	6004			

Table E.2.: Descriptive statistics, biomass.

	Mean	Std. Dev.	Min.	Max.
$\Delta F_{\text{Biomass},t}$	.003	.0071	0	.33
$\Delta F_{\text{Biomass}>1\,\text{MW}_\text{e},t}$	.00011	.00081	0	.034
$\Delta F_{\text{Bio.Cap}>1\,\text{MW}_\text{e},t}$	.49	5.7	0	346
$\Delta\#_{\text{Biomass}>1\,\text{MW}_\text{e},t}$	.066	.29	0	4
$F_{\text{Biomass},t-1}$	.012	.022	0	.17
$F_{\text{Biomass}>1\,\text{MW}_\text{e},t-1}$	.00066	.002	0	.032
$F_{\text{Bio.Cap}>1\,\text{MW}_\text{e},t-1}$	3.4	16	0	346
$\#_{\text{Biomass}>1\,\text{MW}_\text{e},t-1}$	.39	.96	0	9
$W\,F_{\text{Biomass}>1\,\text{MW}_\text{e},t-1}$	.0019	.0048	0	.047
$W\,\#_{\text{Biomass}>1\,\text{MW}_\text{e},t-1}$	.35	.56	0	5.5
$REF_{\text{Biomass},t-1}$	.0015	.039	0	1
$REF_{\text{Biomass,n.o.},t-1}$	.014	.12	0	1
$W\,REF_{\text{Biomass},t-1}$	.0019	.034	0	1
N	6004			

Table E.3.: Descriptive statistics, PV.

	Mean	Std. Dev.	Min.	Max.
$\Delta F_{\mathrm{PV},t}$	.0043	.0074	0	.067
$\Delta F_{\mathrm{PV>100\,kW_p},t}$	.012	.04	0	.83
$\Delta \#_{\mathrm{PV>100\,kW_p},t}$	3.3	9.5	0	196
$F_{\mathrm{PV},t-1}$	.012	.023	0	.25
$F_{\mathrm{PV>100\,kW_p},t-1}$	.018	.062	0	1.1
$\#_{\mathrm{PV>100\,kW_p},t-1}$	4.3	14	0	335
$W\,F_{\mathrm{PV>100\,kW_p},t-1}$	.019	.046	0	.66
$W\,\#_{\mathrm{PV>100\,kW_p},t-1}$	4.6	11	0	159
$REF_{\mathrm{PV},t-1}$	.00078	.028	0	1
$W\,REF_{\mathrm{PV},t-1}$	.00095	.019	0	1
N	6435			

E.2. Estimations with capacity-adjusted measures

Table E.4.: Estimation of successful referendum on adoption of large wind power plants (capacity-adjusted).

	(1)	(2)	(3)	(4)
	$\Delta F_{\text{Wi.Cap>0.5 MW},t}$	$\Delta F_{\text{Wi.Cap>0.5 MW},t}$	$\Delta F_{\text{Wi.Cap>0.5 MW},t}$	$\Delta F_{\text{Wi.Cap>0.5 MW},t}$
Estimator	OLS FE	Cond. Poisson FE	OLS FE	Cond. Poisson FE
$REF_{\text{Wind},t-1}$	-3.491***	-1.013^{+}	-2.698^{+}	-0.682^{+}
	(-8.75)	(-1.85)	(-1.72)	(-1.83)
$F_{\text{Wi.Cap>0.5 MW},t-1}$	0.0299**	-0.00349*	0.0852***	0.00838***
	(2.59)	(-2.00)	(11.61)	(12.94)
NUTS-3 and Year FE	Yes	Yes		
NUTS-2xYear FE			Yes	Yes
R^2	0.111		0.125	
Adj. R^2	0.108		0.124	
LL		-16981.9		-17820.4
F	18.97		70.88	
χ^2		610.6		199.0
$F_{REF=0}$ / $\chi^2_{REF=0}$ (p-value)	76.58 (1.31e-16)	3.424 (0.0643)	2.964 (0.0856)	3.351 (0.0672)
N (DF_M)	6004 (19)	4940 (20)	6004 (1)	4728 (2)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table E.5.: Estimation of successful referendum on adoption of large biomass plants (capacity-adjusted).

	(1)	(2)	(3)	(4)
	$\Delta F_{\text{Bio.Cap>1 MW}_\text{e},t}$	$\Delta F_{\text{Bio.Cap>1 MW}_\text{e},t}$	$\Delta F_{\text{Bio.Cap>1 MW}_\text{e},t}$	$\Delta F_{\text{Bio.Cap>1 MW}_\text{e},t}$
Estimator	OLS FE	Cond. Poisson FE	OLS FE	Cond. Poisson FE
$REF_{\text{Biomass},t-1}$	-0.554***	-15.12***	-0.615*	-14.01***
	(-3.60)	(-14.90)	(-2.03)	(-23.21)
$F_{\text{Bio.Cap>1 MW}_\text{e},t-1}$	-0.0856***	-0.137**	0.00983^{+}	0.0130*
	(-19.28)	(-3.11)	(1.68)	(2.20)
NUTS-3 and Year FE	Yes	Yes		
NUTS-2xYear FE			Yes	Yes
R^2	0.0420		0.000832	
Adj. R^2	0.0388		0.000499	
LL		-4316.8		-5207.7
F	70.69		3.275	
χ^2		428.0		539.1
$F_{REF=0}$ / $\chi^2_{REF=0}$ (p-value)	12.99 (0.000364)	221.9 (3.46e-50)	4.115 (0.0429)	538.8 (3.38e-119)
N (DF_M)	6004 (19)	3382 (20)	6004 (1)	2229 (2)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

E.3. A placebo test – Neighborhood effects of referenda against PV on the NUTS-3 level

Table E.6.: Estimation of successful referendum nearby on adoption of large PV systems.

	(1)	(2)	(3)
	$\Delta F_{\mathrm{PV>100\,kW_p},t}$	$\Delta F_{\mathrm{PV>100\,kW_p},t}$	$\Delta \#_{\mathrm{PV>100\,kW_p},t}$
Estimator	OLS FE	Cond. Poisson FE	Uncond. Neg. Bin. FE
$REF_{\mathrm{PV},t-1}$	0.000730	-0.102	0.209
	(0.11)	(-0.59)	(1.42)
$W\,REF_{\mathrm{PV},t-1}$	-0.00352	0.0238	0.132
	(-0.41)	(0.09)	(0.45)
$F_{\mathrm{PV>100\,kW_p},t-1}$	0.400***	-1.584***	
	(9.50)	(-3.35)	
$W\,F_{\mathrm{PV>100\,kW_p},t-1}$	0.0146	0.490	
	(0.36)	(0.46)	
$\#_{\mathrm{PV>100\,kW_p},t-1}$			-0.00397***
			(-5.13)
$W\,\#_{\mathrm{PV>100\,kW_p},t-1}$			-0.00154
			(-1.21)
θ^{-1}			0.0901
NUTS-3 and Year FE	Yes	Yes	Yes
R^2	0.571		
Adj. R^2	0.570		
LL		-113.9	-6643.4
F	140.7		
χ^2		42799.2	93298.6
$\mathrm{F}_{W\,REF=0}$ / $\chi^2_{W\,REF=0}$ (p-value)	0.169 (0.682)	0.00740 (0.931)	0.201 (0.654)
N ($\mathrm{DF_M}$)	6435 (17)	6420 (18)	6435 (446)

Robust t statistics in parenth., built with HAC SE, estim. constant omitted in column (3)
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

F. Appendix to Chapter 7 – From Green Users to Green Voters

F.1. Proof of Proposition 1

If we adopt technology at t, we get

$$V_t = e^{-rt}\left(\frac{P_t e_j}{r} - c_{j0}e^{-\alpha t}\right). \tag{F.1}$$

If we adopt technology at $t + dt$, we get

$$\begin{aligned} E_t V_{t+dt} = &(1-\lambda dt)\left[e^{-r(t+dt)}\left(\frac{P_t e_j}{r} - c_{j0}e^{-\alpha(t+dt)}\right)\right] \\ &+ \lambda dt\left[e^{-r(t+dt)}\left(\frac{\phi P_t e_j}{r} - c_{j0}e^{-\alpha(t+dt)}\right)\right]. \end{aligned} \tag{F.2}$$

The moment of adoption corresponds to $\lim_{dt\to 0}\frac{E_t V_{t+dt} - V_t}{dt} = 0$, and

$$\begin{aligned} E_t V_{t+dt} = &\ e^{-r(t+dt)}\left(\frac{P_t e_j}{r} - c_{j0}e^{-\alpha(t+dt)}\right) + \lambda e^{-r(t+dt)}\frac{(\phi-1)P_t e_j}{r}dt \\ = &\ e^{-rt}(1-rdt)\left(\frac{P_t e_j}{r} - c_{j0}e^{-\alpha t}(1-\alpha dt)\right) + \lambda e^{-rt}\frac{(\phi-1)P_t e_j}{r}dt + o(dt) \\ = &\ e^{-rt}\left(\frac{P_t e_j}{r} - c_{j0}e^{-\alpha t}\right) \\ &+ e^{-rt}\left(-P_t e_j + rc_{j0}e^{-\alpha t} + \alpha e^{-\alpha t}c_{j0} + \lambda\frac{(\phi-1)P_t e_j}{r}\right)dt + o(dt). \end{aligned} \tag{F.3}$$

Correspondingly, the solution is

$$\lim_{dt\to 0}\frac{E_t V_{t+dt} - V_t}{dt} = e^{-rt}\left(-P_t e_j + rc_{j0}e^{-\alpha t} + \alpha e^{-\alpha t}c_{j0} + \lambda\frac{(\phi-1)P_t e_j}{r}\right) = 0. \tag{F.4}$$

Rearranging, we obtain

$$(r+\alpha)e^{-\alpha t}c_{j0} + \left(\lambda\frac{(\phi-1)}{r} - 1\right)P_t e_j = 0. \tag{F.5}$$

Which yields the optimal adoption condition stated in Proposition 1:

$$c_{j0}/e_j = \frac{\left(1-\lambda\frac{(\phi-1)}{r}\right)P_t}{(r+\alpha)e^{-\alpha t}} \quad \square \tag{F.6}$$

F.2. Tables

Table F.1.: Descriptive statistics, PV.

	Mean	Std. Dev.	Min.	Max.
$F_{\mathrm{PV},t-1}$	.012	.018	8.7e-05	.13
$F_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t}$	.012	.016	8.7e-05	.11
$F_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t}$	.012	.018	8.7e-05	.13
$F_{\mathrm{PV}>100\,\mathrm{kW_p},t}$	.0002	.00048	0	.007
$F_{\mathrm{PV}>1\,\mathrm{MW_p},t}$	.00013	.00042	0	.0064
$F_{\mathrm{PVCapac.},t-1}$	.0077	.035	1.0e-06	.74
$F_{\mathrm{PVCapac.}\leq 30\,\mathrm{kW_p},t-1}$	.0096	.018	2.6e-05	.15
$F_{\mathrm{PVCapac.}\leq 100\,\mathrm{kW_p},t-1}$	.0097	.018	2.1e-05	.17
$F_{\mathrm{PVCapac.}>100\,\mathrm{kW_p},t-1}$	.00011	.00054	0	.011
$F_{\mathrm{PVCapac.}>1\,\mathrm{MW_p},t-1}$	.00011	.00054	0	.011
$\Delta F_{\mathrm{PV},t-1}$	.0088	.012	8.7e-05	.094
$\Delta F_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t}$	.0081	.011	-2.0e-05	.081
$\Delta F_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t}$	.0086	.012	-2.0e-05	.093
$\Delta F_{\mathrm{PV}>100\,\mathrm{kW_p},t}$	.00017	.00041	-3.4e-05	.0059
$\Delta F_{\mathrm{PV}>1\,\mathrm{MW_p},t}$	.00011	.00036	-3.4e-05	.0054
$\Delta F_{\mathrm{PVCapac.},t-1}$	.007	.033	-.00063	.69
$\Delta F_{\mathrm{PVCapac.}\leq 30\,\mathrm{kW_p},t-1}$	.0076	.013	-6.4e-06	.12
$\Delta F_{\mathrm{PVCapac.}\leq 100\,\mathrm{kW_p},t-1}$	.0078	.014	-5.1e-06	.13
$\Delta F_{\mathrm{PVCapac.}>100\,\mathrm{kW_p},t-1}$	.0001	.00051	-1.0e-05	.011
$\Delta F_{\mathrm{PVCapac.}>1\,\mathrm{MW_p},t-1}$	9.9e-05	.00051	-1.2e-05	.011
$F_{\mathrm{PV},t-k-1}$	.0037	.006	0	.047
$F_{\mathrm{PV},t-2k-1}$	.001	.0019	0	.021
$F_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t-k}$	.0035	.0058	0	.045
$F_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t-k}$	.0036	.006	0	.046
$F_{\mathrm{PV}>100\,\mathrm{kW_p},t-k}$	3.1e-05	9.4e-05	0	.0016
$F_{\mathrm{PV}>1\,\mathrm{MW_p},t-k}$	2.2e-05	8.1e-05	0	.0012
$F_{\mathrm{PVCapac.},t-k-1}$	.00073	.0033	0	.046
$F_{\mathrm{PVCapac.}\leq 30\,\mathrm{kW_p},t-k-1}$	.0021	.0045	0	.043
$F_{\mathrm{PVCapac.}\leq 100\,\mathrm{kW_p},t-k-1}$	.002	.0044	0	.038
$F_{\mathrm{PVCapac.}>100\,\mathrm{kW_p},t-k-1}$	9.6e-06	5.0e-05	0	.00069
$F_{\mathrm{PVCapac.}>1\,\mathrm{MW_p},t-k-1}$	9.5e-06	4.9e-05	0	.00068
$p_{\mathrm{PV},t}$	49	4.7	43	55
sun	1033	58	775	1162
$\Delta p_{\mathrm{PV},t-1}/p_{\mathrm{PV},t-k-1} * \mathrm{sun}$	.17	.24	-.022	.55
v_t	.079	.036	.02	.29
Δv_t	.012	.015	-.03	.081
$\ln(\mathrm{GDP}_{\mathrm{cap},t})$	10	.33	9.4	11
N	1239			

Table F.2.: Descriptive statistics, PV (NLS).

	Mean	Std. Dev.	Min.	Max.
$F_{\mathrm{PV},t-k-1}$	.0038	.0061	0	.047
sun	1035	58	871	1162
share si do houses$_{t-k-1}$	83	12	42	97
east	.18	.38	0	1
t	4	.82	3	5
year	2005	2.9	2002	2009
N	1157			

F.2.1. Without south

Table F.3.: Three-stage least squares estimation of increase in PV diffusion on increase in share of green votes (without south of Germany).

	(1) Δv_t	(2) Δv_t	(3) Δv_t	(4) Δv_t
$\Delta \hat{F}_{\mathrm{PV},t-1}$	0.901***	1.978***	0.355	0.541*
	(5.58)	(11.37)	(1.75)	(1.98)
$\ln(\mathrm{GDP}_{\mathrm{cap},t})$	0.00455*	-0.0403***	-0.00517	-0.00259
	(2.43)	(-3.57)	(-0.76)	(-0.24)
share si-do hous_t	-0.000145**	-0.00163	0.000373	0.000475
	(-2.70)	(-1.82)	(1.91)	(0.49)
α	-0.0271		0.0407	
	(-1.29)		(0.79)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.0749	0.257	0.540	0.598
Adj. R^2	0.0711	-0.122	0.537	0.391
F	21.59	55.56	161.9	106.2
N	737	737	737	737

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.4.: Descriptive statistics, PV (without south of Germany).

	Mean	Std. Dev.	Min.	Max.
$F_{\mathrm{PV},t-1}$	.004	.007	0	.051
$\Delta F_{\mathrm{PV},t-1}$	.0036	.0059	-1.4e-05	.042
$F_{\mathrm{PV},t-k-1}$	.0013	.0019	0	.015
sun	1002	38	775	1082
$\Delta p_{\mathrm{PV},t-1}/p_{\mathrm{PV},t-k-1} * \mathrm{sun}$	.12	.21	-.02	.52
v_t	.067	.031	.019	.21
Δv_t	.0065	.015	-.029	.081
$\ln(\mathrm{GDP}_{\mathrm{cap},t})$	10	.32	9.3	11
N	1370			

F.2.2. Solar radiation and green votes

Table F.5.: OLS estimation of solar radiation on increase in share of green votes.

	(1) Δv_t	(2) Δv_t	(3) Δv_t
sun	0.0000117	0.000000291	0.00000372
	(1.42)	(0.03)	(0.71)
$\ln(\mathrm{GDP}_{\mathrm{cap},t})$		0.00826***	0.00585***
		(5.58)	(5.56)
α	0.000675	-0.0710***	-0.0472***
	(0.08)	(-4.75)	(-4.45)
Time fixed effects	No	No	Yes
R^2	0.00212	0.0343	0.577
Adj. R^2	0.00125	0.0326	0.575
F	2.030	16.99	436.7
N	1159	1159	1159
$\mathrm{DF_M}$	1	2	4

Robust t statistics in parentheses
$^{\#}$ $p < 0.15$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

F.2.3. Pre-1998 voting dynamics filtered away from post 1998 voting dynamics

Table F.6.: Descriptive statistics, PV (pre-1998 voting dynamics filtered away).

	Mean	Std. Dev.	Min.	Max.
Δv_t	.0077	.015	-.03	.081
$\Delta v_t - \overline{\hat{\beta_{v_{t-k}}} v_{t-k}}$	.062	.03	.014	.24
v_{t-k}	.067	.03	.019	.29
$\ln(\text{GDP}_{\text{cap},t})$	10	.34	9.3	11
share si-do hous_t	83	12	43	97
$F_{\text{PV},t-1}$	.0094	.016	0	.13
$\Delta F_{\text{PV},t-1}$	.0066	.011	-1.4e-05	.094
$F_{\text{PV},t-k-1}$	.0028	.0054	0	.047
$\hat{F}_{\text{PV},t-k-1}$	.0028	.0046	-.0072	.021
N	1633			

Table F.7.: OLS estimation of increase in PV diffusion on increase in share of green votes (pre-1998 voting dynamics filtered away).

	(1)	(2)	(3)	(4)
	$\Delta v_t - \overline{\hat{\beta_{v_{t-k}}} v_{t-k}}$	$\Delta v_t - \overline{\hat{\beta_{v_{t-k}}} v_{t-k}}$	$\Delta v_t - \overline{\hat{\beta_{v_{t-k}}} v_{t-k}}$	$\Delta v_t - \overline{\hat{\beta_{v_{t-k}}} v_{t-k}}$
$\Delta F_{\text{PV},t}$	0.377***	0.705***	0.121***	0.193***
	(6.22)	(13.76)	(4.78)	(5.25)
$\ln(\text{GDP}_{\text{cap},t})$	0.0352***	0.0637***	0.00585***	-0.00778
	(12.43)	(9.51)	(7.09)	(-1.02)
α	-0.306***		-0.0374***	
	(-10.81)		(-4.42)	
NUTS-3 fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
R^2	0.288	0.563	0.582	0.752
Adj. R^2	0.286	0.343	0.581	0.626
F	114.8	363.9	424.3	462.3
N	1160	1160	1160	1160

t statistics in parentheses, built with Newey-West SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

F.2.4. Industrial vs. household systems

Table F.8.: First stage NLS estimation of logistic PV diffusion (industrial vs. household systems).

	(1)	(2)	(3)	(4)
	$F_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t-k-1}$	$F_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t-k-1}$	$F_{\mathrm{PV}>100\,\mathrm{kW_p},t-k-1}$	$F_{\mathrm{PV}>1\,\mathrm{MW_p},t-k-1}$
a	-0.0977***	-0.0993***	0.616***	0.873***
	(-9.04)	(-9.47)	(4.44)	(9.58)
a_{sun}	0.930***	0.943***	-0.117***	-0.157***
	(9.36)	(9.70)	(-4.32)	(-9.90)
a^2_{sun}			0.564***	0.706***
			(4.26)	(8.66)
$a_{\text{share si-do houses}}$	0.139***	0.144***		
	(5.27)	(5.33)		
a_{urban}			-0.00238	0.000877
			(-0.46)	(0.18)
a_{east}	-0.00497***	-0.00503***	0.00118	0.00479
	(-8.92)	(-8.65)	(1.29)	(1.33)
b	2.988***	3.233***	1.986*	2.011*
	(6.24)	(5.03)	(2.51)	(2.26)
c	4.324***	4.300***	4.943***	4.691***
	(46.09)	(43.68)	(6.05)	(7.45)
NUTS-3 fixed effects	No	No	No	No
Time fixed effects	No	No	No	No
R^2	0.753	0.750	0.220	0.254
Adj. R^2	0.751	0.749	0.215	0.247
N	1157	1157	1131	744

t statistics in parentheses, robust SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.9.: Second stage estimation of increase in PV diffusion on increase in share of green votes (industrial vs. household systems).

	Household installations		Industrial installations	
	(1)	(2)	(3)	(4)
	$\Delta F_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t}$	$\Delta F_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t}$	$\Delta F_{\mathrm{PV}>100\,\mathrm{kW_p},t}$	$\Delta F_{\mathrm{PV}>1\,\mathrm{MW_p},t}$
$\hat{F}_{\mathrm{PV}\leq 30\mathrm{kW_p},t-k-1}$	1.527***			
	(14.32)			
$\hat{F}_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t-k-1}$		1.625***		
		(14.42)		
$\hat{F}_{\mathrm{PV}>100\,\mathrm{kW_p},t}$			5.893***	
			(4.85)	
$\hat{F}_{\mathrm{PV}>1\,\mathrm{MW_p},t}$				1.691
				(1.59)
$\ln(\mathrm{GDP}_{\mathrm{cap},t})$	0.0119**	0.0129**	0.000115	0.000538
	(2.85)	(2.82)	(0.48)	(1.56)
share si-do hous_t	-0.000656	-0.000604		
	(-1.50)	(-1.28)		
R^2	0.763	0.765	0.395	0.320
Adj. R^2	0.641	0.645	0.0877	-0.0287
F	265.2	262.7	71.98	46.57
$\mathrm{F}_{\mathrm{Instrument}=0}$	205.2	207.9	23.53	2.523
$\text{p-value}_{\mathrm{Instrument}=0}$	2.07e-41	7.03e-42	0.00000150	0.113
N	1157	1157	1134	747

t statistics in parentheses, built with Newey-West SE
NUTS-3 and time fixed effects included
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

F.2.5. The diffusion of eolic systems

Table F.10.: Descriptive statistics, eolic.

	Mean	Std. Dev.	Min.	Max.
$F_{\text{Eolic},t-1}$	.036	.072	0	.87
$F_{\text{EolicCapac.},t-1}$	.032	.078	0	1.3
$\Delta F_{\text{Eolic},t-1}$	.012	.028	0	.47
$\Delta F_{\text{EolicCapac.},t-1}$	.015	.044	0	1.1
$F_{\text{Eolic},t-k-1}$	.024	.055	0	.72
$F_{\text{EolicCapac.},t-k-1}$	.017	.045	0	.8
$p_{\text{Eolic},t}$	8.6	.26	8.3	8.8
$\Delta p_{\text{Eolic},t}/p_{\text{PV},t-k} * \text{wind}$	30	147	-335	420
v_t	.079	.036	.02	.29
Δv_t	.012	.015	-.03	.081
$\ln(\text{GDP}_{\text{cap},t})$	10	.33	9.4	11
N	1239			

Table F.11.: First stage NLS estimation of logistic eolic diffusion.

	(1) $F_{\text{Eolic},t-k-1}$	(2) $F_{\text{EolicCapac.},t-k-1}$
a	-0.147***	-0.116**
	(-3.38)	(-3.27)
a_{wind}	0.0674***	0.0547***
	(3.49)	(3.49)
a_{east}	0.00662	0.00681
	(1.11)	(1.14)
b	1.431	1.902***
	(1.90)	(3.62)
c	2.555***	3.015***
	(4.83)	(7.99)
NUTS-3 fixed effects	No	No
Time fixed effects	No	No
R^2	0.440	0.379
Adj. R^2	0.437	0.376
N	1171	1171

t statistics in parentheses, robust SE
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.12.: Second stage estimation of increase in eolic diffusion on increase in share of green votes.

	(1) $\Delta F_{\text{Eolic},t-1}$	(2) $\Delta F_{\text{EolicCapac.},t-1}$
$\hat{F}_{\text{Eolic},t-k-1}$	-0.315***	
	(-3.45)	
$\hat{F}_{\text{EolicCapac.},t-k-1}$		-0.0389
		(-0.38)
$\ln(\text{GDP}_{\text{cap},t})$	0.0555*	0.0697
	(2.02)	(1.42)
R^2	0.0618	0.0101
Adj. R^2	-0.415	-0.493
F	5.913	2.076
$\text{F}_{\text{Instrument}=0}$	11.94	0.148
$\text{p-value}_{\text{Instrument}=0}$	0.000581	0.701
N	1161	1161

t statistics in parentheses, built with Newey-West SE
NUTS-3 and time fixed effects included
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

F.2.6. SOEP

Table F.13.: Descriptive statistics, SOEP.

	Mean	Std. Dev.	Min.	Max.
ΔGreen_t	.024	.15	0	1
PV_{t-1}	.065	.25	0	1
$\Delta\text{PV}_{t-1,t-2,t-3}$	.024	.15	0	1
$\ln \text{RHHINC}_t$	7.8	.59	3.7	11
$\Delta \ln \text{RHHINC}_t$	.014	.28	-3.4	3
ΔPV_{t-1}	.01	.1	0	1
Green2_{t-1}	.056	.23	0	1
$\Delta\text{Green}_{t-1,t-2,t-3}$	.049	.22	0	1
Internet_{t-1}	.43	.5	0	1
PC_{t-1}	.59	.49	0	1
N	68930			

Removed PV systems

Why should we exclude those who claim that they have removed a PV system? Figure F.1 compares the fraction of respondents who claim that they removed PV in the SOEP data set and those in the full sample of PV systems by transmission system operator. The figure illustrates that, according to the SOEP data set, disproportionately many PV systems were removed.

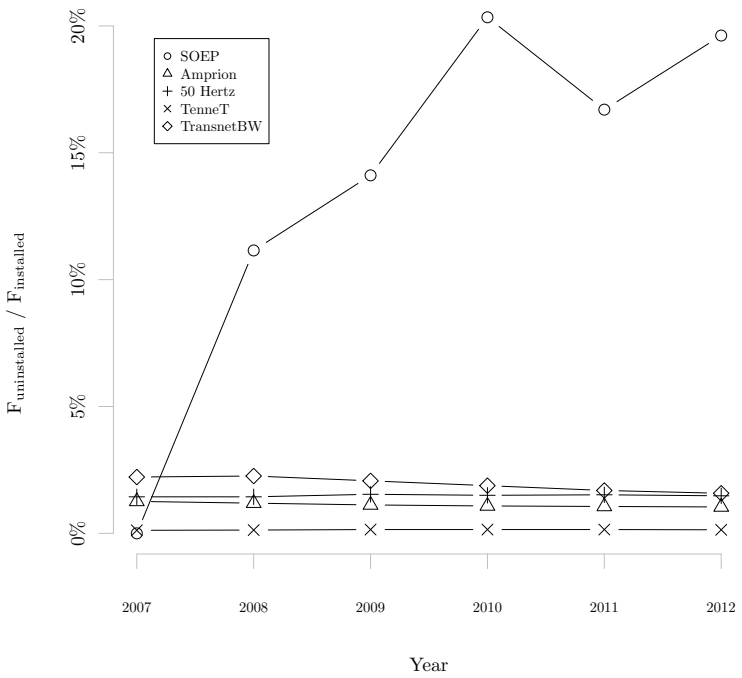

Figure F.1.: Rate of cumulative removed divided by cumulative installed PV systems by year.

Details on controls

All SOEP estimations include the following controls.

A dummy for vocational education. The dummy is set to one if the respondent states that she completed one of the following (zero otherwise): Lehre (Apprenticeship), Berufsfachschule, Gesundheitswesen (Vocational School), Schule Gesundheitswesen (bis 99) (Health Care School), Fachschule, Meister (Technical School), Beamtenausbildung (Civil Service Training), Sonstiger Abschluss (Other Training).

A dummy for college education. The dummy is set to one if the respondent states that she completed one of the following (zero otherwise): Fachhochschule (Technical College), Universitaet, TH (University, Technical College), Hochschule im Ausland (College Not In Germany), Ingenieur-, Fachschule (Ost) (Engineering, Techncial School (East)), Hochschule (Ost) (University (East)).

A dummy for labor status. The dummy is set to one if the respondent states that she has a job (zero otherwise), in SOEP wording: Working (Working).

Unbalanced panel

Section 7.4.6 in Chapter 7 shows the results for the balanced SOEP data, i.e., individuals for whom one observation between 2007 and 2012 is missing are excluded. Why are the results of the balanced panel (see Table 7.23, 7.24, 7.25, 7.26 and 7.27 in Section 7.4.6 of Chapter 7) the most reliable? Using an unbalanced panel biases our results since a missing observation in t prohibits us from including a change at $t+1$. Since we lag $\Delta\text{PV}_{t-1,t-2,t-3}$ we cannot even find a change at $t+2$. Only in the balanced panel, $\Delta\text{PV}_{t-1,t-2,t-3}$ measures the intended effect. If respondents have to possess a PV system in consecutive years to be classified as PV adopters, non-adopters should, conversely, have to possess no PV system in consecutive years. The control group – those who did not install PV – should also be observed in all periods of study.

Still, if we analyze the unbalanced panel but focus on home owners who did not remove their PV system, we find an odds ratio significantly greater than one for the level of PV adoption, see Table F.14 column (2), and the change in PV adoption, see Table F.15 column (2). The descriptive statistics for the unbalanced panel are shown in Table F.16.

Table F.14.: Odds ratio of PV level on change in green attitude for unbalanced panel.

	All	Home owners	Non-home owners
	(1)	(2)	(3)
	ΔGreen_t	ΔGreen_t	ΔGreen_t
PV_{t-1}	1.448***	1.678***	0.646
	(3.43)	(4.39)	(-1.29)
$\ln \text{RHHINC}_t$	1.185**	1.256**	1.256**
	(2.97)	(2.71)	(2.62)
Time∗NUTS-1 dummies	Yes	Yes	Yes
College and vocational degree dummy_t	Yes	Yes	Yes
Labor status dummy_t	Yes	Yes	Yes
Observations	64757	35375	28928
DF_M	67	66	65
Final log-likelihood $\mathcal{L}$	-7363.5	-4025.0	-3291.4

Exponentiated coefficients; Robust t statistics in parentheses clustered on households
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.15.: Odds ratio of PV change on change in green attitude for unbalanced panel.

	All	Home owners	Non-home owners
	(1)	(2)	(3)
	ΔGreen_t	ΔGreen_t	ΔGreen_t
$\Delta\text{PV}_{t-1,t-2,t-3}$	1.316	1.475*	0.554
	(1.47)	(2.01)	(-1.01)
$\Delta \ln \text{RHHINC}_t$	0.903	0.690**	1.249+
	(-0.95)	(-2.72)	(1.65)
Time∗NUTS-1 dummies	Yes	Yes	Yes
College and vocational degree dummy$_t$	Yes	Yes	Yes
Labor status dummy$_t$	Yes	Yes	Yes
Observations	56979	31451	25072
DF_M	67	66	63
Final log-likelihood $\mathcal{L}$	-6614.6	-3631.5	-2942.2

Exponentiated coefficients; Robust t statistics in parentheses clustered on households
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.16.: Descriptive statistics, SOEP unbalanced panel.

	Mean	Std. Dev.	Min.	Max.
ΔGreen_t	.024	.15	0	1
PV_{t-1}	.062	.24	0	1
$\Delta\text{PV}_{t-1,t-2,t-3}$	.022	.15	0	1
$\ln \text{RHHINC}_t$	7.8	.59	0	12
$\Delta \ln \text{RHHINC}_t$	.014	.3	-3.4	3.9
ΔPV_{t-1}	.011	.1	0	1
Green2_{t-1}	.054	.23	0	1
$\Delta\text{Green}_{t-1,t-2,t-3}$	.046	.21	0	1
Internet_{t-1}	.4	.49	0	1
PC_{t-1}	.54	.5	0	1
N	117610			

Instrumental variables regression – Home owners

Table F.17.: Two stage least squares estimation of PV level on change in green attitude (for home owners).

	First stage	Second stage
	(1)	(2)
	PV_{t-1}	$\Delta Green_t$
$\hat{PV}_{t-1}$		0.271***
		(3.35)
$Internet_{t-1}$	0.0194*	
	(2.42)	
PC_{t-1}	0.0293**	
	(3.17)	
$\ln RHHINC_t$	0.0371***	-0.00774
	(4.16)	(-1.44)
Time∗NUTS-1 dummies	Yes	Yes
College and vocational degree $dummy_t$	Yes	Yes
Labor status $dummy_t$	Yes	Yes
R^2	0.0531	-0.218
Adj. R^2	0.0506	-0.221
F	5.083	2.697
Hansen J statistic	0	1.375
Hansen p-value		0.241
Observations	25706	25706
DF_M	69	68
Final log-likelihood $\mathcal{L}$	-5811.2	8399.7

Robust t statistics in parentheses clustered on households
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Instrumental variables regression – All

Table F.18.: Two stage least squares estimation of PV level on change in green attitude (for home and non-home owners).

	First stage	Second stage
	(1)	(2)
	PV_{t-1}	$\Delta Green_t$
$\hat{PV}_{t-1}$		0.544***
		(3.29)
$Internet_{t-1}$	0.0107*	
	(2.12)	
PC_{t-1}	0.0125*	
	(2.31)	
$\ln RHHINC_t$	0.0488***	-0.0259**
	(9.37)	(-2.71)
Time∗NUTS-1 dummies	Yes	Yes
College and vocational degree $dummy_t$	Yes	Yes
Labor status $dummy_t$	Yes	Yes
R^2	0.0494	-0.668
Adj. R^2	0.0480	-0.671
F	6.159	3.357
Hansen J statistic	0	0.246
Hansen p-value		0.620
Observations	45538	45538
DF_M	69	68
Final log-likelihood $\mathcal{L}$	-1177.1	7354.1

Robust t statistics in parentheses clustered on households
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.19.: Estimates of PV level on change in green attitude (for home and non-home owners).

	Probit	Bi-Probit
	(1)	(2)
	$\Delta Green_t$	$\Delta Green_t$
PV_{t-1}	0.159**	0.435
	(2.64)	(1.45)
$\ln RHHINC_t$	0.0485^{+}	0.0342
	(1.65)	(1.06)
First stage		
$Internet_{t-1}$		0.0904*
		(2.13)
PC_{t-1}		0.167**
		(3.19)
$\ln RHHINC_t$		0.431***
		(10.03)
Time∗NUTS-1 dummies	Yes	Yes
College and vocational degree $dummy_t$	Yes	Yes
Labor status $dummy_t$	Yes	Yes
ρ		-0.139
$\chi^2_{\rho=0}$ (p-value)		0.898 (0.343)
$\chi^2_{Instruments=0}$ (p-value)		18.66 (0.0000889)
Observations	45455	45538
DF_M	67	137
Final log-likelihood $\mathcal{L}$	-5143.7	-15503.0

Robust t statistics in parentheses clustered on households
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Instrumental variables regression – Non-home owners

Table F.20.: Estimates of PV level on change in green attitude (for non-home owners).

	Probit
	(1)
	ΔGreen_t
PV_{t-1}	-0.270
	(-1.41)
$\ln \text{RHHINC}_t$	0.0763^{+}
	(1.74)
Time∗NUTS-1 dummies	Yes
College and vocational degree dummy_t	Yes
Labor status dummy_t	Yes
ρ	
$\chi^2_{\rho=0}$ (p-value)	
$\chi^2_{\text{Instruments}=0}$ (p-value)	
Observations	19268
DF_M	61
Final log-likelihood $\mathcal{L}$	-2242.2

Robust t statistics in parentheses clustered on households
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.21.: Two stage least squares estimation of PV level on change in green attitude (for non-home owners).

	First stage	Second stage
	(1)	(2)
	PV_{t-1}	ΔGreen_t
$\hat{\text{PV}}_{t-1}$		-1.596
		(-1.51)
Internet_{t-1}	-0.00281	
	(-0.65)	
PC_{t-1}	-0.00424	
	(-0.98)	
$\ln \text{RHHINC}_t$	0.0157^{***}	0.0275^{+}
	(3.40)	(1.76)
Time∗NUTS-1 dummies	Yes	Yes
College and vocational degree dummy_t	Yes	Yes
Labor status dummy_t	Yes	Yes
R^2	0.0176	-1.720
Adj. R^2	0.0142	-1.729
F	1.278	2.123
Hansen J statistic	0	0.0114
Hansen p-value		0.915
Observations	19832	19832
DF_M	69	68
Final log-likelihood $\mathcal{L}$	11677.6	-1840.3

Robust t statistics in parentheses clustered on households
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Instrumental variables regression – home owners, unbalanced panel

Using the unbalanced panel does not affect the results in which we use the level of Internet and PC adoption to instrument the level of PV adoption. See Table F.22 for the bi-probit estimates and Table F.23 for the two-stage least squares estimates.

Table F.22.: Estimates of PV level on change in green attitude (for home owners, unbalanced panel).

	Probit	Bi-Probit
	(1)	(2)
	ΔGreen_t	ΔGreen_t
PV_{t-1}	0.230***	0.456*
	(4.30)	(2.04)
$\ln \text{RHHINC}_t$	0.110**	0.0986**
	(3.05)	(2.60)
First stage		
Internet_{t-1}		0.120**
		(2.81)
PC_{t-1}		0.231***
		(4.38)
$\ln \text{RHHINC}_t$		0.255***
		(5.91)
Time∗NUTS-1 dummies	Yes	Yes
College and vocational degree dummy_t	Yes	Yes
Labor status dummy_t	Yes	Yes
ρ		-0.119
$\chi^2_{\rho=0}$ (p-value)		1.119 (0.290)
$\chi^2_{\text{Instruments}=0}$ (p-value)		36.11 (1.44e-08)
Observations	35375	35782
DF_M	66	137
Final log-likelihood $\mathcal{L}$	-4021.4	-15238.2

Robust t statistics in parentheses clustered on households
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.23.: Two stage least squares estimation of PV level on change in green attitude (for home owners, unbalanced panel).

	First stage	Second stage
	(1)	(2)
	PV_{t-1}	$\Delta Green_t$
$\hat{PV}_{t-1}$		0.264***
		(3.77)
$Internet_{t-1}$	0.0187**	
	(2.69)	
PC_{t-1}	0.0278***	
	(3.62)	
$\ln RHHINC_t$	0.0419***	-0.00676
	(5.68)	(-1.41)
Time∗NUTS-1 dummies	Yes	Yes
College and vocational degree $dummy_t$	Yes	Yes
Labor status $dummy_t$	Yes	Yes
R^2	0.0504	-0.201
Adj. R^2	0.0486	-0.203
F	5.904	3.548
Hansen J statistic	0	1.916
Hansen p-value		0.166
Observations	35782	35782
DF_M	69	68
Final log-likelihood $\mathcal{L}$	-7764.5	11745.1

Robust t statistics in parentheses clustered on households
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Reverse causality unbalanced panel

The estimates on reverse causality remain unaffected from using the unbalanced panel. See Table F.24 for the level of PV adoption on becoming greener and Table F.25 for the change of PV adoption on becoming greener.

Table F.24.: Odds ratio of green attitude level on PV change for unbalanced panel.

	All	Home owners	Non-home owners
	(1)	(2)	(3)
	ΔPV_{t-1}	ΔPV_{t-1}	ΔPV_{t-1}
$Green2_{t-1}$	0.848	0.606^{+}	1.420
	(-0.89)	(-1.85)	(1.37)
$\ln RHHINC_t$	1.819^{***}	1.795^{***}	1.408^{*}
	(5.95)	(4.37)	(2.15)
Time∗NUTS-1 dummies	Yes	Yes	Yes
College and vocational degree $dummy_t$	Yes	Yes	Yes
Labor status $dummy_t$	Yes	Yes	Yes
Observations	63477	33662	25636
DF_M	61	52	51
Final log-likelihood $\mathcal{L}$	-4028.7	-2686.8	-1256.8

Exponentiated coefficients; Robust t statistics in parentheses clustered on households
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.25.: Odds ratio of change in green attitude on PV change for unbalanced panel.

	All	Home owners	Non-home owners
	(1)	(2)	(3)
	ΔPV_{t-1}	ΔPV_{t-1}	ΔPV_{t-1}
$\Delta Green_{t-1,t-2,t-3}$	0.756	0.475^{*}	1.305
	(-1.31)	(-2.23)	(0.91)
$\Delta \ln RHHINC_t$	0.988	1.054	0.945
	(-0.06)	(0.19)	(-0.18)
Time∗NUTS-1 dummies	Yes	Yes	Yes
College and vocational degree $dummy_t$	Yes	Yes	Yes
Labor status $dummy_t$	Yes	Yes	Yes
Observations	55002	29609	21322
DF_M	58	51	47
Final log-likelihood $\mathcal{L}$	-3331.7	-2271.0	-973.1

Exponentiated coefficients; Robust t statistics in parentheses clustered on households
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Affidavit

I hereby declare that the dissertation entitled

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–
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is my own work. I have used only the sources indicated and have not made unauthorized use of services of a third party. Where the work of others has been quoted or reproduced, the source is always given. I have not presented this thesis or parts thereof to a university as part of an examination or degree.

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