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FROM GREEN USERS TO GREEN VOTERS

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ABSTRACT

We study the effect of the diffusion of photovoltaic (PV) systems on the fraction of votes obtained by the German Green Party in federal elections. Using both regional and household survey data, we show that households that adopted PV systems became more supportive of the Green Party. We estimate that the adoption of domestic PV systems led to 25 percent of the increment in green votes between 1998 and 2009. Our results are robust to instrumentation using regional variation in solar radiation and past experience adopting non-green technologies. We conjecture that these results are driven by cognitive dissonance.

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1 Introduction

Technology is a powerful driver of change in society. It is well documented that the invention and adoption of new technologies is *a* (and maybe even *the*) key driver of a country's productivity growth. It has also been documented that the adoption of a technology facilitates the adoption of subsequent technologies in related fields (Comin and Hobijn, 2004; Comin et al., 2010), and that information technologies foster technology adoption in general because they facilitate the diffusion of information (Dittmar, 2011).[1] However, beyond productivity and knowledge we have relatively little systematic evidence that technology directly impacts other social variables.

In this paper, we explore a new research question. Namely, whether the diffusion of technologies affects political preferences and, ultimately, voting patterns. To study this issue, we consider the diffusion of photovoltaic (PV) systems in Germany. Between 1998 and 2009, the fraction of German roofs with photovoltaic installations increased from virtually zero to 3.6 percent. Over the same period the fraction of valid votes for the Green Party in federal elections increased from 6.5 to 10.5 percent. Is it possible that the diffusion of green energy technologies has caused some of the observed increase in Green Party votes?

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 from PV systems diffusion on green votes.[2] 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 implement two distinct identification strategies that are not affected by these potential biases. Our first strategy constructs an instrument for the adoption rate, i.e. the first difference in the diffusion level, of PV systems at the regional (NUTS-3) level based on the variation in solar radiation. Solar radiation is a valid instrument because it impacts the return to adopting PV systems and does not affect directly the (regional) increment in green votes, our dependent variable. Our second identification strategy uses household survey data from the German Socio-Economic Panel (SOEP) to estimate the effect of adopting

[1] Technology also affects many aspects of life indirectly by raising living standards, and directly by allowing us to do things that were impossible before (for e.g., curing diseases).

[2] The design of the German subsidy system renders this reverse causality argument as unlikely. By law, feed-in tariffs are non-retro-active. That is, the feed-in tariff for each PV system is pre-determined (for a period of twenty years) based on the year of installation of the PV system. As a result, current adopters do not benefit from future increases in feed-in tariffs. Therefore they have no incentive to vote for the Green Party to increase future feed-in tariffs.

a solar system on the likelihood of reporting a greater support for the Green Party. The survey data permits us to investigate whether the change in Green Party support occurs after the household has adopted a solar system or vice-versa. Additionally, we use previous household's experience adopting non-green technologies (i.e., computers and Internet) to instrument for the adoption of solar systems.

The findings from our empirical exercises are very consistent. Our analysis of the regional-level data shows that the diffusion of PV systems is responsible for approximately 25 percent of the increase in the votes for the Green Party. This result is robust to instrumenting PV adoption by the lagged level of diffusion induced by regional solar radiation. The estimate is also robust to controlling for the endogenous dynamics of green support estimated during the 1980s and early 90s, before PV systems started to diffuse. Reassuringly, we find that the estimated effect of PV adoption on the increase in green votes comes entirely from the small household PV systems (vs. industrial systems) and is orthogonal to the adoption of other industrial green technologies such as eolic (wind) and biomass energy plants.

The household survey data shows that the odds that a home owner who has installed a solar energy system experiences an increase in her support for the Green Party is 1.6 times higher than for a home owner who has not installed one. In contrast, we find no evidence that becoming green induces home owners to install solar systems. These findings are robust to instrumenting the adoption of solar systems with prior adoption of non-green technologies such as computers or Internet. The use of two instruments permits us to run endogeneity tests that fail to reject the null that the instruments are exogenous. From this evidence we conclude that there is a causal effect of the adoption of solar energy systems by households on their attitudes and voting behavior towards the Green Party.

After establishing the main finding of the paper, a question that naturally emerges is about the mechanism by which PV adoption increases the likelihood of voting for the Green Party. We present one hypothesis in Section 3 based on the assumption that agents are cognitive dissonant (Festinger, 1957; Akerlof and Dickens, 1982). In our model, voters can adopt a PV system and, beyond the economic return of this investment, they may derive utility directly from their actions. The magnitude of this intrinsic utility depends on the intensity of their green values. In this context, agents have an incentive to embrace green values after they have undertaken a significant green action such as adopting a PV system.

Demonstrating empirically that this is the mechanism by which PV adoption induces Green Party votes is beyond the scope of this paper. However, we find support for two implications of our theory. In particular, a corollary of our theory is that agents that are more directly involved in the decision to adopt PV systems will be more prone to vote for the Green Party. Consistent with this prediction, we document that the association between solar adoption and increase in the likelihood to support the Green Party holds only when the voter is the owner of the dwelling. It also holds mostly in rural areas, where there is a greater prevalence of single and double family dwellings and of owner-occupied dwellings.

We explore two alternative hypothesis for the effect of PV adoption on green votes: a money for votes and a Bayesian learning explanation. We compute the economic gains for PV adopters and find that they are small. We also find that the association between PV adoption and green votes is robust to controlling for proxies of the change in profitability of PV systems. Therefore, it seems unlikely that voters are rewarding the Green Party from creating new income streams. The Bayesian rationale is that PV adoption provides households information about the Green Party values and policies. This Bayesian theory seems inconsistent with the fact that it is precisely in the 'Länder' where the Green Party was in power, and therefore where households presumable knew more about the Green Party, where PV adoption leads to larger increases in green votes.

Our investigation is related to studies on 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.[3] Schumacher (2014) considers similar factors and reaches similar conclusions with respect to Green Party voting in Germany. Our analysis controls for these drivers of voting behavior but focuses on the independent effect of adopting green energy systems on Green Party voting.

The literature on policy feedbacks (Schattschneider, 1935; Pierson, 1993; Soss and Schram, 2007) is also relevant for our empirical analysis. 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 (i.e., growth in feed-in tariffs) and (ii) we exploit exogenous variation in adoption rates which, by definition, is not driven by new policies.[4]

With respect to the potential interpretation of our findings, 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

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

[4]Falck et al. (2014) is related to the general theme of the role of technology diffusion on elections, but very tangentially related to our paper. In particular, they reveal that the availability of Internet technology impacts voter turnout negatively in Germany.

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)). There are not many studies on the role of cognitive dissonance in political attitudes. A recent one by Mullainathan and Washington (2009) finds that the act of voting for a candidate leads to a more favorable opinion of the candidate in the future.

The rest of the paper is organized as follows. Section 2 describes the relevant institutional context of green energy in Germany and presents the aggregate trends in green technology diffusion and green voting. Section 3 develops a model of technology adoption, green values and voting. The model allows us to explore the drivers of diffusion and Green Party votes in a setting where agents are cognitive dissonant. Our model also motivates the instrumentation strategies. Section 4 presents the empirical findings, and discusses their robustness. The interpretation of the results follows in 5. Section 6 concludes.

2 German institutional context and aggregate trends

The last fifteen years have seen how green technologies have become wide-spread in Germany while the support for the Green Party has increased significantly. Next we describe these trends as well as institutional settings in which they have taken place.

In 1998, the Social Democratic-Green coalition won the federal elections. Two years later, the government introduced a new law, the EEG, which raised the feed-in tariff for electricity produced from PV systems. For example, the feed-in tariff for systems with a capacity of at most 30 kW_p was raised to 50 EURCent/kWh (from 8.84 EURCent/kWh).[5] The EEG stipulated vintage-specific feed-in tariffs guaranteed for a twenty year period (Agnolucci, 2006; Altrock et al., 2011; Maurer et al., 2012).[6] In this system, feed-in tariffs were determined (for a period of twenty years) based on the year of installation of the PV system. Furthermore, changes in the system only affected new installations (i.e. they were non-retro-active). 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 0.49 percent, almost 10 times larger than in 1999.

[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].

[6]However, starting in 2002, new installations received a feed-in tariff 5 percent lower than installations put in place the previous year. See Figure 1.

The 2004 Amendment to the EEG further raised the feed-in tariff to 57 EURCent/kWh (see Figure 1). By 2009, 3.6 percent of buildings had PV systems.[7]

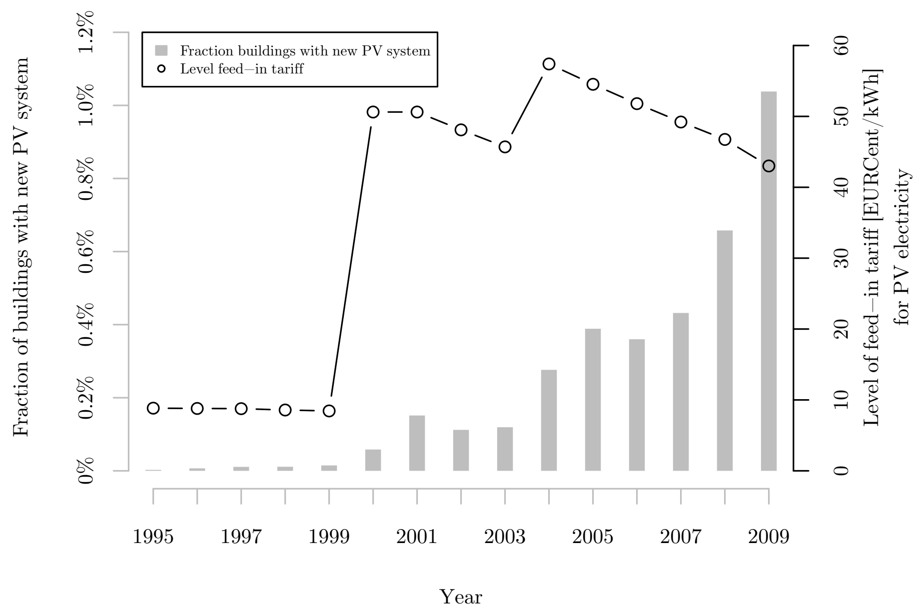

Figure 1: Fraction of buildings with a new PV system and the level of the feed-in tariff for electricity from PV (for systems with a capacity of at most 30 kW_p) in Germany from 1995 through 2009.

Underneath this trend there were important geographic differences. Figure 2 presents the evolution of the share of buildings with PV systems in rural and urban areas. While in urban areas, it increased from 0.07 percent in 1998 to 1.47 percent in 2009, in rural areas it increased from 0.03 to 4.2 percent. Therefore, the diffusion of PV systems was predominantly a rural phenomenon. Furthermore, since three quarter of the buildings are in rural areas, 93 percent of the overall increment of PV systems took place in rural areas.

To further understand the geographic patterns of PV diffusion Figure 3 displays maps with the diffusion levels in 1998, 2002 and 2009 on the NUTS-3 level in Germany.[8] In 1998, the diffusion level of PV systems was low in all regions. By 2009, the highest adoption rates can be observed in the south (where global solar radiation is higher), in the north of Hesse and in the east and the north-west of North Rhine-Westphalia. In contrast, relatively few PV

[7] In 1999, the total capacity installed in eolic plants was seven times larger than the capacity installed in PV systems. The 2000 EEG also introduced new feed-in tariff schemes for electricity from eolic and biomass plants, though they rose comparatively less than for PV systems (to 9.1 EURCent/kWh for eolic and to 10.2 EURCent/kWh for biomass). See Figure 6 in Appendix A for eolic and Figure 8 in Appendix B for biomass plants.

[8] We do not show the map for 2005 for reasons of clarity. We use 2006's classification with 429 German NUTS-3 regions. Due to the restructuring of districts, we lose the data for 2.3 percent of the NUTS-3 regions for 1998 and for 6.9 percent for 2009.

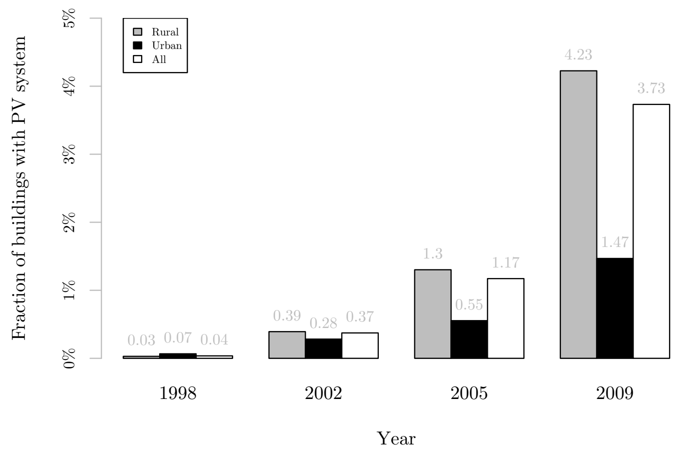

Figure 2: Evolution of the share of buildings with PV systems in rural and urban areas in Germany in 1998, 2002, 2005 and 2009.

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.[9]

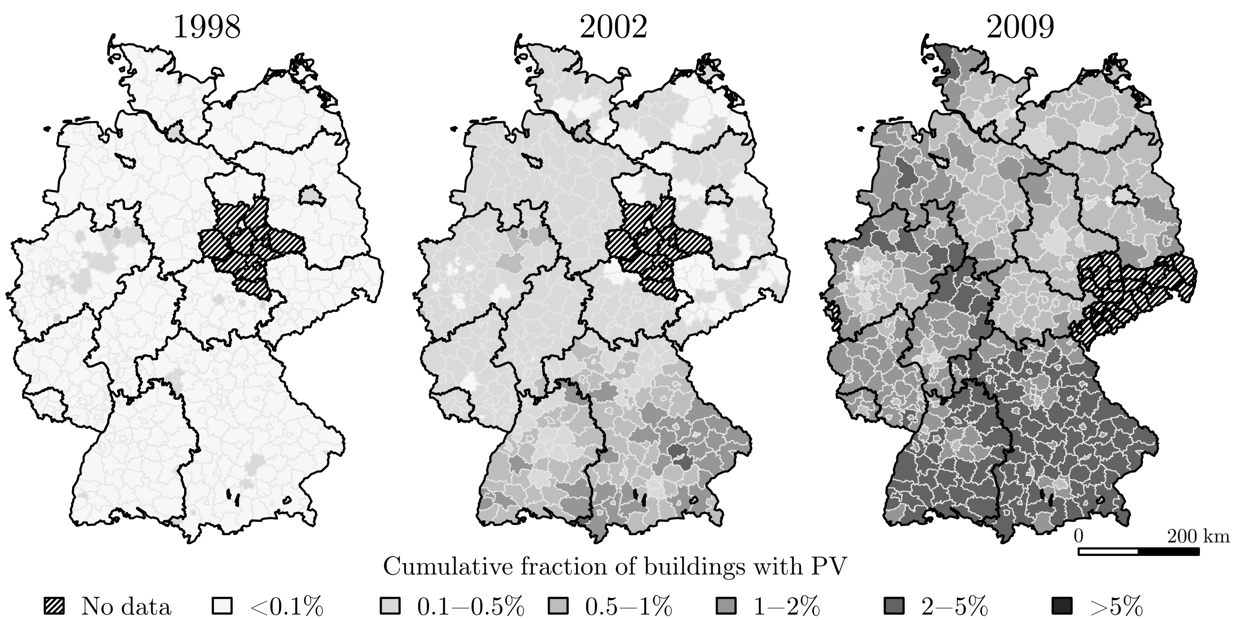

Figure 3: Fraction of buildings with PV at NUTS-3 level for 1998, 2002 and 2009.

Coinciding with the diffusion of green energies, the Green Party experienced a significant increase in votes. (See white bar in Figure 4.)[10] In the 1998 elections, the Green Party received 6.5 percent of valid votes. This share increased to 8.2 percent in 2002, declined

[9]See Figure 7 in Appendix A for a parallel analysis for the diffusion of eolic systems and Figure 9 in Appendix B for biomass plants.

[10]Voting data comes from DESTATIS (2012). We consider second votes ('Zweitstimmen') and only the regions for which data is available at the NUTS-3 level.

to 7.7 percent in 2005 and reached 10.5 percent in 2009 (see Figure 4). The propensity to vote for the Green Party increased in both rural and urban areas. In urban areas the share of valid votes for the Green Party increased from 8.6 percent in 1998 to 13.3 percent in 2009, while in rural areas it increased from 5.8 to 9.6 percent. However, since rural areas approximately concentrated 75 percent of the valid votes, they accounted for a majority of the overall increase in green votes. There was significant regional variation in the increase of the support for the Green Party (see Figure 5).[11] The largest 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.

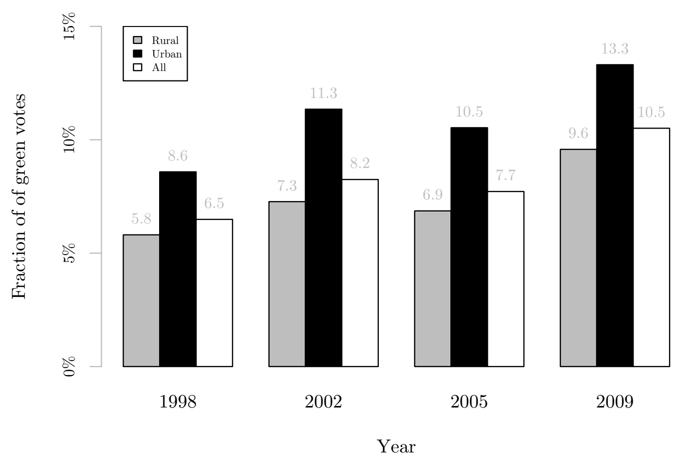

Figure 4: Evolution of fraction of green votes in federal elections in rural and urban areas and overall in Germany from 1998 through 2009.

3 A model of diffusion, green preferences and voting

We develop a model to study the drivers of PV adoption, and how green attitudes may change endogenously as agents adopt PV systems. We start with the case where agents' preferences towards green values are fixed. After presenting this baseline case, we allow agents to shift their intrinsic valuation of green actions, and explore the resulting dynamics for PV adoption and voting. We conclude by deriving some testable predictions from the model.

3.1 Diffusion

Time is continuous. In each region (n), there is a continuum of agents that differ in the cost of adopting a PV system. In particular, agent j faces a sunk cost c_{jt} of adopting a system

[11] Due to the restructuring of districts, we lack data for some 3 percent of the NUTS-3 regions for 1998 and 7.5 percent for 2009.

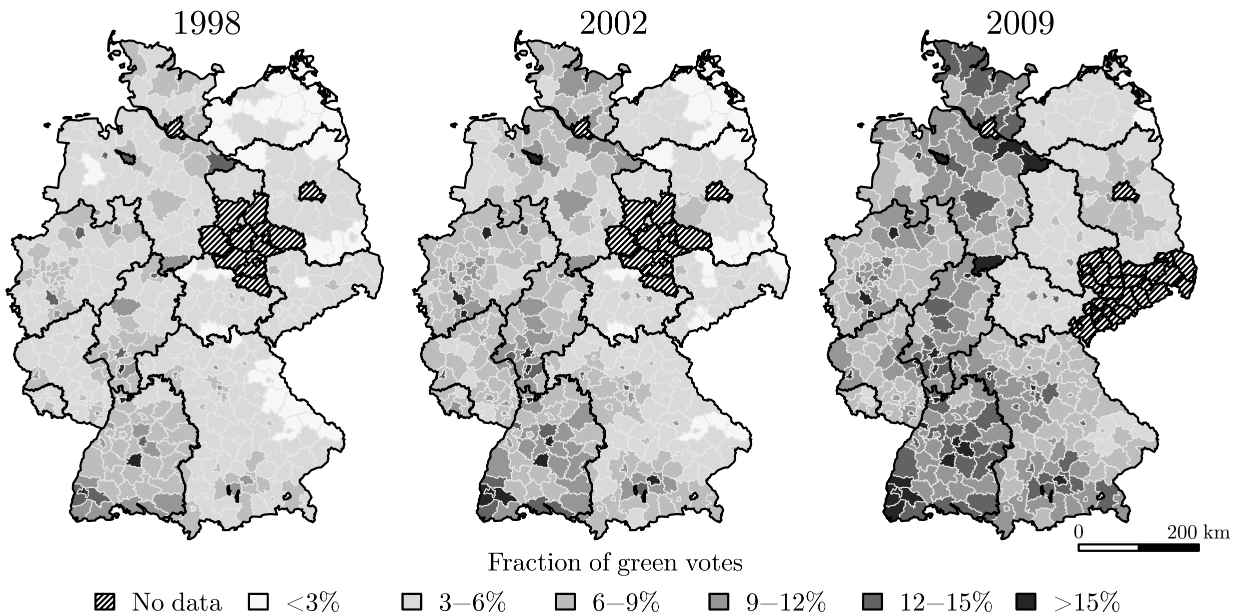

Figure 5: Fraction of green votes at NUTS-3 level for 1998, 2002 and 2009.

at time t given by

$$c_{jt} = c_j e^{-\alpha t},$$

where α is the constant rate of decline of adoption costs. Without loss of generality, we index the potential adopters, j, so that c_j is increasing. Furthermore, we assume that, in each region, $\log(c_j)$ 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.

A PV system can produce e_n units of electricity. The sub-index n captures the fact that electricity production depends on solar radiation and other factors that vary across regions.[12] 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.[13] P_t evolves stochastically according to the following Poisson process:

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

[12] The dependency of e_n on solar radiation may be non-linear.

[13] In Germany, it is for a 20 year period (EEG, 2000, 2004, 2011).

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

The revenues for agents that have adopted a PV system are $P_t e_n$. In addition to this monetary component, installing a PV system provides additional utility with an equivalent monetary value of $\tilde{g}$. That is, the monetary value of the utility experienced by an agent that has installed a PV system is $P_\tau e_n + \tilde{g}$. For the time being, we assume $\tilde{g}$ to be fixed (and small relative to $P_\tau e_n$).[14]

Let r be the constant discount rate, and V_τ denote the value of an agent that has adopted a PV system of vintage τ. V_τ is defined by

$$rV_\tau dt = (P_\tau e_n + \tilde{g})dt, \tag{2}$$

which yields

$$V_\tau = \frac{P_\tau e_n + \tilde{g}}{r}. \tag{3}$$

For those that have not installed a PV system at time t, the option value of installing a PV system, W_t, is defined by

$$W\left(t, P_t\right) = \max\left\{E_t \frac{W(t+dt, P_{t+\mathrm{d}t})}{1+rdt}, V_t - c_{jt}\right\}, \tag{4}$$

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*

$$c_j \leqslant \bar{c}_t = \frac{\left(1 - \lambda\frac{(\phi-1)}{r}\right) P_t e_n + \tilde{g}}{(r+\alpha)e^{-\alpha t}}, \tag{5}$$

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

$$\begin{aligned} & F_n\left(\log \bar{c}_t\right) \\ = \; & \left[1 + \exp\left(-b_n\left(\log\left[(1 - \lambda(\phi-1)/r)P_t e_n + \tilde{g}\right] - \log(r+\alpha) + \alpha t\right)\right)\right]^{-1}. \end{aligned} \tag{6}$$

Proof: See Appendix C.□

Equation (6) characterizes the diffusion pattern of PV systems. Taking a first order Taylor expansion of (6), we can derive an expression for the adoption rate (i.e., the change in diffusion), f_n:

[14] This is just a simplifying assumption. In section 4.2.2, we find direct evidence that supports it.

$$
\begin{aligned}
f_{nt} \quad \equiv \quad & dF_{nt} \simeq F_{nt}(\log \bar{c}_t) * (1 - F_{nt}(\log \bar{c}_t)) * b_n * \underbrace{\left[\frac{dP_t}{P_t} \frac{(1 - \lambda(\phi - 1)/r)P_t e_n}{(1 - \lambda(\phi - 1)/r)P_t e_n + \tilde{g}} + \alpha * dt \right]}_{\text{revision in return}} \\
\simeq \quad & F_{nt}(\log \bar{c}_t) * (1 - F_{nt}(\log \bar{c}_t)) * b_n * \left[\frac{dP_t}{P_t} + \alpha * dt \right] \qquad (7)
\end{aligned}
$$

where we have used the assumption that $\tilde{g}$ is small relative to $P_\tau e_n$.

Equation (7) helps us understand the drivers of adoption. One factor that affects adoption rates is the lagged diffusion level, F_n.[15] One implication of this result is that factors that affect lagged diffusion also impact the adoption rate. In particular, solar radiation in the region, through its impact on the level of electricity produced (e_n), lowers the cutoff adoption cost in (5), leading to higher lagged diffusion levels and to higher adoption rates. Since solar radiation is, arguably, exogenous to changes in attitudes to green parties, we can use the diffusion levels of PV systems predicted by regional solar radiation to instrument for the (actual) adoption rates. This is indeed the identification strategy we implement below.

Beyond, past diffusion levels, adoption rates are affected by changes in the determinants of the cutoff adoption cost, c_{jt}. In particular, adoption rates increase with the growth of feed-in tariffs and with the rate of decline of the cost of installing PV systems. Expression (7) also implies that past green attitudes only affect adoption rates to the extent that they affect the lagged level of diffusion. Exogenous changes in green attitudes also impact the cutoff cost (5) and adoption rates in a way similar to changes in feed-in tariffs (P_t). Note, however, that exogenous revisions in green attitudes are orthogonal to lagged diffusion levels. Therefore, the presence of revisions in green attitudes should not affect the validity of our instrumentation strategy.

3.2 Endogenous environmental values and voting

Our diffusion model assumes a fixed intrinsic valuation of adopting a PV system, $\tilde{g}$. Next, we relax this assumption and allow agents to change their green attitudes in order to derive greater (intrinsic) value for their actions.

Setting .– Let's suppose that the instantaneous intrinsic utility that an agent derives from her actions is

$$\delta * [A * g + B * w] . \qquad (8)$$

[15] In general, the effect of lagged diffusion on adoption is non-linear. However, in the initial diffusion phase (i.e., when F_{nt} is small), adoption is approximately linear in lagged diffusion.

In this formulation, A is a binary variable that measures whether the agent has adopted a PV system, g measures the agent's intrinsic value (in utils) of taking green actions; B represents the agent's actions related to other values orthogonal to the environment (for e.g., gifts to charity), and w measures the agents intrinsic value of those actions (i.e., her preference for the poors' well-being). The parameter δ is the monetary value of utility. Note that, in this formulation, the intrinsic value of adopting a PV system in monetary terms is $\tilde{g} = \delta * g$.

Each period is divided in three moments. In the first moment, agents have the option to adopt a PV system. If they do adopt one, they incur in the installation cost c_{jt} and lock in the prevailing feed-in tariff, P_t. Second, agents learn their cost of changing green preferences and have the opportunity to do so. Finally, agents vote. Next, we describe in more detail these decisions.

Agents' intrinsic utility from green actions, g, can take two values, $\{g_l, g_h\}$, with $g_h > g_l$. For simplicity, we assume that initially all agents have $g = g_l$. Agents can incur in a cost c_v (in terms of utils) and increase g from g_l to g_h. They only learn their cost of changing green attitudes in the second instant, after they have adopted a PV system. A fraction λ of agents face a $c_v = c_l$, and the complementary fraction $(1-\lambda)$ have $c_v = c_h$, with $c_h > c_l$. We make the following assumption about the relative size of g and c_v.

$$c_h > g_h - g_l > c_l. \tag{9}$$

Voting is a truthful revelation of the agent's preferences. In particular, agents have two electoral options: the Green Party and the alternative party. Their preferences for each of these options are, respectively, g and w, where w is distributed according to $W(.)$ in population. We assume that w is independent of c_v or c_j.

Green votes .– Now we can characterize the evolution of the fraction of green votes in our model.

Proposition 2 *The change in green votes is given by*

$$dG = \left(W\left(g_h\right) - W\left(g_l\right)\right) * \lambda * dF\left(\log\left(\bar{c}_t^h\right)\right), \tag{10}$$

where the cutoff cost for adoption, $\bar{c}_t^h$, is given by

$$\bar{c}_t^h = \frac{\left(1 - \lambda\frac{(\phi-1)}{r}\right) P_t e_n + \delta\left[\lambda\left(g_h - rc_l\right) + (1-\lambda) * g_l\right]}{(r+\alpha)e^{-\alpha t}}. \tag{11}$$

Proof: Agents that feel more strongly about environmental matters than for the alternative dimension will vote for the Green Party. Formally, these are the agents for which

$g \geq w$. The rest of the voters will vote for the w party. Given the independence of g and w in population, the fraction of green votes is given by

$$G = \gamma_t W(g_h) + (1-\gamma_t) W(g_l),$$

where γ_t is the fraction of agents with $g = g_h$ in period t, and $W(x)$ is the share of agents with $w \leq x$, for $x \in \{g_l,\ g_h\}$.

Since w is fixed, changes in green voting are driven by changes in the fraction of agents with $g = g_h$, γ_t. Formally,

$$dG = d\gamma_t * (W(g_h) - W(g_l)) . \tag{12}$$

To solve for the change in the fraction of agents with $g = g_h$, $d\gamma_t$, note that green values only affect agent's intrinsic utility if she has taken green actions (i.e., when $A = 1$). Therefore, a necessary condition to incur in the costs of increasing her green values is that the agent has installed a PV system. Condition (9) adds a second necessary condition. Increasing the preference for green actions is only worthwhile for agents with a low cost of changing preferences (*i.e.*, $c_v = c_l$). These two conditions imply that $d\gamma_t$ is equal to the fraction of agents that adopt a PV system and that have a low cost of increasing their green value. That is,

$$d\gamma_t = dF\left(\log\left(\bar{c}_t^h\right)\right) * \lambda \tag{13}$$

where, following Proposition 1, the cutoff cost for adoption, $\bar{c}_t^h$, is given by (11).[16] Combining (12) and (13), we obtain the expression for the change in green votes (10).□

Expression (10) illustrates the main result from our model. Once we endogenize the attitudes of agents, the adoption of PV systems leads to an increase in Green Party votes. This finding is an illustration of the cognitive dissonance phenomena (Festinger, 1957), by which, agents change their preferences/values to derive greater utility from their previous actions. In our context, the action is the decision to adopt a PV system and the change in values is reflected in an increase in Green Party votes.

One corollary to this result is that the more involved voters are in the decision to adopt (and maintain) a PV system, the stronger will be the connection between PV adoption and increased support for the Green Party. There are three dimensions that affect the voter's direct involvement in PV adoption decisions. The first is whether the voter owns the house with PV since renters do not decide whether to install PV systems in their dwellings. In 2011, 25.3 percent of urban dwellings were owner occupied, while the share of owner occupied dwellings in rural areas was 51.7 percent (DESTATIS, 2011). Therefore, voters

[16] Note that the relevant intrinsic value for the PV adoption decision is the net expected green value at time of adoption $(\lambda (g_h - rc_l) + (1-\lambda) * g_l)$.

are more likely to be involved in PV adoption in rural areas. The second dimension of voter involvement in PV adoption is whether the building is occupied by a single or many households. The fewer households live in a building, the stronger the influence of each individual household in the adoption decision. In rural areas, 88.4 percent of dwellings were single or double family houses in 2009 vs. only 65.1 percent in urban areas (DESTATIS, 2013b; BBSR, 2015). Therefore, this second dimension also implies that rural voters are more involved with PV adoption decisions than urban voters. The third dimension of voter involvement in PV adoption is the system capacity. Small capacity systems are adopted by households, while large capacity systems are installed by corporations. Therefore, we should only expect only the adoption of small PV systems to be associated with the evolution of Green Party votes.

In summary, Proposition 2 together with these considerations yield the following predictions:

#1 In regions where we observe greater increases in PV diffusion (i.e. adoption rates) we should see larger increases in the share of votes for the Green Party.

#2 We should observe a stronger association between PV adoption rates and increases in Green Party votes in rural than in urban regions.

#3 We should observe no association between PV adoption rates and increases in Green Party votes in rented properties.

#4 We should see no association between increases in the diffusion of industrial green energy systems and changes in Green Party votes.

4 Empirical evaluation

Next, we evaluate empirically whether the diffusion of PV systems has led to an increase in the votes for the Green Party in Germany. We investigate this question using two distinct data sets. The first is a panel at the NUTS-3 level that we have assembled. The data set includes both the diffusion of PV systems and the fraction of green votes from 1998 until 2009. We complement our analysis using an individual-level data set that covers the diffusion of solar energy systems and individual attitudes towards the Green Party between 2007 and 2012.

4.1 NUTS-3 level evidence

In our baseline specification, 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}) :

$$V_{nt} = \alpha_n + g_n * t + \alpha_t + \beta F_{nt-1} + \rho X_{nt} + \epsilon_{nt}. \tag{14}$$

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-1} is the stock of PV systems installed normalized by the number of potential adopters in the region in year $t-1$,[17] 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 $t-k$), (14) can be expressed as:

$$\triangle V_{nt} = g_n + \delta_t + \beta \triangle F_{nt-1} + \rho \triangle X_{nt} + u_{nt} \tag{15}$$

where $\triangle V_{nt} \equiv V_{nt} - V_{nt-k}$ is the increment in the share of green votes, $\delta_t \equiv \alpha_t - \alpha_{t-k}$ is a time dummy, $u_{nt} \equiv \epsilon_{nt} - \epsilon_{nt-k}$ is an error term and $\triangle F_{nt-1} \equiv F_{nt-1} - F_{nt-1-k}$ is the adoption rate defined as the increase in the ratio of the stock of PV systems adopted over the number of potential adopters.

4.1.1 Ordinary least squares estimates

Table 1 reports the ordinary least squares (OLS) estimates of equation (15).[18] The set of controls, ΔX_{nt}, includes the growth in per capita income in the region. The first four columns report estimates from specifications that 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. NUTS-3 fixed effects capture region-specific trends in attitudes towards the Green Party, education and values, which may lead to regional trends in green votes. Column (5) additionally controls for time dummies interacted with NUTS-1 ('Länder') regional dummies. This specification controls for time varying factors that are common across the regions within a NUTS-1 region. We take the specification with both time and NUTS-3 fixed effects as our baseline and in what follows we just report estimates that include NUTS-3 and time fixed effects. Interestingly, our findings are robust across specifications.

Table 1 shows that increments in the share of green votes are positively associated with adoption rates in the first five specifications. These associations are statistically and econom-

[17] German federal elections (between 1998 and 2009) took place in fall. PV diffusion is measured at the end of the year. By lagging PV diffusion by one year, we ensure that the adoption of PV systems does not

Table 1: OLS estimation of increase in PV diffusion on increase in share of green votes.

	Increase in share of green votes						
	All					Rural	Urban
	(1) ΔV_t	(2) ΔV_t	(3) ΔV_t	(4) ΔV_t	(5) ΔV_t	(6) ΔV_t	(7) ΔV_t
PV adoption rate: $\Delta F_{\text{PV},t-1}$	0.419***	0.671***	0.122***	0.242***	0.234***	0.235***	0.138
	(14.27)	(19.15)	(4.84)	(5.86)	(4.90)	(5.35)	(0.70)
$\Delta \ln(\text{GDP}_{\text{cap},t})$	0.0250***	0.0572***	-0.0155***	0.00154	0.00392	-0.0000617	0.0158
	(4.03)	(6.26)	(-2.99)	(0.24)	(0.96)	(-0.01)	(1.21)
α	0.00720***		0.0235***				
	(12.39)		(25.36)				
NUTS-3 fixed effects	No	Yes	No	Yes	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
NUTS-1×Time fixed effects	No	No	No	No	Yes	No	No
R^2	0.135	0.258	0.568	0.642	0.823	0.666	0.646
Adj. R^2	0.134	-0.117	0.567	0.459	0.724	0.495	0.458
F	110.6	201.3	413.9	313.3	138.7	253.3	71.99
N	1160	1160	1160	1160	1160	849	311

t statistics in parentheses, built with Newey-West SE
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The point estimates for the PV adoption rate $(\Delta F_{\text{PV},t-1})$ in columns (6) and (7) are robust to including NUTS-1×Time fixed effects.

ically significant. Based on our baseline 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 13 in Appendix D for the relevant descriptive statistics). Similarly, the diffusion of PV systems between 1998 and 2009 is associated with an increase in the fraction of green votes of 0.9 percent, which is approximately 25 percent of the actual increase in the voting rate experienced by the Green Party between 1998 and 2009.

In addition to controlling for the robustness of the estimates to regional and time dummies, we also explore their robustness to allowing for spatially correlated error terms. In particular, we follow Yu et al. (2008) and consider a generalization of equation (15) where the error term u_{nt} is modeled as

$$u_{nt} = \psi * \sum_{s=1}^{q} w_{sn} u_{st} + \epsilon_{nt}.$$

w_{sn} is a weighting matrix such that $w_{sn} = 1/N_n$ for the N_n regions that are neighbors of n and zero otherwise, and where ϵ_{nt} is an iid error term. Column (1) of Table 14 in Appendix D.1 shows that the estimate of ψ is positive and significant suggesting that innovations in the increase in Green Party votes are spatially correlated. However, allowing for spatial correlation of the error term does not affect the significance and has a minimal effect on the

occur after the elections have taken place.

[18]Reported standard errors (SE) are (in our NUTS-3 level analyzes) always robust to both arbitrary heteroscedasticity and arbitrary auto-correlation. They have a bandwidth of 2.

magnitude of the coefficient β on lagged adoption.[19] Hence, we conclude that our estimates of the association between increases in green votes and lagged PV adoption rates are robust to allowing for the potential spatial correlation in error terms.

The last two columns of Table 1 explore whether the relation between adoption rates and green votes differs between rural and urban areas. We find that the association between PV adoption rates and the increase in Green votes is significantly positive only for rural regions. Furthermore, the point estimate is almost twice as large for rural than for urban regions. This observation is consistent with the model's predictions. In our model, it is a consequence of the more direct involvement that voters have in the adoption and maintenance of PV systems in rural than in urban environments. Other hypotheses, instead, would have a harder time rationalizing the rural-urban contrast in this association. Take for example the hypothesis that there has been an exogenous variation in green sentiment. There is no a priori reason why we would only see that in rural areas.

Nevertheless, the regressions shown so far are not sufficient to disprove the possibility that the association between adoption rates and the increment in the fraction of green votes is driven by some omitted variable. To confidently argue that the estimates in Table 1 reflect a 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 that may drive voting patterns, other than adoption.

4.1.2 Instrumenting with solar radiation

We construct our instrument for PV adoption rates by exploiting the effect of solar radiation on PV diffusion. Solar radiation may affect the diffusion level because it impacts the amount of electricity a PV system can produce (see equation (6)). Due to the non-linearities in the diffusion process, lagged diffusion affects adoption rates (see equation (7)). Hence, we can exploit regional variation in solar radiation to predict (lagged) diffusion and use this variable to instrument for PV adoption rates.

Forecasts of adoption based on regional solar radiation are clearly exogenous to changes in voting patterns. Even if solar radiation and green voting were associated (e.g., voters from

[19] We have also observed that our findings are robust for more general models with direct dynamic geographic interactions in voting patterns. Interestingly, these exercises validate our current specification since we do not find that the additional features of the econometric specification are significant nor that they increase the explanatory power (as indicated by likelihood ratio tests).

sunnier regions may be more prone to vote for the Green Party), changes in Green Party votes are not directly affected by the intensity of solar radiation.[20]

To implement this strategy, we follow the diffusion literature[21] and conjecture a logistic process for PV system diffusion:

$$F^{i}_{\text{PV},nt-k-1} = \frac{g_i(\frac{sun_n}{10^3})}{1+e^{-b_i(t-k-1-c_i)}} + \zeta_{nt}, \text{ for } i \in \{\text{rural, urban}\}, \tag{16}$$

where $g_i(\frac{sun_n}{10^3})$ is the ceiling diffusion level which we define as a polynomial in solar radiation.[22] The parameters of function $g_i(.)$, the speed of diffusion, b_i, and inflexion point, c_i, are allowed to differ between rural and urban areas. This flexibility intends to capture the differential constraints (both physical and institutional) to the diffusion of PV systems that exist in urban and rural settings.

Estimates .– The first two columns of Table 2 contain the estimates of the diffusion model in rural and urban areas. We have experimented with the degrees of the polynomials. The highest adjusted R^2 are achieved with a third order polynomial for rural regions and a second polynomial for urban. The R^2 is higher in rural than in urban regions suggesting that variation in solar radiation is a more important driver of PV diffusion in rural environments. However, in both samples the fit of the logistic diffusion models is good suggesting that solar radiation is an important driver of cross-regional variation in PV adoption.[23]

Column (3) reports the estimate of the first stage regression of PV adoption on the lagged PV diffusion level predicted by solar radiation with the diffusion models. The instrument is very significant in predicting adoption rates. Note that this is the case even though we have introduced NUTS-3 regional fixed effects.[24] This is the case because, due to the non-linearity in diffusion, radiation impacts the evolution of adoption rates, not just their level.

Column (4) presents the estimates from the second stage regression. We find that the instrumented PV adoption rates have a positive and significant effect on the increase in green votes. The point estimate is in the ballpark of the OLS estimate from Table 1.

[20]This claim is quite natural but it is (empirically) supported by the fact that support for the German Green Party has oscillated over the last thirty years, but our measure of the average solar radiation in a NUTS-3 region is, by construction, fixed.

[21]See Griliches (1957) and Mansfield (1961).

[22]In the context of the model, $g_i(.)$ is related to the amount of electricity produced in a region for which sun is a measure. sun_n is constant over time. Specifically, we use yearly solar radiation averaged for 1981-2000 from DWD (2010).

[23]Both in rural and urban samples we find that in places with very low solar radiation, the cross-sectional relationship between PV diffusion and solar radiation is quite flat. This is reflected by the negative linear terms in the ceiling. Quickly, the relationship becomes positive and steep as captured by the positive quadratic terms. In rural areas, the relationship flattens again in regions with very high solar radiation (hence the negative cubic term).

[24]In columns (3) and (4) we additionally control for time dummies interacted with an urban dummy. This specification controls for time varying factors that are common across urban/rural regions.

Table 2: Instrument variable estimation of increase in PV diffusion on increase in share of green votes for rural and urban regions.

	Diffusion Model			IV					
	Rural	Urban		All		Rural		Urban	
	NLS	NLS		1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
	(1)	(2)		(3)	(4)	(5)	(6)	(7)	(8)
	$F_{\text{PV},t-k-1}$	$F_{\text{PV},t-k-1}$		$\Delta F_{\text{PV},t-1}$	ΔV_t	$\Delta F_{\text{PV},t-1}$	ΔV_t	$\Delta F_{\text{PV},t-1}$	ΔV_t
a_0	8.454***	0.257***	$\Delta\hat{F}_{\text{PV},t-1}$		0.152**		0.169**		-0.276
	(2.95)	(2.94)			(1.99)		(2.20)		(-0.63)
a_1 (sun)	-23.70***	-0.538***	$\hat{F}_{\text{PV},t-k-1}$	1.306***		1.295***		1.490***	
	(-2.84)	(-3.08)		(11.06)		(10.51)		(5.58)	
a_2 (sun^2)	22.00***	0.285***	$\Delta\ln(\text{GDP}_{\text{cap},t})$	-0.00151	0.00366	-0.00220	-0.00104	0.000461	0.0143
	(2.73)	(3.26)		(-0.40)	(0.55)	(-0.42)	(-0.13)	(0.19)	(1.09)
a_3 (sun^3)	-6.754***								
	(-2.61)								
b (speed)	3.327***	2.445***							
	(26.47)	(8.69)							
c (inflexion point)	4.312***	4.199***							
	(105.45)	(29.22)							
NUTS-3 FE	No	No	NUTS-3 FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Urban×Time FE	No	No	Urban×Time FE	Yes	Yes	No	No	No	No
R^2	0.785	0.708	R^2	0.766	0.657	0.768	0.665	0.739	0.641
Adj. R^2	0.784	0.703	Adj. R^2	0.646	0.481	0.649	0.493	0.601	0.450
			F	234.5	207.1	274.4	242.6	82.25	71.02
$\text{F}_{a_1,a_2,a_3=0}$	67.46	16.55	$\text{F}_{\hat{F}_{\text{PV},t-k-1}=0}$	122.4		110.6		31.18	
p-value$_{a_1,a_2,a_3=0}$	4.15e-39	1.5e-7	p-val.$_{\hat{F}_{\text{PV},t-k-1}=0}$	1.69e-26		1.00e-23		7.50e-08	
N	849	311	N	1160	1160	849	849	311	311

t statistics in parentheses, built with Newey-West-SE

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Column (1) shows the estimates of the Diffusion Model (equation 16) with non-linear least squares for rural regions. Column (2) the same for urban regions. a_1, a_2, a_3 affect the diffusion ceiling, b the diffusion speed and c the inflexion point. Column (3) presents the first stage (2SLS) estimates with the lagged, predicted instrument $(\hat{F}_{\text{PV},t-k-1})$. Column (5) presents the first stage (2SLS) estimates with the lagged, predicted instrument for rural regions only, column (7) the same for urban regions only. The lagged instrument is predicted according to the Diffusion Model from column (1) for rural and according to the Diffusion Model from column (2) for urban regions. Column (4) shows the second stage estimates (2SLS) of the adoption rate $(\Delta\hat{F}_{\text{PV},t-1})$ on the increase in green votes (ΔV_t) for all regions. Column (6) shows the same for rural regions only and column (8) for urban regions only.

Table 2 also explores whether the effect of adoption on the increase in green votes comes from rural or from urban regions. We find that in rural regions there is a strong and significant effect of instrumented PV adoption on the increase in green votes (see column (6)). In contrast, we find no effect in urban regions (see column (8)). This finding is consistent with our model. The model rationalizes the finding by the larger involvement that voters in rural areas have on the decisions to install PV systems.

Interpretation .– At this point, it is worthwhile reflecting about our instrumentation strategy. Identification comes from systematic variation in adoption rates driven by cross-regional variation in solar radiation. For an omitted variable to invalidate our identification, it needs to drive changes in voting patterns and be correlated with variation in the lagged PV diffusion levels predicted by solar radiation levels.

Finding such a variable seems a difficult task. As argued above, changes in green voting are not directly affected by solar radiation. Even if there was a direct effect of solar radiation on the change in green votes, it would be completely absorbed by the NUTS-3 fixed effects included in our specification. Therefore, the omission of (fixed) drivers of green votes that co-move with solar radiation will not bias our estimates.

Some omitted drivers of green votes may vary over time. However, to bias our instrumental variable (IV) estimates, the omitted variables need to increase faster in regions with higher solar radiation than in regions with lower solar radiation.[25] Again, there is no a priori rationale for why green sentiment or other drivers of green votes increase faster in regions with solar radiation. Furthermore, to fully account for our findings this upward trend in green sentiment in sunnier regions should only be present in rural regions.

Let's ignore, for the time being, the difficulty of finding a trigger for the increase in green sentiment that is correlated with solar radiation. It might be argued that the non-linear dynamics in the instrument reflects the endogenous dynamics of green sentiment rather than the (non-linear) diffusion of PV systems.[26] Under this alternative interpretation, exogenous shocks to green sentiment endogenously "diffused" in the population causing the observed increase in green votes.

To rule out this possibility, we explore the endogenous dynamics of green attitudes in the absence of green technologies by focusing on the period 1980-1998 when the Green Party participated in federal elections but PV systems had not diffused.[27] Our proxy for green sentiment is the fraction of votes for the Green Party. In column (1) of Table 3, we report the coefficient of 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 period 1980 to 1998. We find that the lagged share of Green Party votes is negatively associated with the increase in Green Party votes.

Next, we use the pre-1998 estimates from column (1) in Table 3 to filter from the increase in green votes (after 1998) the endogenous dynamics of green votes. We then estimate the effect of PV adoption on the increase in adjusted green votes.[28] Column (2) in Table 3 reports the OLS estimates, and column (3) reports the IV estimates. In both cases, filtering away the endogenous voting dynamics does not impact the effect of PV adoption on the change in Green Party votes.

[25] Note that the emphasis on the differential rates of change comes from the inclusion of time fixed effects which capture variation in voting patterns that is common across NUTS-3 regions.

[26] A counter-argument is that non-linear diffusion patterns have been documented for a wide range of technologies (from hybrid corn to cell-phones to industrial processes (Griliches, 1957; Davies, 1979)). Most of these technologies are orthogonal to political attitudes, in general, and to green values, in particular. Therefore, it is unlikely that variation in adoption rates forecast by our solar instrument is driven by changes in attitudes towards the Green Party or by any other driver of changes in green votes.

[27] This is similar to a diffs-in-diffs specification.

[28] We obtain similar estimates when including lagged green votes as an additional control when estimating equation (15).

In contrast to PV systems, green votes diffusion is reverting. This implies that shocks to green sentiment monotonically die down. Therefore, it does not seem likely that the non-linear evolution of PV systems after 1998 is driven by the endogenous dynamics of green attitudes. To account for the increase in green votes, we need to rely on a persistent effect that builds up over time and that is exogenous to green sentiment. The evidence presented above provides strong support for one such force: the adoption of PV systems and the impact that undertaking those investments had in the green attitudes of voters.

Table 3: Estimation of pre-1998 voting dynamics and of increase in PV diffusion on adjusted increase in share of green votes (pre-1998 voting dynamics filtered away).

	OLS		IV (2nd stage)
	(1)	(2)	(3)
	ΔV_t	$\Delta V_t - \widehat{\beta_{V_{t-k}}} V_{t-k}$	$\Delta V_t - \widehat{\beta_{V_{t-k}}} V_{t-k}$
$\Delta \hat{F}_{\text{PV},t}$			0.317***
			(6.79)
$\Delta F_{\text{PV},t}$		0.196***	
		(5.76)	
$\Delta \ln(\text{GDP}_{\text{cap},t})$		0.00224	0.00341
		(0.46)	(0.71)
V_{t-k}	-0.822***		
	(-15.89)		
R^2	0.934	0.752	0.748
Adj. R^2	0.918	0.626	0.620
F	2946.5	530.1	465.1
N	1621	1160	1160

t statistics in parentheses, built with Newey-West SE
NUTS-3 and time fixed effects included
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Column (1) shows the OLS (with FE) estimates of the lagged level of the share of green votes (V_{t-k}) on the increase in the share of green votes (ΔV_t) for 1980 to 1998. Column (2) reports the OLS estimates of PV adoption on the adjusted increase in green votes $\left(\Delta V_t - \widehat{\beta_{V_{t-k}}} V_{t-k}\right)$. The pre-1998 estimates from column (1) are used to filter from the increase in green votes (after 1998). Column (3) shows the second stage estimates (2SLS) of the adoption rate $(\Delta \hat{F}_{\text{PV},t-1})$ on the adjusted increase in green votes $\left(\Delta V_t - \widehat{\beta_{V_{t-k}}} V_{t-k}\right)$.

Robustness .– We conduct various exercises to show the robustness of the estimates of the effect of PV adoption on green voting. The first one consists in lagging further the forecasts of the diffusion equation (16) to instrument for adoption rates.[29] The second exercise consists in constructing a synthetic instrument for PV adoption rates based on the lagged diffusion

[29]In particular, we use $\hat{F}_{\text{PV},t-2*k-1}$ instead of $\hat{F}_{\text{PV},t-k-1}$ to instrument for $\Delta F_{\text{PV},t-1}$. Table 15 in Appendix D.2 shows that lagging further the predicted diffusion level does not diminish the magnitude or the significance of the estimated effect in rural areas.

in regions with similar solar radiation.[30] Finally, our IV estimates are also robust to allowing for spatial correlation in the error terms.[31]

4.1.3 The diffusion of industrial vs. household systems

Testable prediction #4 from our model is that the diffusion of industrial green energy systems should not be associated with an increase in green votes. This implication follows from the fact that corporations (instead of voters) decide whether to construct an industrial green energy system. Next, we explore whether there is any association between the diffusion of industrial systems (PV, eolic and biomass) and the evolution of green votes.

We focus first on PV systems and consider two possible cutoffs for the maximum capacity of household PV systems, 30 $\mathrm{kW_p}$ and 100 $\mathrm{kW_p}$. In addition, we study the effects of the diffusion of large (100 $\mathrm{kW_p}$ or more) and very large PV systems (1,000 $\mathrm{kW_p}$ or more) which are definitely industrial. Industrial systems are often installed on fields. We therefore normalize their adoption rates by the agricultural area in square kilometers (instead of the number of buildings).[32] Table 4 presents the OLS estimates of the association between the adoption of PV systems of a given capacity and the increment in green votes. For household systems, we obtain an estimate very close to the full sample estimate (shown in Table 2). The estimated effect is slightly higher for systems with a capacity of at most 30 $\mathrm{kW_p}$ than for systems of at most 100 $\mathrm{kW_p}$. In both cases, the association of PV adoption on green voting is significant with p-values smaller than one percent.[33] The estimates change dramatically for industrial systems for which we find an insignificant association between adoption rates and changes in green votes.

An alternative way to measure the diffusion of PV systems consists in using a capacity-weighted measure that takes into account the amount of electricity that a system can produce. In particular, the capacity-weighted adoption rate is given by

$$\triangle F_{\text{PVCapac.},nt} = \frac{\triangle \text{ Total PV capacity installed}_{nt}}{\text{Agricultural area}_n * \text{Avg. capacity}}, \tag{17}$$

[30]Specifically, we rank the NUTS-3 regions according to their solar radiation. Then, we compute the synthetic diffusion level of a region, $F_{\text{PV, synthetic},t-k-1}$, by taking the average value of diffusion, $F_{\text{PV},t-k-1}$, in the four regions that are closest in the solar radiation ranking. We then use $F_{\text{PV, synthetic},t-k-1}$ to instrument for $\Delta F_{\text{PV},t-1}$, and finally, we use the instrumented diffusion levels to estimate the impact of adoption on green votes. Table 16 (in Appendix D.3) shows that the synthetic instrument predicts diffusion levels well, and the estimate we obtain for the effect of PV adoption rates on the increase in green votes is significant and in line with the OLS and IV estimates.

[31]See columns (2) and (3) of Table 14 in Appendix D.1. In section 4.3.1, we further show the robustness of our estimates by controlling for changes in the profitability of PV systems.

[32]The particular scaling variable is not critical since they are fixed and therefore captured by the NUTS-3 fixed effects.

[33]In Appendix D.4, we confirm that the effect of household PV adoption on green voting is robust to instrumenting adoption rates by our solar radiation instrument.

Table 4: OLS 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
$\Delta F_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t}$	0.268***			
	(5.98)			
$\Delta F_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t}$		0.250***		
		(6.01)		
$\Delta F_{\mathrm{PV}>100\,\mathrm{kW_p},t}$			-0.00891*	
			(-1.72)	
$\Delta F_{\mathrm{PV}>10^3\,\mathrm{kW_p},t}$				-0.00988
				(-1.63)
$\Delta \ln(\mathrm{GDP}_{\mathrm{cap},t})$	0.00153	0.00161	-0.000757	-0.000366
	(0.23)	(0.25)	(-0.11)	(-0.05)
R^2	0.642	0.642	0.631	0.631
Adj. R^2	0.459	0.460	0.444	0.444
F	317.9	313.2	272.5	272.6
N	1160	1160	1160	1160

t statistics in parentheses, built with Newey-West SE
NUTS-3 and time fixed effects included
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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

Columns (1)-(4) of Table 5 reproduce the regressions from Table 4 using the measure of capacity-weighted adoption. The estimates show that the patterns are the same for standard and capacity-weighted adoption rates. In particular, we find a strong positive association between the increment in green votes and capacity-weighted adoption for household PV systems, but no relationship for industrial systems.

We next turn to eolic and biomass installations.[34] Unlike PV systems, only companies can afford the magnitude of the sunk costs required to install eolic or biomass systems. Column (5) reports the association between the increase in green votes and capacity-weighted eolic system adoption.[35] Column (6) presents the equivalent results for biomass systems. As predicted by our model, we find that these two variables are not significantly associated. Therefore, we conclude that our identification strategy passes the placebo test.

4.2 Survey evidence

The evidence presented so far to study the effect of the diffusion of PV systems on the fraction of votes obtained by the German Green Party has been based on data aggregated

[34] Table 11 in Appendix A shows the descriptive statistics for the eolics analysis and Table 12 in Appendix B for biomass plants.

[35] Because of the large dispersion in the capacity of eolic and biomass systems, we focus on the capacity-weighted measures.

Table 5: OLS estimation of increase in PV, eolic or biomass diffusion (capacity-weighted measure) on increase in share of green votes.

	Household PV		Industrial PV		Eolic	Biomass
	(1)	(2)	(3)	(4)	(5)	(6)
	ΔV_t	ΔV_t	ΔV_t	ΔV_t	ΔV_t	ΔV_t
$\Delta F_{\text{PVCapac.}\leq 30\,\text{kW}_\text{p},t-1}$	0.197***					
	(5.94)					
$\Delta F_{\text{PVCapac.}\leq 100\,\text{kW}_\text{p},t-1}$		0.191***				
		(5.75)				
$\Delta F_{\text{PVCapac.}>100\,\text{kW}_\text{p},t-1}$			-0.00246			
			(-0.43)			
$\Delta F_{\text{PVCapac.}>10^3\,\text{kW}_\text{p},t-1}$				-0.00244		
				(-0.42)		
$\Delta F_{\text{EolicCapac.},t-1}$					-0.0102	
					(-1.39)	
$\Delta F_{\text{BiomassCapac.},t-1}$						-0.00488
						(-1.31)
$\Delta \ln(\text{GDP}_{\text{cap},t})$	0.00133	0.00145	-0.00156	-0.00156	-0.00125	-0.000975
	(0.20)	(0.22)	(-0.24)	(-0.24)	(-0.19)	(-0.15)
R^2	0.642	0.642	0.630	0.630	0.631	0.631
Adj. R^2	0.460	0.461	0.442	0.442	0.443	0.444
F	301.3	294.4	273.6	273.6	275.0	277.6
N	1160	1160	1161	1161	1161	1161

t statistics in parentheses, built with Newey-West SE
NUTS-3 and time fixed effects included
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

at the NUTS-3 level. Next, we continue our investigation by using individual survey data from 2013's Socio-Economic Panel (SOEP). The SOEP is a representative longitudinal survey that is administered to approximately 30,000 individuals from 11,000 German households. It covers a wide range of socio-economic topics including the party supported by the individual and the intensity of the support. Since 2007, the SOEP has included a question about whether households live in dwellings with solar energy systems.[36] By combining the answers on political preferences and the presence of solar energy systems, we can explore whether the adoption of solar systems has impacted the political preferences of individuals in a way that is consistent with the evidence we have uncovered at the regional level.

[36]Solar energy includes both PV systems and solar thermal systems. The difference between PV and solar thermal systems is that while the latter produce energy that can only be used to heat water, the former produce electricity that can be either used or sold to the electric grid. For the purposes of the mechanisms explored in this paper, there is a priori no relevant difference between these two types of solar energy systems. Since 2007, a majority of the solar energy systems installed in Germany have been PV systems. According to BSW-Solar (2014), in 2007 there were 1 million solar thermal systems installed in Germany while there were only 360,000 PV systems. By 2012, the number of PV systems was 1.3 million while the number of solar thermal systems was 1.8 million.

4.2.1 Baseline estimates

To measure the increase in support towards the Green Party, we construct a categorical variable, $\Delta Green_t$, which takes the value of one if the individual states a change in support from another party to the Green Party or if she states an increase in the intensity of support for the Green Party between years $t-1$ and t, and it is zero in all other cases.[37] Our independent variable $Solar_{t-1}$, measures whether the household had a solar energy system installed in its dwelling in year $t-1$.[38]

We estimate a logit model where, in addition to the adoption of solar systems, the probability of a change in the support for the Green Party can be affected by (log) household income, labor status, having a college degree, having graduated from vocational training school, and other variables captured by a full set of year dummies interacted with a full set of NUTS-1 regional dummies.[39]

As suggested by our model, it may be relevant to account for whether households have made a conscious decision to install a solar system or whether they live in a rented dwelling. Accordingly, we split the sample between those households that own the dwelling (and presumably have decided to install the system) and those that do not own it.

Columns (1), (3) and (5) in Table 6 present the odds that a person who has installed a solar energy system becomes greener relative to one that has not installed a system, for each of the three samples. For the full sample, column (1) shows that the odds ratio is 1.4. The estimate is significant at the 1 percent level.[40] Consistent with our theory, columns (3) and (5) reveal a relevant difference in the odds ratios for home-owners and non-home owners. Column (3) shows a significant association between having a solar system and becoming greener for home owners with an odds ratio of 1.73 (significant at the .1 percent). For non-home owners the odds ratio is 0.52 (and statistically insignificant).[41]

[37] See footnote 41 for the results from considering separately these two margins. Table 19 in Appendix E contains the descriptive statistics.

[38] We only contemplate at respondents who do not claim to have removed their solar 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 solar systems were removed according to the SOEP data, see Figure 10 in Appendix E.1.

[39] See Appendix E.2 for details.

[40] T-statistics are computed using standard errors clustered at the household level (in our survey analyzes).

[41] In Appendix E.3, we unpack the relationship between the adoption of solar energy systems and green support by decomposing the dependent variable into two categorical variables that separately capture the presence of support for the Green Party and the intensity of such a support. We find that both of these margins are important for the point estimates in columns (1), (3) and (5) of Table 6.

Table 6: Odds ratio of solar level and solar change on change in green attitude.

	All		Home owners		Non-home owners	
	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta Green_t$	$\Delta Green_t$	$\Delta Green_t$	$\Delta Green_t$	$\Delta Green_t$	$\Delta Green_t$
$Solar_{t-1}$	1.438***		1.728***		0.521	
	(2.76)		(3.84)		(-1.38)	
$\Delta Solar_{t-3:t-1}$		1.297		1.563**		0.438
		(1.21)		(2.01)		(-1.16)
$\ln(\text{Real Income}_t)$	1.093		1.167		1.169	
	(1.31)		(1.51)		(1.56)	
$\Delta\ln(\text{Real Income}_t)$		0.959		0.699**		1.263
		(-0.31)		(-2.04)		(1.49)
Observations	45455	42019	25062	22263	19268	18550
DF_M	67	67	64	63	61	61
Final log-likelihood $\mathcal{L}$	-5144.0	-4744.4	-2853.3	-2420.4	-2240.9	-2275.4

Exponentiated coefficients; robust t statistics in parentheses clustered on households
Time$*$NUTS-1, college, vocational degree and labor status dummies included
Columns (2), (4) and (6): only those who did not have a Solar system in 2007
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2.2 Further checks on omitted variable bias

Omitted variables can bias the estimates if they are correlated with having installed a solar system in the past and affect the likelihood that an individual *becomes* a green supporter. Note that the required lead-lag relationship between the omitted variable and our variables of interest is very specific. In particular, the omitted variable needs to be correlated with the adoption of solar systems at $t-1$ or earlier, and with the agent preferences towards the Green Party at t but not at $t-1$. In our view, the stringency of this requirement makes omitted variables an unlikely explanation for our estimates.

To further explore the causal nature of our estimates, we conduct three exercises. First, we restrict attention to households that had not adopted a solar energy system before 2007, and study how adopting the system over the previous three years affects the odds of becoming more green within the next year. Second, we directly explore the reverse relationship between adoption and becoming green by studying if agents that became green were more likely to adopt solar energy systems afterwards. Third, we instrument for the adoption of solar systems by using information on prior adoption of other non-green technologies such as computers or the Internet.

Solar system adoption .– As we have argued above, the likelihood that an omitted variable drives our estimates diminishes as the temporal requirements (on the omitted variable) become more stringent. To minimize the chances of omitted variable bias, we narrow the period over which individuals have adopted the solar energy systems. In particular, we restrict attention to agents that had not installed a solar system before 2008, and consider as independent variable $\Delta Solar_{(t-3:t-1)}$ which measures whether the individual adopted a solar system over the previous three years.[42]

Columns (2), (4) and (6) of Table 6 show the estimates for the odds of changing the Green Party support for those that adopted a solar energy system during the previous three years vs. those that did not. We find that home owners that installed a solar energy system over the previous one to three years are 56 percent more likely to increase their support for the Green Party than those that did not install one. This estimate is statistically significant at the 5 percent level. As in column (5) of Table 6, we find no significant effect for non-home owners.

Reverse causation .– One possible explanation of the survey evidence presented so far is that it results from reverse causation. That is, agents that experience exogenous increases in support for the Green Party become more prone to adopt solar energy systems. Next, we directly explore this hypothesis. Our dependent variable, $\Delta Solar_t$, takes the value of 1 if the individual lived in a dwelling where a solar system has been installed between year $t-1$ and t. As before we restrict attention to dwellings that did not have a system in 2007. We consider two independent variables. $Green_{t-1}$ is 1 if the respondent claims to support the Green Party in year $t-1$, and zero otherwise. $\Delta Green_{(t-3:t-1)}$ is a categorical variable that is 1 if the individual moved to support the Green Party or if she increased the strength of the support for the Green Party over the previous three years, and zero otherwise.[43]

Table 7 reports odds ratios from the logit regression. In columns (1), (3) and (5) of Table 7 we see that Green Party supporters are not more likely to adopt solar systems than those who do not support the Green Party. Columns (2), (4) and (6) of Table 7 illustrate that individuals who became greener also are not more likely to install solar energy systems than those who did not become greener in a previous three-year period. These findings suggest that greater green support does not increase the likelihood of adopting solar energy systems. The relevance of this conclusion goes beyond the assurance it provides us that reverse causation is not driving our estimates. Because many omitted variable bias operate through variables that proxy for green sentiment, the fact that green sentiment itself (or at least the best available measure) does not drive solar systems adoption renders implausible most omitted variable concerns.

Instrumenting for solar energy adoption .– The final exercise we conduct to assess the causal interpretation of the relationship between solar system adoption and green support is

[42] Conditioning on not having a system is relevant to prevent a downward bias in the estimates because for those that initially had a system, the independent variable is always 0, and the dependent can be either 0 or 1, forcing either a negative association or no association at all. Since SOEP started to ask households about solar energy systems only in 2007, we consider a 1-year adoption interval for 2008, a 2-year interval for 2009 and a 3-year interval afterwards.

[43] Our results are robust to lagging *Green*, and $\triangle Green$ by another period.

Table 7: Odds ratio of level and change in green attitude on solar change.

	All		Home owners		Non-home owners	
	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta Solar_t$	$\Delta Solar_t$	$\Delta Solar_t$	$\Delta Solar_t$	$\Delta Solar_t$	$\Delta Solar_t$
$Green_{t-1}$	0.757		0.695		0.903	
	(-1.21)		(-1.24)		(-0.26)	
$\Delta Green_{t-3:t-1}$		0.745		0.715		0.870
		(-1.40)		(-1.25)		(-0.40)
$\ln(\text{Real Income}_t)$	1.794***		1.515***		1.695***	
	(4.94)		(2.62)		(2.69)	
$\Delta \ln(\text{Real Income}_t)$		0.784		0.830		0.751
		(-1.10)		(-0.65)		(-0.81)
Observations	38979	38797	20557	20449	14252	14196
DF_M	53	53	47	47	42	42
Final log-likelihood $\mathcal{L}$	-2407.7	-2411.4	-1665.6	-1657.9	-674.0	-677.1

Exponentiated coefficients; robust t statistics in parentheses clustered on households
Time∗NUTS-1, college, vocational degree and labor status dummies included
Only those who did not have a Solar system in 2007
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

an IV estimation. Following the literature on technology adoption,[44] we exploit the idea that some agents have a higher propensity to adopt all sorts of technologies, probably because they have lower adoption costs or derive a higher for novelties. This intrinsic propensity to adoption produces a cross-technology correlation in adoption across technologies at the individual level that may help us construct an instrument for solar system adoption. In particular, our instrument will be based on whether an agent adopted other non-green technologies (e.g., PCs and Internet) in the past. Because these (prior) technologies are non-green in nature, their adoption decision should be orthogonal to the agent's green sentiment, ensuring the exogeneity of our instrument. There are two further considerations that should increase our confidence in the exogeneity of the variation introduced by our instrument. First, by using as dependent variable the increment in green sentiment ($\Delta Green_t$), our estimates only reflect changes in green attitudes that took place after the solar system was installed. Second, our regressions control for other potential drivers of green attitudes such as education, employment status and income.

We use information in SOEP to determine whether individuals have an Internet connection in the dwelling ($Internet_{t-1}$) and a personal computer (PC_{t-1}). Table 8 reports the probit (column (1)) and bi-probit (columns (2) and (3)) results for home owners. The first column shows that the probit estimates are consistent with the logit estimates in Table 6. Column (2) shows that both adopting Internet and PC are strong predictors for solar system adoption. Interestingly, both technologies are independently significant in the first stage re-

[44] Comin et al. (2006) found strong cross-correlations across technologies in the patterns of diffusion in a large sample of countries. Skinner and Staiger (2007) found a similar cross-technology correlation in diffusion at the state level in the U.S.

gression. A χ^2 test confirms that they are jointly significant at any level (i.e., the χ^2 statistic is over 25).[45]

The first row of column (3) in Table 8 shows the IV estimate of the effect of having a solar system installed on the probability of increasing the support for the Green Party. Consistently with our previous estimates, we find that the instrumented adoption of solar energy systems leads to a significant increase in the probability of strengthening the support for the Green Party.

The bottom part of Table 8 contains various tests of the exogeneity of the instruments. ρ is the correlation between the error terms of the first and the second stage regression which we find not to be significantly different from zero. This indicates that, ex-post, our instruments are not endogenous to changes in green voting.[46] A Wald test on $\rho = 0$ points in the same direction as the p-value is greater than 0.05.[47] As we have two instruments, we can conduct an over-identification restriction test which, again, does not reject the validity of our instruments.[48]

Table 8: Estimation of solar level on change in green attitude (for home owners).

	Probit	Bi-Probit		IV (2SLS)	
	(1)	(2)	(3)	(4)	(5)
	$\Delta Green_t$	$Solar_{t-1}$	$\Delta Green_t$	$Solar_{t-1}$	$\Delta Green_t$
$\hat{Solar}_{t-1}$			0.652**		0.271***
			(2.10)		(3.35)
$Solar_{t-1}$	0.241***				
	(3.71)				
$Internet_{t-1}$		0.124**		0.0194**	
		(2.54)		(2.42)	
PC_{t-1}		0.236***		0.0293***	
		(3.74)		(3.17)	
ln (Real Income$_t$)	0.0808*	0.226***	0.0630	0.0371***	-0.00774
	(1.86)	(4.35)	(1.41)	(4.16)	(-1.44)
ρ		-0.214			
$\chi^2_{\rho=0}$ (p-value)		1.855 (0.173)			
$\chi^2_{\text{Instruments}=0}$ (p-value)		25.87 (0.00000241)		11.47 (0.0000108)	
Hansen J statistic (p-value)					1.375 (0.241)
Observations	25062	25706		25706	25706
DF_M	64	135		69	68
Final log-likelihood $\mathcal{L}$	-2851.0	-11009.2		-5811.2	8399.7

Robust t statistics in parentheses clustered on households
Time$*$NUTS-1, college, vocational degree and labor status dummies included
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[45] This is well above the rule of thumb of 10 in Stock and Watson (2010).

[46] For details see Wooldridge (2002, p. 477).

[47] In columns (4) and (5) of Table 8 we report that a two-stage least squares estimation also indicates that our instruments are, ex-post, not endogenous to changes in green voting. The p-value of the Hansen J statistic is above 0.05.

[48] In Appendix E.4, we show that for the full sample that includes home owners and non-home owners, the effect is significant for the probit and the two-stage least squares estimation (column (1), (2) and (3) in Table 21) but not for bi-probit (column (4) and (5) in Table 21). There is no effect for non-home owners (see Appendix E.4, Table 22 column (1) for the probit estimation and columns (2) and (3) for the two-stage least squares estimation).

In summary, the survey evidence has shown that individuals that adopted solar energy systems were more likely to develop a stronger support for the Green Party. By validating the details of the mechanism we have hypothesized above, the survey evidence reinforces a causal interpretation of the regional evidence.

5 Interpretation

After showing that the adoption of PV systems has been a significant driver of the increase in Green Party votes observed in Germany between 1998 and 2009, it is natural to explore what mechanisms drive this effect. An empirical demonstration of the mechanisms that are responsible is beyond the scope of our paper. Our more modest goal is to speculate about the plausibility of some candidate mechanisms in the light of our data.

We consider three hypotheses. The first is whether voters reward the Green Party for the monetary transfers that may come with the installation of PV systems. The second possible hypothesis is based on Bayesian learning about the Green Party. Specifically, agents that adopt a PV system may be more prone to discover that the Green Party proposals are not unreasonable and this information may induce them to vote for the Green Party in the federal elections. A third hypothesis, we have already discussed, is that agents are cognitive dissonant and that, after adopting PV systems, they increase their appreciation for green values/actions to maximize the utility from their past actions.

5.1 Votes for money

The Green Party was the key proponent of the feed-in tariff scheme, EEG, implemented in 2000. The EEG was significantly more generous than the previous scheme (see Figure 1). Agents that adopted PV systems after 2000 may have voted for the Green Party in subsequent elections to reward the party for the income they accrued by selling the electricity they produced at the higher tariffs.

If the effect of PV adoption on green votes is driven by the profitability of PV systems, controlling for changes in profitability should render insignificant the coefficient of lagged PV diffusion. Furthermore, if the variation in the instrument is contaminated by changes in profitability, we should see a significant decline in the second stage coefficient once we control for changes in the profitability of PV system adoption.

We measure changes in profitability by the growth rate of the feed-in tariff interacted with the average solar radiation of the NUTS-3 region. Note that this measure captures the asymmetric effect that feed-in tariffs have on the return to PV systems across regions.

Table 23 (in Appendix F.1) presents the estimates. Changes in the profitability of PV systems do not have a significant effect on the increase in Green Party votes. Furthermore, controlling for changes in profitability does not impact significantly the estimates of the effect of PV adoption on changes in green votes. This is the case both for the OLS and IV regressions, implying that changes in electricity income for adopters is an irrelevant factor in explaining the increase in green votes. Additionally, the effect of the instrument in the first stage remains unchanged when we include the profitability measure as a control, which suggests that the variation in PV adoption used to identify the effect of adoption on voting patterns is orthogonal to changes in profitability.

We can also explore the votes for money hypothesis by directly computing the net income from installing a PV system relative to household income. We report the calculations for the median and 90^{th} percentile of capacity installed and full load hours (i.e. solar radiation). 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 (see Table 9).[49] The profit to income ratio ranges from -2.7 percent to 0.8 percent with lower values for earlier years and for systems with lower capacity and full-load hours. This exercise suggests that even for systems with high capacity and installed in areas with high solar radiation, the net revenues from PV electricity production are (at best) relatively small. Therefore, we do not consider plausible that PV adopters are compensating to the Green Party with their votes *in exchange for* the net income they earn from PV systems.

Table 9: 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 percent	-1.0 percent	-2.7 percent	-1.6 percent
2004	-0.5 percent	0.2 percent	-0.9 percent	0.3 percent
2006	-0.3 percent	0.3 percent	-0.5 percent	0.5 percent
2009	0.0 percent	0.5 percent	0.0 percent	0.8 percent

5.2 Learning on Green Party policies

The second interpretation of our findings is based on Bayesian learning. Suppose that agents were Bayesian and in the process of adopting a PV system they obtained precise signals about

[49]The calculations details are explained in Appendix F.2.

the plausibility of the Green Party proposals. In that case, PV adopters would update upwards their prior on the value of the Green Party vis-à-vis the rest of the parties, and they would be more prone to vote for the Green Party in the next elections. Note that under this interpretation, adopters do not change their preferences. They just gather additional information that reduces the uncertainty they have about the value of the Green Party and of their policies.

We explore the relevance of this hypothesis 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). It is reasonable to assume that voters in federal states that in 1998 had been ruled by the Green Party, had more precise priors about the Green Party than those in federal states where the Green Party had not ruled. Therefore, if our findings are driven by Bayesian learning, we should expect a smaller effect of PV system adoption on green voting in federal states where the Green Party had ruled.

Table 10 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 had been in a governing coalition in the NUTS-1 regions before 1998. The first column reports the OLS estimates and the second the IV estimates. In both cases, the differential effect of adoption on green voting is not significantly smaller in regions where the Green Party was in power through 1998.

We have conducted a similar exercise for the survey data in SOEP by introducing an interaction of $Solar_{t-1}$ or $\triangle Solar_{t-3:t-1}$ with the $Green_{Laender}$ dummy. The coefficient of this interactions is insignificant, pointing in the same direction of the regional regressions reported in Table 10. Therefore it does not seem likely that the effect that PV adoption has on the propensity to vote for the Green Party is due to a Bayesian updating process.

5.3 Cognitive Dissonance

Finally, the third hypothesis is that agents are cognitive dissonant. To experience a greater utility from past PV adoption decisions, they change their appreciation for green actions. This change in green sentiment is also reflected in an increased likelihood to vote for the Green Party.

In our empirical analysis, we have uncovered evidence that is consistent with this hypothesis. In particular, the facts that the adoption of PV systems increases the likelihood of voting for the Green Party votes only in rural areas, and in owner-occupied dwellings

Table 10: Estimation of increase in PV diffusion on increase in share of green votes (Bayesian learning).

	OLS	IV (2nd stage)
	(1)	(2)
	ΔV_t	ΔV_t
$\Delta F_{\text{PV},t-1}$	0.242***	
	(5.88)	
$\Delta F_{\text{PV},t-1} * Green_{\text{Laender}}$	0.161*	
	(1.74)	
$\Delta \hat{F}_{\text{PV},t-1}$		0.163**
		(2.06)
$\Delta F_{\text{PV},t-1} * \hat{Green}_{\text{Laender}}$		-0.00601
		(-0.04)
$\Delta \ln(\text{GDP}_{\text{cap},t})$	0.000876	0.000805
	(0.13)	(0.12)
R^2	0.643	0.640
Adj. R^2	0.461	0.457
F	257.9	245.0
N	1160	1160

t statistics in parentheses, built with Newey-West SE
NUTS-3 and time fixed effects included
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

are predictions of the cognitive dissonance model presented in Section 3. However, further analysis is necessary to prove that the effects of PV adoption on voting patterns that we have uncovered in this paper are indeed a consequence of cognitive dissonant behavior.

6 Conclusions

In this paper we have empirically explored a new hypothesis. Namely, whether the adoption of technologies may change the political preferences and the voting behavior of citizens. Focusing on the diffusion of PV systems in Germany, we have found evidence of a causal effect of PV system adoption on the increase in the share of valid votes for the Green Party. Our estimates indicate that this effect is significant, accounting for approximately 25 percent of the increase in the share of votes experienced by the Green Party between the federal elections of 1998 and 2009.

Our study has not intended to demonstrate the mechanism that drives this effect. However, we have informally explored the plausibility of three possible hypotheses. We have found evidence against the votes for money and Bayesian learning hypotheses. We have found indirect evidence consistent with a cognitive dissonance interpretation, formalized by our model. Finding direct evidence that the adoption of PV systems induces agents to strengthen their affinity with green values would be an important step we leave for future research.

There are a number of relevant questions that our study motivates. 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 PV systems installed were industrial, and households have not yet adopted solar systems in a significant way. In addition to voting patterns, does the diffusion of technology affect other political phenomena such as campaign contributions, party affiliation, civic involvement in politics, etc. Finally, are there other technologies whose adoption trigger other changes in values and actions?

We consider that our findings are relevant for various literatures. First, they contribute to the literature on drivers of voting behavior. Traditionally, political scientists have focused on socio-economic factors – such as race, income, occupation, education level, and civil status – as well as on political campaign strategies – such as total spending, endorsements, aggressiveness of the message, party position on key issues, etc. Our findings show the relevance of another type of drivers that are related to significant decisions/actions taken by the voters in the past.

Our findings also suggest that the adoption of new technologies have broader implications than those traditionally explored in the literature. Studies on the consequences on technology diffusion have tended to focus on variables such as productivity, wages, employment and inequality. Our analysis opens the possibility that the adoption of technology affects the values and preferences of adopters. Changes in adopters values may have consequences for a variety of settings. Here we have focused on voting behavior. But it may be possible to think of impacts in education decisions, labor force participation, crime, health care expenditures, disease prevention, group formation, or driving behavior to name a few.

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Appendix

For Online Publication: The following is not intended to be included in the journal version of the article, but as online appendix.

A The diffusion of eolic systems in Germany

Figure 6 illustrates the diffusion of eolic systems and the level of the feed-in tariff for electricity from eolic systems. In contrast to the feed-in tariffs for PV systems, the feed-in tariff schemes for electricity from eolic plants rose comparatively less through EEG.

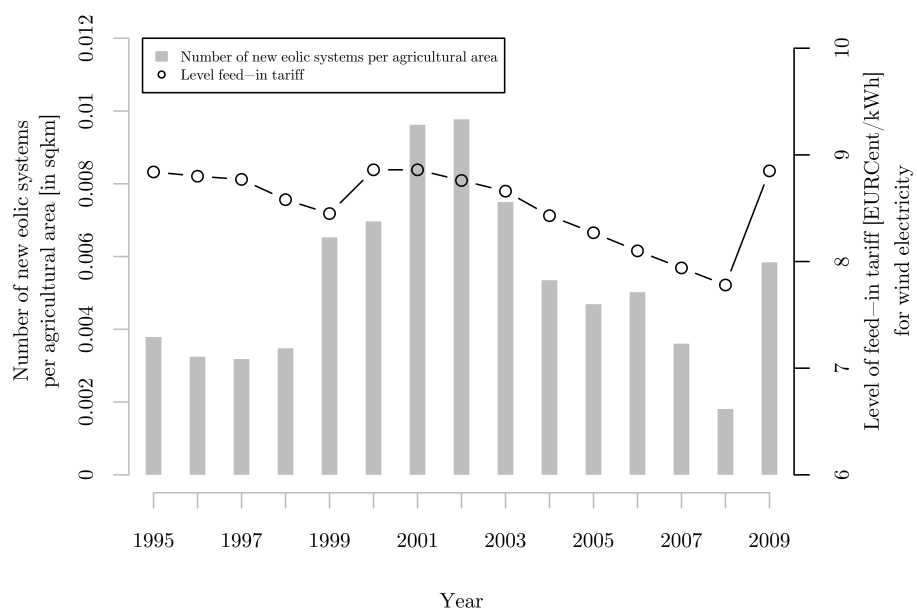

Figure 6: Number of new eolic (onshore) systems per agricultural area [in sqkm] and the level of the average feed-in tariff for electricity from eolic (onshore) systems (of 90 percent reference yield without system service or repowering bonus) in Germany from 1995 through 2009.

Figure 7 illustrates the diffusion of eolic systems. By 1998, there were already significant regional differences in the diffusion of eolic systems. Some northern regions such as Dithmarschen, Schleswig-Holstein, (0.32 wind mills per agricultural sqkm) and Hamburg (0.36) had considerable diffusion of eolic systems. In contrast, 48 percent 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, (0.94 wind mills per sqkm) and Bremerhaven, Bremen, (0.94). The share of regions without eolic systems installed dropped to 24 percent, and these are concentrated in Bavaria, North Rhine-Westphalia and Baden-Württemberg.

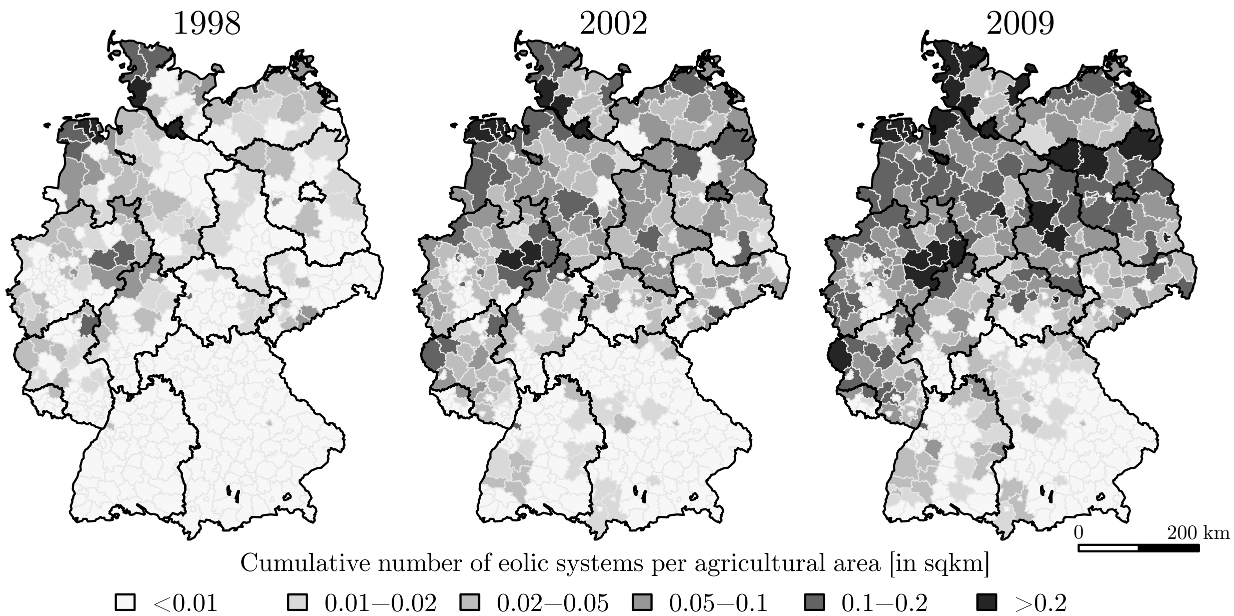

Figure 7: Number of eolic (onshore) systems per agricultural area [in sqkm] at NUTS-3 level for 1998, 2001, 2005 and 2009.

Table 11: Descriptive statistics, eolic.

	N	Mean	Std. Dev.	Min.	Max.
$F_{\text{EolicCapac.},t-1}$	1171	.044	.098	0	1.7
$F_{\text{EolicCapac.},t-k-1}$	1171	.024	.056	0	.86
$\Delta F_{\text{EolicCapac.},t-1}$	1171	.02	.058	0	1.4
V_t	1171	.082	.035	.02	.29
ΔV_t	1171	.013	.015	-.03	.081
N	1171				

B The diffusion of biomass systems in Germany

Figure 8 illustrates the diffusion of biomass systems and the level of the feed-in tariff for electricity from biomass systems. In contrast to the feed-in tariffs for PV systems, the feed-in tariff schemes for electricity from biomass plants rose comparatively less but still significantly through EEG.

Table 12: Descriptive statistics, biomass.

	N	Mean	Std. Dev.	Min.	Max.
$F_{\text{BiomassCapac.},t-1}$	1171	.042	.2	0	3.5
$F_{\text{BiomassCapac.},t-k-1}$	1171	.02	.14	0	3.2
$\Delta F_{\text{BiomassCapac.},t-1}$	1171	.022	.12	0	3.2
V_t	1171	.082	.035	.02	.29
ΔV_t	1171	.013	.015	-.03	.081
N	1171				

Figure 9 illustrates the diffusion of biomass systems. By 1998, regional differences in the diffusion of biomass systems were low. Still, some regions such as Freiburg, Baden-

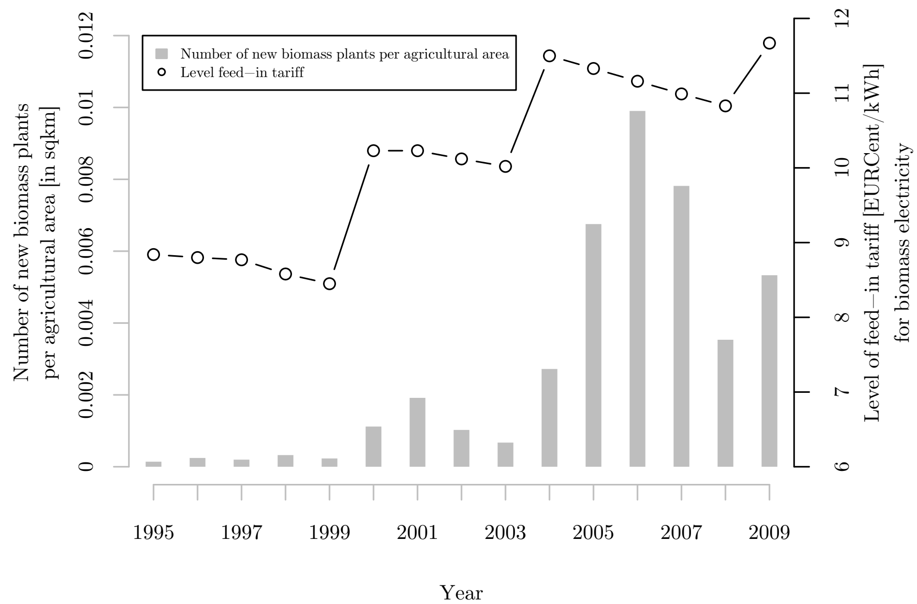

Figure 8: Number of new biomass systems per agricultural area [in sqkm] and the level of the feed-in tariff for electricity from small (at most 150 kW_{el}) biomass plants (without any bonus) in Germany from 1995 through 2009.

Württemberg (0.07 wind mills per agricultural sqkm) and Kassel, Hessen (0.06) had biomass plants. In contrast, 73 percent of the regions had no biomass plant installed. In 2009, the picture changed. The share of regions without biomass systems dropped to 5 percent. The regions with highest diffusion levels of biomass plants were Pforzheim, Baden-Württemberg, (0.78 wind mills per sqkm) and Amberg, Bavaria, (0.73).

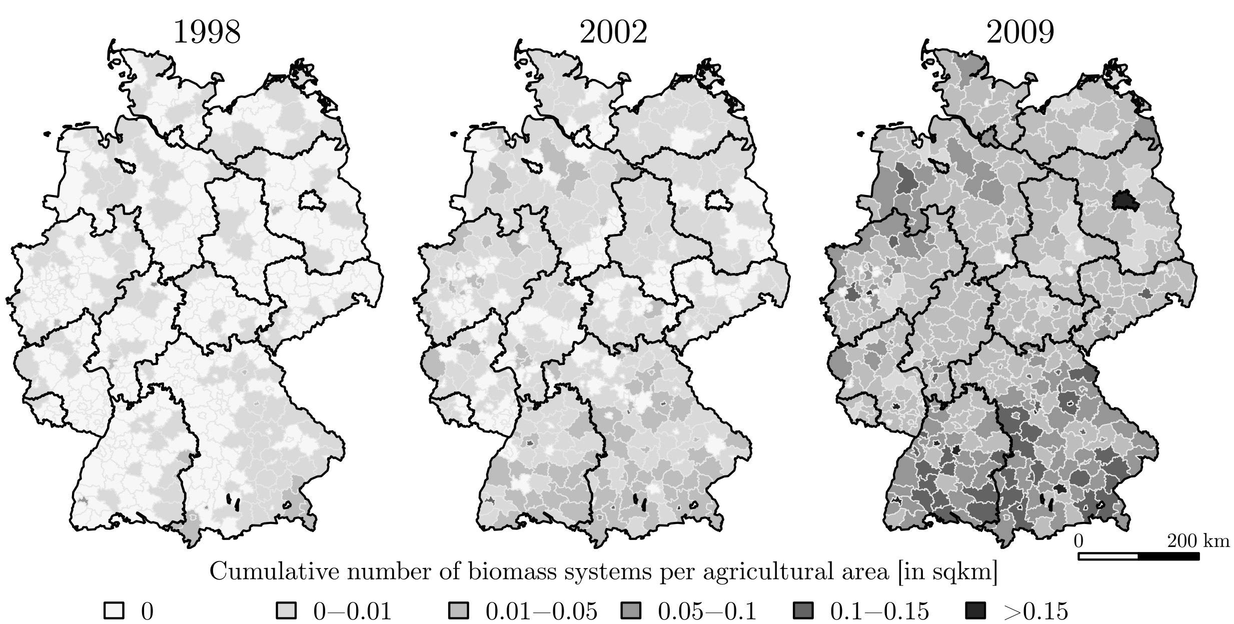

Figure 9: Number of biomass plants per agricultural area [in sqkm] at NUTS-3 level for 1998, 2001, 2005 and 2009.

C Proof of Proposition 1

If we adopt technology at t, we get

$$V_t = e^{-rt}\left(\frac{P_t e_n + \tilde{g}}{r} - c_j e^{-\alpha t}\right). \tag{18}$$

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

$$\begin{aligned} E_t V_{t+dt} = & (1 - \lambda dt)\left[e^{-r(t+dt)}\left(\frac{P_t e_n + \tilde{g}}{r} - c_j e^{-\alpha(t+dt)}\right)\right] \\ & + \lambda dt\left[e^{-r(t+dt)}\left(\frac{\phi P_t e_n + \tilde{g}}{r} - c_j e^{-\alpha(t+dt)}\right)\right]. \end{aligned} \tag{19}$$

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

$$\begin{aligned} E_t V_{t+dt} = & \quad e^{-r(t+dt)}\left(\frac{P_t e_n + \tilde{g}}{r} - c_j e^{-\alpha(t+dt)}\right) + \lambda e^{-r(t+dt)} \frac{(\phi - 1) P_t e_n}{r} dt \\ = & \quad e^{-rt}(1 - r dt)\left(\frac{P_t e_n + \tilde{g}}{r} - c_j e^{-\alpha t}(1 - \alpha dt)\right) + \lambda e^{-rt} \frac{(\phi - 1) P_t e_n}{r} dt + o(dt) \\ = & \quad e^{-rt}\left(\frac{P_t e_n + \tilde{g}}{r} - c_j e^{-\alpha t}\right) \\ & + e^{-rt}\left(-P_t e_n - \tilde{g} + r c_j e^{-\alpha t} + \alpha e^{-\alpha t} c_j + \lambda \frac{(\phi - 1) P_t e_n}{r}\right) dt + o(dt). \end{aligned} \tag{20}$$

Correspondingly, the solution is

$$\lim_{dt\to 0} \frac{E_t V_{t+dt} - V_t}{dt} = e^{-rt}\left(-P_t e_n - \tilde{g} + r c_j e^{-\alpha t} + \alpha e^{-\alpha t} c_j + \lambda \frac{(\phi - 1) P_t e_n}{r}\right) = 0. \tag{21}$$

Rearranging, we obtain

$$(r + \alpha) e^{-\alpha t} c_j + \left(\lambda \frac{(\phi - 1)}{r} - 1\right) P_t e_n - \tilde{g} = 0. \tag{22}$$

Which yields the optimal adoption condition stated in Proposition 1:

$$c_j = \frac{\left(1 - \lambda \frac{(\phi - 1)}{r}\right) P_t e_n + \tilde{g}}{(r + \alpha) e^{-\alpha t}} \quad \square \tag{23}$$

D Further Tables on NUTS-3 level evidence

Table 13: Descriptive statistics, PV.

	Total				Rural				Urban			
	Mean	St. Dev.	Min.	Max.	Mean	St. Dev.	Min.	Max.	Mean	St. Dev.	Min.	Max.
$F_{\mathrm{PV},t-1}$	.013	.018	8.7e-05	.13	.015	.02	8.7e-05	.13	.0073	.0087	.00016	.051
$F_{\mathrm{PV},t-k-1}$	.0038	.0061	0	.047	.0043	.0068	0	.047	.0026	.0035	0	.021
$\Delta F_{\mathrm{PV},t-1}$	.0092	.012	8.7e-05	.094	.011	.014	8.7e-05	.094	.0047	.0057	9.4e-05	.035
sun	1035	58	871	1162	1038	58	938	1162	1026	58	871	1160
V_t	.082	.035	.02	.29	.075	.029	.02	.21	.1	.043	.033	.29
ΔV_t	.013	.015	-.03	.081	.012	.014	-.028	.081	.015	.017	-.03	.057
N	1160				849				311			

D.1 Robustness spatial

Table 14: Spatial error model estimation of increase in PV diffusion on increase in share of green votes.

	SER	SER IV	
	(1)	(2)	(3)
	ΔV_t	$\Delta F_{\mathrm{PV},t-1}$	ΔV_t
$\Delta F_{\mathrm{PV},t-1}$	0.177***		
	(3.79)		
$\Delta \hat{F}_{\mathrm{PV},t-1}$			0.226**
			(2.13)
$\hat{F}_{\mathrm{PV},t-k-1}$		1.686***	
		(10.56)	
$\Delta \ln(\mathrm{GDP}_{\mathrm{cap},t})$	0.00168	0.000571	0.00159
	(0.52)	(0.23)	(0.49)
Spatial			
γ	0.758***	0.684***	0.763***
	(31.68)	(16.58)	(32.52)
Final log-likelihood $\mathcal{L}$	4239.3	4821.7	4233.9
N	1158	1158	1158

t statistics in parentheses, built with Newey-West SE
NUTS-3 and time fixed effects included
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Column (1) shows the estimates of the spatial error model for rural regions. Column (2) presents the first stage (2SLS with spatial error model) estimates with the lagged forecast instrument $(\hat{F}_{\mathrm{PV},t-k-1})$ predicted according to the Diffusion Model from column (1) in Table 2 for rural regions and according to the Diffusion Model from column (2) in Table 2 for urban regions. Column (3) shows the second stage estimates (2SLS with spatial error model) of the adoption rate $(\Delta \hat{F}_{\mathrm{PV},t-1})$ on the increase in green votes (ΔV_t). The number of observations drops to 1158 (in contrast to Table 1) since we analyze the balanced panel when including a spatial error term.

D.2 Robustness lagging the predicted diffusion level by two periods

This section contains a robustness check of the effect of PV adoption on green voting. Here, we lag further the forecasts of the diffusion equation (16) to instrument for adoption rates. In particular, we use $\hat{F}_{\text{PV},t-2*k-1}$ instead of $\hat{F}_{\text{PV},t-k-1}$ to instrument for $\Delta F_{\text{PV},t-1}$. Table 15 shows that lagging further the predicted diffusion level does not diminish the magnitude or the significance of the estimated effect for rural areas.

Table 15: Instrument variable estimation of increase in PV diffusion on increase in share of green votes for rural regions.

	Diffusion Model		IV	
	NLS (1) $F_{\text{PV},t-2*k-1}$		1st stage (2) $\Delta F_{\text{PV},t-1}$	2nd stage (3) ΔV_t
a_0	0.238***	$\Delta\hat{F}_{\text{PV},t-1}$		0.177***
	(10.74)			(2.00)
a_1 (sun)	-0.368***	$\hat{F}_{\text{PV},t-2*k-1}$	4.041***	
	(-10.88)		(8.03)	
a_2 (sun^2)	0.0148***	$\Delta\ln(\text{GDP}_{\text{cap},t})$	-0.00572	-0.000924
	(4.21)		(-1.01)	(-0.12)
a_3 (sun^3)	0.118***			
	(9.88)			
b (speed)	3.636***			
	(14.06)			
c (inflexion point)	4.976***			
	(41.40)			
NUTS-3 fixed effects	No	NUTS-3 fixed effects	Yes	Yes
Time fixed effects	No	Time fixed effects	Yes	Yes
NUTS-1×Time fixed effects	No	NUTS-1×Time fixed effects	No	No
R^2	0.768	R^2	0.741	0.665
Adj. R^2	0.767	Adj. R^2	0.608	0.494
		F	251.9	250.2
$\text{F}_{a_1,a_2,a_3=0}$	42.38	$\text{F}_{\hat{F}_{\text{PV},t-2*k-1}=0}$	64.56	
$\text{p-value}_{a_1,a_2,a_3=0}$	1.63e-25	$\text{p-value}_{\hat{F}_{\text{PV},t-2*k-1}=0}$	5.54e-15	
N	849	N	849	849

t statistics in parentheses, built with Newey-West-SE

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Column (1) shows the estimates of the Diffusion Model (equation 16 but lagged by two periods) with non-linear least squares for rural regions. a_1, a_2, a_3 affect the diffusion ceiling, b the diffusion speed and c the inflexion point. Column (2) presents the first stage (2SLS) estimates with the (by two periods) lagged, predicted instrument $\left(\hat{F}_{\text{PV},t-2*k-1}\right)$ for rural regions. The lagged instrument is predicted according to the Diffusion Model from column (1). Column (3) shows the second stage estimates (2SLS) of the adoption rate $\left(\Delta\hat{F}_{\text{PV},t-1}\right)$ on the increase in green votes (ΔV_t) for rural regions.

D.3 Robustness synthetic instrument

This section contains another robustness check of the effect of PV adoption on green voting. We rank the NUTS-3 regions according to their average solar radiation. Then, we compute the synthetic diffusion level of a region, $F_{\text{PV, synthetic},t-k-1}$, by taking the average value of diffusion, $F_{\text{PV},t-k-1}$, in the four regions that are closest in the solar radiation ranking. We then use $F_{\text{PV, synthetic},t-k-1}$ to instrument for $\Delta F_{\text{PV},t-1}$,. $F_{\text{PV, synthetic},t-k-1}$, is, by definition, exogenous to variation in the adoption rate $\Delta F_{\text{PV},t-1}$ in region i. Finally, we use the instrumented adoption rate to estimate the impact of adoption on green votes. Table 16 shows that the synthetic instrument predicts diffusion levels well and the estimate we obtain for the effect of PV adoption rates on the increase in green votes is significant and in line with the OLS and IV estimates.

Table 16: Two-stage least squares estimation of increase in PV diffusion on increase in share of green votes using synthetic instrument.

	(1) $\Delta F_{\text{PV},t-1}$	(2) ΔV_t
$\Delta \hat{F}_{\text{PV},t-1}$		0.230**
		(2.28)
$F_{\text{PV, synthetic},t-k-1}$	2.951***	
	(8.76)	
$\Delta \ln(\text{GDP}_{\text{cap},t})$	-0.00599	0.000552
	(-1.40)	(0.08)
R^2	0.662	0.644
Adj. R^2	0.491	0.463
F	221.5	317.9
$\text{F}_{\text{Instrument}=0}$	76.75	
$\text{p-value}_{\text{Instrument}=0}$	1.23e-17	
N	1158	1158
DF_M	390	390

t statistics in parentheses, built with Newey-West SE
NUTS-3 and time fixed effects included
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D.4 Industrial vs. household systems

In this section, we confirm that the effect of household PV adoption on green voting is robust to instrumenting adoption rates by our solar radiation instrument. We consider two possible cutoffs for the maximum capacity of household PV systems, 30 $\mathrm{kW_p}$ and 100 $\mathrm{kW_p}$.[50]

Column (1) in Table 17 shows the estimates of the diffusion model (equation 16) with non-linear least squares for household systems below 30 $\mathrm{kW_p}$. Column (1) in Table 18 shows the same for household systems below 100 $\mathrm{kW_p}$. a_1, a_2, a_3 affect the diffusion ceiling, b the diffusion speed and c the inflexion point. When studying household systems, all coefficients have the expected signs and are highly significant at both cutoff capacities. The speed of diffusion, b, is positive and the inflexion point lies between years 2001 and 2004. For household systems, the high R^2 confirms the good fit of the logistic model where cross-regional variation in PV diffusion is driven by solar radiation.

Table 17: Instrument variable estimation of increase in PV diffusion on increase in share of green votes for household PV systems $\left(\text{below } 30\,\mathrm{kW_p}\right)$ in rural regions.

	Diffusion Model		IV	
	NLS		1st stage	2nd stage
	(1)		(2)	(3)
	$F_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t-k-1}$		$\Delta F_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t-1}$	ΔV_t
a_0	8.144***	$\Delta \hat{F}_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t-1}$		0.190***
	(2.98)			(2.19)
a_1 (sun)	-22.83***	$\hat{F}_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t-k-1}$	1.199***	
	(-2.88)		(10.42)	
a_2 (sun^2)	21.19***	$\Delta \ln(\mathrm{GDP}_{\mathrm{cap},t})$	-0.00201	-0.00104
	(2.76)		(-0.42)	(-0.13)
a_3 (sun^3)	-6.506***			
	(-2.64)			
b (speed)	3.345***			
	(26.31)			
c (inflexion point)	4.296***			
	(106.65)			
NUTS-3 fixed effects	No	NUTS-3 fixed effects	Yes	Yes
Time fixed effects	No	Time fixed effects	Yes	Yes
NUTS-1×Time fixed effects	No	NUTS-1×Time fixed effects	No	No
R^2	0.788	R^2	0.760	0.664
Adj. R^2	0.786	Adj. R^2	0.637	0.493
		F	262.5	242.9
$\mathrm{F}_{a_1,a_2,a_3=0}$	71.95	$\mathrm{F}_{\hat{F}_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t-k-1}=0}$	108.6	
$\text{p-value}_{a_1,a_2,a_3=0}$	1.93e-41	$\text{p-value}_{\hat{F}_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t-k-1}=0}$	2.24e-23	
N	849	N	849	849

t statistics in parentheses, built with Newey-West-SE
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Column (1) shows the estimates of the Diffusion Model (equation 16) with non-linear least squares for household PV systems $\left(\text{below } 30\,\mathrm{kW_p}\right)$ in rural regions. a_1, a_2, a_3 affect the diffusion ceiling, b the diffusion speed and c the inflexion point. Column (2) presents the first stage (2SLS) estimates with the lagged, predicted instrument $\left(\hat{F}_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t-k-1}\right)$ for household systems in rural regions. The lagged instrument is predicted according to the Diffusion Model from column (1). Column (3) shows the second stage estimates (2SLS) of the adoption rate $\left(\Delta F_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t-k-1}\right)$ on the increase in green votes (ΔV_t) for rural regions.

[50] Estimations with a smaller, less conservative cutoff at 10 $\mathrm{kW_p}$ confirm the shown results.

Table 18: Instrument variable estimation of increase in PV diffusion on increase in share of green votes for household PV systems $\left(\text{below } 100\,\mathrm{kW_p}\right)$ in rural regions.

	Diffusion Model		IV	
	NLS		1st stage	2nd stage
	(1)		(2)	(3)
	$F_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t-k-1}$		$\Delta F_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t-1}$	ΔV_t
a_0	8.583***	$\Delta \hat{F}_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t-1}$		0.170***
	(3.00)			(2.21)
a_1 (sun)	-24.07***	$\hat{F}_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t-k-1}$	1.297***	
	(-2.90)		(10.69)	
a_2 (sun^2)	22.35***	$\Delta \ln(\mathrm{GDP}_{\mathrm{cap},t})$	-0.00197	-0.00107
	(2.78)		(-0.38)	(-0.14)
a_3 (sun^3)	-6.865***			
	(-2.66)			
b (speed)	3.336***			
	(26.40)			
c (inflexion point)	4.310***			
	(105.63)			
NUTS-3 fixed effects	No	NUTS-3 fixed effects	Yes	Yes
Time fixed effects	No	Time fixed effects	Yes	Yes
NUTS-1×Time fixed effects	No	NUTS-1×Time fixed effects	No	No
R^2	0.785	R^2	0.762	0.665
Adj. R^2	0.784	Adj. R^2	0.641	0.494
F		262.8	243.4	
$\mathrm{F}_{a_1,a_2,a_3=0}$	65.07	114.2		
p-value$_{a_1,a_2,a_3=0}$	7.46e-38	p-value$_{\hat{F}_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t-k-1}=0}$	2.13e-24	
N	849	N	849	849

t statistics in parentheses, built with Newey-West-SE
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Column (1) shows the estimates of the Diffusion Model (equation 16) with non-linear least squares for household PV systems $\left(\text{below } 100\,\mathrm{kW_p}\right)$ in rural regions. a_1, a_2, a_3 affect the diffusion ceiling, b the diffusion speed and c the inflexion point. Column (2) presents the first stage (2SLS) estimates with the lagged, predicted instrument $\left(\hat{F}_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t-k-1}\right)$ for household systems in rural regions. The lagged instrument is predicted according to the Diffusion Model from column (1). Column (3) shows the second stage estimates (2SLS) of the adoption rate $\left(\Delta F_{\mathrm{PV}\leq 100\,\mathrm{kW_p},t-k-1}\right)$ on the increase in green votes (ΔV_t) for rural regions.

Column (2) in Table 17 presents the first stage (2SLS) estimates with the lagged predicted instrument $\left(\hat{F}_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t-k-1}\right)$ according to the diffusion model from column (1) in Table 17. The same applies to column (2) and column (1) in in Table 18 for a cutoff capacity of 100 $\mathrm{kW_p}$. The predicted instrument is strong for household systems at both cutoff capacities.

In column (3) of Table 17, we see the second stage estimates (2SLS) of the adoption rate $\left(\Delta\hat{F}_{\mathrm{PV}\leq 30\,\mathrm{kW_p},t-1}\right)$ for household systems on the increase in green votes (Δv_t) for a cutoff capacity of 30 $\mathrm{kW_p}$. We obtain an estimate very close to the full sample estimate (Table 2). The estimated effect is slightly higher for systems with a capacity of at most 30 $\mathrm{kW_p}$ than for systems of at most 100 $\mathrm{kW_p}$ (see column (3) in Table 18). In both cases, the association of PV adoption on green voting is significant with p-values smaller than one percent.

E Further Tables on survey evidence

Table 19: Descriptive statistics, SOEP.

	Mean	Std. Dev.	Min.	Max.
$\Delta Green_t$	.023	.15	0	1
$Solar_{t-1}$	.065	.25	0	1
$\Delta Solar_{t-3:t-1}$	.024	.15	0	1
$\Delta Solar_t$	.01	.1	0	1
$\Delta GreenSwitch_t$	.016	.13	0	1
$\Delta GreenIntens_t$	.06	.43	0	5
$\Delta Green_{t-3:t-1}$	.073	.26	0	1
$Internet_{t-1}$	.43	.5	0	1
PC_{t-1}	.59	.49	0	1
N	69456			

E.1 Removed PV systems

We exclude respondents who claim that they have removed a PV system. Figure 10 compares the fraction of respondents who state that they removed a solar system 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 systems were removed.

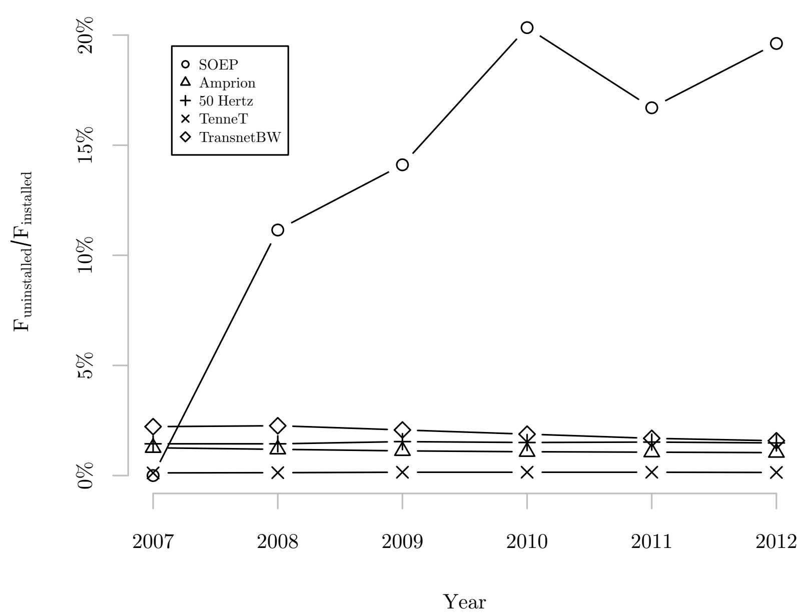

Figure 10: Rate of cumulative removed divided by cumulative installed PV systems by year.

E.2 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), Universität, TH (University, Technical College), Hochschule im Ausland (College Not In Germany), Ingenieur-, Fachschule (Ost) (Engineering, Technical 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).

E.3 Presence vs. intensity of support for the Green Party

In this section, we confirm that the presence of support for the Green Party and the intensity of support for the Green Party are higher for solar adopters than for non-adopters. We define $\Delta GreenSwitch_t$ to be one if the individual states a change in support from another party to the Green Party between years $t-1$ and t and it is zero in all other cases. $\Delta GreenIntens_t$ is one if the individual states an increase in the intensity of support for the Green Party between years $t-1$ and t (and zero in all other cases). In column (3) of Table 20, we show that under home owners the odds of becoming green are 1.4 times higher for solar adopters than for non adopters. Similarly, in column (4) of Table 20, we illustrate that under home-owners the odds of increasing the intensity of Green Party support are 1.7 times higher for those who adopted a solar system compared to those who did not.

Table 20: Odds ratio of solar level on change in green attitude (starting 2009).

	All		Home owners		Non-home owners	
	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta GreenSwitch_t$	$\Delta GreenIntens_t$	$\Delta GreenSwitch_t$	$\Delta GreenIntens_t$	$\Delta GreenSwitch_t$	$\Delta GreenIntens_t$
$Solar_{t-1}$	1.228	1.430***	1.471**	1.714***	0.355*	0.524
	(1.45)	(2.71)	(2.54)	(3.77)	(-1.79)	(-1.37)
ln (Real Income$_t$)	1.053	1.096	1.108	1.169	1.138	1.170
	(0.71)	(1.35)	(0.90)	(1.53)	(1.22)	(1.57)
Observations	45344	45835	24871	25293	19195	19413
DF_M	65	67	60	64	60	61
Final log-likelihood $\mathcal{L}$	-4045.4	-5175.3	-2218.1	-2876.5	-1786.9	-2249.6

Exponentiated coefficients; robust t statistics in parentheses clustered on households
Time$*$NUTS-1, college, vocational degree and labor status dummies included
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

E.4 IV

For the full sample (home owners and non-home owners), the effect from solar adoption on becoming green is significant for the probit and the two-stage least squares estimation (columns (1), (2) and (3) in Table 21) but not for bi-probit (columns (4) and (5) in Table 21). Table 22 illustrates that there is no effect from solar adoption on becoming green for non-home owners.

Table 21: Estimation of solar level on change in green attitude (for home and non-home owners).

	Probit	IV (2SLS)		Bi-Probit	
		1st stage	2nd stage	1st stage	2nd stage
	(1)	(2)	(3)	(4)	(5)
	$\Delta Green_t$	$Solar_{t-1}$	$\Delta Green_t$	$Solar_{t-1}$	$\Delta Green_t$
$\hat{Solar}_{t-1}$			0.544***		0.435
			(3.29)		(1.45)
$Solar_{t-1}$	0.159***				
	(2.64)				
$Internet_{t-1}$		0.0107**		0.0904**	
		(2.12)		(2.13)	
PC_{t-1}		0.0125**		0.167***	
		(2.31)		(3.19)	
ln (Real Income$_t$)	0.0485*	0.0488***	-0.0259***	0.431***	0.0342
	(1.65)	(9.37)	(-2.71)	(10.03)	(1.06)
ρ				-0.139	
$\chi^2_{\rho=0}$ (p-value)				0.898 (0.343)	
$\chi^2_{\text{Instruments}=0}$ (p-value)		7.671 (0.000470)		18.66 (0.0000889)	
Observations	45455	45538	45538	45538	
DF_M	67	69	68	137	
Final log-likelihood $\mathcal{L}$	-5143.7	-1177.1	7354.1	-15503.0	

Robust t statistics in parentheses clustered on households
Time∗NUTS-1, college, vocational degree and labor status dummies included
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 22: Estimation of solar level on change in green attitude (for non-home owners).

	Probit	IV (2SLS)	
		1st stage	2nd stage
	(1)	(2)	(3)
	$\Delta Green_t$	$Solar_{t-1}$	$\Delta Green_t$
$\hat{Solar}_{t-1}$			-1.596
			(-1.51)
$Solar_{t-1}$	-0.270		
	(-1.41)		
$Internet_{t-1}$		-0.00281	
		(-0.65)	
PC_{t-1}		-0.00424	
		(-0.98)	
ln (Real Income$_t$)	0.0763*	0.0157***	0.0275*
	(1.74)	(3.40)	(1.76)
R^2		0.0176	-1.720
Adj. R^2		0.0142	-1.729
F		1.278	2.123
Hansen J statistic			0.0114
Hansen p-value			0.915
Observations	19268	19832	19832
DF_M	61	69	68
Final log-likelihood $\mathcal{L}$	-2242.2	11677.6	-1840.3

Robust t statistics in parentheses clustered on households
Time∗NUTS-1, college, vocational degree and labor status dummies included
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

F Votes for money

F.1 Profitability estimations

Table 23: Instrument variable estimation of increase in PV diffusion on increase in share of green votes (controlling for profitability).

	OLS	IV	
		1st stage	2nd stage
	(1)	(2)	(3)
	ΔV_t	$\Delta F_{\mathrm{PV},t-1}$	ΔV_t
$\Delta \hat{F}_{\mathrm{PV},t-1}$	0.281***		0.239**
	(5.14)		(2.26)
$\hat{F}_{\mathrm{PV},t-k-1}$		1.394***	
		(10.03)	
$\Delta p_{\mathrm{PV},t-1}/p_{\mathrm{PV},t-k-1} * sun$	0.00432	-0.00230	0.00345
	(1.41)	(-1.44)	(0.88)
$\Delta \ln(\mathrm{GDP}_{\mathrm{cap},t})$	-0.000405	0.00106	-0.000345
	(-0.06)	(0.28)	(-0.05)
R^2	0.643	0.753	0.643
Adj. R^2	0.461	0.626	0.460
F	244.9	251.9	251.3
$\mathrm{F}_{\hat{F}_{\mathrm{PV},t-k-1}=0}$		100.7	
$\text{p-value}_{\hat{F}_{\mathrm{PV},t-k-1}=0}$		2.40e-22	
N	1160	1160	1160

t statistics in parentheses, built with Newey-West-SE
NUTS-3 and time fixed effects included
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Column (1) presents the OLS estimates of the adoption rate on the increase in green votes for rural regions while controlling for profitability $(\Delta p_{\mathrm{PV},t-1}/p_{\mathrm{PV},t-k-1} * sun)$. Column (2) presents the first stage (2SLS) estimates with the lagged, predicted instrument $(\hat{F}_{\mathrm{PV},t-k-1})$ for rural regions according to the Diffusion Model from Table 2 column (1) and according to the Diffusion Model from Table 2 column (2) for urban regions. Column (3) shows the second stage estimates (2SLS) of the adoption rate $(\Delta \hat{F}_{\mathrm{PV},t-1})$ on the increase in green votes (ΔV_t) for rural regions. In the first and the second stage, we control for profitability $(\Delta p_{\mathrm{PV},t-1}/p_{\mathrm{PV},t-k-1} * sun)$.

F.2 Details on calculation of the profit to income ratios

We calculate the profit income ratio of PV systems as follows:

$$\begin{aligned} \text{Profit Income Ratio} = \text{Capacity} * \Bigg[& \sum_{t=0}^{T=19} \left(\frac{1-v}{1+r}\right)^t [\text{ Feed-in Tariff} \\ & * \#\text{ Full-load Hours }] - \text{Investment per kW}_\mathrm{p} \\ & * \left(1 + \sum_{t=0}^{T=19} \frac{b}{(1+r)^t}\right) \Bigg] / (\text{Household Income} * 20). \end{aligned} \tag{24}$$

See Table 24 for a definition of the parameters in expression (24), their value and source. 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,[51] 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).

Table 24: 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 percent	Cooley and Prescott (1995), BMU (2011),Wirth (2013)
b	Yearly operating costs	1.0 percent	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 percent	BMU (2011), Wirth (2013)
Capacity	Median capacity $[kW_p]$	4	KEK (2010), DESTATIS (2013b)
	90^{th} percentile capacity $[kW_p]$	6.4	KEK (2010), DESTATIS (2013b)
Full-load Hours	Average [hours/year]	900	BMU (2011), Wirth (2013)
	90^{th} percentile [hours/year]	1110	DWD (2010), BMU (2011), Wirth (2013)

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). We also consider a value for the full-load hours of 1,110, which is at the 90^{th} percentile for all the systems installed in Germany through 2009.[52]

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

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

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

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 percent of the cost of installation (BMU, 2011; Wirth, 2013).

We calculate the median and 90^{th} percentile capacity installed in single household residences in two steps. First, we use the information from a roof census conducted by the Karlsruher Energie- und Klimaschutzagentur (KEK) for Karlsruhe,[53] Baden-Württemberg, to calculate the potential area in single household roofs to install PV systems.[54] It follows that the median potential area for PV installation in single household residences is 37 sqm, and the 90^{th} percentile is 58 sqm. KEK (2010) documents that it is necessary to install between 8 and 10 sqm of solar modules to reach a capacity of 1 $\mathrm{kW_p}$. Based on this range, we use a value of 9 sqm per $\mathrm{kW_p}$ in our calculations. The calculation yields a median capacity supported by single-family residences of 4 $\mathrm{kW_p}$, while for the 90^{th} percentile it is 6.4 $\mathrm{kW_p}$.

[53]Karlsruhe is a 300,000 city (among the 25 largest in Germany) with a 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.

[54]In particular, the census used information on the roof inclination, area, orientation and solar radiation to calculate the potential capacity of PV systems on each roof. The census covered 40,043 residential buildings in Karlsruhe. DESTATIS (2013b) reports that in 2010 there were 17,631 single-family homes in Karlsruhe. KEK does not identify which of the residential buildings correspond to single-family dwellings. We assume in our calculations that they are the 17,631 residential buildings with smaller potential roof area for PV installation.