From Green Users to Green Voters

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Abstract

We estimate the effect of the diffusion of photovoltaic (PV) systems on the fraction of votes obtained by the German Green Party. The logistic diffusion of PV systems offers a new identification strategy. We take first differences and instrument adoption rates (i.e. the first difference in the diffusion level) by lagged diffusion levels. The existing rationales for non-linearities in diffusion, and ubiquity of logistic curves ensure that our instrument is orthogonal to variables that directly affect voting patterns. We find that the diffusion of domestic PV systems caused 25 percent of the increment in green votes between 1998 and 2009.

Keywords: Voting, Technology Diffusion, PV Systems, Feed-in Tariff.

JEL Classification: E13, O14, O33, O41.

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Can the diffusion of technologies affect voting patterns? Do political parties reap political benefits from the diffusion of certain technologies? Technology is usually not aligned with a specific ideology or political party. Indeed, to the extent that technology raises living standards, all parties tend to favor technology diffusion. However, in some cases, voters may associate a political party with a specific technology. This may be the case because the technology is important for the fulfillment of the party's aspirations or because the party has actively supported policies that affect the diffusion of the technology. One example where both of these nexes are present is environmentally-friendly technologies. Green parties advocate for the diffusion of green energy technologies and pursue policies that foster the diffusion of green energies. In Germany, for example, when the Social Democratic-Green coalition won the 1998 federal elections, it raised the feed-in tariffs paid for electricity produced from wind and solar power.[1]

Coinciding with the diffusion of PV systems, the German Green Party experienced a significant increase in its share of votes, from 6.7 percent in 1998 to 10.7 percent in the 2009 elections. This observation raises a question that the literature has not contemplated yet. Has the diffusion of green energy technologies helped the Green Party increase its share of votes?[2]

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.

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

[2]In section 3.4, we provide two possible rationales for why adopting PV systems may affect voting patterns. One is based on Bayesian updating and the other based on cognitive dissonance (Akerlof and Dickens, 1982).

Such reverse causality logic may result in biased estimates of the effect of PV systems diffusion on green votes. Similarly, failing to control for unobserved heterogeneity may result in biased estimates if omitted drivers of Green Party votes are correlated with diffusion patterns.

We avoid these potential biases by exploiting variation in adoption rates (i.e. the increment in diffusion) **exogenous** to the political process. To find a valid instrument for adoption rates, we build on the key finding of over 50 years of economic and marketing research on diffusion curves. Namely, that new technologies in a wide range of sectors, countries and periods diffuse approximately following logistic curves (e.g., Griliches (1957) and Mansfield (1961)).[3] Logistic curves are characterized by low initial adoption rates that eventually accelerate to reach a technology's long-run penetration rate. One implication of the non-linear nature of logistic curves is that current adoption rates can be forecasted by lagged diffusion levels.

The literature has provided four distinct rationales for the non-linearity of diffusion curves. Epidemic models (Bass, 1969; Rogers, 1995) argue that initial lack of information on the technology prevents potential adopters from adopting profitable technologies. As the number of adopters increases, information flows faster accelerating the adoption rate. Probit models rely on exogenous bell-shaped distributions of adoption costs or profits among potential adopters to generate heterogeneity in the timing of adoption.[4] The tension between the legitimization of the technology in the population and competition for limited resources required to adopt it may also generate S-shaped diffusion (Hannan

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

[4]See, for example, the vintage human capital model of Chari and Hopenhayn (1991).

and Freeman, 1989). Finally, in information cascades models (Arthur (1989) and Banerjee (1992)) agents initially adopt slowly because they are experimenting with various technological options. Followers, instead, find it optimal to copy their predecessors as in a herd, leading to an acceleration of the speed of diffusion.[5]

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

We implement this identification strategy by constructing a balanced panel at the NUTS-3 level that covers both the diffusion of PV systems and the fraction of total votes that went to the Green Party in all the federal elections between 1998 and 2009. Our baseline regression includes year dummies and region-specific trends in green voting. We find a significant effect of PV adoption on the increase in the share of votes for the Green Party. In particular, the increase in the diffusion rate of PV systems between 1998 and 2009 led to an increase in the fraction of green votes of 1 percent, which represents 25 percent of the actual increase in the voting rate experienced by the Green Party between 1998 and 2009.

[5]See Geroski (2000) for a survey.

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

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

Our analysis is related to various literatures that have explored the drivers of voting behavior. Deacon and Shapiro (1975) and Fischel (1979) use survey data from voters in referenda on environmental issues to study which factors affect the probability of voting in support of the environment. They find that occupation, political affiliation, education, income and location are important drivers of green voting.[6] A number of studies have explored the role of monetary incentives in voting both from the perspective of voters and of politicians. The existing evidence suggests that monetary rewards are relatively ineffective in driving votes both when trying to affect the position taken by elected representatives (Ansolabehere et al., 2003) and the votes of the electorate (Cornelius (2004), Wang and Kurzman (2007), Schaffer and Schedler (2007)). The specific driver of voting patterns we explore is the diffusion of PV systems. To the best of our knowledge, our paper is the first to explore the effects of technology diffusion on votes.[7]

As mentioned above, our identification strategy exploits the logistic diffusion pattern observed for many technologies. In addition to the standard forces that induce logistic diffusion patterns, a few other drivers have been pointed out as relevant for the adoption of green technologies. These include regulation (Snyder et al., 2003), feed-in tariffs (Dewald and Truffer, 2011; Jacobsson et al., 2004), environmental ideology (Kahn, 2007), consumption patterns of reference persons and habit (Welsch and Kühling, 2009).[8]

The rest of the paper is organized as follows. Section 1 describes the relevant institutional context of green energy in Germany and presents the aggre-

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

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

[8] Two other mechanisms that deliver logistic dynamics have been studied in the context of green technologies: information (Rode and Weber, 2012) and peer effects (Bollinger and Gillingham, 2012; Müller and Rode, 2013).

gate trends in green technology diffusion and green voting. Section 2 develops a model of technology adoption to explore the drivers of diffusion and motivate the instrumentation strategy. Section 3 presents the empirical findings, and discusses their robustness and interpretation. Section 4 concludes.

1 German institutional context and aggregate trends

In 1998, the Social Democratic-Green coalition won the federal elections. Two years later, the government introduced a new feed-in tariff scheme, the EEG, which raised the feed-in tariff for electricity produced from solar energy. 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).[9] The feed-in tariff was vintage-specific and was guaranteed for twenty years (Agnolucci, 2006; Altrock et al., 2011; Maurer et al., 2012).[10] 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. 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.

[9]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].

[10]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.

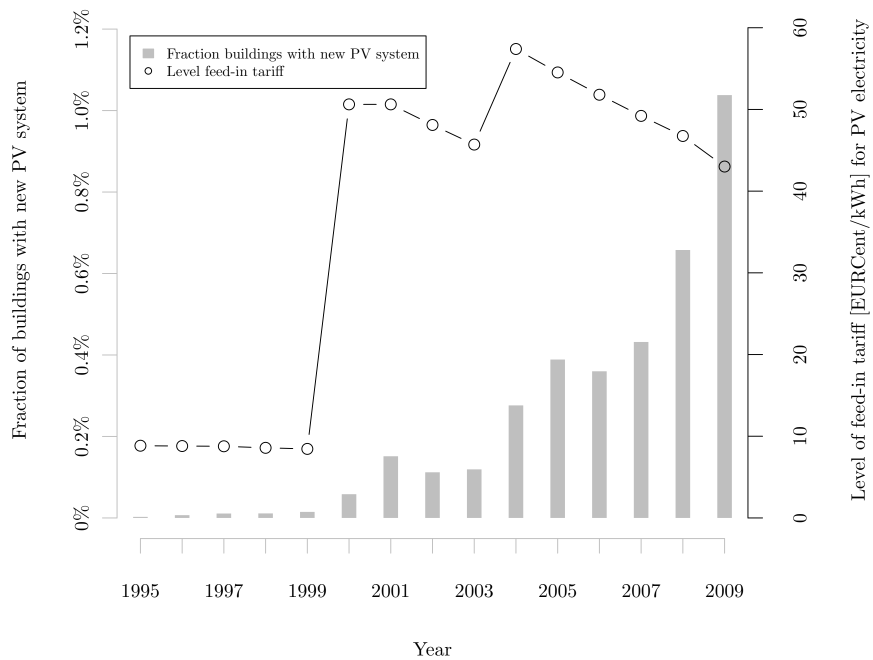

Figure 1: Fraction of buildings with a new PV system and the level of the feed-in tariff for electricity from PV (for systems with a capacity of at most 30 kW_p) in Germany from 1995 through 2009.

All Figures created using R (2013).

In 1999, the total capacity installed in eolic plants was seven times larger than the capacity installed in solar plants. The 2000 EEG also introduced new feed-in tariff schemes for electricity from eolic plants, though they rose comparatively less than for PV systems (9.1 EURCent/kWh).[11] (See Figure 2.) Since 2000, eolic systems diffused more slowly than PV systems, and by 2009, the total capacity installed in PV systems was 6 times higher than in eolic plants.

[11]Unlike PV systems, the feed-in tariff for eolic systems was not fixed for 20 years. For the first five years they were fixed at a certain amount and then at some point after the installation was five years old, the feed-in tariff dropped to a new level. The date of reset of the feed-in tariff depended on the efficiency of the installation. In less efficient installations, the high feed-in tariff period was longer. For eolic systems installed in 2000, the reset level of the feed-in tariff was 6.19 EURCent/kWh.

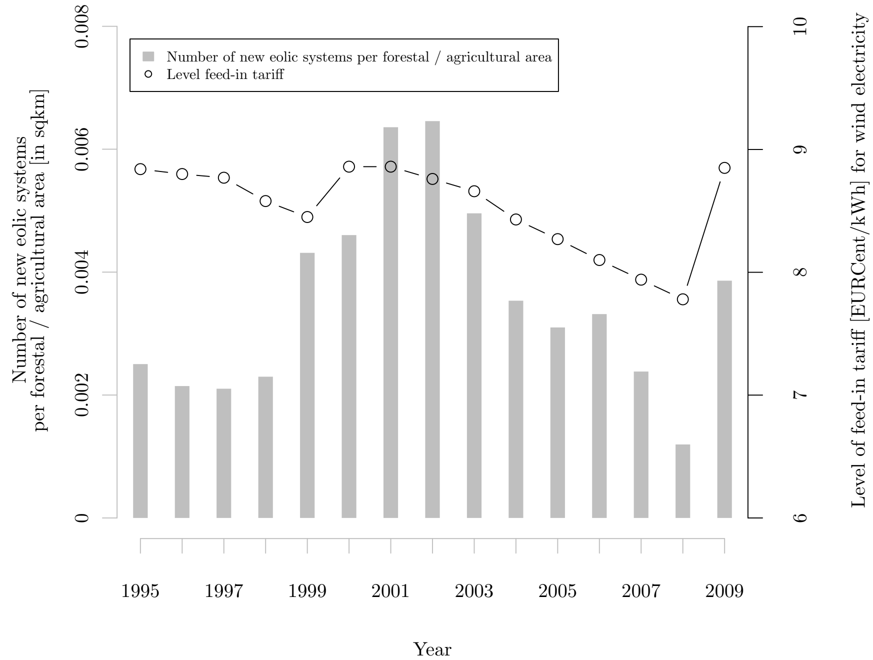

Figure 2: Number of new eolic (onshore) systems per forestal and agricultural area [in sqkm] and the level of the average feed-in tariff for electricity from eolic (onshore) systems (of 90 percent reference yield without system service or repowering bonus) in Germany from 1995 through 2009.

Coinciding with the diffusion of green energies, the Green Party experienced a significant increase in votes. (See Figure 3.)[12] In the 1998 elections, the Green Party received 6.7 percent of valid votes. This share increased to 8.6 percent in 2002, declined to 8.1 percent in 2005 and reached 10.7 percent in 2009.

Beneath these aggregate trends in votes and green energy diffusion there are important regional differences. Figure 4 shows the evolution of the fraction of buildings equipped with PV systems for the years 1998, 2002, 2005 and 2009 on

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

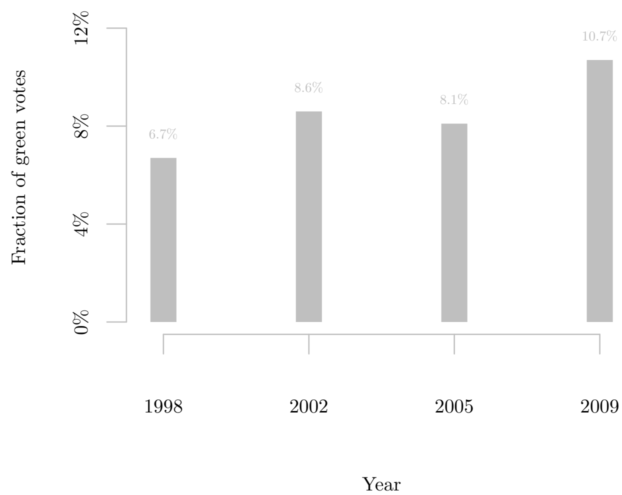

Figure 3: Fraction of green votes in federal elections in Germany from 1998 through 2009.

the NUTS-3 level in Germany.[13] In 1998, the diffusion level of PV systems was low in all regions. By 2002, we begin to notice significant regional differences, with higher diffusion rates in the south – Baden-Württemberg and Bavaria – where global solar radiation is higher. Through 2005 and 2009, the highest diffusion rates can be observed in the south, in the north of Hesse and in the east and the north-west of North Rhine-Westphalia. In contrast, relatively few PV systems were installed in the middle of North Rhine-Westphalia, the east of Lower Saxony, the south of Schleswig-Holstein and, in general, the eastern part of Germany.

Figure 5 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, (0.30 wind mills

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

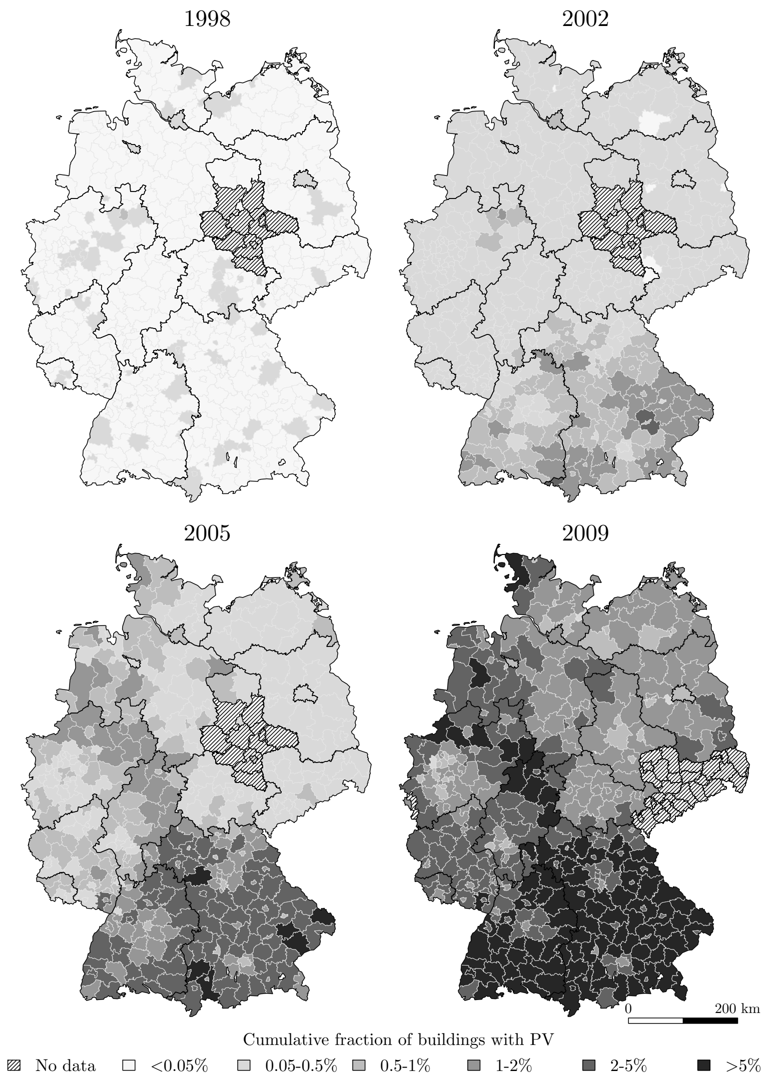

Figure 4: Fraction of building with PV at NUTS-3 level for 1998, 2001, 2005 and 2009.

per sqkm) and Hamburg (0.29) 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, (0.88 wind mills per sqkm) and Bremerhaven, Bremen, (0.71).

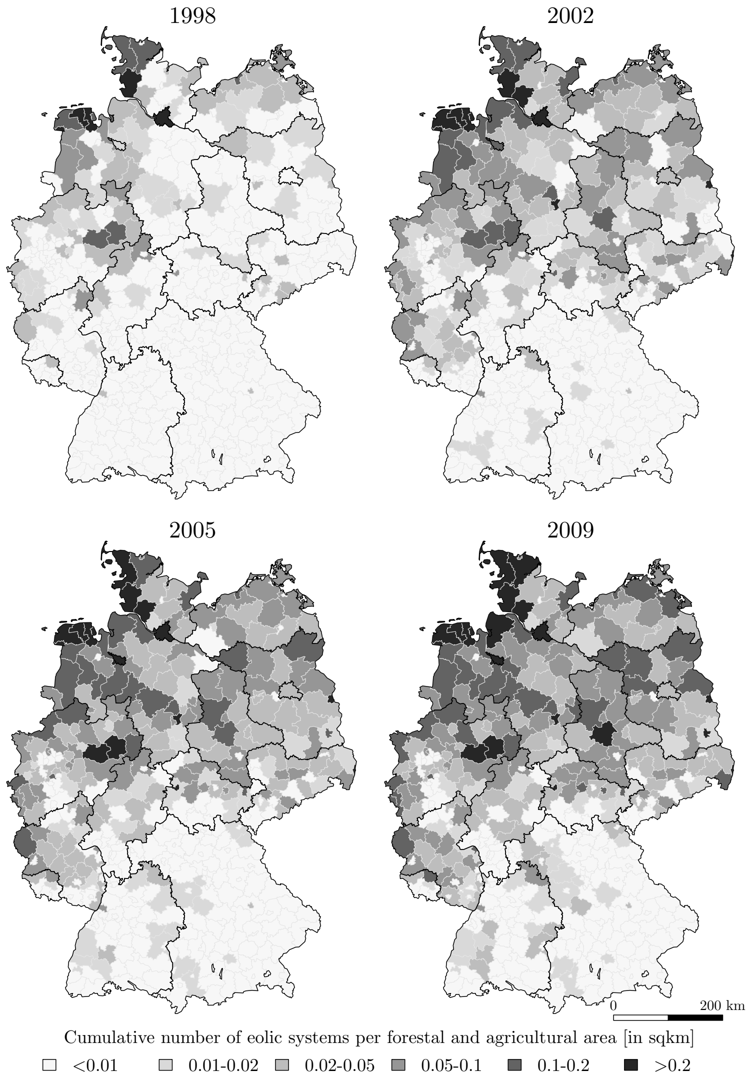

Figure 5: Number of eolic (onshore) systems per forestal and agricultural area [in sqkm] at NUTS-3 level for 1998, 2001, 2005 and 2009.

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

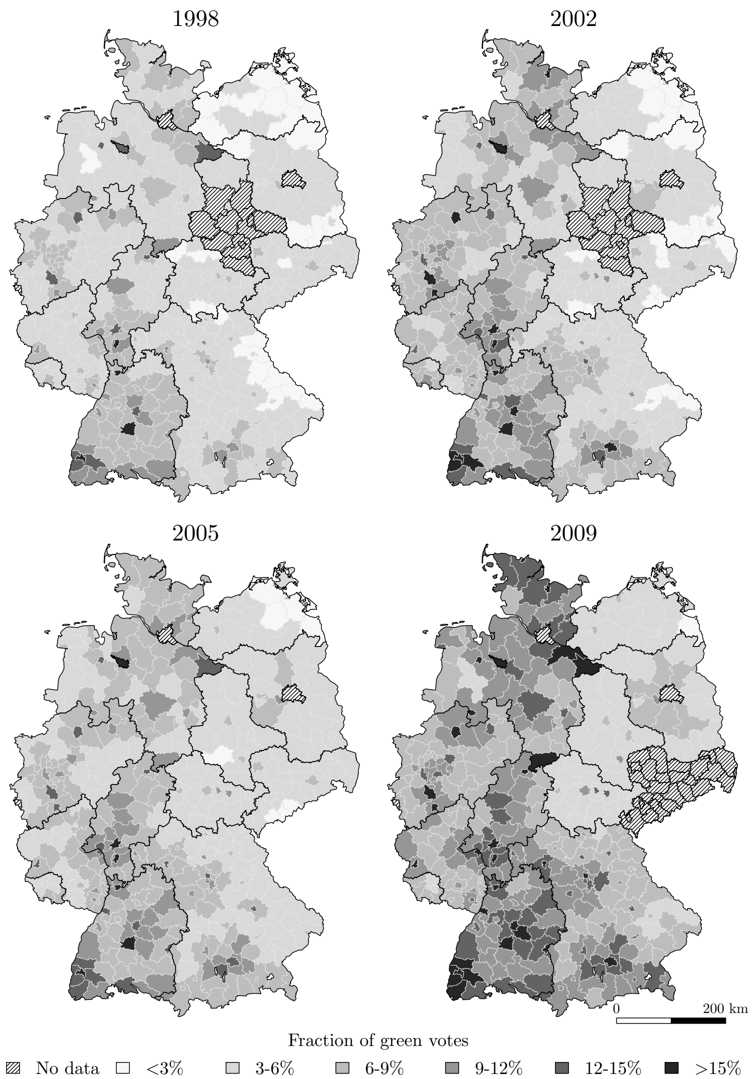

Figure 6: Fraction of green votes at NUTS-3 level for 1998, 2001, 2005 and 2009.

Finally, the cross-sections of the share of green votes are plotted in Figure 6.[14] In 1998, the Green Party obtained large voting shares in Freiburg, Baden-Württemberg, in Heidelberg, Baden-Württemberg, in Tübingen, Ba-

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

den-Württemberg, and in Darmstadt, Hesse. On the contrary, the Green Party did poorly in the eastern part of Germany. In the next decade, we observe an increase in green votes in most regions. The highest increases in the share of green votes between 1998 and 2009 took place in Lüneburg, Lower-Saxony, in Flensburg, Schleswig-Holstein, and in Würzburg, Bavaria.

2 A simple model of diffusion

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

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

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

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

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

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

The instant t in which a PV system is installed defines its vintage. For simplicity, we assume that adopters of vintage-τ PV systems obtain a constant feed-in tariff of P_τ forever.[15] P_t evolves stochastically according to the following Poisson process:

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

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

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

$$rV_\tau dt = P_\tau e_j dt \tag{2}$$

which yields

$$V_\tau = \frac{P_\tau e_j}{r}. \tag{3}$$

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

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

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

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 her ratio*

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

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

$$\begin{aligned} & F_n\left(\log\left[(1-\lambda(\phi-1)/r)P_t\right] - \log(r+\alpha) + \alpha t\right) \qquad (5) \\ = \; & \left[1+\exp\left(-b_n\left(\log\left[(1-\lambda(\phi-1)/r)P_t\right] - \log(r+\alpha) + \alpha t\right)\right)\right]^{-1}. \end{aligned}$$

Proof: See Appendix A.□

Taking a first order Taylor expansion of (5), it follows that the fraction of newly installed PV systems, f_n, is approximately equal to

$$\begin{aligned} dF_{nt} &\equiv f_{nt}\left(\log\left[(1-\lambda(\phi-1)/r)P_t\right] - \log(r+\alpha) + \alpha t\right) \\ &\simeq F_{nt} * (1-F_{nt}) * b_n * \underbrace{\left[\frac{dP_t}{P_t} + \alpha * dt\right]}_{\text{revision in return}}. \qquad (6) \end{aligned}$$

Equation (6) characterizes the determinants of the adoption rate. Adoption rates are increasing in the revisions of the return to adopting PV systems. In particular, the return to adopting PV systems increase with the growth rate of the feed-in tariff (dP_t/P_t) , and with the rate of decline of installation costs, α. Adoption rates also increase with the concentration of the ratio c_{j0}/e_j (b_n), and, in the initial stages of adoption (i.e., when $(1 - F_{nt}) \simeq 1$), it is also increasing in the diffusion level, F_{nt}. Note that, the diffusion level is a driver of adoption rates that varies both over time and across regions. Therefore, we can exploit exogenous variation in diffusion levels to instrument for adoption rates in the presence of both time and region-specific fixed effects.

3 Econometric evidence

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

$$V_{nt} = \alpha_n + g_n * t + \alpha_t + \beta F_{nt} + \rho X_{nt} + \epsilon_{nt}. \tag{7}$$

α_n is a region (NUTS-3) level effect, g_n is a region-specific trend, α_t is an aggregate time dummy, F_{nt} is the stock of PV systems installed in the region, X_{nt} is a vector of other potential drivers of green votes, and ϵ_{nt} is an error term. Taking differences between consecutive election years (t and $t - k$), (7) can be expressed as:

$$\triangle V_{nt} = g_n + \gamma_t + \beta \triangle F_{nt} + \rho \triangle X_{nt} + u_{nt} \tag{8}$$

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

Table 1 reports the ordinary least squares (OLS) estimates of equation (8).[16] We consider four specifications which differ according to whether time and NUTS-3 fixed effects are included. Time dummies capture time-varying factors that have a symmetric effect in voting patterns across regions. For example, nation-wide changes in green sentiment or political changes in the Green Party and how these are perceived by voters. Regional dummies capture region-specific trends in attitudes towards the Green Party, education and values, which may lead to regional trends in green votes. Because the specification that includes both time and NUTS-3 dummies controls for these trends, we consider it to provide a cleaner identification than the other three alternatives. In addition, all specifications control for the logarithm of per capita income in the region.

Turning back to Table 1, we find that increments in the share of green votes are positively associated with adoption rates in all four specifications. These associations are statistically and economically significant. Based on the estimates in our preferred specification (column 4), an increase in the adoption rate by one standard deviation is associated with an increase in the fraction of green votes by .2 standard deviations (see Table 15 in Appendix B for the relevant descriptive statistics). Similarly, the diffusion of PV systems between

[16]Reported standard errors (SE) are always robust to both arbitrary heteroskedasticity and arbitrary autocorrelation. They have a bandwidth of 3.

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

	(1) Δv_t	(2) Δv_t	(3) Δv_t	(4) Δv_t
$\Delta F_{\mathrm{PV},t}$	0.272***	0.448***	0.0796***	0.177***
	(12.43)	(13.93)	(4.35)	(6.79)
$\log(\mathrm{GDP}_{\mathrm{cap},t})$	0.00702***	0.0115	0.00597***	-0.00384
	(7.38)	(1.79)	(7.21)	(-0.52)
α	-0.0618***	-0.111	-0.0381***	0.0481
	(-6.47)	(-1.79)	(-4.48)	(0.67)
NUTS-3 dummies	No	Yes	No	Yes
Time dummies	No	No	Yes	Yes
N	1157	1157	1157	1157
adj. R^2	0.129	-0.069	0.582	0.525
F	116.4	8.658	416.6	11.21

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

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.

At this point, we do not interpret the estimates in Table 1 as a causal effect of PV diffusion on green votes. The correlation between adoption rates and the increment in the fraction of green votes could also result from omitting relevant variables from the vector of controls, $\triangle X_{nt}$. To confidently argue that the estimates reflect the causal effect of PV adoption on green voting, we need some exogenous source of variation in the adoption of PV systems. That is, variation in PV adoption that is driven by factors that do not affect directly voting patterns or that are not correlated with factors other than adoption that may drive voting patterns.

Finding valid instruments is, in general, a difficult task. However, in our context, the non-linear diffusion patterns of new technologies provide us with a natural instrumental variable. As shown in Section 2, a property of logistic diffusion curves is that current adoption rates are a function of the lagged diffusion level. Indeed, in the early stages of diffusion, current adoption is (approximately) a linear function of the lagged diffusion level. But, what is the nature of this relationship? Is it orthogonal to voting patterns?

The literature has proposed several hypotheses on the source of the non-linearities of diffusion patterns. These theories include epidemic models (Bass, 1969; Rogers, 1995) where information diffuses slowly, probit models where the exogenous distribution of adoption costs and profits in the population is bell-shaped (Griliches, 1957), legitimization theories where the population accepts slowly the validity of the technology (Hannan and Freeman, 1989) and information cascades models where agents initially experiment with multiple forms of the technology until a dominant form emerges (Arthur (1989) and Banerjee (1992)). Importantly, in none of these theories is the non-linear nature of diffusion dynamics related to politics or voting dynamics.

Furthermore, S-shape diffusion patterns have been documented for a wide range of technologies, periods and countries with very diverse political and contextual factors. The ubiquity of S-shaped diffusion patterns strongly supports the premise that variation in the adoption of PV systems driven by the non-linearities of diffusion are exogenous to changes in voting patterns. In particular, we find it difficult to make the argument that factors that drive changes in green votes between $t-k$ and t are correlated in any way with the stock of adoption until the previous election year $(t-k)$; especially, after controlling for time and regional dummies that capture cross-regional differences in attitudes towards the Green Party, and in their trends, as well as any pattern of aggregate time-variation in green vote drivers.

Table 2 reports the estimates of the first stage regression where we use the PV diffusion level in the previous election year $(t-k)$ to forecast the adoption rate over the electoral cycle (i.e. from $t-k$ to t). The findings are quite similar for all four specifications, including our preferred one with both region and time fixed effects. Lagged diffusion levels are a very strong predictor of current adoption rates. The t-statistics of this coefficient are close to 20 or above. The null that the instrument is irrelevant is rejected at any level of significance. Furthermore, the high R^2 (around 0.85 in all four specification) shows that the logistic curve provides a very good approximation for the diffusion process of PV systems at the NUTS-3 level.

Table 2: First stage estimation of increase in PV diffusion on increase in share of green votes.

	(1) $\Delta F_{\mathrm{PV},t}$	(2) $\Delta F_{\mathrm{PV},t}$	(3) $\Delta F_{\mathrm{PV},t}$	(4) $\Delta F_{\mathrm{PV},t}$
$F_{\mathrm{PV},t-k}$	1.721***	1.417***	1.641***	1.278***
	(30.74)	(24.88)	(24.58)	(18.93)
$\log(\mathrm{GDP}_{\mathrm{cap},t})$	-0.00186***	0.0329***	-0.00212***	0.00829*
	(-3.43)	(9.95)	(-3.94)	(2.02)
α	0.0218***	-0.313***	0.0271***	-0.0717
	(4.03)	(-9.82)	(4.93)	(-1.79)
NUTS-3 dummies	No	Yes	No	Yes
Time dummies	No	No	Yes	Yes
N	1157	1157	1157	1157
adj. R^2	0.837	0.864	0.843	0.877
F	471.5	99.07	472.4	131.3
$\chi^2_{\mathrm{Instrument}=0}$	945.0	618.9	604.0	358.4
p-value$_{\mathrm{Instrument}=0}$	1.65e-207	1.31e-136	2.30e-133	6.29e-80

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

Table 3 shows the estimates from the second stage regression. In all specifications we find a positive and significant effect of instrumented adoption rates on the increment in Green Party votes. The point estimates vary from 0.12 to 0.4 depending on the specification. In our preferred specification with region and time fixed effects the point estimate is 0.21 which implies that one standard deviation increase in the adoption rate of PV systems over one electoral period induces an increase in the share of votes for the Green Party by 0.36 percentage points. Cumulating that over the three elections that took place after 1998 until 2009 implies that the diffusion of PV systems accounts for a cumulative increase in the fraction of green votes of 1.1 percentage points. This increment represents approximately a quarter of the actual increase in votes experienced by the Green Party over this period.

Table 3: Two-stage least squares estimation of increase in PV diffusion on increase in share of green votes.

	(1) Δv_t	(2) Δv_t	(3) Δv_t	(4) Δv_t
$\Delta\hat{F}_{\mathrm{PV},t}$	0.284***	0.402***	0.117***	0.205***
	(12.95)	(12.49)	(5.33)	(6.75)
$\log(\mathrm{GDP}_{\mathrm{cap},t})$	0.00697***	0.0171**	0.00596***	-0.00368
	(7.32)	(2.64)	(7.21)	(-0.50)
α	-0.0614***	-0.165**	-0.0390***	0.0460
	(-6.43)	(-2.65)	(-4.59)	(0.65)
NUTS-3 dummies	No	Yes	No	Yes
Time dummies	No	No	Yes	Yes
N	1157	1157	1157	1157
adj. R^2	0.129	-0.071	0.580	0.525
F	121.7	8.757	412.0	10.92

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

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

3.1 The profitability of PV systems

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

3.1.1 Controlling for profitability

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

As implied by Section 2, we proxy changes in profitability by the growth rate of the feed-in tariff interacted by the average solar radiation of the NUTS-3 region. Note that this measure captures the asymmetric effect that the feed-in tariff has on the return to PV systems. Therefore, it has variation even after including time and regional fixed effects.

Table 4 presents the first stage estimates after controlling for profitability. Consistent with the literature (Dewald and Truffer (2011), Jacobsson et al. (2004) and Jacobsson and Bergek (2004)), we find that changes in profitability have a positive effect on adoption rates if we include time dummies (third column). However, once NUTS-3 dummies are considered, changes in profitability do not affect adoption rates. This observation suggests that the potential for omitted variables to drive the relationship between PV adoption and voting patterns is very limited.[17] Also note that the strength of the instrument is not affected by controlling for profitability. In particular, the coefficient of the lagged diffusion level in the first stage regression, its significance or the R^2 of this regression are not affected by the additional control. All this suggests that although changes in profitability may have some effects on adoption rates, the variation we use to identify the effect of adoption on voting patterns is orthogonal to changes in profitability.

Table 5 explores the second stage regression. Columns 1, 2, and 4 show a positive and significant association between changes in profitability and the increment in green votes. We interpret this coefficient as reflecting the larger increase in green votes in the southern regions of Germany during the 2002 election, the first after the EEG raised the feed-in tariff. The main finding from Table 5 is that the effect of PV adoption rates on voting patterns is unaffected by the profitability control. This further confirms that our estimates are not driven by omitted variable biases.

3.1.2 Money for votes?

The hypothesis we test in this paper is whether the adoption of PV increases the propensity to vote for the Green Party. An alternative hypothesis to

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

Table 4: First stage estimation of increase in PV diffusion on increase in share of green votes.

	(1) $\Delta F_{\mathrm{PV},t}$	(2) $\Delta F_{\mathrm{PV},t}$	(3) $\Delta F_{\mathrm{PV},t}$	(4) $\Delta F_{\mathrm{PV},t}$
$F_{\mathrm{PV},t-k}$	1.638***	1.425***	1.563***	1.267***
	(23.93)	(22.90)	(19.32)	(16.06)
$\log(\mathrm{GDP}_{\mathrm{cap},t})$	-0.00286***	0.0347***	-0.00342***	0.00852*
	(-5.29)	(9.96)	(-6.32)	(2.08)
$\Delta p_{\mathrm{PV},t}/p_{\mathrm{PV},t-k} * \mathrm{sun}$	-0.000000207*	9.58e-08	0.00000537**	-0.000000949
	(-2.09)	(0.95)	(3.23)	(-0.59)
sun	0.0000270***		0.0000237***	
	(6.17)		(3.32)	
α	0.00488	-0.331***	0.0180*	-0.0741
	(0.78)	(-9.83)	(2.17)	(-1.86)
NUTS-3 dummies	No	Yes	No	Yes
Time dummies	No	No	Yes	Yes
N	1157	1157	1157	1157
adj. R^2	0.843	0.864	0.854	0.877
F	530.6	103.5	475.0	158.1
$\chi^2_{\mathrm{Instrument}=0}$	572.7	524.4	373.2	257.9
p-value$_{\mathrm{Instrument}=0}$	1.47e-126	4.71e-116	3.85e-83	4.82e-58

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

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

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

Table 5: Two-stage least squares estimation of increase in PV diffusion on increase in share of green votes.

	(1) Δv_t	(2) Δv_t	(3) Δv_t	(4) Δv_t
$\Delta \hat{F}_{\text{PV},t}$	0.522***	0.660***	0.162***	0.254***
	(13.15)	(14.57)	(5.45)	(5.94)
$\log(\text{GDP}_{\text{cap},t})$	0.0107***	0.0882***	0.00668***	-0.00541
	(10.39)	(10.52)	(7.87)	(-0.74)
$\Delta p_{\text{PV},t}/p_{\text{PV},t-k} * \text{sun}$	0.00000236***	0.00000421***	0.00000261	0.00000536*
	(13.61)	(19.89)	(0.98)	(1.97)
sun	-0.0000683***		-0.0000208**	
	(-9.99)		(-2.71)	
α	-0.0349**	-0.860***	-0.0254*	0.0629
	(-3.11)	(-10.61)	(-2.38)	(0.89)
NUTS-3 dummies	No	Yes	No	Yes
Time dummies	No	No	Yes	Yes
N	1157	1157	1157	1157
adj. R^2	0.231	0.245	0.580	0.525
F	79.29	6.851	262.4	10.74

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

$$\begin{aligned} \text{Profit Income Ratio} = \text{Capacity} * \Bigg[\sum_{t=0}^{T=19} \left(\frac{1-v}{1+r}\right)^t [\ \text{Feed-in Tariff} \\ * \#\ \text{Full-load Hours}\ ] - \text{Investment per kW}_\text{p} \qquad (9) \\ * \left(1 + \sum_{t=0}^{T=19} \frac{b}{(1+r)^t}\right) \Bigg] / (\text{Household Income} * 20). \end{aligned}$$

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,[18] while the second term is the cost of installing and operating the PV system per unit

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

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, 2013b).

Revenues from PV systems are calculated by multiplying the level of the feed-in tariff times the number of full-load hours the system operates per year. The feed-in tariff varies with the year of installation of the system. The number of full-load hours depends on the location and alignment of the installation. The average for the number of full-load hours in Germany is 900 hours (Klaus et al., 2010; Wirth, 2013). To assess the sensitivity of our calculations to variation in solar radiation, we also compute the profit to income ratio when calibrating the number of full-load hours to 1,110 hours which is at the 90^{th} percentile of the full-load hours for all the systems installed in Germany through 2009.[19] The depreciation of the PV systems reduces its efficiency at a rate (v) of 0.5 percent per year (BMU, 2011; Wirth, 2013). (See Table 6 for a definition of the parameters, their value and their source.)

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

Because we use household income as the benchmark for net PV income, we should calibrate the capacity level to that of systems installed in single

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

Table 6: 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 $\mathrm{kW_p}$	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 $[\mathrm{kW_p}]$	4	KEK (2010), DESTATIS (2013b)
	90^{th} percentile capacity $[\mathrm{kW_p}]$	6.4	KEK (2010), DESTATIS (2013b)
Full-load Hours	Average [hours]	900	BMU (2011), Wirth (2013)
	90^{th} percentile [hours]	1110	DWD (2010), BMU (2011), Wirth (2013)

household residences. Unfortunately, this information is not directly available. However, we can make some back of the envelope calculations by using information collected in 2010 by the Karlsruher Energie- und Klimaschutzagentur (KEK) for Karlsruhe, Baden-Württemberg.[20] KEK is a government agency which authorized SUN-AREA (a private company) to use information on the roof inclination, area, orientation and solar radiation to calculate the potential capacity of PV systems on each roof. Combining this data with information on the fraction of single-family residences in Karlsruhe,[21] it fol-

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

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

lows that the median potential area for PV installation in single household residences is 37 sqm, and the 90^{th} percentile is 58 sqm.[22] Given this potential roof area, we estimate that the capacity supported by the median single-family residence is approximately 4 $\mathrm{kW_p}$, while for the residence at the 90^{th} percentile it is 6.4 $\mathrm{kW_p}$.

Table 7 reports the value of (9) for four combinations of full-load hours and capacity, that represent the average/median and 90^{th} percentile values in each dimension. Given the time series variation in the feed-in tariff and installation costs, we report the ratios for four years over the period 2000-2009. The profit to income ratio ranges from -2.7 percent to 0.8 percent with lower values for earlier years and for systems with lower capacity and full-load hours.

Table 7: 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 $\mathrm{kW_p}$		PV system with 6.4 $\mathrm{kW_p}$	
	Full load hours [kWh]		Full load hours [kWh]	
	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

Beyond this variation, the main conclusion we extract from the table is that, even for systems with high capacity and installed in areas with high global solar radiation, the net revenues from PV electricity production are negligible for households. Therefore, we do not consider plausible that current and future

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

PV adopters compensate the Green Party with their votes *in exchange for* the net income from PV systems.[23]

3.2 Lagged diffusion

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

Tables 8 and 9 report the results from the first and second stage regressions, respectively. The main finding from the first stage regression is that, as implied by the theory, the diffusion level at $t - 2 * k$ is a good predictor of the adoption rate between $t-k$ and t. When comparing Tables 8 and 2, we see very small reductions in the R^2. The second stage estimates are also very similar to those in Table 3. There is no significant difference in the estimated effects of adoption rates on voting patterns or in the R^2 of this relationship under both instrumentation strategies. These findings further confirm the validity of our instruments

[23]In results not reported here, we have shown that the effect of adoption on Green Party votes is robust to eliminating the regions from the south of Germany (where solar radiation is highest) from the sample. This observation implies that the effects of adoption on green votes are general and not just driven by the southern regions.

Table 8: First stage estimation of increase in PV diffusion on increase in share of green votes.

	(1) $\Delta F_{\text{PV},t}$	(2) $\Delta F_{\text{PV},t}$	(3) $\Delta F_{\text{PV},t}$	(4) $\Delta F_{\text{PV},t}$
$F_{\text{PV},t-2k}$	4.870***	3.659***	4.502***	3.130***
	(18.94)	(18.41)	(13.54)	(13.27)
$\log(\text{GDP}_{\text{cap},t})$	-0.00221*	0.0469***	-0.00265**	0.00738
	(-2.51)	(11.53)	(-2.99)	(1.39)
α	0.0279**	-0.447***	0.0351***	-0.0611
	(3.14)	(-11.40)	(3.89)	(-1.18)
NUTS-3 dummies	No	Yes	No	Yes
Time dummies	No	No	Yes	Yes
N	1157	1157	1157	1157
adj. R^2	0.630	0.773	0.643	0.792
F	181.3	36.47	258.6	36.58
$\chi^2_{\text{Instrument}=0}$	358.8	339.0	183.4	176.0
p-value$_{\text{Instrument}=0}$	5.27e-80	1.07e-75	8.66e-42	3.60e-40

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

Table 9: Two-stage least squares estimation of increase in PV diffusion on increase in share of green votes (instrument: $F_{\text{PV},t-2k}$).

	(1) Δv_t	(2) Δv_t	(3) Δv_t	(4) Δv_t
$\Delta \hat{F}_{\text{PV},t}$	0.433***	0.645***	0.112***	0.157***
	(13.72)	(14.18)	(3.52)	(3.72)
$\log(\text{GDP}_{\text{cap},t})$	0.00628***	-0.0127	0.00596***	-0.00395
	(6.34)	(-1.72)	(7.22)	(-0.54)
α	-0.0563***	0.122	-0.0389***	0.0495
	(-5.68)	(1.70)	(-4.54)	(0.70)
NUTS-3 dummies	No	Yes	No	Yes
Time dummies	No	No	Yes	Yes
N	1157	1157	1157	1157
adj. R^2	0.095	-0.097	0.581	0.525
F	124.3	8.137	414.2	11.78

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

3.3 Placebo tests

The hypothesis we are testing in this paper is that **using** green technology makes **voters** more prone to vote for the Green Party. If this is the case, the effect of green adoption on green voting should be entirely driven by the adoption of household systems. By the same token, we should observe no effect of the adoption of industrial green energy systems on voting patterns. Next, we implement this placebo test in two exercises. Firstly, we differentiate between large PV systems which are feasible only in industrial installations and small PV systems that are typically installed by households. Secondly, we also explore the relationship between the diffusion of eolic systems and voting patterns, since the investments required to install eolic systems are too large to be financed by households.

3.3.1 Industrial vs. household PV systems

To assess whether the relationship between PV systems diffusion and green voting is driven by the diffusion of household or industrial systems we construct series for the diffusion of low and high capacity systems. We use two thresholds for the maximum capacity of household systems, 30 kW_p and 100 kW_p. In addition we study the effects of the diffusion of very large PV systems (1,000 kW_p or more) which definitely are industrial. To save space, we focus on our preferred specification with regional and time dummies and only report the two-stage least square estimates which are entirely consistent with the OLS estimates. Table 16 in Appendix B presents the first stage regressions for the adoption of PV systems of various capacities. For all capacity groupings, the lagged diffusion level is a strong and very significant predictor of current adoption rates. The R^2 of the first stage regressions are very high suggesting that the logistic provides a good characterization of the diffusion of both industrial and household PV systems.

Table 10 reports the estimates of the instrumented adoption rates and changes in green voting rates for industrial and household systems. For household systems we basically estimate the same effects as in the full sample (Table 3). The estimated effect is slightly higher for systems with a capacity of at most 30 kW_p than for systems of at most 100 kW_p. In both cases, the effect of PV adoption on green voting is strongly significant with p-values smaller than 0.001. The estimates change dramatically for industrial systems. When we focus on systems with capacity above 100 kW_p, we find a positive but insignificant association between instrumented adoption rates and changes in green votes. For very large PV systems (over 1,000 kW_p capacity), the relationship between instrumented adoption rates and voting patterns disappears completely. These findings are consistent with the view that using (rather than seeing) green technologies is what induces voters to vote for the Green Party.

3.3.2 Capacity-weighted measures of diffusion

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

$$\triangle F_{\text{PVCapac.}} = \frac{\triangle \text{ Total solar capacity installed}_{nt}}{\# \text{ Buildings}_{nt} * \text{Avg. capacity}} \tag{10}$$

Table 10: Two-stage least squares estimation of increase in PV diffusion on increase in share of green votes.

	Household installations		Industrial installations	
	(1)	(2)	(3)	(4)
	Δv_t	Δv_t	Δv_t	Δv_t
$\Delta\hat{F}_{\mathrm{PV}\leq 30\mathrm{kW_p},t}$	0.239***			
	(6.87)			
$\Delta\hat{F}_{\mathrm{PV}\leq 100\mathrm{kW_p},t}$		0.207***		
		(6.78)		
$\Delta\hat{F}_{\mathrm{PV}>100\mathrm{kW_p},t}$			0.174	
			(0.23)	
$\Delta\hat{F}_{\mathrm{PV}>10^3\mathrm{kW_p},t}$				-0.0951
				(-0.12)
$\log(\mathrm{GDP}_{\mathrm{cap},t})$	-0.00355	-0.00345	-0.00506	-0.00477
	(-0.49)	(-0.47)	(-0.67)	(-0.63)
α	0.0446	0.0439	0.0631	0.0605
	(0.63)	(0.62)	(0.86)	(0.83)
N	1157	1157	1157	1157
adj. R^2	0.524	0.525	0.510	0.511
F	11.20	11.50	21.08	20.89

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

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

Column (1) of Table 11 presents the OLS estimates of the effect of the increase in capacity on the increase in the share of green votes in our preferred specification with both year and region fixed effects. The main finding is that now the relationship between the two is negative (and significant at the 1 percent level).

As one could expect from the previous analysis, this change in the sign is entirely driven by the fact that capacity-weighted adoption measures, such as $\Delta F_{\mathrm{PVCapac.}}$, are dominated by industrial installations which have much larger capacity than household installations. To make this clear, columns (2) and (3)

Table 11: OLS estimation of increase in PV diffusion (capacity weighted measure) on increase in share of green votes.

	All inst.	Household installations		Industrial installations	
	(1)	(2)	(3)	(4)	(5)
	Δv_t	Δv_t	Δv_t	Δv_t	Δv_t
$\Delta F_{\text{PVCapac.},t}$	-0.0176**				
	(-2.77)				
$\Delta F_{\text{PVCapac.}\leq 30\text{kW}_\text{p},t}$		0.131***			
		(6.85)			
$\Delta F_{\text{PVCapac.}\leq 100\text{kW}_\text{p},t}$			0.130***		
			(7.17)		
$\Delta F_{\text{PVCapac.}>100\text{kW}_\text{p},t}$				-1.195**	
				(-2.86)	
$\Delta F_{\text{PVCapac.}>10^3\text{kW}_\text{p},t}$					-1.199**
					(-2.87)
$\log(\text{GDP}_{\text{cap},t})$	-0.00317	-0.00407	-0.00366	-0.00310	-0.00310
	(-0.42)	(-0.56)	(-0.50)	(-0.42)	(-0.42)
α	0.0453	0.0511	0.0468	0.0446	0.0446
	(0.62)	(0.72)	(0.66)	(0.62)	(0.62)
N	1157	1157	1157	1157	1157
adj. R^2	0.514	0.525	0.528	0.514	0.514
F	77.59	14.53	17.90	71.23	70.86

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

of Table 11 use the capacity-weighted measure of adoption but consider only installations with a capacity of at most 30 kW_p in column (2) and of at most 100 kW_p in column (3). After excluding industrial installations, the sign of the relationship between capacity-weighted adoption rates of PV systems and changes in the Green Party share of votes is again positive and significant as we found in the previous section.[24] In contrast, when we only consider

[24] The point estimate for systems with a capacity of 30 kW_p or below is 0.13 which implies that one standard deviation increase in the adoption rate of PV systems over one electoral period induces an increase in the share of votes for the Green Party by 0.3 percentage points. Cumulating that over the three elections that took place after 1998 until 2009 indicates that the diffusion of PV systems accounts for an increase in the fraction of green votes of approximately one quarter of the actual increase in votes experienced by the Green Party over this period.

installations with a capacity larger than 100 kW_p (column 4) or 1,000 kW_p (column 5) we find a negative relationship between adoption rates and green votes, again.

The conclusions from the OLS estimates remain after instrumenting capacity-weighted adoption rates with lagged capacity-weighted diffusion levels. In results not shown here, we find that the instrument is strong, especially for household systems. As before, instrumenting does not change the magnitude or sign of the OLS estimates. In particular, Table 12 shows the second stage regression coefficients. We only find positive and significant effects of capacity-weighted measures of adoption on the increase in the Green Party share of votes in the small capacity systems. Therefore, we conclude that our findings are robust to using capacity-weighted measures of diffusion.

3.3.3 The diffusion of eolic systems

A similar investigation can be conducted with eolic installations which, because of the large investments they require, are all industrial. Table 13 column (1) and (2) report the OLS estimates of the relationship between eolic adoption rates and increase in green share of votes.[25] In particular, column (1) focuses on the number of new eolic installations over the electoral period normalized by the forestal and agricultural land area in the region. Note that this normalization reflects the fact that, unlike most PV systems, eolic plants are not installed on buildings. Column (2) uses a capacity-weighted measure of

[25] See Table 17 in Appendix B for the descriptive statistics.

Table 12: Two-stage least squares estimation of increase in PV diffusion (capacity weighted measure) on increase in share of green votes.

	All inst.	Household installations		Industrial installations	
	(1)	(2)	(3)	(4)	(5)
	Δv_t	Δv_t	Δv_t	Δv_t	Δv_t
$\Delta\hat{F}_{\text{PVCapac.},t}$	-0.0149				
	(-0.95)				
$\Delta\hat{F}_{\text{PVCapac.}\leq 30\text{kW}_\text{p},t}$		0.135***			
		(6.39)			
$\Delta\hat{F}_{\text{PVCapac.}\leq 100\text{kW}_\text{p},t}$			0.119***		
			(5.96)		
$\Delta\hat{F}_{\text{PVCapac.}>100\text{kW}_\text{p},t}$				-1.144	
				(-1.12)	
$\Delta\hat{F}_{\text{PVCapac.}>10^3\text{kW}_\text{p},t}$					-1.146
					(-1.12)
$\log(\text{GDP}_{\text{cap},t})$	-0.00343	-0.00405	-0.00376	-0.00318	-0.00318
	(-0.45)	(-0.55)	(-0.52)	(-0.42)	(-0.42)
α	0.0478	0.0508	0.0480	0.0454	0.0453
	(0.65)	(0.71)	(0.68)	(0.62)	(0.62)
N	1157	1157	1157	1157	1157
adj. R^2	0.513	0.525	0.528	0.514	0.514
F	65.44	14.65	17.73	76.98	77.12

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

adoption given by this formula

$$\triangle F_{\text{EolicCapac.}} = \frac{\triangle \text{ Total eolic capacity installed}_{nt}}{\text{Agricultural \& forestal area}_{nt} \text{ * Avg. capacity}} \tag{11}$$

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

For both measures of adoption, the OLS estimates are statistically insignificant. Table 18 in Appendix B and Table 13 column (3) and (4) present the estimates in the first and second stage regressions. After instrumenting adoption rates for eolic systems, we still find no effect on the increase in the share

Table 13: Estimation of increase in eolic diffusion on increase in share of green votes.

	OLS		Two-stage least squares	
	(1)	(2)	(3)	(4)
	Δv_t	Δv_t	Δv_t	Δv_t
$\Delta F_{\text{Eolic},t}$	-0.0189			
	(-1.62)			
$\Delta F_{\text{EolicCapac.},t}$		-0.00753		
		(-1.25)		
$\Delta \hat{F}_{\text{Eolic},t}$			-0.0380	
			(-1.71)	
$\Delta \hat{F}_{\text{EolicCapac.},t}$				-0.114
				(-0.85)
α	0.0323	0.0353	0.0233	-0.0481
	(0.45)	(0.49)	(0.32)	(-0.30)
N	1161	1161	1161	1161
adj. R^2	0.508	0.507	0.507	0.425
F	20.65	24.83	11.40	10.96

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

of Green Party votes. This result confirms our hypothesis that observing the diffusion of green technologies is not sufficient for voters to vote for the Green Party. Our findings suggest that voters need to actually adopt/use green technologies to become more prone to vote for the Green Party.

3.4 Discussion

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

Both of these hypotheses are consistent with the new findings uncovered in this paper. To fully discern between the two hypothesis would require the use of survey data. However, we may learn about their plausibility by studying how the effect of PV adoption on green votes varies between NUTS-1 regions (Länder) where the Green Party was in power and those where it was not. One feature of Bayesian learning is that the marginal effect on the posterior of a given signal diminishes with the information the agent has (i.e. with the precision of the prior). We consider safe to assume that voters in NUTS-1 regions ruled by the Green Party have more precise priors about the Green Party and green values than those in NUTS-1 regions where the Green Party had not ruled before 1998 (i.e. our first data point on Green Party votes). Therefore, if our findings are the result of Bayesian learning, we should expect a smaller effect of PV system adoption on green voting in NUTS-1 regions where the Green Party had ruled.

Table 14 evaluates this prediction by introducing an additional regressor in our baseline specification which is an interaction between the adoption rate of PV systems and a dummy that equals one if the Green Party was in a governing coalition in the NUTS-1 regions before 1998. The first column reports the OLS estimates and the second the IV estimates. In both cases, the differential effect of adoption on green voting is, if anything, positive in regions where the Green Party was in power through 1998. This is precisely the opposite of what we would expect from a Bayesian learner. Therefore, we interpret this result as suggestive that voters' cognitive dissonance is likely to be the mechanism driving our findings. However, as emphasized above, much more work needs to be undertaken to establish that.

Table 14: Estimation of increase in PV diffusion on increase in share of green votes.

	OLS	Two-stage least squares
	(1)	(2)
	Δv_t	Δv_t
$\Delta F_{\mathrm{PV},t}$	0.177***	
	(6.80)	
$\Delta \hat{F}_{\mathrm{PV},t} * Green_{\mathrm{Land}}$	0.107	
	(1.84)	
$\Delta \hat{F}_{\mathrm{PV},t}$		0.228***
		(6.88)
$\Delta F_{\mathrm{PV},t} * \hat{Green}_{\mathrm{Land}}$		0.188*
		(1.98)
$\log(\mathrm{GDP}_{\mathrm{cap},t})$	-0.00409	-0.00398
	(-0.56)	(-0.54)
α	0.0501	0.0478
	(0.70)	(0.67)
N	1157	1157
adj. R^2	0.526	0.524
F	29.86	35.06

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

4 Conclusions

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

Our findings raise many new questions. First, more work is needed to uncover the mechanism by which adoption of PV systems leads to vote for the Green Party. Second, do we see similar effects of the diffusion of PV systems in other countries? In Spain, for example, green parties continued to be irrelevant despite the large diffusion of PV systems. However, unlike Germany, in Spain most of the systems installed were industrial and households have not yet adopted them in any significant way. Third, are there political consequences of the diffusion of other technologies? Do they also affect voting patterns?[26]

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

Fourth, in addition to voting patterns, does the diffusion of technology affect other political phenomena such as campaign contributions, party affiliation, voter turnout, civic involvement in politics, etc. Finally, for which technologies do we observe these effects and what do they have in common?

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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 Proof of Proposition 1

If we adopt technology at t, we get

$$V_t = e^{-rt}\left(\frac{P_t e_j}{r} - c_{j0}e^{-\alpha t}\right). \tag{12}$$

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

$$\begin{aligned} E_t V_{t+dt} = &(1-\lambda dt)\left[e^{-r(t+dt)}\left(\frac{P_t e_j}{r} - c_{j0}e^{-\alpha(t+dt)}\right)\right] \\ &+ \lambda dt\left[e^{-r(t+dt)}\left(\frac{\phi P_t e_j}{r} - c_{j0}e^{-\alpha(t+dt)}\right)\right]. \end{aligned} \tag{13}$$

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

$$\begin{aligned} E_t V_{t+dt} = \;& e^{-r(t+dt)}\left(\frac{P_t e_j}{r} - c_{j0}e^{-\alpha(t+dt)}\right) + \lambda e^{-r(t+dt)}\frac{(\phi-1)P_t e_j}{r}dt \\ = \;& e^{-rt}(1-rdt)\left(\frac{P_t e_j}{r} - c_{j0}e^{-\alpha t}(1-\alpha dt)\right) + \lambda e^{-rt}\frac{(\phi-1)P_t e_j}{r}dt + o(dt) \\ = \;& e^{-rt}\left(\frac{P_t e_j}{r} - c_{j0}e^{-\alpha t}\right) \\ & + e^{-rt}\left(-P_t e_j + rc_{j0}e^{-\alpha t} + \alpha e^{-\alpha t}c_{j0} + \lambda\frac{(\phi-1)P_t e_j}{r}\right)dt + o(dt). \end{aligned} \tag{14}$$

Correspondingly, the solution is

$$\lim_{dt \to 0} \frac{E_t V_{t+dt} - V_t}{dt} = e^{-rt} \left(-P_t e_j + r c_{j0} e^{-\alpha t} + \alpha e^{-\alpha t} c_{j0} + \lambda \frac{(\phi - 1) P_t e_j}{r} \right) = 0. \tag{15}$$

Rearranging, we obtain

$$(r + \alpha) e^{-\alpha t} c_{j0} + \left(\lambda \frac{(\phi - 1)}{r} - 1 \right) P_t e_j = 0. \tag{16}$$

Which yields the optimal adoption condition stated in Proposition 1:

$$c_{j0}/e_j = \frac{\left(1 - \lambda \frac{(\phi-1)}{r}\right) P_t}{(r + \alpha) e^{-\alpha t}} \quad \square \tag{17}$$

B Tables

Table 15: Descriptive statistics, PV.

	Mean	Std. Dev.	Min.	Max.
$F_{\mathrm{PV},t}$	.019	.026	.00013	.19
$F_{\mathrm{PV}\leq 30\mathrm{kW_p},t}$	.017	.023	.00013	.16
$F_{\mathrm{PV}\leq 100\mathrm{kW_p},t}$	.018	.025	.00013	.18
$F_{\mathrm{PV}>100\mathrm{kW_p},t}$	.00035	.0007	0	.009
$F_{\mathrm{PV}>10^3\mathrm{kW_p},t}$	.00021	.00058	0	.0083
$F_{\mathrm{PVCapac.},t}$	.015	.059	2.7e-06	.85
$F_{\mathrm{PVCapac.}\leq 30\mathrm{kW_p},t}$	.016	.027	4.1e-05	.23
$F_{\mathrm{PVCapac.}\leq 100\mathrm{kW_p},t}$	.016	.029	3.3e-05	.25
$F_{\mathrm{PVCapac.}>100\mathrm{kW_p},t}$	.00022	.0009	0	.013
$F_{\mathrm{PVCapac.}>10^3\mathrm{kW_p},t}$	.00022	.0009	0	.013
$\Delta F_{\mathrm{PV},t}$	.013	.017	.00011	.13
$\Delta F_{\mathrm{PV}\leq 30\mathrm{kW_p},t}$	.012	.015	-1.6e-05	.12
$\Delta F_{\mathrm{PV}\leq 100\mathrm{kW_p},t}$	.013	.017	-1.6e-05	.13
$\Delta F_{\mathrm{PV}>100\mathrm{kW_p},t}$	.00029	.00057	-2.7e-05	.007
$\Delta F_{\mathrm{PV}>10^3\mathrm{kW_p},t}$	.00017	.00047	-2.7e-05	.0067
$\Delta F_{\mathrm{PVCapac.},t}$	.013	.054	-.00024	.81
$\Delta F_{\mathrm{PVCapac.}\leq 30\mathrm{kW_p},t}$	.012	.02	-5.1e-06	.18
$\Delta F_{\mathrm{PVCapac.}\leq 100\mathrm{kW_p},t}$	.013	.022	-4.0e-06	.19
$\Delta F_{\mathrm{PVCapac.}>100\mathrm{kW_p},t}$	.00019	.00081	-4.6e-06	.012
$\Delta F_{\mathrm{PVCapac.}>10^3\mathrm{kW_p},t}$	.00019	.00081	-4.9e-06	.012
$F_{\mathrm{PV},t-k}$	.0057	.0091	0	.066
$F_{\mathrm{PV},t-2k}$	.0015	.0028	0	.024
$F_{\mathrm{PV}\leq 30\mathrm{kW_p},t-k}$	.0054	.0086	0	.063
$F_{\mathrm{PV}\leq 100\mathrm{kW_p},t-k}$	.0056	.009	0	.066
$F_{\mathrm{PV}>100\mathrm{kW_p},t-k}$	5.8e-05	.00016	0	.0028
$F_{\mathrm{PV}>10^3\mathrm{kW_p},t-k}$	3.9e-05	.00014	0	.0023
$F_{\mathrm{PVCapac.},t-k}$	.0018	.0097	0	.19
$F_{\mathrm{PVCapac.}\leq 30\mathrm{kW_p},t-k}$	.0037	.0076	0	.065
$F_{\mathrm{PVCapac.}\leq 100\mathrm{kW_p},t-k}$	.0036	.0075	0	.06
$F_{\mathrm{PVCapac.}>100\mathrm{kW_p},t-k}$	2.5e-05	.00015	0	.0029
$F_{\mathrm{PVCapac.}>10^3\mathrm{kW_p},t-k}$	2.4e-05	.00015	0	.0028
$p_{\mathrm{PV},t}$	49	4.7	43	55
sun	1035	58	871	1162
$\Delta p_{\mathrm{PV},t}/p_{\mathrm{PV},t-k} * \mathrm{sun}$	1562	2276	-245	5351
v_t	.082	.035	.02	.29
Δv_t	.013	.015	-.03	.081
$\log(\mathrm{GDP}_{\mathrm{cap},t})$	10	.33	9.4	11
N	1158			

Table 16: First stage estimation of increase in PV diffusion on increase in share of green votes.

	Household installations		Industrial installations	
	(1)	(2)	(3)	(4)
	$\Delta F_{\mathrm{PV}\leq 30\mathrm{kW_p},t}$	$\Delta F_{\mathrm{PV}\leq 100\mathrm{kW_p},t}$	$\Delta F_{\mathrm{PV}>100\mathrm{kW_p},t}$	$\Delta F_{\mathrm{PV}>10^3\mathrm{kW_p},t}$
$F_{\mathrm{PV}\leq 30\mathrm{kW_p},t-k}$	1.168***			
	(17.95)			
$F_{\mathrm{PV}\leq 100\mathrm{kW_p},t-k}$		1.273***		
		(18.89)		
$F_{\mathrm{PV}>100\mathrm{kW_p},t-k}$			1.865***	
			(5.63)	
$F_{\mathrm{PV}>10^3\mathrm{kW_p},t-k}$				2.193***
				(6.43)
$\log(\mathrm{GDP}_{\mathrm{cap},t})$	0.00694	0.00734	0.000815***	0.000608**
	(1.84)	(1.82)	(3.31)	(2.86)
α	-0.0595	-0.0629	-0.00754**	-0.00574**
	(-1.62)	(-1.60)	(-3.17)	(-2.78)
N	1157	1157	1157	1157
adj. R^2	0.871	0.878	0.679	0.648
F	142.5	118.8	23.37	12.90
$\chi^2_{\mathrm{Instrument}=0}$	322.1	357.0	31.68	41.29
p-value$_{\mathrm{Instrument}=0}$	4.97e-72	1.27e-79	1.81e-08	1.31e-10

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

Table 17: Descriptive statistics, eolic.

	Mean	Std. Dev.	Min.	Max.
$F_{\mathrm{Eolic},t}$	.04	.078	0	.88
$F_{\mathrm{EolicCapac.},t}$	.037	.089	0	1.5
$\Delta F_{\mathrm{Eolic},t}$	.013	.031	0	.52
$\Delta F_{\mathrm{EolicCapac.},t}$	.016	.051	0	1.3
$F_{\mathrm{Eolic},t-k}$	.027	.06	0	.77
$F_{\mathrm{EolicCapac.},t-k}$	.021	.054	0	.97
v_t	.082	.035	.02	.29
Δv_t	.013	.015	-.03	.081
$\log(\mathrm{GDP}_{\mathrm{cap},t})$	10	.33	9.4	11
N	1161			

Table 18: First stage estimation of increase in eolic diffusion on increase in share of green votes.

	(1)	(2)
	$\Delta F_{\text{Eolic},t}$	$\Delta F_{\text{EolicCapac.},t}$
$F_{\text{Eolic},t-k}$	-0.535***	
	(-8.64)	
$F_{\text{EolicCapac.},t-k}$		-0.124
		(-0.90)
$\log(\text{GDP}_{\text{cap},t})$	0.0406	0.0806
	(1.59)	(1.44)
α	-0.385	-0.777
	(-1.55)	(-1.43)
N	1161	1161
adj. R^2	0.590	0.387
F	34.08	29.77
$\chi^2_{\text{Instrument}=0}$	74.66	0.805
p-value$_{\text{Instrument}=0}$	5.59e-18	0.370

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