Projection Bias in Solar Electricity Markets *

Stefan Lamp †

Toulouse School of Economics

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Abstract

Durable purchases require households to forecast future utility flows, which might be subject to projection bias. I test for such a bias in a market where weather can be directly linked to decision utility: the market for residential rooftop solar. I investigate whether short-lived weather events have an impact on household investment decisions. I find evidence that choices are over-influenced by the current state of sunshine, but not by other weather variables. I consider a large range of rational and behavioral explanations, but only projection bias is able to fully explain the empirical findings. A standard deviation sunshine shock impacts uptake by one installation on average. I find evidence that both positive and negative sunshine anomalies impact aggregate technology uptake. Evidence for projection bias in the case of solar investment points to the importance of behavioral channels in explaining low adoption of otherwise profitable renewable energy technologies.

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†Toulouse School of Economics, Environmental Economics and Natural Resources, contact: stefan.lamp@tse-fr.eu

1 Introduction

The traditional rational agent framework assumes that people evaluate private costs and benefits and make choices that maximize utility. However recent work in behavioral economics has shown that this is not always the case. When preferences are context dependent, optimal decision-making involves the prediction of future tastes. Evidence from the psychological literature suggests that although people understand qualitatively how tastes change over time, they systematically underestimate the magnitudes of such changes, which can lead to misguided purchase decisions. Loewenstein, O'Donoghue and Rabin (2003) label this phenomenon projection bias.

This paper studies the presence of projection bias in the context of a high-stake household investment decision: the decision to install a rooftop solar photovoltaics (solar) system. I ask whether variations in local weather have an impact on household adoption decisions. The rational agent framework suggests that long-term investments in rooftop solar should not be affected by short-term variations in weather. In contrast, I predict that behavioral agents will respond to variations in sunshine, as sunshine impacts their expected returns and consequently decision utility. I test for a wide variety of mechanisms, but find strong evidence that household decisions are indeed influenced by projection bias. Only a handful of papers have been able to provide evidence for projection bias using field data. The present paper is the first to do so involving a high-stake household investment decision. It is moreover the first paper to test for projection bias in the renewable energy (energy-efficiency) context, where investment is associated with important positive externalities, but technology adoption typically happens at sub-optimal levels.[1]

The solar market is particularly well-suited for this analysis given its unique institutional features. First, I take advantage of randomness in local weather, which I use as credible exogenous variation in perceived investment profitability. Second, there is an average time lag of eight weeks between the decision to adopt solar and the time the installation is connected to the grid, which means that rational agents should not make investment decisions based on short-term variations in weather. Third, investing in a rooftop solar system is a large financial investment with a long project horizon, meaning that short-term fluctuations in mood should not affect choices. I focus my empirical analysis on Germany, the world's largest market in solar deployment, as the presence of renewable energy support policies led to profitable and comparable investment conditions over the period 2000-2011.

[1]The 'energy-efficiency gap' describes the fact that although investment in energy-efficient technologies are financially attractive and environmentally beneficial, investors do not adopt them or only at sub-optimal levels. Gerarden, Newell, Stavins *et al.* (2015) point out three main explanations for the investment gap: market failures, behavioral biases, and measurement errors in the quantification of the economic benefits.

I build on the theoretical model of projection bias by Loewenstein *et al.* (2003) and derive testable implications for the case of solar investment. The model predicts that behavioral agents respond to variations in sunshine, but not to other weather variables. Given the average time between decision-making and completion of the installation, I expect to find the main effect at a two-month lag. The model moreover predicts that behavioral agents respond to both positive and negative deviations from the long-term sunshine mean.

To test these predictions, I construct a unique panel data set by merging administrative data on household solar installations with official weather data obtained from the German Weather Service (DWD). My analysis relies on both weather station data and gridded weather data. I use weather station data to construct long-term weather averages (normals) in 51 German regions and define idiosyncratic weather shocks as weather realizations outside the standard deviation of the long-term normals.

I find strong evidence in favor of the projection bias hypothesis. My results show that residential solar uptake increases 7-12 weeks after an exceptional sunshine week. This time lag precisely corresponds to the average installation time. A standard deviation sunshine shock leads on average to one additional solar installation per county, representing 10% of new installations. While rain and cloud cover lead to less adoption at a similar time lag, snow affects installations only in the same week. The effect of snow shows that the empirical specification is able to capture the short-run response to supply shocks, as snow and ice hinder installers from site access. Temperature does not affect uptake. Testing for a non-linear response of sunshine reveals that both positive and negative deviations from the long-term sunshine mean affect uptake. In line with projection bias, my results indicate that profit expectations at the time of decision-making are overly influenced by the current state of sunshine. This leads to impulse purchases in periods of exceptionally high levels of sunshine and to under-investment in periods of atypical low sunshine. Even though the monetary equivalent of an exceptional poor sunshine month is rather low, about 94 Euros or half a percent of the total investment, it can lead to the observed aggregate impact on technology adoption through projection.

I attempt to rule out a variety of alternative explanations for my empirical results. In particular, I use a distributed lag model to show that exceptional sunshine leads to an aggregate effect on uptake and that the findings cannot be explained by inter-temporal substitution. Similarly, using data on cloud cover I exclude the possibility that people make rational choices, but leave their home only in periods when it is not raining. Data on news coverage shows that while information is positively correlated with uptake, my main sunshine effects are not derogated. Moreover, the eight-week time lag and large-financial investment makes present bias (Laibson, 1997) and consumer myopia a highly unlikely explanation, as it would imply households receive their entire weather related utility in the first months of purchase. The non-linear response to sunshine allows me to discard salience (Bordalo, Gennaioli and Shleifer, 2012; Bordalo, Gennaioli and Shleifer, 2013), as salience cannot account for the negative response to exceptionally low sunshine realizations. Finally, I consider the possibility of supply-side responses to weather. For that purpose, I obtain detailed installer bid-price data, but find no evidence of price downward adjustments. In addition, I perform an installer survey to exclude the possibility that firms adapt marketing strategies in periods of exceptional sunshine.

I perform extensive robustness checks in order to test for the validity of my empirical findings. In particular I split the sample in two sub-periods and include data on Internet information searches. Also, I compare the ordinary least squares (OLS) estimates with a negative binomial count data model and allow explicitly for spatial correlation and autocorrelation in the standard errors. In order to show that my results are not driven by confounding factors, I perform two placebo tests: first, focusing on a subgroup of commercial solar investors, I show that their choices are not influenced by current or lagged levels of sunshine. Second, I look at a market that follows a very similar overall dynamic, but where investment decisions should not be affected by sunshine: wind turbines.

This paper relates to several strands of literature, foremost testing for the presence of behavioral biases in inter-temporal decision-making. Field evidence for projection bias has been provided only by a handful of papers. Conlin, O'Donoghue and Vogelsang (2007) look at catalogue orders of cold-weather items and find that people's choices are over-influenced by the weather at the time of decision-making. Simonsohn (2010) provides field evidence for the students' decision to enroll to college. Documenting evidence that cloudiness increases the appeal of academic activities, he finds that an increase in cloud cover of one standard deviation on the day of the campus visit is associated with an increase in the probability of enrollment of 9 percentage points.[2] In a recent article Busse, Pope, Pope and Silva-Risso (2015) show that idiosyncratic variations in weather affect people's choices of vehicle types. In particular, they find evidence that a sunny day leads to more sales of convertibles while a day with snow leads to an increased share of four-wheel drive vehicles sold. Their findings are both in line with projection bias and salience.

The present paper complements these previous studies, providing evidence for projection bias in a high-stake investment decision. While the empirical findings in Conlin *et al.* (2007) might be affected by cold weather reminding people about the need to buy winter items, this is unlikely to be the case in a large financial investment decision. Moreover, the long time gap of eight weeks allows me to credibly

[2]Projection bias has been also documented in financial markets (Kliger and Levy, 2008; Mehra and Sah, 2002; Grable, Lytton and O'Neill, 2004) and health related decision-making (Acland and Levy, 2015; Loewenstein, 2005).

exclude the possibility of people having biased beliefs about the short-term weather evolution. Finally, compared to the case of vehicle purchases, the time gap guarantees that investors do not receive utility in the period of investment. In the case of Busse *et al.* (2015), people might acquire and drive the vehicle on the same day. This means that customers might derive utility directly from purchasing a convertible on a sunny day. Their findings might hence be influenced by a fraction of consumers with highly myopic preferences.[3] Myopia implies that consumers bias is a result of non-standard time preferences rather than non-standard beliefs, as it would be the case for projection bias.

The present article also contributes to the discussion of the energy-efficiency gap (Gerarden *et al.*, 2015; Gillingham, Newell and Palmer, 2009; Jaffe and Stavins, 1994), describing the fact that even though investment in renewable (energy-efficient) technologies is both financially attractive and environmentally beneficial, individuals tend to not adopt these technologies, or only at socially sub-optimal rates. Finding evidence for projection bias in high-stake investment decisions point towards the importance of behavioral channels in explaining low adoption of energy-efficient goods. Understanding the precise reasons for under-investment is key in designing well-targeted policies and information campaigns with the objective to increase technology adoption.

The paper proceeds as follows: in the next section I briefly describe the institutional features of the German market for solar. Section 3 introduces the theoretical framework of projection bias as developed by Loewenstein *et al.* (2003) to the extent relevant for this study, while section 4 introduces the data. Section 5 presents the empirical specification and discusses the identification strategy more in detail. Section 6 presents the main results and alternative potential mechanisms, while robustness is evaluated in section 7. Finally, section 8 concludes.

2 Institutional Market Features

Germany, the largest market for solar deployment in the world, accounts for more than 35% of total solar operating capacity in 2011.[4] Figure 1 shows the uptake of small-scale household solar installations, defined as solar plants with a nominal production capacity smaller or equal to 10 kilowatt-peak (kWp), both for newly added installations and cumulatively for the period 2000-2011. The wide diffusion of household solar in Germany has been mainly attributed to the introduction of the *Renewable Energy Act* (EEG, for its letters in German) in 2000 and the related Feed-In tariff (FIT) policy.

[3]The recent literature (see for instance Allcott and Wozny, 2013; Busse, Knittel and Zettelmeyer, 2013) points towards mixed evidence for consumer myopia in the case of car purchases.

[4]REN21 (2012), Renewables 2012. Global Status Report

The EEG guarantees investors access to the electrical grid for a period of 20 years and allows them to resell electricity produced directly to their provider at a fixed rate, FIT, above the market price for electricity. Selling electricity at a guaranteed tariff allows households to obtain a positive return on investment over the 20-year project horizon. FITs are downward adjusted once per year for new installations in order to account for decreasing trends in costs. During the time period 2000-2011, there have been two major amendments to the original EEG. The first amendment in 2004 increased FIT for household solar installations and removed the initial cap on capacity. The second amendment in 2009 was aimed at counteracting the increasing cost pressures resulting from technology uptake. Even though there have been reforms to the original EEG, it was not until 2012 that the law changed importantly, introducing mandatory on-site consumption and a more aggressive downward revision of FIT. The period 2000-2011 hence provides a highly homogeneous time-span in terms of profitability for solar installations. The expected annual return for a solar installation of average size is 6-9%.[5] Overall, household solar investment in Germany in the period 2000-2011 can be characterized by low-risk and high financial returns.

FIT are designed as budget neutral to the government and are financed through a levy on electricity prices. Increased deployment of solar and other renewable energy sources led to a sharp increase in the levy over the years. The total amount spent on the support of solar accounted for 7.7 billion Euros in 2011, translating to a ‘tax’ on electricity of 3.53 Eurocents per kilowatt-hour (kWh).[6] Even though the market has grown importantly, by the end of 2011 the total installed capacity accounted for only a small share of electricity production and there were no signs of market saturation.[7]

Weather and the Profitability of Solar

Climate and weather conditions have an important impact on the profitability of solar. As pointed out by King, Boyson and Kratochvil (2002), energy produced by a solar module is directly related to the availability of solar energy and sunshine hours, which is site-dependent but can be influenced by factors such as the module’s orientation relative to the sun. Average solar radiation in Germany ranges from 950 kWh to 1150 kWh per square meter and is higher in the south.

Cloud cover and shading are the enemies of solar production, as they can decrease total output by

[5]Individual profits might vary due to site characteristics and rely on factors such as rooftop orientation, technology, and sunshine radiation.

[6]Federal Network Agency (2013), EEG Statistics Report 2011

[7]In 2011, the share of solar energy in the German electricity mix was about 3.1%. Household installations represent about 9% of total installed solar capacity in Germany (2010). Appendix A1 provides a detailed overview on the main market drivers for solar investment in Germany.

up to 90%. Other weather variations, such as temperature, rain, and snow have ambiguous effects on the performance of solar plants. They are typically short-lived and have little impact on the overall profitability of the investment. I discuss these potential effects more closely in appendix A2.

3 Theoretical Links between Weather and Solar Investment

As variation in local weather has no direct impact on future utility received from solar investments, idiosyncratic variation in sunshine should not affect the investment decisions of rational agents. However, as pointed out by the recent behavioral economic literature (DellaVigna, 2009; Huck and Zhou, 2011), many individual decisions might deviate from the standard economic model. These biases might affect the willingness to pay, search, and product quality choices. While biases in search and quality affect the choice set of the customer (which product to buy), changes in the willingness to pay might alter the purchase decision itself or the timing of the buying decision. This section discusses the main theoretical channels that might bias consumer's willingness to pay in inter-temporal decision-making: present-biased preferences (Laibson, 1997), projection bias (Loewenstein and Schkade, 1999; Loewenstein *et al.*, 2003), and salience (Bordalo *et al.*, 2012; Bordalo *et al.*, 2013). I will also discuss alternative neoclassical mechanisms, for which I test in the main section of this paper.

A Theoretical Framework for Projection Bias

Based on experiments and previous studies (see for instance Loewenstein and Adler, 1995), Loewenstein *et al.* (2003) formally introduce the theory of projection bias to the economic literature. The authors give evidence that individuals tend to mispredict their future sequence of preferences in that they systematically exaggerate how future tastes resemble present tastes. Projection bias can have important implications in the case of durable goods purchases with multiple buying opportunities and irreversibility, where it can lead to misguided purchase decisions.

Suppose that a person's instantaneous utility can be written as $u(c, s)$, where c is consumption good and s is the state that parameterizes the tastes of the decision maker. In case of a *simple projection bias*, people with current state s' form linear expectations about their future utility in state s. Thus, the person's predicted utility lies in between the true future tastes $u(c, s)$ and the current tastes $u(c, s')$ which implies that a person's behavior needs not to correspond to correct inter-temporal utility maximization.[8]

[8]Loewenstein *et al.* (2003) define simple projection bias as: $\tilde{u}(c, s|s') = (1-\alpha)u(c, s) + \alpha u(c, s')$, where α measures the degree of projection bias, i.e. α = 0 implies correct prediction of future utility and α = 1 implies fully myopic habits.

In the specific case of durable good purchases, suppose that a person's valuation in period t is given by a random variable μ_t, which is identically and independently distributed across periods and has a finite sample mean $\overline{\mu}$. The realization of μ_t is known at the beginning of the period and the durable good lasts M months. Furthermore, without loss of generality Loewenstein *et al.* (2003) assume that future utilities are not discounted. More importantly, the good is not consumed in the month of purchase. If a person decides to buy at period 1, she obtains utility from the purchase, but has to pay price P which implies forgone consumption of other goods. Assume that the utility for the durable good is additively separable from utility of other goods and the current state is equal to the random variable, $s_t = \mu_t$. Then, in a one-time buying decision, *true* expected inter-temporal utility is given by

$$E_1[U_1] = E_1[\sum_{k=1}^{M} \mu_{1+k} - P] = M\overline{\mu} - P.$$

While in the presence of projection bias we have that

$$E_1[\widetilde{U_1}] = E_1[\sum_{k=1}^{M} [(1-\alpha)\mu_{1+k} + \alpha\mu_1] - P] = M\overline{\mu} + \alpha M(\mu_1 - \overline{\mu}) - P.$$

Clearly, $\mu_1 > \overline{\mu}$ implies $E_1[\widetilde{U_1}] > E_1[U_1]$ and vice versa. Thus, if the period 1 valuation is larger than the average valuation and the consumer predicts this into the future, she will be prone to overvaluation of the durable good, or in other words, the person's buying decision will be too sensitive to the valuation at the purchasing time. In the more realistic case of multiple buying decisions, the consumer can buy at most once in any period $t \in \{1,2,...\}$ A rational person would buy the good in period 1 or never, i.e. she buys if and only if $M\overline{\mu} - P \geqslant 0$. A high valuation $\mu_H > \overline{\mu}$, implies that $M\overline{\mu} + \alpha M(\mu_H - \overline{\mu}) - P > 0$, or in other words, projection bias can lead to impulse purchases in the case where the buying decision is highly irreversible. A low valuation, $\mu_L < \overline{\mu}$, on the other hand, implies that no purchase is taking place, although it would be generally profitable to buy the product.

Projection Bias and Solar Investment

As FIT guarantees a high return-on-invest and low uncertainty, it is not surprising that most household solar investment decisions are guided by financial considerations.[9] The individual household investment decisions can be modeled as a simple static utility maximization problem based on expected

[9] I surveyed installers regarding the main motivations and variables affecting the investment decisions of their customers. Main drivers are savings on the electricity bill and financial return considerations. More details on the installer survey can be found in appendix A3.

profits.[10] In this simple framework the household chooses to invest if the expected net present value (NPV) in period p exceeds the total investment cost. The NPV is given by the discounted cash flow (CF) over the project horizon ($T = 20$ years) times the expected units of electricity production (ele), $NPV_p = \sum_{t=1}^{T} \delta^{t-1} CF_p * E[ele(sun, \cdot)]$. The Cash Flow itself is a function of the FIT rate and the installation cost, both defined by the period of investment p.[11] The expected electricity production $E[ele(sun, \cdot)]$, on the other hand, depends on factors such as the size of the installation, location, panel orientation, and sunshine radiation. As information on long-term sunshine radiation is readily available to agents, I ascribe a change in investment behavior, induced by idiosyncratic variations in sunshine, to increased profit expectations of the agents.[12] In line with projection bias, agents project their perceived profits into the future when making purchase decisions, which leads to instantaneous (impulse) purchases in the case of positive sunshine events, and to non-investment in periods of exceptional low sunshine. The model of projection bias leads to the following testable implications for the solar market:

1. Behavioral consumers respond to idiosyncratic variations in sunshine.

2. Given the average time lag from decision-making to completion of the installation, I expect to find the main effect of sunshine on technology uptake at a two-month lag.

3. Temperature and other weather events do not affect installation decisions (or only to a degree in which they are correlated with sunshine or driven by supply-side considerations).

4. Projection bias predicts that both positive and negative deviations from the long-term sunshine mean impact investment decisions of behavioral consumers.

Other Potential Mechanisms

Clearly, projection bias is not the only possible behavioral explanation leading to impulse purchases and over-consumption in decision-making. In the following, I discuss alternative behavioral and neoclassical explanations for which I test in the main section of this paper.

[10] Most installations are either cash purchased or financed through interest-free loans offered by the German bank for reconstruction; credit constraints do not play a role in this setting. The fact that FIT are adjusted annually to mimic cost evolution makes strategic waiting (option value) irrelevant.

[11] Installation costs can be thought to include both capital costs and soft costs. Without loss of generality, annual operating and maintaining costs are omitted from the profit calculations as they are negligible in the case of solar.

[12] Solar radiation maps can be obtained Online from sources such as the European Commission or the German Weather Service. The installer survey moreover highlights that most installers confront their customers with detailed financial planning and return-on-invest calculations, based on long-term regional climatic conditions.

Present bias and hyperbolic discounting (O'Donoghue and Rabin, 1999; Laibson, 1997) can lead to similar implications in the case of repeated consumer purchase decisions. Salience, as in Bordalo *et al.* (2012), and Bordalo *et al.* (2013), refers to the idea that consumers' attention may be systematically biased towards certain product features. When consumers make their investment choices, some product characteristics will receive disproportionate weight, affecting final purchase decisions. In the present case, an extremely sunny period might lead to selective perception, making the benefits (financial return) of solar more salient or leading to biased perceptions (increased visibility of solar technology).

Possible neoclassical explanations for the effect of sunshine on investment include inter-temporal substitution (harvesting), news and information search that might be correlated with sunshine, supply-side effects, and learning. Harvesting and inter-temporal substitution may arise as consumers make rational choices, but an exceptional sunny period leads more people to invest that already have decided to do so. In that scenario sunshine shifts aggregate demand but has no impact on the aggregate number of installations. Moreover, people might prefer to leave their house only on a nice weather day, leading to a similar data pattern. Another possibility is that journalists discuss solar energy and climate change more broadly in the news in an exceptional sunny period and that this is the main underlying driver of investment decisions. Focusing on equilibrium market outcomes, the number of new solar installations might be furthermore affected by a supply-side response to weather. Suppliers might offer special price deals or increase their promotional activity in response to weather events. Finally, learning can be thought to affect the uptake decision in two ways: either in a product-awareness sense, or learning about weather and climate. First, an extremely sunny month might lead households to realize the benefits of investing in solar, which after all means that their decisions are affected by behavioral factors, similar to projection bias and salience. Second, if idiosyncratic variations in weather carried information about future weather and change in climatic conditions, it might be fully rational for households to invest as new weather related information becomes available. In that sense, exceptional sunshine might also induce biases in beliefs about future weather. Learning about preferences, as it is the case with test-driving in car purchases (Busse *et al.*, 2015), does not apply in the case of a highly irreversible financial investment decision.

4 Data

Administrative data on solar installations in Germany is available from the information platform of the electricity network operator (Netztransparenz.de). The data provides information on all individual installations that are connected to the electricity grid and provides information on the exact address, size of the solar system, and date of first grid access. Focusing on small-scale (household) installations with a capacity smaller or equal to 10 kWp and the sample period 2000-2011, I count with a total of 616,978 installations. I drop obvious duplicates, i.e. observations with the same plant id (77 observations) or with all identifiers coinciding (9,924 observations), which may arise when an individual plant has been disconnected and newly registered in case of a change of network operator. As I am interested in household decision-making for new installations, I furthermore exclude all installations that happen at the same address, as those are either extensions of existing plants, or investment decisions that likely have not been made independently. I aggregate the remaining 441,321 installations at county level at weekly and monthly frequency and construct fully balanced panel data sets. Figure 2 shows the distribution of solar installations across Germany.

In a next step, I combine the solar installations with two distinct weather data sets obtained from the German weather service (DWD). First, I use weather station data available for 51 locations in Germany, ranging back until 1971 that provide daily information on sunshine, temperature, rain, snow, and cloud cover. Sunshine, rain, and snow are cumulative measures. Temperature is available as daily mean, minimum and maximum. Cloud cover is an index describing the percentage of visible clear sky. In addition to this high-frequency data, I obtain gridded weather data for the entire Republic of Germany. Gridded data is based on observations from around 400 weather stations, and uses a methodological model to interpolate weather variables such as sunshine hours, temperature (mean, min, max), and rain at a 1x1 km resolution at monthly frequency. I use ArcGIS, a commercial Geographic Information Systems mapping software, to match counties to its nearest weather station and to aggregate gridded weather data at county level.[13] Panel a of Figure A4 provides a graphical illustration of the aggregate sunshine hours at county level, highlighting the important year-on-year variation. The figure also shows the distribution of the freely available weather stations across Germany. Using both gridded data and weather station data allows me to perform the statistical analysis at different time frequencies and spatial resolutions. More importantly, the weather station data allows me to test for additional variables such as snow and cloud cover. Finally, contrasting my main results for both type of weather data helps me to overcome potential pitfalls related to either data source (Dell, Jones and Olken, 2014; Auffhammer, Hsiang, Schlenker and Sobel, 2013).

I add covariates to the analysis in order to control for time varying differences at county level and to perform additional robustness checks. First, I download official demographics at county level from the *German Statistical Agency*. Main covariates include population, household income, education, unemployment, voting outcomes, agricultural surface, as well as the number of new residential and non-residential buildings. This data is available at annual frequency. In order to control for possible confounding factors,

[13]Each individual climate observation is assigned to a county if the centroid falls inside the county boundaries. I then average across all data points in a given county to obtain the monthly weather averages.

I also obtain data from Google trends regarding web searches on solar and climate change, and data from LexisNexis, an Online database covering news in major German newspapers on the same topic. Finally, I obtain bid-price data on solar installation prices from an Online consumer portal for the years 2010 and 2011.[14] In addition, I conduct an installer survey in Germany. The survey has three main objectives: first, to obtain precise information on the customer decision-making process, second, to get detailed information on the timing in solar installations, and third, to understand if local installers adopt their sales and marketing strategies to variations in weather. Appendix A3 provides a detailed overview on the survey design and discusses other data sources more in detail.

Definition of Weather Shocks

I construct weather shocks in order to test for the impact of exceptional weather periods on solar uptake. In a first step, I define long-term weather averages (normals) of sunshine, temperature, rain, etc. for 51 climate regions in Germany, using weather station data for the period 1990-2011.[15] Figure A6 shows the distribution of sunshine, temperature, and rain for weather station data and gridded data and provides evidence that the distribution of the two sources are highly aligned. I am thus confident to use weather station data to define long-term weather normals in the 51 regions. In a second step, I identify shocks as a county-week (month) weather realization outside the standard deviation bands of the weather normal in that region. I construct this measure for each of my weather variables and for both positive and negative deviations.

One potential concern about using local variations in weather is spatial correlation and autocorrelation of exceptional weather events. The appendix provides evidence that weather shocks, as opposed to weather levels, are less likely to be affected by this critique. Figure A7 shows that the construction of sunshine shocks does lead to a positive shock probability in every month of the year and in every year of my sample. In order to test for autocorrelation at county level, i.e. a sunshine shock today carries information on future sunshine shocks, Table A1 provides summary statistic on the Portmanteau (Q) test statistic for white noise. I construct the test statistic for each county independently (for different lag structures) and

[14]The price data is based on installer bids (offers) from an Online solar web portal that allows households to obtain individualized offers for comparable installations from local installers. The author would like to thank EuPD Research for making this data available.

[15]Using the period 1990-2011 leads to 22 data points for each station-week (month) combination, and hence a sufficiently large number of observations to calculate the mean and standard-deviation. I also experiment with the international climate reference period 1971-2000 for the definition of weather normals. However as Figure A5 suggests, the period 1970 to 1990 has been influenced by years of exceptional low temperature (and sunshine) realizations leading to an excessive number of shocks in the sample period.

present the percentage of counties where the null hypothesis of no autocorrelation can be rejected at 1% and 5% significance level respectively. The table indicates that autocorrelation, especially in sunshine shocks, is not of a big concern. Moreover, looking at global spatial correlation of sunshine shocks at each point in time, I calculate Moron's I test statistic for each of the 144 monthly time periods separately and list the percentage of periods for which the null of no spatial autocorrelation can be rejected at the 1% and 5% significance level, assuming different spatial weighting matrices (Table A2). The table suggests that spatial correlation of shocks is overall very low. Panel b of Figure A4 provides additional graphical evidence that spatial correlation and autocorrelation of the sunshine shock should not be of concern.

Summary Statistics

Combining the above data to a fully-balanced panel data set leaves me with 250,848 observations at the weekly level and 57,888 observations at monthly frequency.[16] Figure A8 shows the evolution of the main dependent variable, county-month solar installations over time. The figure clearly suggests an increase in technology adoption and in volatility over time. The figure furthermore highlights that announced FIT adjustments lead to important bunching behavior in the month of the policy change. Figure A9 depicts the related histogram.

The summary statistic for the main variables of interest as well as demographics is provided in Table 1. While column 1 displays the means and standard deviations for the entire sample, column 2 and column 3 split the sample into high and low sunshine shock counties, according to the median sunshine shock over the sample period. The sample split reveals that there are more solar installations in counties that have more sunshine shocks. This finding can be seen as a first indication for projection bias, especially as the total number of sunshine hours does not differ significantly across the two subgroups. Moreover, the summary statistic shows that there are only small differences in observables between high and low sunshine shock counties and shocks are distributed fairly homogeneously across counties.[17]

As I do not observe the precise moment in time when the investment decision is made, but rather the moment in time when the installation is completed, I perform an Online survey with installers to understand the exact timing of decision-making. Figure A10 shows the distribution of the average declared time gap between customer decision-making and completion of the installation. The median is 8 weeks (9 week mean with a standard deviation of 5 weeks).[18]

[16] There are a total of 402 counties (2011 county boundaries) for the period 2000-2011.

[17] The shock discretization leads to distinct number of observations for each of the subgroups. The large difference in population emerges from the presence of city states (Berlin and Hamburg) that are classified as counties in my data.

[18] As the survey was conducted in 2015, but my main analysis refers to the years 2000-2011, I explicitly ask if the time gap has

5 Empirical Strategy and Identification

The causal effect of sunshine and other weather variables on solar adoption is identified given the randomness of local weather. I make use of the unique institutional features of the solar market in Germany to test for the theoretical predictions as developed in section 3 and to identify projection bias. Employing county-week data, I construct an indicator variable $\mathbf{I}_{c,t}$ equal to one if there has been at least one solar installation in county c at week t.[19] First, I estimate the following reduced form model by ordinary least squares (OLS),

$$\mathbf{I}_{c,t} = \alpha + \sum_{i=0}^{W} \beta_i weather_{c,t-i} + \delta_{f,w} + \gamma_w \mathbf{I}(FITadjust) + \theta_{c,y} + \epsilon_{c,t} \tag{1}$$

where $weather_{c,t-i}$ represents a vector of current and lagged weather variables such as sunshine, temperature, rain, snow, and cloud cover. I control for the seasonal sales pattern by introducing a flexible set of weekly dummies that is allowed to vary with the three main FIT policy periods $\delta_{f,w}$.[20] In addition, I include a dummy for each two-week period prior to an announced change in the FIT schedule to account for observed bunching of installations. Finally, I include a set of flexible county-year fixed effects, $\theta_{c,y}$, which allows me to relax the parallel trend assumption of the standard fixed-effect model. Second, using county-month data, I redefine my main dependent variable as $Installation_{c,t}$, the total number of solar installations in county c in month t, and use the following empirical model,

$$Installation_{c,t} = \alpha + \sum_{i=0}^{M} \beta_i weather_{c,t-i} + \delta_{f,m} + \gamma_m \mathbf{I}(FITadjust) + \theta_{c,y} + \epsilon_{c,t} \tag{2}$$

where $weather_{c,t-i}$ now includes current and lagged weather variables for sunshine, temperature, and rain. As in specification (1), I account for the seasonality in sales, $\delta_{f,m}$, which is allowed to vary with the three main FIT periods. In addition, I include a dummy for each period of FIT adjustment, $\mathbf{I}(FITadjust)$, and take into account a flexible set of county-year fixed effects $\theta_{c,y}$. Given the count nature of my main dependent variable, I estimate the model using both OLS and a negative binomial count data model. In case the main identification assumption, the conditional exogeneity of weather shocks holds, OLS should lead to unbiased and consistent estimates. Given the time lag in installations, weather this period does not directly affect the profitability of the investment in the same period and is uncorrelated with the error term. All standard errors are clustered at weather station level to allow for spatial correlation

changed over recent years. I do not find such evidence.

[19] In about half the county-week observations (46.39%), there are zero installations.

[20] The three main FIT periods are January 2000 - March 2004, April 2004-December 2009, and January 2010 - December 2011.

within region over time. This choice takes into account that weather observations might be correlated at a very fine grid. Moreover, using a small number of clusters (50 is considered the minimum in applied work), leads to more conservative inference. As additional robustness, I explicitly allow for spatial correlation and autocorrelation in the error term applying Driscoll and Kraay (1998) and Conley (1999) standard errors in the robustness section.

6 Main Results

This section focuses on my main regression results for both weekly and monthly data. I first evaluate the predictions from the theoretical model and then discuss potential alternative channels more in detail.

Figure 3 is based on regression specification (1) and displays the point estimates and 95% confidence intervals for the four main weather variables. It shows the current and lagged impact of sunshine, temperature, rain, and snow at weekly frequency. The dependent variable is an indicator equal to one if there has been at least one installation in county c in week t. All standard errors are clustered at weather station level. The upper panel shows the regression coefficients for sunshine and mean temperature. It indicates that sunshine is positively and significantly correlated with household solar installations between lag 7 and lag 12, in line with prediction one and two from the theoretical model. Earlier lags are generally not significant but lag 1 and lag 2 which show the same magnitude but opposite signs, leading to a zero cumulative effect. This short-term response might be driven by a substitution of installations, as suppliers likely schedule more site visits if the current week is sunny. Temperature does not lead to a similar data pattern as sunshine. Higher lags of the temperature variable show negative coefficients which are likely driven by negative correlation between sunshine and temperature in the winter months. Looking at rain and snow, I find that rain does not have any significant impact on uptake, with the exception of lags 5 and 7 that are negative and significant. However, in line with projection bias, lags 7 to 11 show negative point estimates. The negative and significant effect of snowfall at impact provides a good first check for the validity of my empirical model. As a week of snow and ice disrupts installer rooftop access, a negative impact in a week with more snow that is counterbalanced in the following weeks is in line with inter-temporal substitution due to supply-side limitations. In general, this first set of results provides strong support to the hypothesis that sunshine is the main weather variable affecting household investment decisions.

In a second step, I test for the impact of positive weather shocks on adoption. Figure 4 shows the effect for sunshine, temperature, rain, and snow shocks on uptake. While sunshine shocks lead to a very similar pattern as sunshine levels, with lags 7 to 10 being positive and significant, temperature shocks are generally not significant. Looking at rain and snow shocks, I find an effect similar to those in Figure 3;

however with larger magnitudes. Rain shocks show a negative and significant impact for lags 7 to 12. An exceptional week of snow leads to a large decrease in installation probability in the week of the shock and the week thereafter. The effect is offset by a positive response in week three. Further lags, from week 9 onwards are generally positive and significant. This is a mechanic response, as snowfall in Germany is seasonal. Generally, the use of weather shocks confirms my findings regarding a strong behavioral impact of sunshine on decision-making. I also include a lead in the regression model to see if weather events can be forecasted, i.e. serial correlation in weather might lead to predictability of exceptional weather events. It would hence be rational for decision makers to respond to sunshine shocks at shorter lags. While this hypothesis can be clearly rejected for sunshine, temperature, and rain shocks, only snow shocks display some degree of predictability. Again, this finding is in line with the seasonality of snow.

Aggregating the data at monthly frequency, Table 2 compares different regression models following specification (2). The dependent variable in column 1 is the number of new solar installations at county-month level, column 2 uses a first-difference transformation of the same. Column 3 estimates the original specification employing a negative binomial model to account for the count nature of the main dependent variable. The results in column 1 show a strong and positive effect for sunshine shocks at lags 2 and 3 that are in line with my previous findings. In column 2, a sunshine shock relates to the change in new installations from period $t-1$ to period t, conditional on year and FIT-month fixed effects. The specification includes further county covariates to account for time-varying observable differences across counties. I find that both results are highly aligned with my previous findings, pointing towards an aggregate impact of a sunshine shock of 0.7 - 1.1 additional installations per county. Employing the negative binomial count data model in column 3 confirms these findings further. In order to compare the estimated coefficients to the marginal effects of OLS, I transform the coefficients exponentially. The main effect at lag 2 hence translates to 1.2 additional installations. This is further evidence that my main identifying assumption, conditional exogeneity of weather shocks holds, and OLS leads to valid estimates. Evaluating this effect at the mean number of new installations in my sample period, I find that a sunshine shock accounts for roughly 10% of new installations.[21]

Figure 5 shows the main effects for jointly including sunshine, temperature, and rain shocks at monthly frequency. While sunshine shocks show the expected size and sign, temperature shocks do not have any significant impact on uptake. Rain shocks have a negative impact at lags 2 and 3, which is compensated at lag 4. Finally, testing for the prediction that both positive and negative deviations from the sunshine

[21]The quantitative findings are in line with Simonsohn (2010), who uses standard deviation weather shocks as credible exogenous variation to identify projection bias in college enrollment decisions.

mean affect adoption decisions, Figure 6 shows the main regression coefficients with negative sunshine shocks, defined as a sunshine realization below the weather normal in a given region. The figure reveals that sunshine shocks at lags 2 and 3 are negatively and significantly correlated with new installations. Negative temperature shocks, on the other hand, do not affect uptake from lag 1 to lag 4. Figure 7 investigates possible non-linear effects, showing the coefficients for lag 2 of demeaned sunshine on uptake. The regression follows main specification (2), but uses bins for demeaned sunshine hours rather than the binary shock variable. The figure shows point estimates together with 95% confidence intervals and is normalized with respect to the sunshine mean, which is omitted from the regression. The figure indicates that both positive and negative deviations from the long-term sunshine mean affect investment decisions. While all positive deviations lead to a positive and significant effect, for negative deviations, I find that only very large deviations are statistically different from zero. The estimated effect for negative deviations is furthermore smaller in absolute magnitudes.

To summarize, the empirical results reveal that there exists an important impact of sunshine on solar adoption. My findings are in line with the theoretical predictions of projection bias. The remainder of this section discusses alternative neoclassical and behavioral explanations for these findings. If not mentioned otherwise, all results refer to monthly data aggregation.

Potential Alternative Channels Affecting Solar Adoption

Harvesting: In order to directly address inter-temporal substitution of purchases, I analyze the coefficients related to the distributive-lag model. Similar to Jacob, Lefgren and Moretti (2007), Deschenes and Moretti (2009), and Busse *et al.* (2015), I add up all lagged coefficients and verify that the aggregate effect is different from zero. A zero aggregate effect would imply that an exceptional sunshine month displaces the timing in the decision to install (harvesting), but has no impact on aggregate technology adoption. The main results report regression coefficients up to 5 month after a sunshine shock. In all specifications, the positive and significant impact of sunshine on adoption does not cancel out at higher lags.

Sunny day hypothesis: A related concern is that individuals decide rationally, but it happens to be a bad weather period and they prefer to leave their home only on a day when it is not raining. Using data on cloud cover helps me to eliminate this potential concern, as I can compare rainy periods to periods that are cloudy, but do not impede people from leaving their homes. Projection bias predicts that an exceptional cloudy period has a negative impact on technology uptake, independent from rain. Figure A11 regresses solar adoption on 'bad' weather shocks such as rain, snow, and cloud cover. I find that rain has a negative impact on uptake, which is in line with both projection bias and the sunny day hypothesis; however I find that cloud cover shows an additional effect at lags 8 to 11, which is statistically significant. This evidence suggests that it is indeed cloud cover (missing sunshine) affecting household investment decisions.

News and information: Households might not respond to sunshine shocks themselves, but rather to information that becomes available in sunny periods. One possible explanation is that in periods of exceptional sunshine journalists are more likely to report on solar installations and climate change. In order to test for this possibility, I obtain data on print media news coverage from the Online database *LexisNexis* and create a monthly time series aggregating the number of articles that appear in the press for solar (990 entries), and climate change (922 entries). The time series is plotted together with the series of new solar installations in Figure A12. Table 3 shows the regression results for my main model, including data on news, column 1, as well as climate change, column 2. While both variables have a statistically significant impact on technology uptake at a one to two month lag, the main effect of sunshine shocks remains unchanged. The estimates for lag 2 are also robust to the inclusion of both types of information (column 3).

Supply side response: As my analysis is based on equilibrium market outcomes, the number of new solar installations, the main findings might be affected by both a demand and supply response to weather shocks. To test for the possibility that solar installers observe a good weather period and adopt their pricing strategy, I obtain solar bid-price data from *EuPD Research.* Price data is available for the years 2010 and 2011 at quarterly frequency. One major advantage of the bid-price data is that it is locally disaggregated (at zip code level), and includes also the size of the installations. This allows me to construct a county-quarter panel dataset of solar installations, prices and sunshine shocks.[22] As I do not observe a sale for each county-quarter pair, I interpolate missing observations using a flexible regression model that includes a nationwide price trend, county intercepts as well as variation by state half-year. Table 4 shows the main results regressing equilibrium solar prices on lagged solar installations as well as current and lagged sunshine shocks. While column 1 uses the original sample, columns 2 and 3 employ the interpolated data. The overall results indicate that the number of lagged solar installations have a negative impact on prices, which is in line with learning-by-doing in the solar industry (Van Benthem, Gillingham and Sweeney, 2008; Bollinger and Gillingham, 2014). Lagged household installations show a negative point estimate in the same quarter; however are not statistically significant. As learning-by-doing in the industry is likely affected by total installed capacity rather than household systems alone, column 3 uses as main regressor the total number of added solar systems in Germany. In line with this conjecture, I find that

[22]The original price data consists of 8,881 observations for household solar installations (system prices) that I aggregate to county-quarter prices per kWp installed.

prices decrease with more installations. Focusing on the sunshine shock, I do not find evidence that prices are downward adjusted in periods of exceptional sunshine. On contrary, there is limited evidence that prices are higher with all point estimates in the same quarter being positive and significant at 10%. This effect might be driven by an increase in demand related to exceptional weather periods. In order to further investigate the possibility of supply responses to weather shocks, I perform an Online survey with local installers in Germany.

The survey reveals that most installers are small businesses that do not have specific sales and marketing personnel for promotional activities. Installers mention that in most cases customers approach them directly with the aim to install a solar system and that their marketing outreach is rather limited. One third of respondents mention that they adjust their sales strategies seasonally (summer versus winter) or due to an upcoming change in the FIT scheme. Investigating the possibility of current weather having an impact on marketing and sales activities, only 7 installers (13%) respond that weather affects their sales activities directly. The main reason is that poor weather conditions limits on-site visits. Only 3 installers (5.8%) mention that sunshine has a positive impact on business. To conclude, the survey suggests that most installers are not aware of the possibility that customers have biased perceptions in their decision-making due to current levels of sunshine and do not use this information strategically to increase their sales volumes.

Present bias: In the case of a one-time investment decision, fully myopic preferences or present bias would imply that households receive their entire weather related utility in the first months of product purchase. This is unlikely for an investment that involves a large financial stake (see also Busse *et al.*, 2015). The model of projection bias accommodates the possibility of myopia in preferences.

Learning: Customers might learn from exceptional sunshine periods about future weather and climate conditions. However, as pointed out in the data section, short-lived weather fluctuations do not carry information on future climate conditions and information on average solar radiation is easily accessible to customers. Alternatively, learning might take place in a technological (product) sense, i.e. households learn about the existence of the technology due to exceptional weather periods. This type of learning, however, implies a behavioral response that is very closely linked to salience.

Salience: Salience implies that sunshine-rich periods draw people's attention to the benefits of solar, or the technology itself, affecting investment decisions. Testing for both positive and negative shocks as well as non-linear responses to sunshine clearly indicates that the main results cannot be driven by salience alone. While projection bias predicts that the current levels of sunshine impacts investment decisions, salience is more likely associated with extremes (Busse *et al.*, 2015). In the particular case of solar investment, positive weather shocks might lead to a biased perception of the technology, i.e. over-emphasizing the financial return component. Evidence that negative sunshine deviations affect uptake, Figures 6 and 7, indicates that salience cannot be the only explanation for the empirical findings.

Climate change beliefs: One additional concern might be that the results are affected by wrong beliefs about climate change influenced by current weather. Recent papers in the behavioral climate change literature (Li, Johnson and Zaval, 2011; Deryugina, 2013) have shown that the current temperature can have an impact on climate change beliefs. Deryugina (2013) shows that especially long-term fluctuations (of several months) can impact people's beliefs about the occurrence of climate change. However, this literature points to a relationship between exceptional hot weather and climate change. As I do not find a significant response in uptake behavior due to temperature, I can credibly exclude this possibility in the case of solar investment. In addition, scientific research points out that climate change is likely to affect climate extremes in Central Europe, such as heavy rain, storms, and droughts, which do not necessarily lead to an increase in average sunshine duration.[23]

Biased weather forecast: A related issue is that current weather might lead to biased weather forecasts. However, given the eight-week time lag between decision-making and installation, this is a rather hypothetical possibility. An indirect test for this hypothesis would be to see by how much people are able to predict their local weather patterns. Krueger and Clement (1994) ask students at Brown University in the United States to predict average high and low temperatures in their region for given days of the year and found that students are generally able to forecast the weather accurately. For the specific case of Germany, Burger-Scheidlin (2014) investigates the local weather perception of farmers related to climate change and long-term climatic evolutions. Her results clearly show that farmers have an ample knowledge about how the weather should be at a given time of the year. The main information sources for farmers are inherited knowledge, observational data, and official weather information. Although it is save to assume that farmers pay more attention to local weather patterns than the general public, official weather information is available to both audiences. Besides, the discussion of weather (small-talk) is a large social phenomenon (Johnson, 2009). Taken these points together, it is unlikely that investment decisions are consistently biased due to wrong short-term weather forecasts.

7 Robustness

This section performs additional robustness concerning the econometric specification and results. In a first attempt, I split the sample in two equal periods and verify that my main findings are not driven by any specific sub-sample. Table 5 presents these results, including variables on information search behavior.

[23] See for instance IPCC (2014), 5th Assessment Report.

Columns 1 and 2 show the results for the two separate sub-periods and indicate that lag 2 remains positive and significant with a coefficient highly aligned with the main results. For the later sub-period, 2006-2011, I additionally include data from Google to proxy for customer information search behavior. I find that increased search behavior leads to more installations with a two to three month lag. Column 4 interacts sunshine shocks with information searches, and finds that the interaction term at lag 2 is positive and significant, meaning that an exceptional sunny period leads to more interest in solar. Column 5 confirms these results by regressing the number of Internet searches in a given region on sunshine shocks. I find that a month of exceptional sunshine leads to significantly more Internet searches for solar systems.

The design of the EEG allows me to perform two additional robustness tests to validate my empirical model. First, there exists a sharp discontinuity in FIT rates for plants above 30 kWp. As small-scale installations are more expensive on average, they receive higher FIT rates. The cutoff is clearly visible in the histogram of installed capacity (Figure A13), as it leads to bunching of installations just below the size threshold of 30 kWp. I look at the group of strategic (profit maximizing) installers that invests precisely in a plant of size 29-30 kWp and hypothesize that their investment decisions should not be affected by projection bias. Figure 8 shows the regression coefficients for the group of all household installations, as before, and the group of profit maximizers. Indeed, I find that profit maximizers are not affected in their investment decisions. Second, in an additional attempt to test for my empirical model, I look at a related renewable investment decision, that follows a similar market dynamic that is dominated by institutional investors and where current weather should not impact decision-making: wind turbines. Figure A15 provides this evidence.[24]

Finally, I preform a series of robustness tests concerning the regression specification and standard errors. First, I verify that my main results are not driven by any specific German region. For this purpose, I estimate the main regression model excluding each of the 16 states separately. The results are depicted in Figure 9 and show that the main effect for lag 2 is consistently estimated ranging from 0.77 to 1.19. In order to test for the possibility that the installation basis in a given county has an impact on uptake and might bias my findings, as second robustness, I include lagged installations at time $t-1$ in the regression specification.[25] Third, as sunshine shocks are defined as a deviation from the mean and are correlated with sunshine levels by construction, I include sunshine levels and sunshine shocks in the same specification. The results remain robust to these tests. Forth, given the large dispersion of my main dependent variable, I reestimate the main regression model, limiting the dependent variable at the 99th percentile. Again,

[24]The aggregate market dynamic for wind turbine investments is depicted in Figure A14.

[25]Given the time lag in decision-making, installations in the previous month do not have a direct impact on uptake this period and are uncorrelated with the error term.

the effects for lags 2 and 3 remain significant and highly aligned with the main findings. Finally, given concerns about spatial correlation and autocorrelation in the error term, I test for robustness in inference using standard errors that are robust to autocorrelation and heteroskedasticity following the approaches by Driscoll and Kraay (DK, 1998) and Conely (1999). Both DK and Conley standard errors lead to significant point estimates for lag 2 of the sunshine shock.[26]

Putting Projection Bias in Context

In an attempt to quantify the impact of projection bias on consumer demand, in a back-of-the-envelope calculation, I determine the monetary equivalent of a sunshine shock. I use the freely available *Online tool* from the European Commission to calculate the electricity production of one hour of sunshine for a solar installation of average size in Germany, equal to 3.67 kWh.[27] Using the average FIT over my sample period, weighted by the probability of a sunshine shock happening in a given year, I find that a negative sunshine shock has a monetary equivalent of roughly 94 Euros. According to the projection bias hypothesis, fully myopic households ($\alpha = 1$) would predict that their financial return will be 94 Euros lower in every month of the investment horizon, leading to negative return expectations and non-investment. Even though the expected return difference of 94 Euros is small compared to the total average installation cost of 20,100 Euros, about 0.5%, the inter-temporal nature of the decision problem makes this bias relevant for the investment decisions of behavioral agents. Although the reduced form results do not allow me to make a precise statement on the exact magnitude of the bias and the forecast horizon, my results indicate that behavioral agents are strongly influenced in their investment decisions.[28]

8 Conclusion

This paper provides evidence that an important household investment decision is affected by projection bias. Using data from solar installations in Germany, I show that both positive and negative deviations from the long-term sunshine mean in a given region have a significant impact on the number of new

[26]For DK I estimate the model with both county and year fixed-effects and allow for autocorrelation in the error of degree one. The Conley standard errors are estimated with the same set of covariates and allow for 100km of spatial correlation and up to 4 lags of autocorrelation. Depending on the specification, only lag two of the sunshine variable remains significant.

[27]Given seasonal differences in returns, I calculate for each month the expected return per hour of sunshine and take the average of this series. The mean difference between an average sunshine month and a month that I label negative sunshine shock is 67 hours.

[28]Conlin *et al.* (2007) develop a structural model to recover the projection bias parameter in the case of catalogue orders and find $\alpha \in [0.3, 0.5]$.

solar installations. While neoclassical theory and alternative behavioral mechanisms fail to explain the empirical results, my findings are in line with projection bias.

Evidence for projection bias in a high-stake financial investment decision implies that likely also other important consumer decisions are affected by projection bias. As pointed out by Busse *et al.* (2015), so far no clear recipe exists on how to de-bias consumers, which leaves an interesting field for future research. On the other hand, in the case of environmental goods, technology adoption suffers from the so-called energy-efficiency gap. Even though investments are privately profitable and socially beneficial, they find little adoption. The present study points towards the importance of behavioral mechanisms in explaining this investment gap. Targeted information campaigns could help to overcome this biased perception and increase product uptake. In the specific case of solar diffusion, installers should adapt their sales activities to the current state of sunshine. According to my findings, de-biasing consumers in exceptionally bad weather periods can lead to additional installations at little cost. As solar investments are profitable for households as well as beneficial for the society, these interventions can be overall welfare improving.

It remains challenging to provide field evidence for projection bias. Future research concerning the exact magnitude of the bias in distinct contexts and regarding the projection horizon would be beneficial to fully understand its impact on decision-making. Moreover, distinct subpopulations might be affected differently by projection bias. So far no convincing evidence exists testing for this heterogeneity using field data. Understanding heterogeneous responses can make targeted policy interventions more effective and can shed further light on the way projection bias affects market outcomes.

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Figures and Tables

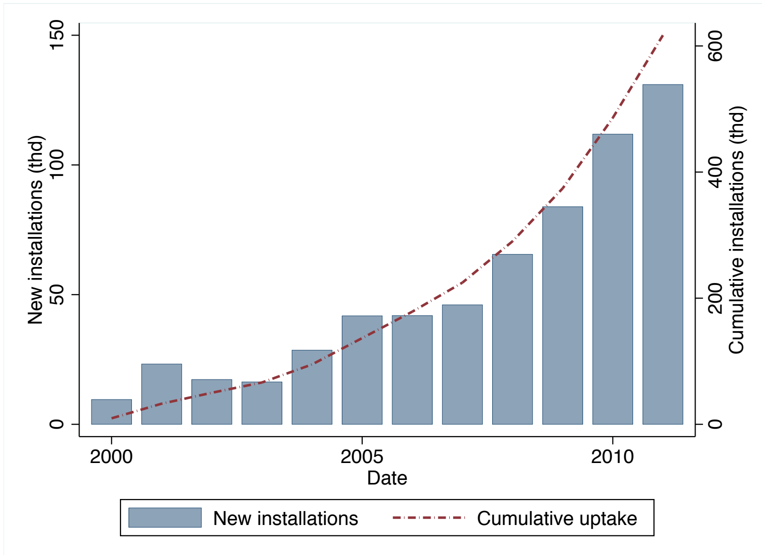


Figure 1: Household solar installations and cumulative technology uptake in Germany (2000-2011).

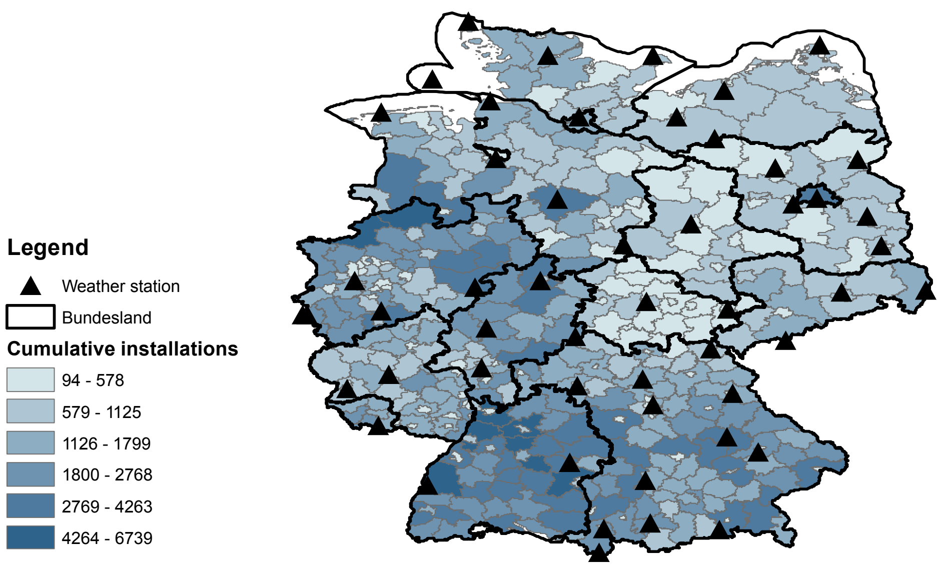


Figure 2: Total number of solar installations by county (December 2011). Darker areas represent more installations. The graph depicts the location of the 51 weather stations that are used to define the long-term weather averages.

Table 1: Summary statistics

	All	High	Low
New solar installations	9.52	10.00	9.15
	(17.59)	(18.14)	(17.14)
Sunshine hours	139.66	139.13	140.07
	(77.38)	(77.02)	(77.65)
Mean temperature (C)	9.45	9.56	9.37
	(6.62)	(6.59)	(6.65)
Sunshine shock	0.17	0.20	0.15
	(0.38)	(0.40)	(0.36)
Distance to weather station (km)	36.06	39.14	33.71
	(31.65)	(33.81)	(29.68)
Population	204019	243982	173522
	(228264)	(309659)	(128620)
Household income per capita (2010)	18823	18826	18822
	(2304)	(2184)	(2391)
Vocational training (%)	62.50	61.78	63.05
	(6.04)	(6.05)	(5.97)
University degree (%)	8.43	8.85	8.11
	(3.93)	(4.07)	(3.79)
Unemployment rate (%)	9.77	9.87	9.69
	(4.62)	(4.36)	(4.82)
New residential buildings /population	0.18	0.18	0.17
	(0.11)	(0.11)	(0.10)
Agricultural surface (%)	0.47	0.48	0.47
	(0.16)	(0.16)	(0.15)
Green voters (%)	7.69	7.93	7.51
	(3.49)	(3.41)	(3.53)
Vote participation (%)	76.66	77.02	76.38
	(5.53)	(5.47)	(5.55)
Former Eastern Germany (excl. Berlin) (%)	18.91	17.24	20.18
	(39.16)	(37.77)	(40.13)
Observations	57888	25056	32832

Note: Summary statistics for county-month observations in the period 2000-2011. Column 1 (all) refers to the full sample, while column 2 and 3 split the sample according to the median value of the sunshine shock in high (column 2) and low (column 3) sunshine shock counties. A sunshine shock is defined as a sunshine realization outside the standard deviation of the long-term sunshine average in a given region. Standard deviations in parentheses.

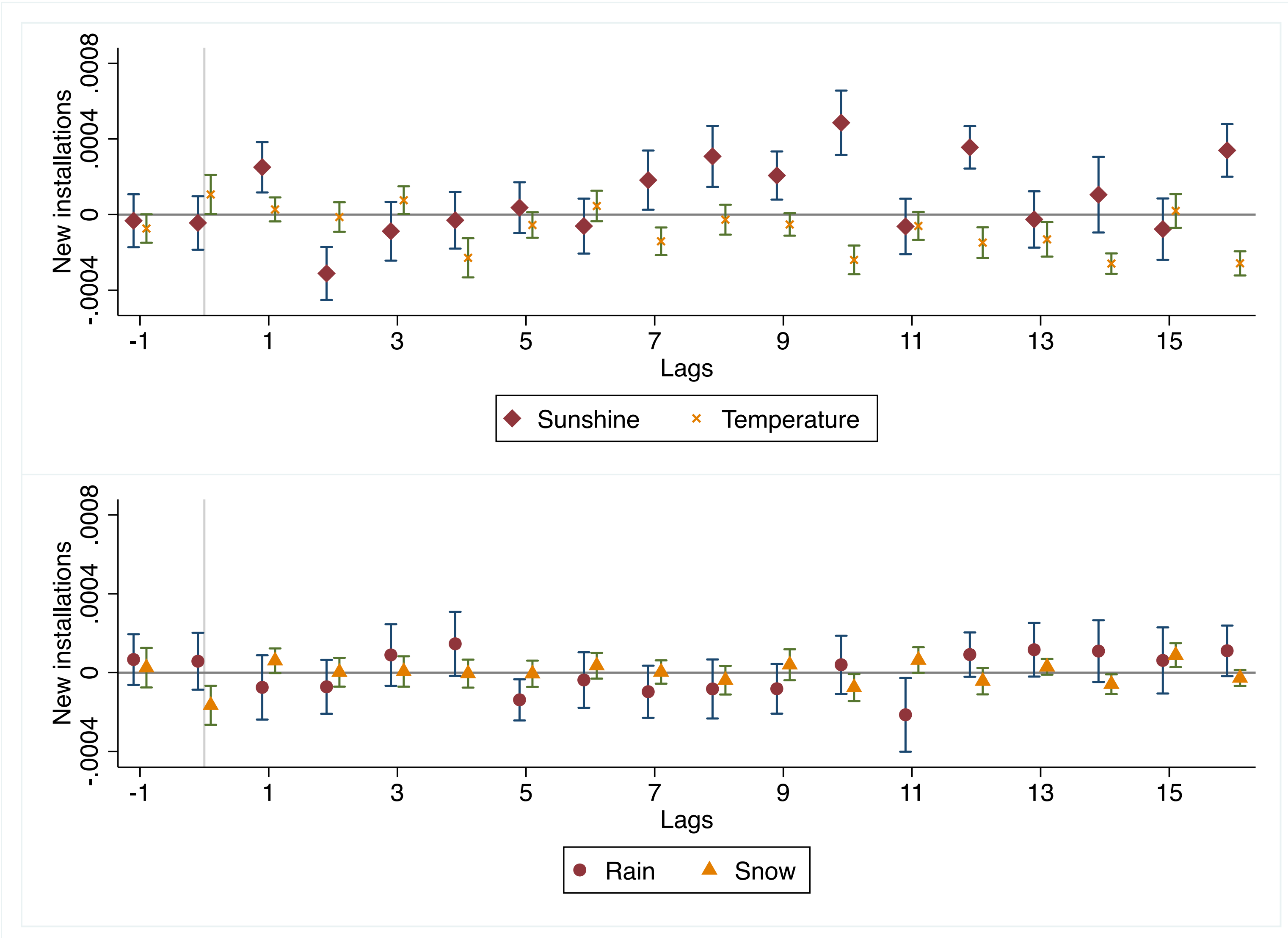


Figure 3: Main regression results following specification (1). Data aggregated at county-week level for the period 2000-2011. The dependent variable is an indicator equal to one if there is at least one solar installation in county c in week t. Lags indicate leads and lags of the main weather variables. All weather variables are included jointly in the regression, but plotted in two graphs for ease of representation. R^2= .415 , N = 244,014 . Point estimates with 95% confidence interval. All standard errors are clustered at weather-station.

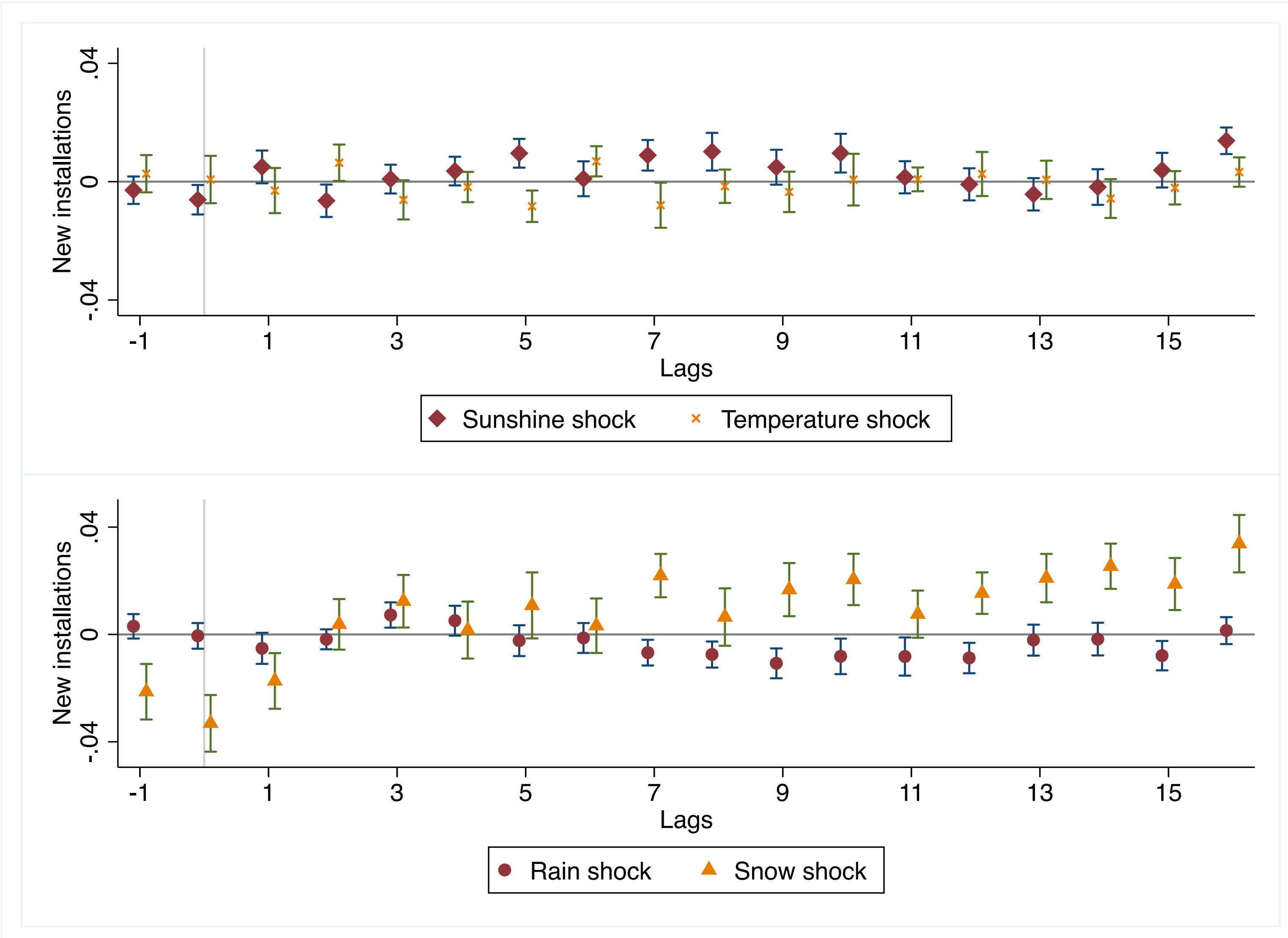


Figure 4: Main regression results following specification (1). Data aggregated at county-week level for the period 2000-2011. The dependent variable is an indicator variable equal to one if there is at least one solar installation in county c in week t. Lags indicate leads and lags of weather shocks. All variables are included jointly in the regression model, but represented in two graphs for ease of representation. R^2= .412 , N = 244,014. Point estimates with 95% confidence interval. All standard errors are clustered at weather-station.

Table 2: Model comparison

New installations	OLS	FD	NB-reg
Sunshine shock	-0.658^{***}	-0.845^{***}	-0.033
	(0.184)	(0.163)	(0.024)
Lag Sunshine shock	0.399	0.282	0.015
	(0.285)	(0.223)	(0.025)
Lag 2 Sunshine shock	0.939^{***}	0.825^{***}	0.111^{***}
	(0.261)	(0.230)	(0.022)
Lag 3 Sunshine shock	0.840^{***}	0.697^{***}	0.046^{**}
	(0.198)	(0.194)	(0.019)
Lag 4 Sunshine shock	-0.084	-0.219	0.040^{**}
	(0.155)	(0.131)	(0.020)
Lag 5 Sunshine shock	0.307	0.174	0.050^{***}
	(0.187)	(0.137)	(0.019)
Observations	55878	55878	55878
R^2	0.688	0.462	
County-Year FE	Y	N	N
FIT-Month FE	Y	Y	Y
Year FE	N	Y	Y
Covariates	N	Y	Y

Note: Main regression results following specification (2). Data aggregated at county-month level for the period 2000-2011. The dependent variable is the number of solar installations in county c in month t. Column 1 estimates the main model by OLS. Column 2 transforms the main dependent variable in first-differences and relaxes the fixed-effect structure. Column 3 estimates the main specification employing a negative binomial count data model. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at weather-station in parentheses.

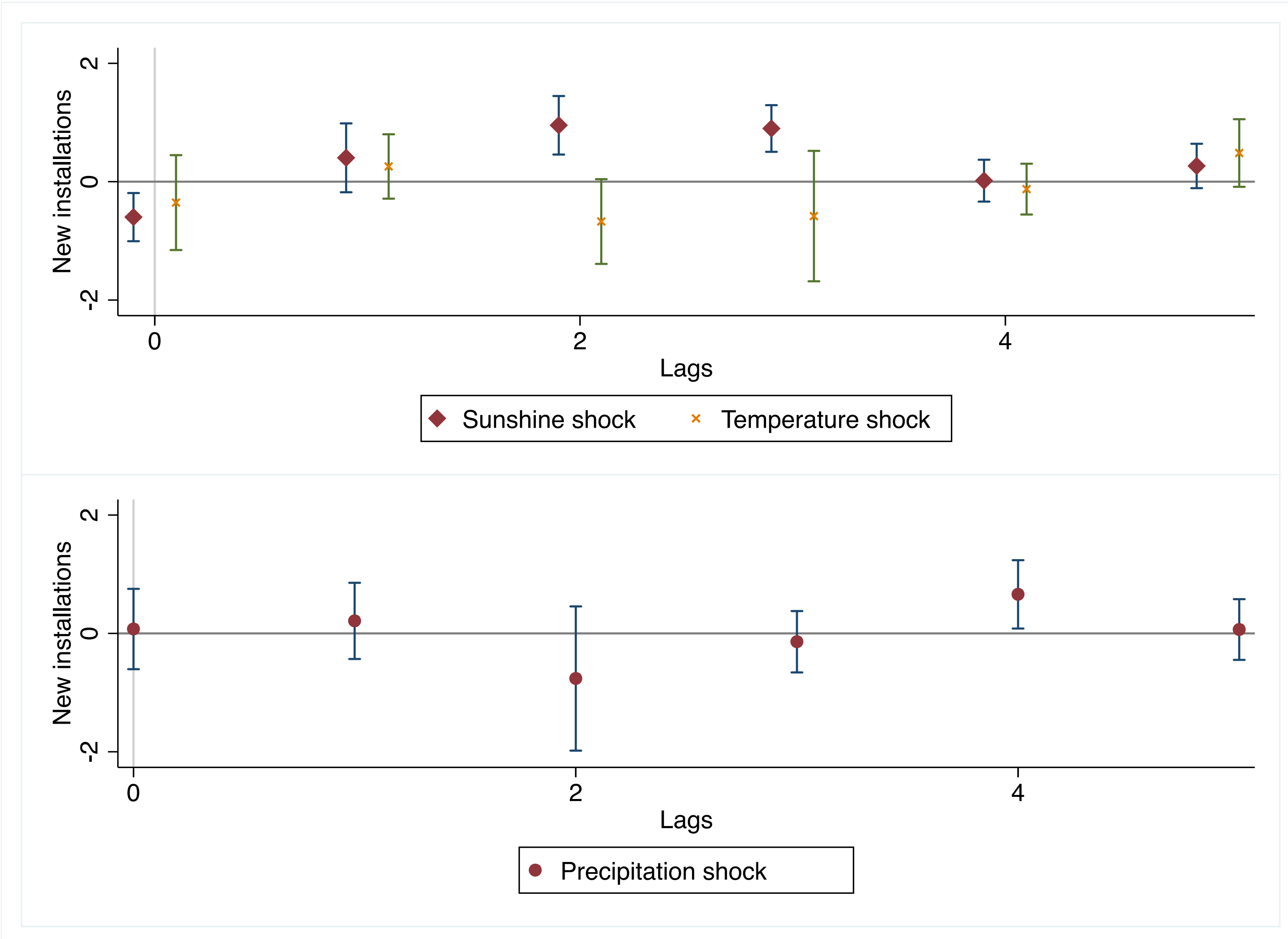


Figure 5: Main regression results following specification (2). Data aggregated at county-month level for the period 2000-2011. The dependent variable is the number of solar installations in county c in month t. All variables are included jointly in the regression model, but presented in two graphs for ease of representation. R^2 =.688, N= 55,878. Point estimates with 95% confidence interval. All standard errors are clustered at weather-station.

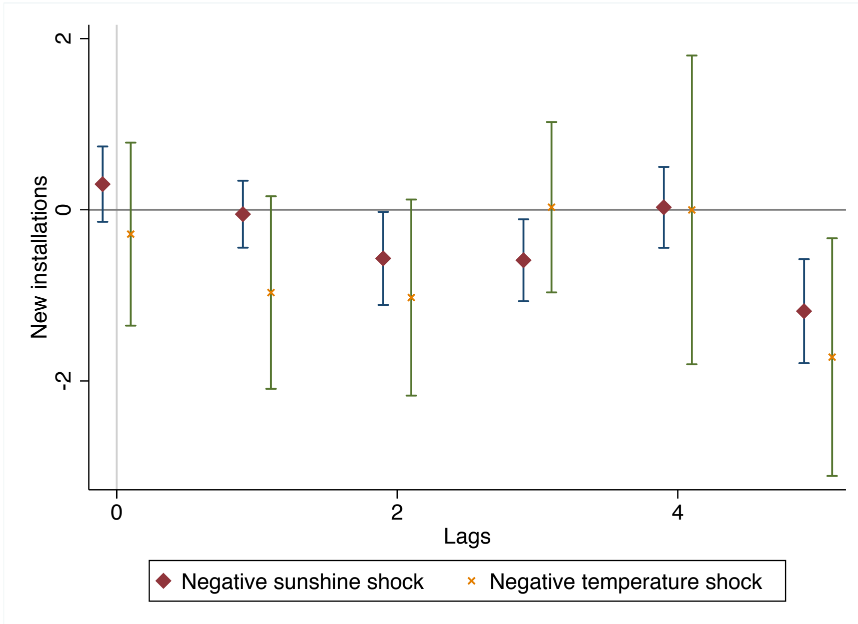


Figure 6: Main regression results following specification (2). Data aggregated at county-month level for the period 2000-2011. The dependent variable is the number of solar installations in county c in month t. Lags indicate lags of the negative sunshine and temperature shocks. R^2=.688, N=55,878. Point estimates with 95% confidence interval. All standard errors are clustered at weather-station.

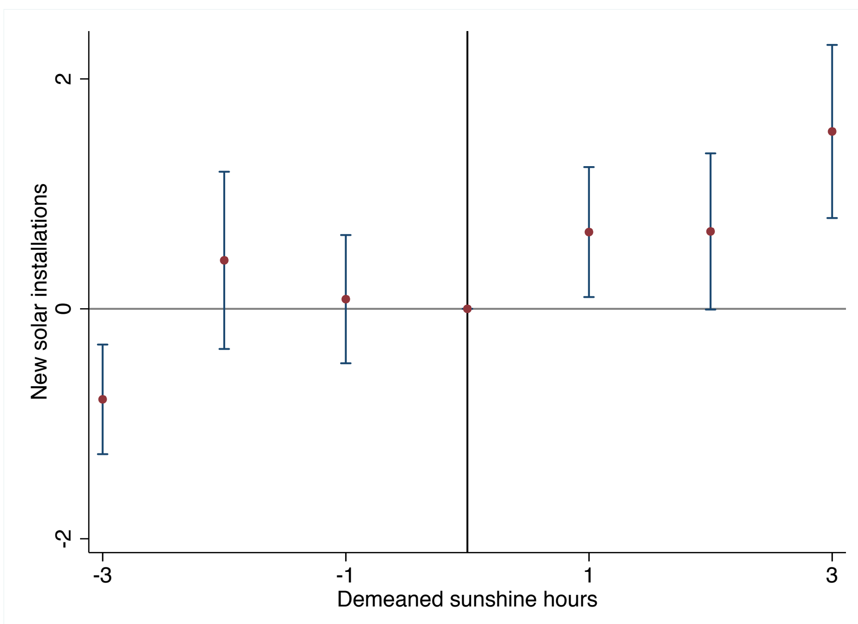


Figure 7: Non-linear effect for lag 2 of the sunshine variable. The regression follows specification (2), however uses bins for demeaned sunshine hours. The coefficients are normalized with respect to the sunshine normal (zero bin omitted from the regression). R^2 =.689, N = 56,682. All standard errors are clustered at weather-station.

Table 3: News on solar and climate change

New installations	(1)	(2)	(3)
Lag Sunshine shock	0.687**	0.634**	0.871***
	(0.293)	(0.305)	(0.310)
Lag 2 Sunshine shock	1.142***	0.939***	1.052***
	(0.255)	(0.252)	(0.270)
Lag 3 Sunshine shock	1.318***	0.642***	0.983***
	(0.205)	(0.191)	(0.197)
Lag 4 Sunshine shock	0.230	0.447***	0.404***
	(0.148)	(0.133)	(0.138)
Lag 5 Sunshine shock	−0.267*	0.215	−0.364***
	(0.148)	(0.159)	(0.136)
Lag News solar	0.343***		0.319***
	(0.029)		(0.027)
Lag 2 News solar	0.444***		0.445***
	(0.039)		(0.042)
Lag 3 News solar	0.028		0.063**
	(0.021)		(0.024)
Lag 4 News solar	−0.071***		−0.099***
	(0.008)		(0.012)
Lag 5 News solar	−0.115***		−0.138***
	(0.019)		(0.021)
Lag News climate change		0.201***	0.148***
		(0.019)	(0.016)
Lag 2 News climate change		0.089***	0.136***
		(0.010)	(0.015)
Lag 3 News climate change		0.100***	0.149***
		(0.019)	(0.024)
Lag 4 News climate change		0.165***	0.140***
		(0.014)	(0.014)
Lag 5 News climate change		0.170***	0.082***
		(0.016)	(0.009)
Observations	55878	55878	55878
R^2	0.698	0.693	0.702
County-Year FE	Y	Y	Y
FIT-Month FE	Y	Y	Y
Covariates	N	N	N

Note: Main regression results following specification (2). Data aggregated at county-month level for the period 2000-2011. The dependent variable is the number of solar installations in county c in month t. The regression additionally controls for lagged news on solar and climate change. * p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors at weather station in parentheses.

Table 4: Supply side effects

Price per kWp installed	(1)	(2)	(3)
Lag Cumulative Hh installations	−0.137	−0.173	
	(0.185)	(0.136)	
Lag 2 Cumulative Hh installations	0.099	0.051	
	(0.227)	(0.143)	
Lag 3 Cumulative Hh installations	0.004	−0.127	
	(0.181)	(0.091)	
Lag 4 Cumulative Hh installations	−0.282	−0.142	
	(0.185)	(0.111)	
Sunshine shock	47.101	19.657	14.844
	(32.743)	(21.205)	(21.273)
Lag Sunshine shock	55.485*	46.974**	41.405*
	(27.836)	(20.985)	(20.731)
Lag 2 Sunshine shock	7.688	−1.948	−6.100
	(49.515)	(38.835)	(38.113)
Lag 3 Sunshine shock	21.316	43.567	39.822
	(50.431)	(37.691)	(36.635)
Lag 4 Sunshine shock	−50.428	−4.356	−9.062
	(50.254)	(51.156)	(50.172)
Lag Total cumulative installations			−0.101**
			(0.045)
Lag 2 Total cumulative installations			0.006
			(0.050)
Lag 3 Total cumulative installations			−0.087**
			(0.035)
Lag 4 Total cumulative installations			−0.121***
			(0.034)
Observations	1835	3104	3104
R^2	0.620	0.640	0.645
State-by-quarter FE	Y	Y	Y
County FE	N	N	N

Note: Data aggregated at county-quarter level for the period 2010-2011. The dependent variable is the system cost per kWp for household solar installations. Columns 2 and 3 use an interpolated price dataset as I do not observe data for each county-quarter pair. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at weather station in parentheses.

Table 5: Sample split: Online information search

New installations	⩽ 2005	⩾ 2006	⩾ 2006	⩾ 2006	Google
Sunshine shock	0.069	0.033	0.214	0.232	8.161***
	(0.247)	(0.361)	(0.372)	(0.378)	(1.756)
Lag Sunshine shock	0.723***	−0.331	−0.232	0.857	1.004
	(0.179)	(0.530)	(0.525)	(0.674)	(1.158)
Lag 2 Sunshine shock	1.253***	1.319***	1.258***	0.506	−2.287**
	(0.407)	(0.385)	(0.414)	(0.477)	(1.127)
Lag 3 Sunshine shock	0.232	−0.796***	−0.830***	−0.869***	−2.403***
	(0.178)	(0.286)	(0.300)	(0.320)	(0.821)
Lag 4 Sunshine shock	0.270	−1.952***	−1.710***	−1.001***	4.049***
	(0.234)	(0.187)	(0.175)	(0.238)	(1.253)
Lag Google search			0.003	0.009*	
			(0.005)	(0.005)	
Lag 2 Google Search			0.022***	0.015**	
			(0.006)	(0.006)	
Lag 3 Google Search			0.022***	0.018**	
			(0.007)	(0.008)	
Lag 4 Google Search			−0.017***	−0.010**	
			(0.003)	(0.004)	
Lag Sunshine shock X Google				−0.018***	
				(0.004)	
Lag 2 Sunshine shock X Google				0.011***	
				(0.003)	
Lag 3 Sunshine shock X Google				0.002	
				(0.002)	
Lag 4 Sunshine shock X Google				−0.014***	
				(0.003)	
Observations	26934	28944	28944	28944	28944
R^2	0.423	0.592	0.597	0.599	0.842
County-Year FE	Y	Y	Y	Y	N
FIT-Month FE	Y	Y	Y	Y	Y
Covariates	N	N	N	N	Y

Note: Main regression results following specification (2). Data aggregated at county-month level for two sub-periods: 2000-2005 and 2006-2011. The dependent variable is the number of solar installations in county c in month t. The regression additionally controls for Online searches (Google) in column 3, and an interaction term between the sunshine shocks and Google (column 4). Column 5 regresses the number of Google searches for ‘solar’ on current and lagged sunshine shocks.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at weather station in parentheses.

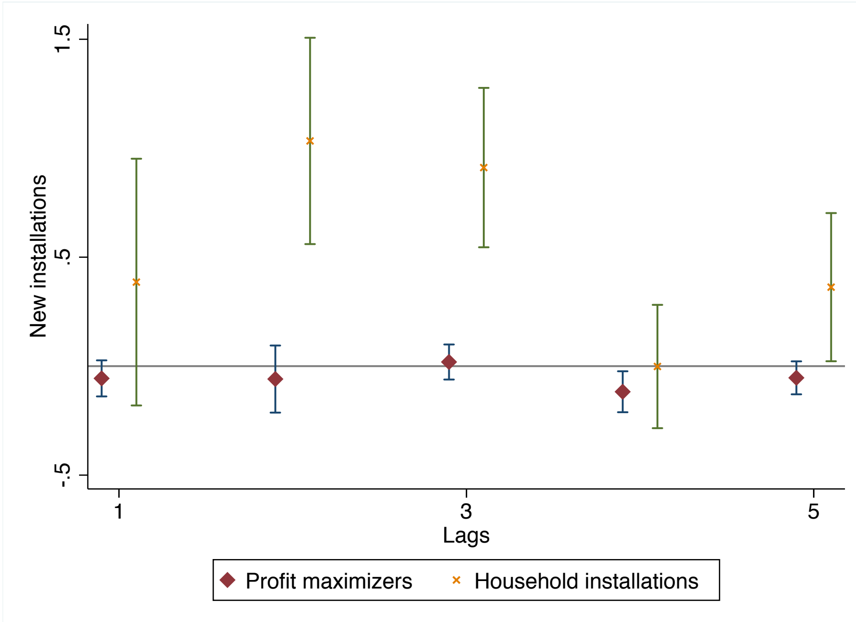


Figure 8: Main regression results following specification (2) at county-month level for the period 2000-2011. The dependent variable is the number of solar installations in county c in month t for two distinct groups: profit maximizers and household installers. I define as profit maximizers commercial installers that take advantage of a discontinuity in the FIT policy design to maximize their expected profit. N=55,878. Point estimates with 95% confidence interval. All standard errors are clustered at weather station.

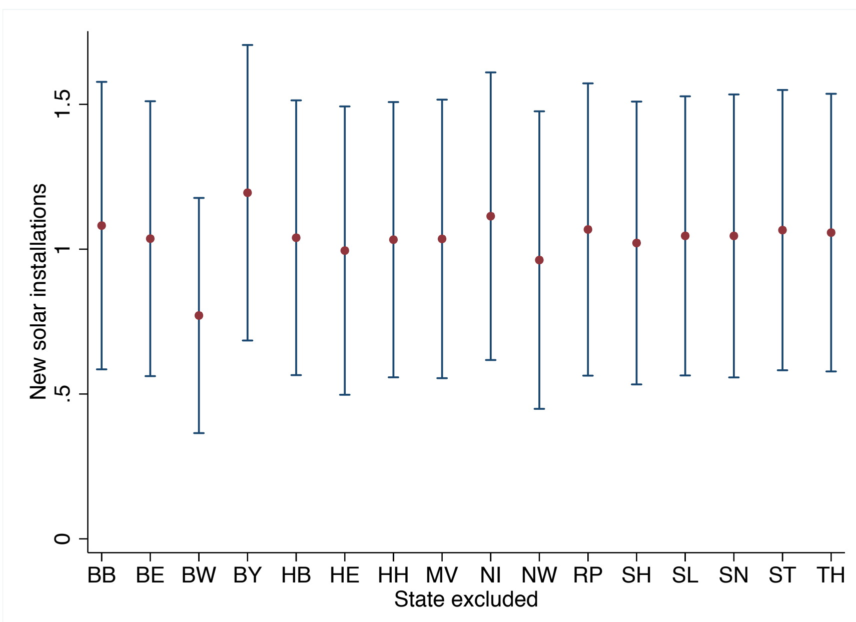


Figure 9: Main regression results following specification (2) at county-month level. Each observation represents the estimated coefficient for lag 2 of the sunshine shock excluding one of the federal states from the regression. BB: Brandenburg; BE: Berlin; BW: Baden-Wurttemberg; BY: Bavaria; HB: Bremen; HE: Hesse; HH: Hamburg; MV: Mecklenburg-Vorpommen; NI: Lower Saxony; NW: Northrine-Westfalia; RP: Rhineland-Palatine; SH: Schleswig-Holstein; SL: Saarland; SN: Sachsen; ST: Sachsen-Anhalt; TH: Thuringen. Point estimates with 95% confidence interval. All standard errors are clustered at weather-station.

Appendix

A1. The German Market for Solar

Figure A1 summarizes the main phases for solar-support policies in Germany. Overall support for renewable energy started in 1991 with the *Electricity Feed-In Act* and the introduction of Feed-In tariffs (FIT) for large-scale hydroelectric power plants. The first important step towards the deployment of solar energy at household level was accomplished in 1999, with the introduction of the so-called 100,000 rooftop program. The program had the objective to add a total of 300 Mega Watt (MW) of installed solar capacity to the electricity grid. It mainly operated through interest free loans offered by the German bank for reconstruction in addition to the existing FIT schemes. In 2000, the federal government agreed to introduce the *Renewable Energy Act* as part of a larger 'sustainability' incentive.

The *Renewable Energy Act* (EEG for its letters in German) introduced a revised FIT scheme that offered higher incentives for private investments in solar. The EEG guarantees investors access to the electric grid for 20 years at fixed FIT over the investment horizon. It furthermore set a fixed 'degression rate', the annual rate at which FIT decreases for new installations, to mimic market trends in cost developments. As Figure A1 depicts, there have been two main amendments to the original EEG: the first one enacted in 2004 aimed at increasing deployment of solar, while the second one in 2009 aimed at reforming the benefits for new installations to make the existing policy more cost-effective.

Even though the 2009 amendment introduced several changes to the law, such as a degression rate that responds to the aggregate number of installations (corridor degression) and the option to consume electricity locally (on-site consumption), the overall incentives for households to invest in solar did not change considerably. In fact, solar remained a very attractive investment opportunity, leading to a record number of installations in both 2010 and 2011. It was not until 2012 that the economic incentives for solar investment changed importantly with a thoroughly revised version of the EEG and the related FIT scheme.[29]

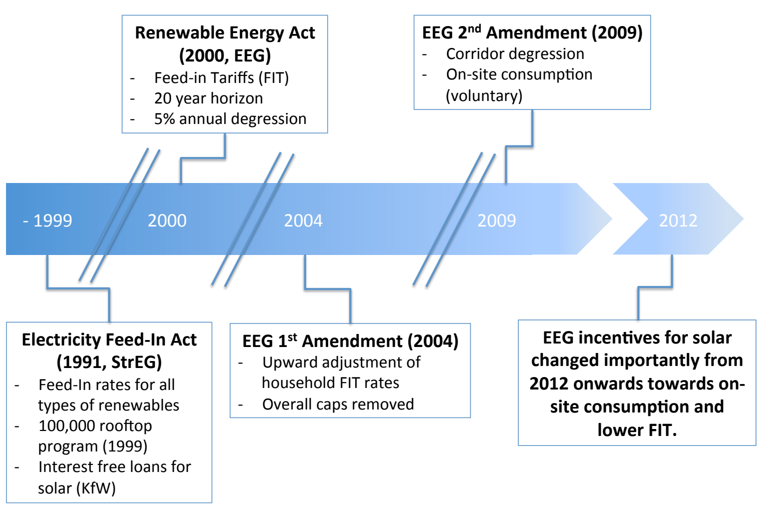


Figure A1: Evolution of solar support policies in Germany.

[29] A detailed discussion of the evolution of Feed-In tariff policies, with focus on Germany is given by Jacobs (2012).

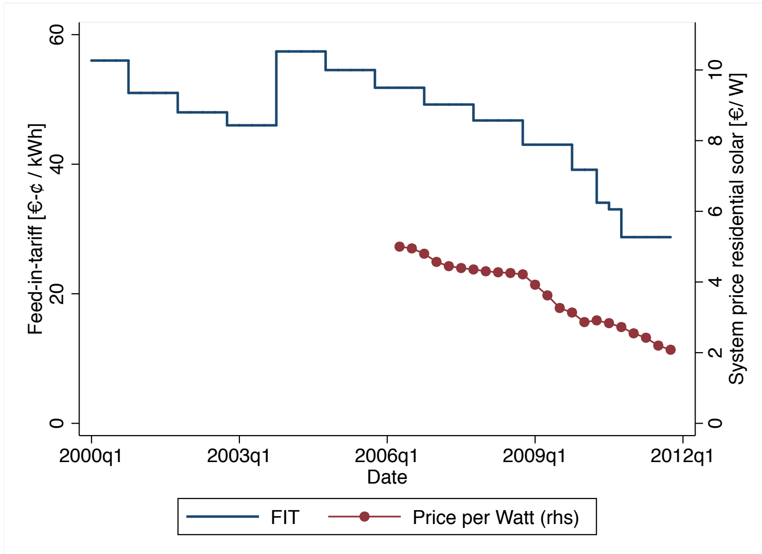


Figure A2: Feed-In tariffs and solar system prices in Germany. The system price includes both module costs and soft costs. Source: German Solar Association.

Figure A2 depicts the FIT schedule for the period 2000-2011. FIT are typically adjusted at the 31 of December, but there have been some periods of inter-annual revisions: the 2004 EEG amendment (August 1), and two adjustments in 2010. All changes have been previously announced and do not affect installations retrospectively. The evolution of household system prices shows clearly the decrease in costs. Precise data for small-scale installations is available for the period 2006-2011. Even though FIT led to an important number of solar installations, the share of solar in the total electricity production in Germany reached only about 3.1% in 2011. Household capacity accounted for about 9% of total added solar capacity. At the end of 2011, the household market has been growing at fast rates and the overall market has been far from saturation.

A2. The Impact of Weather on Solar Profitability

In addition to sunshine, different weather variables can affect the profitability of solar, at least in the short-run.[30] The main variables to consider are temperature and cloud cover:

Temperature - High temperature can affect the performance of solar cells negatively. Both the electric current generated and its voltage are influenced by the operating temperature. However as the positive change in current is offset by a negative change in voltage, and given the fact that solar modules are typically made up of a number of cells connected in series, the output voltage decrease due to temperature may become significant. Especially very hot days in the summer can lead to significantly less electricity production. These effects are typically short-lived and should not affect the overall performance of a solar installation over its lifespan. Generally, temperature is a factor benefitting electricity production from solar in a country like Germany compared to other countries with more solar radiation but hat also have higher temperatures.

[30]See for example the *EEPQRC (2011) Guide for Small Scale Domestic Rooftop Solar.*

Cloud cover - Cloud cover and shade can be considered the enemies of solar production, as they diminish electricity production by solar cells significantly. A rainy day, with thick cloud cover, can reduce the production from solar energy by as much as 90%. Short-term electricity production from solar may however peak on mixed days, when the sun moves between the clouds, as then solar cells will receive direct sunlight plus the one reflected from the clouds.

Other - Similarly, other weather events such as snow and ice can affect the quantity of sunlight absorbed by the solar panels, but their effects are typically short-lived and should not affect the average profitability of solar investments over the project horizon.

A3. Additional Data Sources

In addition to the two main data sources, solar installations and weather, I consider the following covariates:

Demographics - Data on population, household income, education, unemployment, buildings, surface, and voting can be obtained from the regional statistical database ('Regionaldatenbank') of the German statistical agency. Annual data is available at county level ('Kreis' and 'kreisfreie Stadt').

LexisNexis - Provides detailed data on news and media coverage in specific geographic markets. I obtain data on news related to solar ('Photovoltaik') and 'climate change', that has been published in major German print media. The data is aggregated at monthly frequency.

Google trends - Can be accessed through Google. I download the time series of search intensity (number of searches) for solar ('Photovoltaik') in each of the 16 German states separately. Data is collected for the period 2006-2011 at monthly frequency.

Price data - On solar installations comes from EuPD Research, and is based on confidential installer bid-price data from a German solar webforum which allows potential customer to compare installation prices locally.

Installer Survey - I conduct an Online survey among solar installers to obtain additional information on marketing and sales activities as well as information on the main consumer decision variables. The survey covers three main areas: motivation and decision variables affecting customer investment decisions, time gap in decision-making, and the impact of weather and climate on installer sales activities.[31]

I use an automated Python script (web crawler) to obtain a large database of German solar installers from the Online solar website `Photovolatik.info`. I extract a total of 3,217 contacts, for which I observe name, address, email and website. Using the address information allows me to assess the geographical representativeness of this sample. I find that the states with most solar installations also represent the largest share of my installer data: 21% Bavaria, 19% Baden-Wurttemberg, 19% North-Rhein Westfalia, 9.2% Lower Saxony, etc.

I use the Online survey tool *Qualtrics* to send out the questionnaire in August 2015. In addition to the original email, all installers receive one survey reminder two weeks after the first contact. Survey participation was voluntary and not related to any forms of payment or other benefits. Following this

[31] The full questionnaire can be obtained from the author upon request.

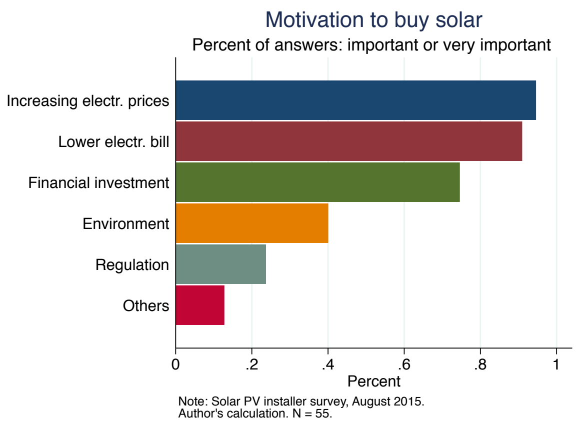
protocol, I am able to collect a total of 56 complete answers, representing a sampling share of 1.7%. Even though the response rate is low, the geographical representation of the installer sample mimics the one from my universe of installers: 25.4% Bavaria, 18.2 % North-Rhine Westfalia, 16.4% Lower Saxony, 14.6% Baden-Wurttemberg, etc. I am hence confident that regional selection is not of concern.

Analyzing self-reported company demographics reveals that most businesses are specialized solar installers (60%). My sample also includes 12% of electricians and 12% of heating & water installers that install solar panels as secondary business activity. Most of the companies are small with 1-5 employees (52%), while 20% have more than 20 employees. More than half of my sample reports that they have been installing solar panels for at least 10 years. Thus, they can make credible statements about the market conditions in the early 2000s. I also find that installer markets are rather local: 60% of businesses state that their main commercial activity is concentrated either in the same county or adjacent counties. Even though the survey is not fully representative, the business demographics indicate that my sample covers a large variety of installer types. The collected responses should be indicative for the overall market conditions in Germany. The main insights from the survey are:

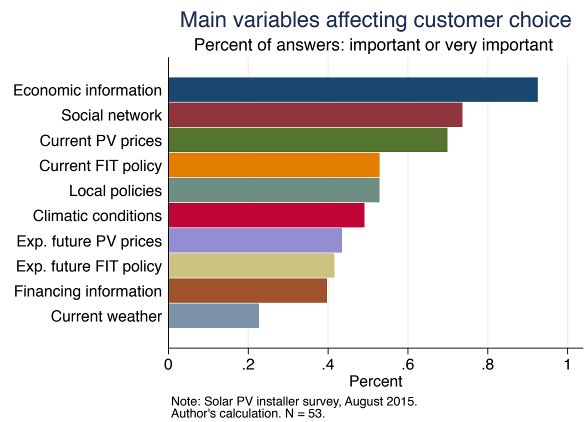
1. Customers acquisition effort is low: typically customers contact installers directly with the aim to install a solar system.
2. The household investment decisions are mainly driven by financial return considerations.
3. The average time lag between first customer contact and completion of the installation is 8 weeks.
4. Installers do not adopt their marketing and sales strategies due to idiosyncratic variations in weather.

Figure A3 shows the main factors playing a role in the solar investment decision. The main motivations are economical, either related to the electricity bill (due to the 2012 FIT reform, on-site usage has become mandatory and investment profitability depends on the evolution of the electricity prices), or financially motivated. Environmental concerns are only mentioned by about 40%. Panel b of Figure A3 shows the main decision variables affecting the investment choice of customers. Again, economic variables dominate the discussion. Financing and weather, on the other hand, are not considered to be important factors. Panel c of the same figure shows the main marketing channels used to promote solar. Most installers rely on word-of-mouth and local events. Advertisement, both in Online and print media is only used by about 30-40%. As most of the installers are small businesses it is furthermore not surprising that only 25% of them have specific personal involved in sales and marketing activities.

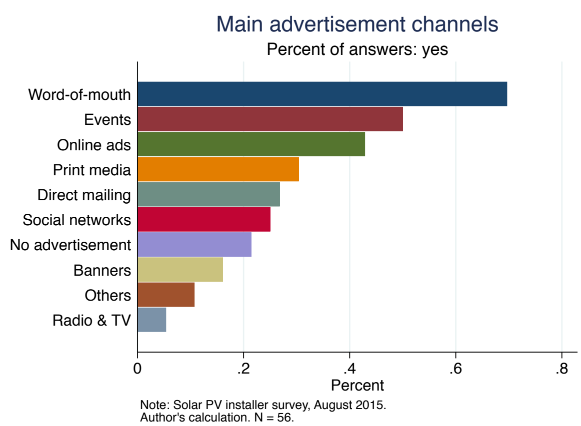
In order to understand to what extend installers respond to idiosyncratic variations in weather, in a first step I ask if their overall marketing strategies are affected by seasonal variations in climatic conditions (winter versus summer). This is the case for 35% of all installers. In a second step, I ask if current weather affects the marketing and sales activities. Only 7 (13%) of all answers respond that weather has an impact on sales activities. The main reason is limited site access due to poor weather conditions and only 3 installer (5.8%) mention that sunshine has a positive impact on business actities.



(a) Main motivation to invest in solar



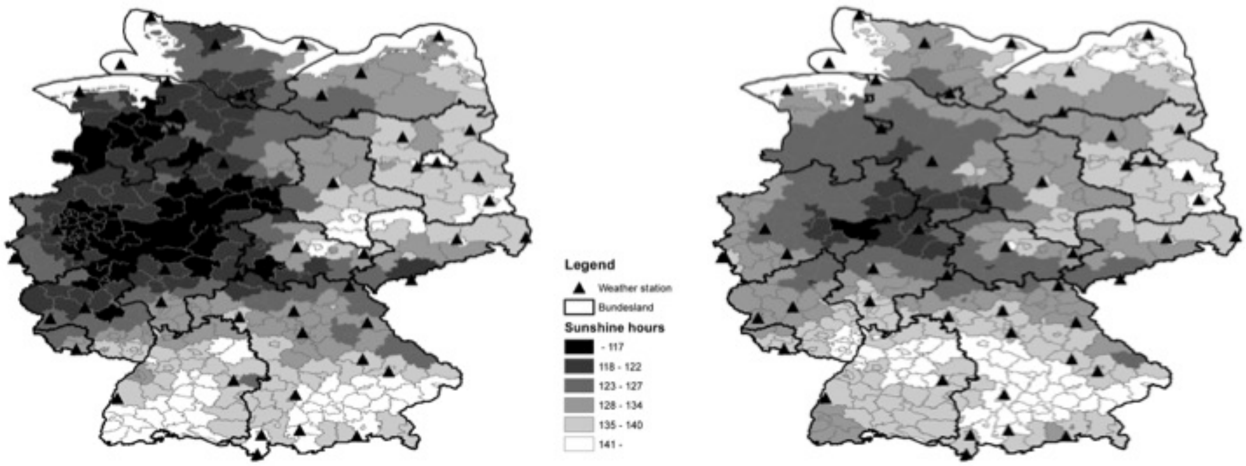
(b) Main decision variables affecting choices



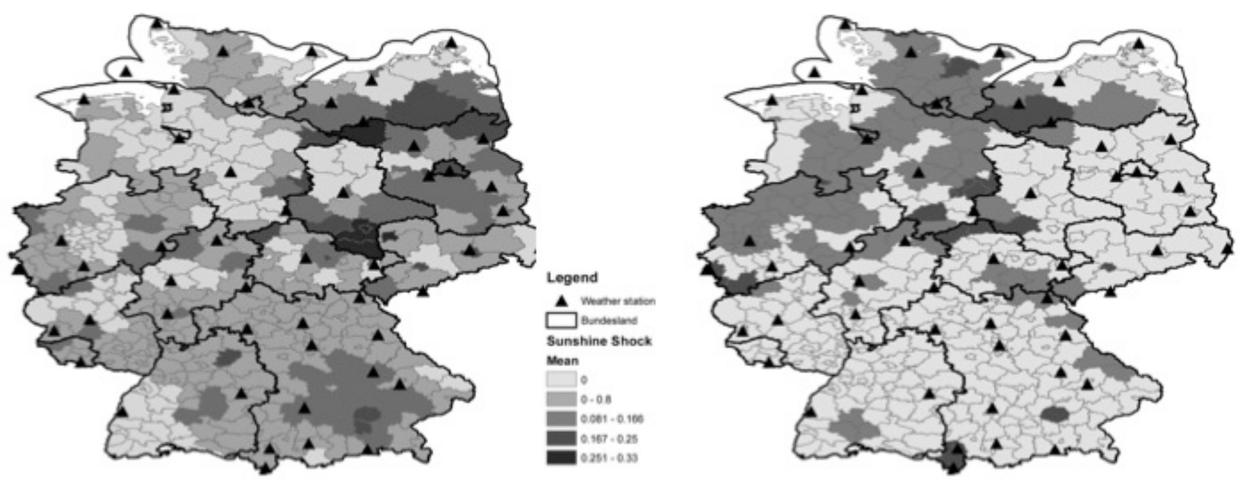
(c) Main marketing channels used by installers

Figure A3: Solar installer survey: main factors affecting household choices and marketing channels.

A4. Additional Tables and Figures



(a) Mean sunshine hours by county, 2000 and 2004 (rhs). Lighter areas represent more sunshine.

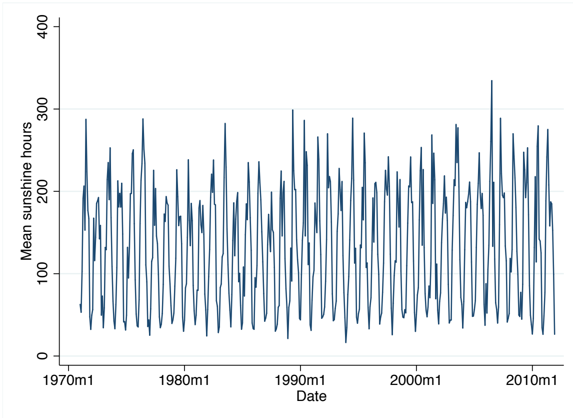


(b) Mean of sun shock by county, 2000 and 2004 (rhs). Darker areas represent more shocks.

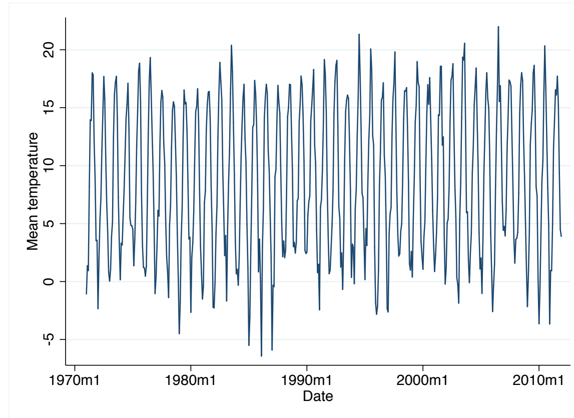
Figure A4: Spatial distribution of sunshine hours and sun shocks in 2000 (left hand side) and 2004 (right hand side).

	Sunshine Shock			Temperature Shock
	12 lags	24 lags	40 lags	40 lags
Percent counties with Q-statistic at 1%	0.022	0.054	0.067	0.154
Percent counties with Q-statistic at 5%	0.089	0.176	0.189	0.268

Table A1: I calculate the Q-(Portmanteau) test for white noise for each of the 402 counties separately. The table displays the percent of counties in which the null hypothesis of no autocorrelation can be rejected at the 1% and 5% significance level. Lags indicates the number of lags considered for the calculation.

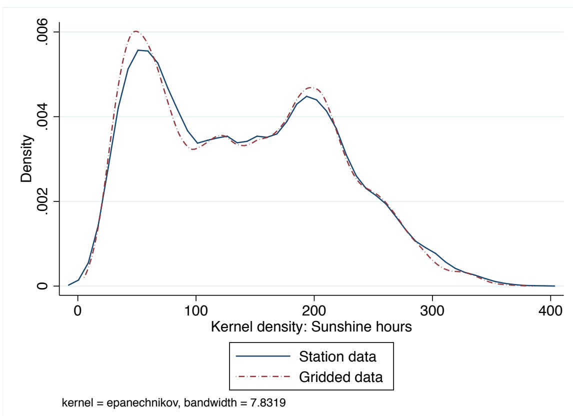


(a) Long-term sunshine hours: 1971-2011

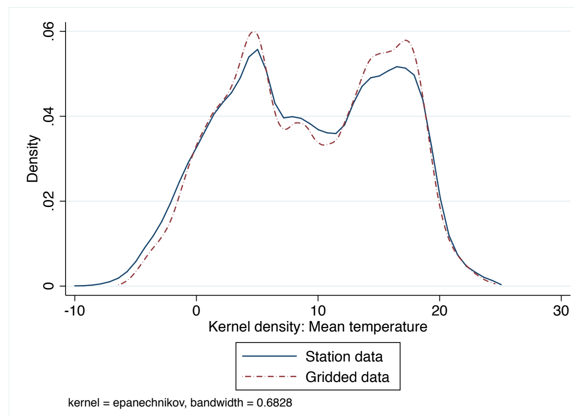


(b) Long-term mean temperature: 1971-2011

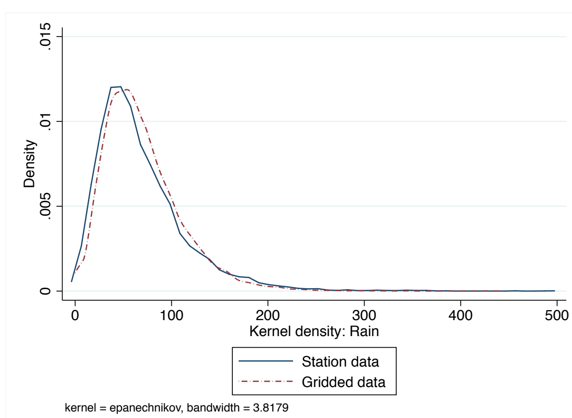
Figure A5: Sunshine hours and mean temperature trends in Germany. Source: DWD



(a) Kernel density: sunshine hours

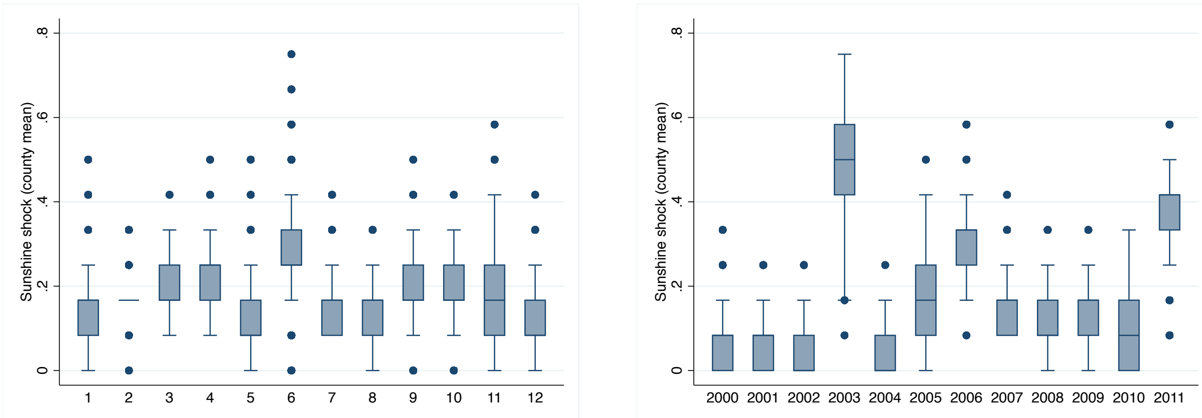


(b) Kernel density: mean temperature



(c) Kernel density: rain

Figure A6: Distribution of key weather variables for gridded data and weather station data.



(a) Sun shock: over months

(b) Sun shock: over years

Figure A7: Mean of the sun shock variable over months and years.

	Sunshine			Sunshine shocks		
	full	median distance	median binary	full	median distance	median binary
Percent counties with Moran's I at 1%	0.083	0.076	0.09	0.067	0.067	0.133
Percent counties with Moran's I at 5%	0.027	0.027	0.042	0.012	0.012	0.06

Table A2: I calculate Moran's I statistic of global spatial correlation for every month of my sample. The table displays the percent of periods where the null of no spatial correlation can be rejected at the 1% and 5% significance level. The spatial weighing either takes into account that all counties are correlated (full), or that correlation is possible up to the median distance. Binary assumes 0/1 weights.

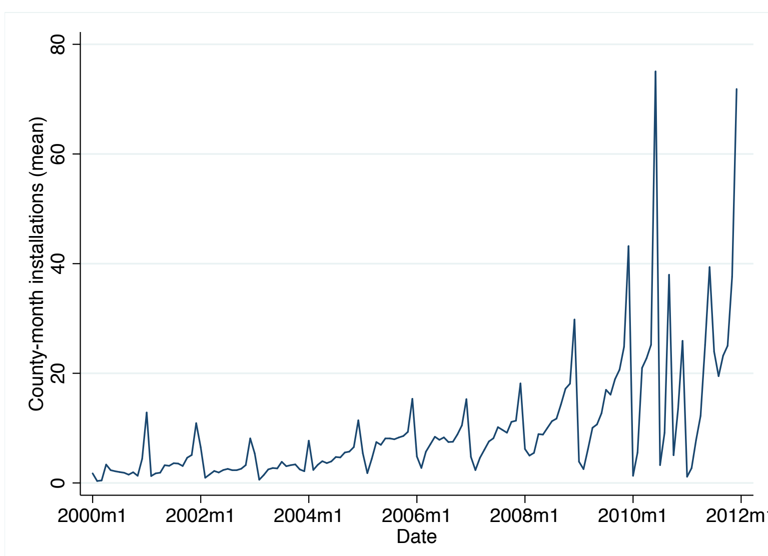


Figure A8: Time series of solar installations at county-month level.

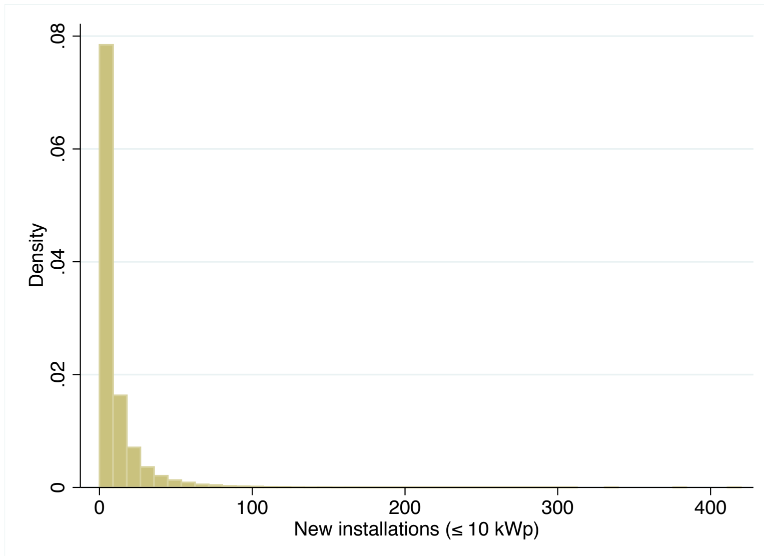


Figure A9: Histogram of solar installations at county-month level.

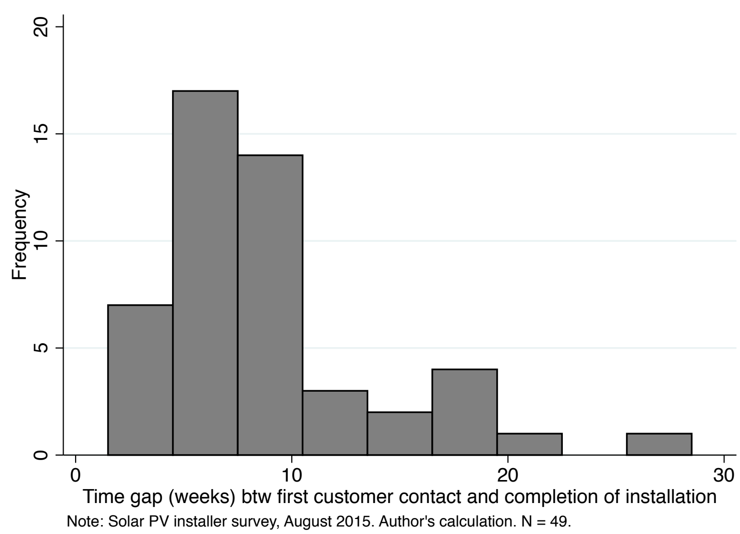


Figure A10: Average time gap from purchasing to completion of the installation (weeks).

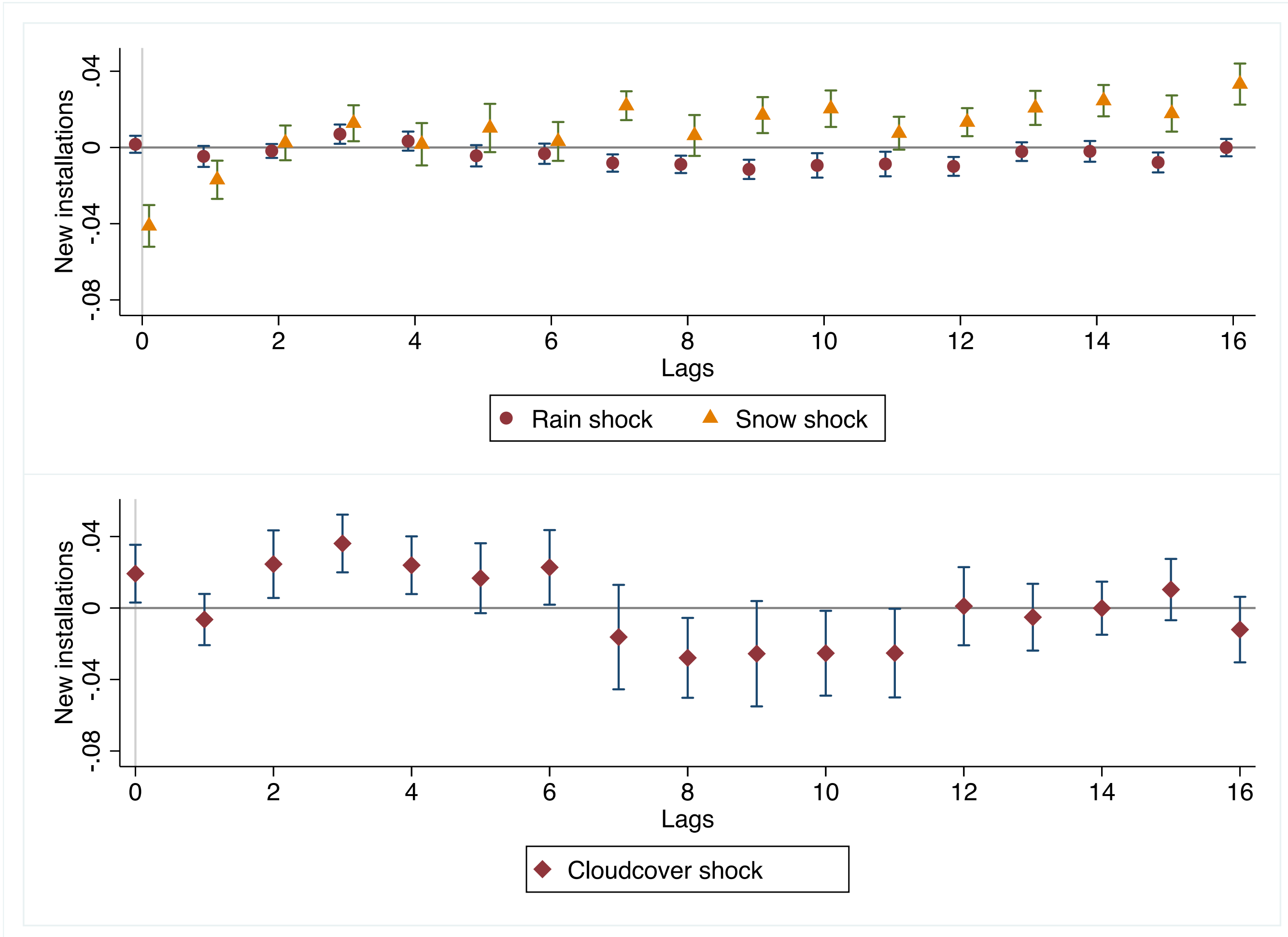


Figure A11: Main regression results following specification (1). Data aggregated at county-week level for the period 2000-2011. The main dependent variable is an indicator equal to one if there has been at least one installation in county c in week t. All weather variables are included jointly in the regression but displayed in two separate graphs for ease of representation. R^2= .412 , N =237,945 . Point estimates with 95% confidence interval. All standard errors are clustered at weather-station.

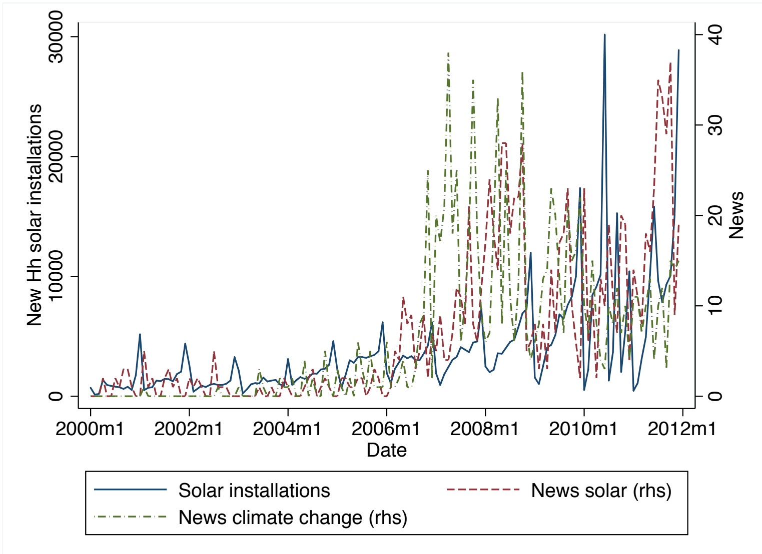


Figure A12: Time series for news on 'solar' and 'climate change' plotted together with the time series for solar installations.

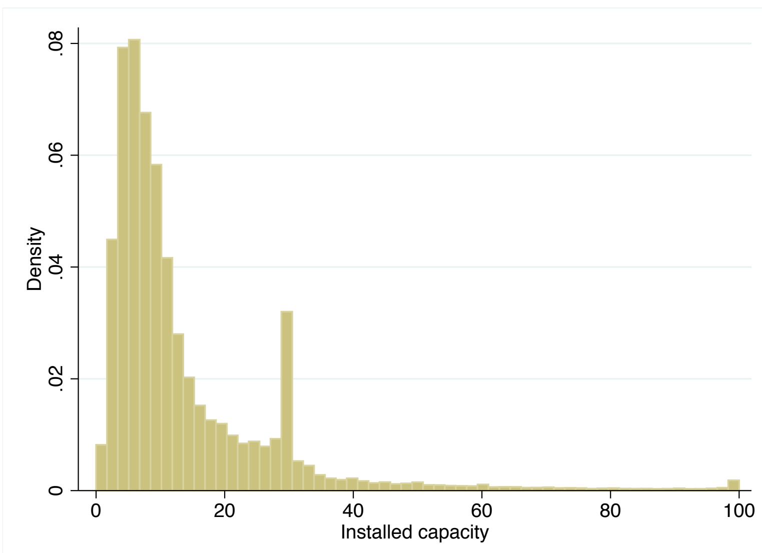


Figure A13: Histogram of solar installations in Germany ($\leqslant$ 100 kWp).

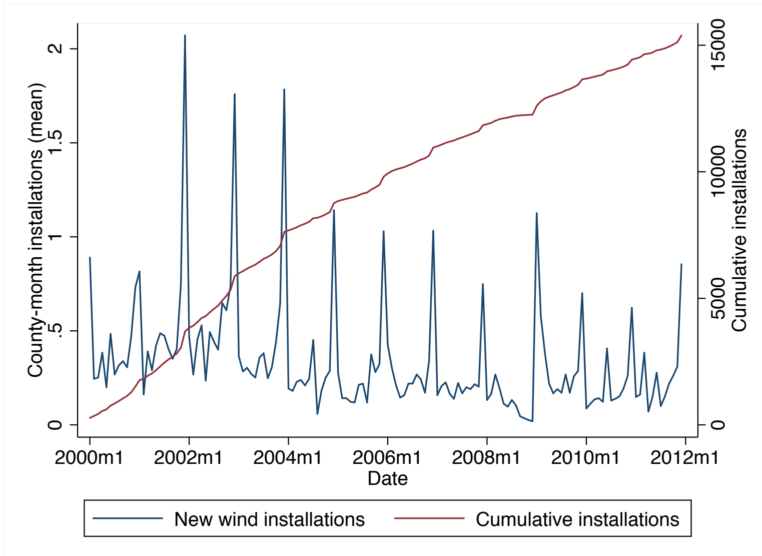


Figure A14: Mean of wind turbine installations at county-month level and cumulative technology uptake over time.

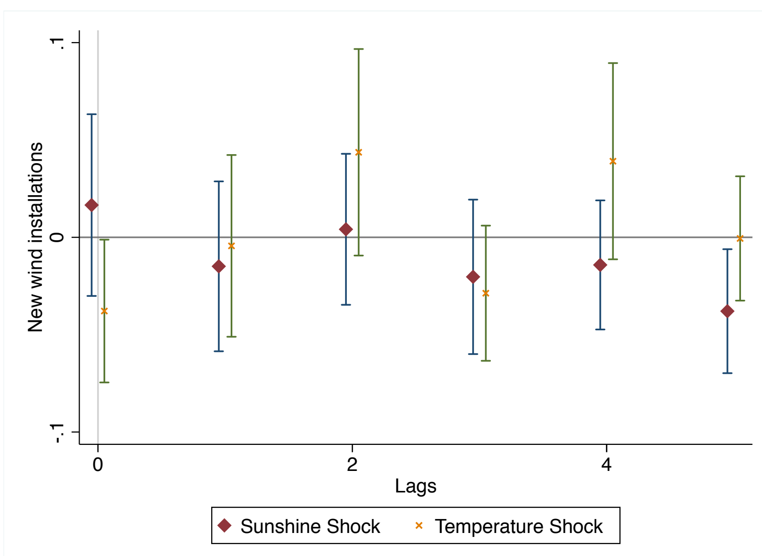


Figure A15: Main regression results following specification (2). Data aggregated at county-month level for the period 2000-2011. The dependent variable is the number of new wind turbines in county c at time t. Point estimates with 95% confidence interval. All standard errors are clustered at weather-station.