



Sunspots That Matter: The Effect of Weather on Solar Technology Adoption

Stefan Lamp¹

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Abstract

This paper tests for the presence of behavioral biases in household decisions to adopt solar photovoltaic installations using exogenous variation in weather. I find that residential technology uptake responds to exceptional weather, defined as deviations from the long-term mean, in line with the average time gap between decision-making and completion of the installation. In particular, a one standard deviation increase in sunshine hours during the purchase period leads to an approximate increase of 4.7% in weekly solar PV installations. This effect persists in aggregate data. I consider a range of potential mechanisms and find suggestive evidence for projection bias and salience as key drivers of my results.

Keywords Renewable energy · Solar photovoltaics · Projection bias · Salience · Energy policy · Technology diffusion

JEL Classification D12 · D91 · Q42

1 Introduction

Electricity markets remain a crucial sector in the ongoing energy transition from fossil fuels to renewable energy sources (RES). To incentivize private investment in RES, governments around the world engage in costly support mechanisms that mostly come in the form of investment or production subsidies.¹ These subsidies implicitly build on the assumption that decision-makers act rationally by evaluating private costs and benefits when making their investment choices. Behavioral economics, however, has shown in different contexts that rationality is not necessarily a good assumption (DellaVigna 2009). When utility is context dependent and optimal decision-making involves the prediction of future utility levels, behavioral biases can lead to consumers misvaluing costs and benefits, influencing their decision-making (Loewenstein et al. 2003; Bordalo et al. 2012, 2013, see for instance).

¹ See for instance Fouquet and Johansson (2008) and Abdmouleh et al. (2015).

✉ Stefan Lamp
slamp@eco.uc3m.es

¹ Universidad Carlos III Madrid, Madrid, Spain

This paper studies the presence of behavioral deviations from the rational agent framework in the decision of households to adopt rooftop solar photovoltaics (PV) systems. More precisely, I ask whether variations in local weather conditions have an impact on household solar PV adoption decisions. The rational agent framework suggests that long-term investments in rooftop solar PV should not be affected by short-term weather fluctuations, as these do not impact the long-term investment profitability. In contrast, I show that households respond to variations in sunshine and related weather variables and in particular, that exceptionally sunny episodes can lead to increased solar PV uptake. I test for a variety of competing mechanisms and find suggestive evidence that household decisions are affected by factors in line with projection bias and salience. According to projection bias, weather deviations from the long-term mean can impact investment decisions when households ‘project’ profit expectations, based on current weather, into the future. On the other hand, exceptional sunny periods can make the financial benefits related to solar PV investment more ‘salient’, leading to adoption decisions. Providing evidence for behavioral anomalies in the context of solar PV panel adoption, a highly irreversible investment good that receives large amount of subsidies, can offer important insights into the diffusion process of other environmentally-friendly technologies.²

To empirically test for the impact of short-lived weather variations on solar PV adoption decisions, I rely on administrative data for solar PV installations in Germany and combine these with detailed weather data. I focus on Germany, a world leader in solar PV deployment, as its institutional features are particularly well-suited for this analysis. First, the distinctive design of feed-in tariffs (FiTs), the main support mechanism for renewable energy investment, guarantees positive financial returns to investors and provides rather stable investment conditions prior to 2014 in an otherwise quickly changing market environment. The presence of this single policy instrument allows potential solar PV customers to calculate their expected financial returns of the investment with little uncertainty. Second, given the long project horizon of approximately 20 years, rational agents should not respond to short-term variations in weather as their average returns will not be affected. This is particularly true as there exists a time gap between the decision to adopt solar PV (purchase period) and the time when the installation is completed and starts to produce electricity.³ Third, the adoption of a rooftop solar PV system involves a large financial commitment, comparable to the purchase of a car, which makes it a particularly interesting setting to study.

For my analysis, I recover the long-term weather (climate) distribution for each county and look at the differences of actual weather from the long-term averages in a typical county-week. This measure captures the intensity of the weather deviation with respect to the climatic normal. As a second measure, I also consider discretized weather shocks, defined as a weather realization one standard deviation above the long-term mean. In my main specification, I regress solar PV uptake on these weather variables during the purchase period, 6–12 weeks prior to the observed installation date, controlling for a rich set

² RES technologies typically received large amounts of public subsidies. In 2019, for example, total RES support in Germany accounted for approximately 27.6 billion Euros. The largest share was linked to solar PV technology, with 11 billion Euros. Source: EEG in Zahlen, Federal Network Agency.

³ To elicit information on the average time gap between decision making and completion of the solar PV plant, I perform an online survey with German solar PV installers. I find an average time gap of 9 weeks with an interquartile range of 6–12 weeks prior to the observed date of grid connection. I provide additional information on the installer survey in Online Appendix B.2.

of county and time fixed-effects. My empirical identification strategy takes advantage of the randomness of local weather as well as the time gap between decision-making and completion of the installation.

I find strong evidence that sunshine during the purchase period impacts residential solar PV installation decisions in line with the average installation timing. A one standard deviation increase in sunshine hours leads to an approximate increase of 4.7% in solar PV installations. On the other hand, I find a negative and significant impact for precipitation and cloud cover, and a non-significant response to temperature on solar PV uptake. I provide additional evidence to support the causal interpretation of my findings and perform several robustness checks for the main empirical analysis. In particular, I show that large installations, which are typically adopted by profit-maximizing firms are not affected by the same weather response. Moreover, I show that short-lived sunshine shocks lead to additional solar PV installations at the aggregate level, employing monthly data.

An important question concerns the underlying channels that explain these effects. In order to further elaborate on the mechanisms, I test for non-linear effects of weather variables and heterogeneous responses to sunshine deviations due to differences in average profitability (solar radiation). I find evidence that households respond to both large and small deviations from the long-term averages and that these effects are non-symmetric. Moreover, I show that sunshine can have heterogeneous impacts based on the average financial profitability of the investment. While these results do not allow me to clearly disentangle projection bias from salience as main mechanism, they indicate that both these mechanisms are present in my setting. I provide additional evidence that the results are likely not driven by other mechanisms affecting investment decisions such as consumer learning, myopia, and beliefs about climate change.

Another major concern is that some of the effect could be driven by supply-side responses to weather. To provide evidence that the impact of weather on solar PV installations is driven by the demand, I take advantage of regional summer holiday schedules in Germany to show that in case exceptional sunny periods coincide with the main vacation period, exceptional sunshine does not lead to new installations, while installer activity does not seem to be affected. Furthermore, I obtain data on solar PV prices from a price-comparison website and marketing activities of solar installers through an online survey to show that there are no price discounts during exceptionally sunny periods and that installers do not appear to adapt their outreach activities to the weather. Finally, I study the interaction between online search behavior and exceptional sunshine. All these tests indicate that the main effects on solar PV adoption are not driven by the supply.

This paper contributes to several strands of literature. First, there exists a large and growing body of literature, that tests for the impact of weather on people's behavior and how this might affect economic outcomes. Several studies have related weather variables to financial markets, consumer spending, and other outcomes such as crime.⁴ Most of these studies relate pleasant weather, such as sunshine, with good mood, which might affect behavior of economic agents. Weather has been also used in recent work to test for the presence of behavioral biases in field data. The present paper builds on the literature on projection bias in other consumer domains, such as the purchase of winter clothes (Conlin

⁴ Evidence of weather on financial markets: stock returns (Hirshleifer and Shumway 2003), the processing of earning news (Dehaan et al. 2017), and merger and acquisitions performance (Tunyi and Machokoto 2021). Weather and consumer spending: Murray et al. (2010). Weather and crime: see for instance Cohn (1990).

et al. 2007), college enrollment (Simonsohn 2010), car purchases (Busse et al. 2015), and outdoor movie sales (Buchheim and Kolaska 2017)⁵, and provides evidence for behavioral biases in a large investment good, where weather (sunshine) can be directly linked to profit expectations.

Much of the this literature relies on daily variations in weather and looks at short-run outcomes. In contrast, the institutional setting of the German solar PV market, specifically the time gap between decision-making and completion of the installation, allows me to rule out possible alternative mechanisms such as myopia for my findings. Benefits from the installation will only be perceived several weeks after the decision is made. This makes it unlikely that my results are driven by a share of highly myopic consumers that prefer to purchase the good on a sunny day or consumers with biased beliefs about the short-term evolution of weather.

Second, this paper is among the first studies to provide empirical evidence for projection bias and salience as an important driver in the household decision to adopt a solar PV panel using administrative data and a revealed-preferences approach.⁶ The paper most closely related is Liao (2020), who studies the impact of weather on solar PV cancellations in California, showing that households are more likely to cancel their contract in case the sign-up period is followed by unfavorable weather. Compared to her study, my contributions are twofold. First, in contrast to California, the German setting is particularly well-suited to study adoption decisions, as the presence of the FiT policy makes it profitable for households to invest in solar and to export all electricity produced rather than to self-consume electricity.⁷ This feature allows me to neglect the potential impact of solar PV production on electricity demand and electricity prices and to focus purely on adoption decisions. Furthermore, given the richness of my data, I am able to test for the impact of individual weather variables, non-linear weather effects on adoption, and heterogeneity by average solar radiation in the county. Non-linear and heterogeneous effects are important as they provide evidence of salience in addition to projection bias effects. Moreover, studying factors influencing product sales is of first-order importance, if the main challenge in new technology diffusion, such as solar PV panels, is to generate uptake.⁸ Second, I provide extensive evidence on alternative channels, collecting novel data from the installer market, elaborating on the link between online search behavior, weather, and solar PV adoption. In particular, I am able to provide evidence against supply-side effects, the most relevant alternative mechanism, when studying market-level outcomes.

One potential caveat of focusing on adoption decisions is that sunshine might be related to other channels that impact adoption decisions through increased awareness rather than changes in valuations. However, my findings indicate that customers are responsive

⁵ Other, non-weather related forms of projection bias include exposure to pollution and health insurance (Chang et al. 2018), and gym attendance (Acland and Levy 2015).

⁶ Projection bias has also been discussed as potential driver for hypothetical solar PV adoption and sustainable transport choices in Clot et al. (2022), relying on a survey experiment.

⁷ The fact that FiT is the main policy instrument for residential customers in Germany make the calculations of the expected financial return particularly easy in this setting. This feature allows me to directly relate the impact of individual weather variables on update decisions. This link is not as clear when there is a multitude of policies and different channels through which weather can affect financial return expectations, for example in the case of California, where solar PV production is also related to electricity rates and tariffs through self-consumption and net-metering.

⁸ The German setting presents one of the largest markets for residential solar PV with more than 1.3 million residential rooftop installations in 2020 [see EUPD Research (2021)].

to large exceptional weather periods as well as to smaller deviations from the long-term weather averages, making increased awareness and interaction effects with peers and media unlikely to be the only driver for my results. Furthermore, exceptional sunshine might simply lead to short-term displacement of installations, with little impact on aggregate uptake and overall welfare. Yet, my findings show that short-lived sunshine shocks do have an impact on aggregate sales.

In the energy context, the rationality of consumer choice has been extensively studied by how much consumers ‘undervalue’ fuel economy when purchasing a vehicle and in the context of the ‘energy-efficiency gap’, which describes the idea that even though investment in energy efficient goods is privately beneficial, technology uptake is generally low.⁹ Behavioral biases in consumer decision-making and cognitive limitations in mental accounting have been put forward as potential channels to account for the existence of the energy-efficiency gap.¹⁰ This paper contributes more broadly to the understanding of how behavioral factors can impact the adoption of energy-efficient technologies, such as solar PV panels. In this context, De Groote and Verboven (2019) estimate a dynamic discrete choice model of solar PV adoption in Belgium and show that households are myopic, in a sense that they significantly undervalue the future benefits from solar PV investment. Other papers have found strong evidence for peer-effects in the diffusion of solar PV panels (Bolling and Gillingham 2012; Rode and Weber 2016, see for instance).

Finally, in the context on solar PV adoption in Germany and the role of FiT policies, several papers model the diffusion of residential solar PV panels, with the objective to simulate policy changes in the FiT rates (Baur and Uriona 2018) or to highlight the importance of additional factors, such as geography and demographic factors, in modeling uptake (Schaffer and Brun 2015; Dharshing 2017). Germeshausen (2018) provides causal evidence for the impact of FiT on solar PV adoption, employing a bunching estimator. Concerning the application of behavioral factors on solar PV adoption, peer effects and influence from neighbors have been studied in the German context in Müller and Rode (2013), Rode and Weber (2016), Rode and Müller (2021). Similarly, Klein and Deissenroth (2017) analyze the role of loss aversion on solar PV adoption, relying on a “techno-economic” modeling approach in which they combine a net-present value analysis with prospect theory. They show that their proposed model fits the adoption dynamics well in the German residential sector. I contribute to this literature by testing for behavioral biases such as projection bias and salience in solar PV adoption, relying on rich micro-level data and credible exogenous identification from variations in local weather patterns.

The paper proceeds as follows. Section 2 provides additional institutional details on the German solar PV market and discusses the implications of projection bias and salience on solar PV investment. Section 3 describes the data and empirical strategy. The main results are presented in Sect. 4, while Sect. 5 discusses the findings in light of competing mechanisms. Finally, Sect. 6 concludes.

⁹ Evidence on consumer’s undervaluing fuel economy, see for example: Allcott and Knittel (2019), Anderson et al. (2013), Busse et al. (2013), Sallee et al. (2016). The energy-efficiency gap: Allcott and Greenstone (2012), Jaffe and Stavins (1994).

¹⁰ Allcott et al. (2014), Gillingham et al. (2009), Gillingham and Palmer (2014)

2 Background

2.1 Institutional Setting

Despite its small size and relatively poor insolation, Germany is a world leader in solar PV deployment. In 2013, it accounted for more than 35% of the global operating capacity.¹¹ Solar PV investment in Germany has been privately profitable thanks to the presence of a national feed-in tariff (FiT) scheme. FiTs are long-term contracts between the renewable energy producers and the electric utilities that guarantee access to the electric grid for a period of 20 years and allow producers to sell electricity at a fixed rate, the FiT, set by the policy-maker to guarantee positive investment returns. Germany was the first country to introduce FiTs to residential solar PV investors with the establishment of the *Renewable Energy Act* (Erneuerbare Energien Gesetz, EEG) in 2000. The EEG involves an annual adjustment of FiT rates to account for decreasing solar PV module prices. This ‘degression rate’ is set by the policy maker to keep the overall investment profitability comparable over time. Changes in the FiT affect only new installations and are announced several months prior to the actual adjustment date. Until 2014, it has been profitable for residential solar investors to sell the electricity produced with the solar PV panel (at a high FiT), and to continue purchasing their electricity from retailers (at the residential rate).¹² As a consequence, the presence of FiT led to a low share of households engaging in auto-consumption of electricity produced.¹³

Given these incentives, solar PV investment in Germany led to an internal rate of return of approximately 5–12% over the 20-years period that are guaranteed by FiTs (Andor et al. 2015; Prol 2018). Solar PV panels are usually maintenance free and require little to no follow-up investments. The most common replacements are electric inverters that have a life-expectancy of about 10 years. Battery storage was not widely available to customers during the period 2000–2013, so that the financial return is a direct function of the energy produced (insolation) and the FiT rate. During this period, there have been several amendments to the original EEG, that, however, did not lead to important changes in the investment incentives for residential solar PV adopters. Only a major reform in 2014 changed FiTs fundamentally, introducing growth corridors for renewable energies and a more stringent downward revision of FiTs for new installations.¹⁴ For my analysis, I thus focus on the period 2000–2013 of relatively stable return expectations and will perform robustness checks concerning the years included in the analysis. Even though the market for residential solar PV has grown importantly over this time period, there were no signs of market saturation.¹⁵

¹¹ REN21 (2014), Global Status Report on Renewables. At the end of 2019, Germany has the fourth largest cumulative solar PV capacity in the world after China, the US, and Japan.

¹² Online Appendix Fig. B.1 depicts the average residential electricity rates as well as FIT. In 2007, for instance, the FiT for residential solar PV was 49.21 Eurocents per kilowatt-hour (kWh) electricity, while the average electricity rate for residential customers was 20.6 Eurocents per kWh, including all taxes and levies.

¹³ The Federal Network Agency reports data on self-consumption until 2011. In this year, the share of auto-consumption from solar PV production to total solar PV production was 1.3% (Source: EEG Statistical Report 2011).

¹⁴ The 2014 amendment to the EEG also announced the introduction of renewable auctions for large scale solar PV plants and wind farms.

¹⁵ A recent study on the German residential solar PV market confirms large potential for solar PV adoption even after 2020 (EUPD Research 2021).

A particularity of the solar PV market is that installations need to be handled by qualified installers and require site-specific planning and installation. This market feature introduces a time gap between decision-making and completion of the installation, which will be key to my empirical strategy that I discuss in Sect. 3.2.

2.2 Climatic Conditions, Weather, and Solar PV Uptake

Climatic conditions have an important impact on the profitability of solar PV. Energy produced by a solar module is directly related to the availability of solar energy (radiation), 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 about 1000 to 1400 kWh per square meter and is higher in the South. Panel (a) of Appendix Fig. 4 depicts the average solar radiation in Germany. Panels b–d of the same figure show actual weather averages for sunshine hours, mean temperature, and precipitation during the sample period 2000–2013.

Weather variations might impact decision-making of individuals if they change the way individuals perceive the benefits and costs of solar PV investment.¹⁶ For example, if individuals forecast financial returns from solar PV investment based on observed sunshine, their investment decisions might be overly influenced by the current state of weather in line with projection bias (Loewenstein and Schkade 1999; Loewenstein et al. 2003). Similarly, an exceptionally sunny period may draw the consumer's attention to certain product attributes, such as profitability of the investment. In this case salience (Bordalo et al. 2012, 2013) might affect the adoption decision of the consumer. In the next subsection, I elaborate on the basic framework that explains projection bias and salience and show how they can impact individual solar PV purchase decisions. In the empirical analysis (Sect. 3.2), I identify a behavioral deviation from the rational agent framework by focusing on atypical weather compared to the historical average and follow this framework to relate my results to these behavioral mechanisms.

2.3 Projection Bias and Salience in Solar PV Adoption

Suppose that a person's instantaneous utility depends on two arguments: a consumption good and a state, that parameterizes the tastes of the decision maker. Loewenstein et al. (2003) defines *projection bias* as using current state s to form linear expectations about 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.¹⁷

In the specific case of a durable good purchase, such as solar PV, suppose that a person's valuation in period t is given by the random variable, μ_t that is identically and independently distributed across periods and has a finite sample mean $\bar{\mu}$. The realization of μ_t is known at the beginning of the period and the durable good lasts a total of T periods. Without loss of generality, let us further assume that future utilities are not discounted.

¹⁶ As pointed out by a growing literature in behavioral economics (DellaVigna 2009; Huck and Zhou 2011, see literature surveys in), many individual decisions might deviate from the standard economic model.

¹⁷ *Simple projection bias* is defined as $\tilde{u}(c, s' | s) = (1 - \alpha)u(c, s') + \alpha u(c, s)$, where α measures the degree of the bias, i.e. $\alpha = 0$ implies correct prediction of future utility and $\alpha = 1$ implies fully myopic habits.

More importantly, the durable good does not lead to any utility in the period 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. In this simple example, 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

$$E_1[U_1] = E_1 \left[\sum_{k=1}^T \mu_{1+k} - P \right] = T\bar{\mu} - P.$$

While in the presence of projection bias we have that

$$E_1[\widetilde{U}_1] = E_1 \left[\sum_{k=1}^T [(1 - \alpha)\mu_{1+k} + \alpha\mu_1] - P \right] = T\bar{\mu} + \alpha T(\mu_1 - \bar{\mu}) - P.$$

Clearly, $\mu_1 > \bar{\mu}$ 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 projects 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 case of multiple buying decisions where the consumer can buy at most once in any period $t \in \{1, 2, \dots\}$, a rational person would buy the good in period 1 or never, i.e., she buys if and only if $M\bar{\mu} - P \geq 0$. A high valuation $\mu_H > \bar{\mu}$, implies that $T\bar{\mu} + \alpha T(\mu_H - \bar{\mu}) - P > 0$, or in other words, projection bias can lead to impulse purchases in the case where the buying decision is highly irreversible as it is in the case of solar PV investment.

This model makes several simplifications to the solar PV purchase decision. Most importantly, it abstracts from dynamic purchase considerations that has been highlighted in recent work dealing with solar PV adoption (Bollinger and Gillingham 2019; De Groot and Verboven 2019, see for instance). An advantage of the German setting with a national FiT policy is that financial returns have been on average positive and large over the time period 2000–2013 so that private investments were almost always profitable.¹⁸ This means that even the simple static model is able to highlight how exogenous states, such as weather, may influence investment (purchase) decisions of individuals through biased beliefs.

A related behavioral channel is salience (Bordalo et al. 2012, 2013), which refers to the idea that consumers' attention may be systematically biased towards certain product attributes. When consumers make their purchase decisions and an attribute is very salient, it will receive a disproportionately high weight in the purchase decision, affecting their purchase choice. In the basic model, a good's salient attributes stand out from those of the 'reference good', defined as having the average level of each attribute or choice set. However, this might also be the case for the value of the attribute itself, which might vary over time and causes the attribute's salience to vary (see for instance Hastings and Shapiro 2013). In the

¹⁸ Andor et al. (2015) and Profl (2018) calculate internal rates of return for residential solar PV investment in Germany and confirm that average returns range from approximately 5–12% for self-financed installations. Some individual years (2009–2011) had even higher returns mainly related to drops in module prices due to an expansion in global solar PV supply and an reduction in global demand in the aftermath of the economic crisis. Therefore, during this time period investments were generally profitable. Importantly, in the empirical analysis I include a flexible set of time fixed effects to account for aggregate changes in profitability.

present paper, salience might be related to the product attribute ‘profitability’, i.e., sunshine and related weather variables can make the (financial) investment potential of solar PV more or less salient.

As in the solar PV setting, both projection bias and salience act through profit expectations that are influenced by the weather, I am unable to distinguish clearly between the two channels theoretically. Yet, in my empirical analysis in Sect. 3.2, I will show suggestive evidence that both behavioral mechanisms are likely at play. Projection bias predicts that any deviation, large and small, from the long-term mean will affect the customer’s profit expectations and thus can influence adoption decisions. Moreover, the effects should be similar for positive and negative weather deviations. Salience, on the other hand, is defined with respect to the average good, so larger deviations should lead to stronger impacts. Finding evidence for non-linear weather effects on adoption, and heterogeneity by average solar radiation in the county can provide evidence of salience in addition to projection bias effects.

3 Data and Empirical Strategy

3.1 Data

The empirical analysis is based on three main types of data. First, I employ administrative data on solar PV installations in Germany, which is publicly available from the information platform of the transmission network operator ‘netztransparenz.de’. This data includes information on all grid-connected solar PV installations that receive policy support in terms of FiTs.¹⁹ This dataset provides information on the location of each installation, the date of grid connection (completion of the installation), and the size of each solar PV installation. For the period 2000–2013, the raw data contains close to 800,000 residential installations, defined as solar PV plants with a installed capacity smaller or equal to 10 kilowatt (kW). I aggregate all installations at county-week level and construct a balanced panel data set containing 292,656 observations (402 counties observed for 728 weeks). Appendix Fig. 5 plots the cumulative uptake of residential solar PV, as well as the average number of weekly installations. The figure indicates pronounced seasonality in uptake, coinciding with the annual revisions of the FiT policy.

Second, I obtained official weather data from the German weather service (DWD) and combine the data on solar PV installations with weather data from 115 stations that report daily measures of sunshine, temperature (minimum, mean, maximum), rain, snowfall, and cloud cover, ranging back to the 1960s.²⁰ Appendix Fig. 6 depicts the location of the individual weather stations and shows that these are evenly distributed across Germany. I assign each county to its closest weather station based on the geodesic distance from the county centroid. The median distance from weather station to county centroid is 23 kilometers (km) and the 95th percentile is within 50 km (see Appendix Fig. 7, Panel c). As this

¹⁹ As investment in solar PV during the time period 2000–2013 was highly unprofitable without policy support, this dataset is likely to contain the universe of residential solar PV installations in Germany.

²⁰ Sunshine hours, rain, and snowfall are cumulative measures; cloud cover is an index describing the percentage of visible clear sky. For the analysis, I rely exclusively on these 115 stations that report sunshine duration for the entire period 1961–2013 and whose location has not been altered over time. Similarly, I exclude stations in mountainous areas located at 1000 meters above sea-level or higher.

might lead to potential measurement error in the weather variable, as robustness check, I limit the sample to counties that are within the median distance to the weather station.²¹

Third, I expand these data with a list of additional covariates that can impact solar PV adoption at the county level. I use official data on population, household income, education, unemployment, agricultural surface, as well as the number of newly constructed residential and non-residential buildings. These data are available at the annual frequency from GENISIS, the regional database of the German Statistical Agency. I further complement this information with data from Google trends on web searches for the terms ‘solar PV’ and ‘climate change’, available at the state-month frequency from 2004 onwards. Finally, I obtained data on solar PV prices for residential installations²² and perform a survey with solar installers in Germany to obtain information on their marketing and sales outreach activities. The survey provides also additional insights on the timing of solar PV installations, in particular on the average time gap between first customer contact and completion and the solar PV installation. This survey was conducted in the summer of 2015 through an online questionnaire with a group of solar PV installers covering different local markets in Germany. Overall, I was able to obtain 56 valid responses. While this survey is likely not fully representative of the entire German market, the geographical representation of the installer sample mimics the one from the universe of contacted installers. The sample is mainly composed by professional solar PV installation companies, electricians, and heating and water installers. About half of the companies are small in size with 1–5 employees, while 20% have more than 20 employees. In line with other sectoral surveys²³, I find that installer markets are mainly local and that most commercial activity is concentrated in or around the county of business registration. I discuss more details on the installer survey as well as the results in Online Appendix B.2.

Appendix Table 5 presents summary statistics for the main variables over the sample period 2000–2013. The average county has a population of about 200,000 inhabitants, representing both urban and rural areas.²⁴ While the mean number of residential solar PV installations per county-week is 2.7, there exists strong heterogeneity over time and by region. I plot histograms of key outcome variables in Appendix Fig. 7. Similarly, I provide the spatial distribution of solar PV uptake in Fig. 8.

3.2 Empirical Strategy

I am mainly interested in measuring the impact of *exceptional* weather on solar PV uptake. As weather follows a seasonal trend, a correlation between weather levels and solar PV

²¹ Classical measurement errors in the weather variables might attenuate my main coefficients of interest towards zero. An alternative to weather station data would be to use ‘gridded’ weather data. These type of data is available at the monthly frequency for a 1×1 km grid from DWD and is based on meteorological models. Yet, the low time frequency and spatial dependence due to the underlying meteorological models makes this dataset less attractive for studying adoption decisions.

²² Price data is based on installer bids from an online price comparison website for small-scale solar PV. Households can use this platform to compare personalized offers based on location, rooftop-type, and type and size of solar PV installation from installers from their region. These data are available at county-quarter frequency for the years 2010–2011. The author would like to thank *EUPD Research* for making these data available.

²³ See for instance Muehlhausen Consulting, 2014, last accessed 29 December 2020.

²⁴ German counties (districts) coincide with the official NUTS 3 definition of territorial units in Europe and consist of both cities (*Kreisfreie Stadt*) as well as rural areas (*Landkreis*).

adoption cannot be directly attributed to a behavioral bias. Rather, to identify a behavioral deviation from the rational agent framework, I focus on atypical weather *compared to the historical average* (see Sect. 2.3). To do so, I average daily weather observations at the weekly level and rely on historic data covering the period 1971–2013 to de-mean current weather observations by their long-term historic averages in a given county in a ‘typical’ weather week.²⁵ Using this extended period to define weather normals allows me to capture the extent to which current weather is different from long-term climatic conditions. This is particularly relevant given strong year-on-year fluctuations in weather realizations. The transformed weather variable, e.g. sunshine, will therefore provide me with a useful measure of the intensity of the exceptional weather period compared to the long-term average in a given county. Alternatively, I also consider a binary weather shock measure defined as a weather realization above one standard deviation from the long-term averages in a given region.²⁶

Since I only observe the date of the solar PV installation, the exact timing of the purchase decision is unobserved in my dataset. I use the information from the solar PV installer survey to define the purchase period. Figure 1 plots the histogram for the average time gap between first customer contact and completion of the installation. The average time gap is 9 weeks (median: 8 weeks) with a standard deviation of 5 weeks. This time gap between decision-making and completion of the installation can be mainly explained by customized planning of the installation (which often involves site visits), but also customers soliciting bids from competing installers, given the large financial stake of solar PV investment. Similarly, the installer has to deal with permitting and inspection in addition to the actual installation work.²⁷

In line with this information, I define as the relevant time period the 6–12 weeks prior to the observed installation date, which corresponds to the interquartile range between first customer contact and completion of the installation and label it ‘purchase period’. My main empirical specification tests for the impact of exceptional sunshine and other weather variables during this purchase period on solar PV uptake. In Sect. 4.2, I provide robustness concerning this timing assumption.

I estimate the following linear regression model:

$$y_{c,t} = \alpha + \beta \text{weather}_{c,t=\tau} + \delta_{c,m} + \theta_y + \epsilon_{c,t}, \quad (1)$$

where $y_{c,t}$ is the number of new residential solar PV installations in county c in week t . The variable $\text{weather}_{c,t=\tau}$ describes the average deviation of the weather variable during the

²⁵ I extend the 30-years climate reference period starting in 1971 until 2013 to account for possible climatic differences over time, such as a potential increase in observed mean temperature. Appendix Fig. B.4 plots the distribution of the weather normals for the 30-years international reference period 1961–1990 and my sample 1971–2013, highlighting that only for temperature there have been potential changes over time. The 1971–2013 reference period also leaves me with a sufficient amount of datapoints (43) to calculate the mean and standard deviation of historic weather (climate) distribution for each county \times week.

²⁶ Online Appendix B.3 provides the distribution of annual weather for the main study period and the long-term climatic normals. Similarly, I provide a histogram of the main weather variable, sunshine, together with the distribution of sunshine shocks for both monthly and weekly data aggregation.

²⁷ An earlier survey performed with German installers by Seel et al. (2013) finds that it takes about 38 man-hours per system installation and about 5–10 h for permitting, interconnection and inspection, not considering additional site-specific planning, material availability, and installer workload from the moment of contract signature to the completion of the installation. In another study, Bollinger and Gillingham (2012) found that in California the average time gap between purchase decision and completion of the installation is considerably longer, with a median of 163 days (and greater than 40 days in 99% of the time).

purchase period, e.g. in case of sunshine, deviations in the average sunshine hours from the long-term mean 6–12 weeks prior to the observed installation date. The main regression specification includes county by month-of-the-year and year fixed effects (FEs). These FEs allow counties to follow distinct climatic patterns, i.e. spring might start earlier in some regions than in others, which might impact the installation of solar PV panels. Moreover, year FEs capture aggregate market conditions, such as (national) FiT policy support. I provide robustness concerning the choice of FEs in the appendix, using county and year-quarter FEs that can differ by federal state to further relax the parallel trend assumption. I cluster standard errors at the weather station (115 clusters), to account for potential serial correlation within region and provide robustness for inference using heteroskedasticity and autocorrelation consistent (HAC) standard errors (Conley 1999) that account for both temporal and spatial dependence.

3.2.1 Identification

There are two main identification concerns. The first is regarding the causal effect of weather on solar PV adoption. This effect is identified given the randomness of local weather realizations with respect to their long-term averages (climate). The fact that solar PV installations are highly seasonal makes it necessary to use a flexible set of FEs. The second is whether this effect is driven by behavioral biases. If solar PV installations were instantaneous, finding evidence for additional adoption in an exceptionally sunny period cannot be interpreted as a behavioral deviation from the neoclassical framework. In this case, the investor would be able to increase her return, even though only in the very short-term, by installing solar PV in the same time period. However, in the solar PV setting, there is a time gap from decision-making to completion of the installation. By regressing solar PV uptake on past weather realizations, coinciding with the purchase period, I overcome this issue. The length of the time gap furthermore ensures that there is no contemporaneous correlation between current (and lagged) weather variables and the error term, i.e. $E(\text{weather}_{c,t-i}, \epsilon_{c,t}) = 0$ for all $i \geq 0$.²⁸

Finding evidence that product adoption is correlated with atypical weather is in line with both projection bias and salience. The fact that sunshine (weather) enters directly the perceived financial profitability of the household for solar PV investment means that both behavioral mechanisms would lead to increased product uptake on an exceptionally sunny week. A key difference between the two channels is that salience is usually defined with regard to the ‘average good’, or in the present case regarding the long-term average climate. This implies that if a consumer mostly responds to extreme weather deviations, this should be more closely linked to salience effects regarding the financial profitability of solar PV investment or increased awareness of the technology itself. Additionally, salience can also lead to asymmetric responses in the case of positive and negative weather deviations if positive weather deviations raise awareness in ways negative ones do not. Projection bias, on the other hand, predicts that any deviation from the long-term weather averages will impact product purchase decisions in a linear fashion, as it will impact the customer’s return expectations that are projected into the future and thus can lead to more or less adoption. I proceed by testing for non-linear effects.

²⁸ I provide robustness concerning this assumption by presenting the total cumulative effect over lags 1–12 that might be affected by correlated weather and by including contemporaneous weather as additional control variable.

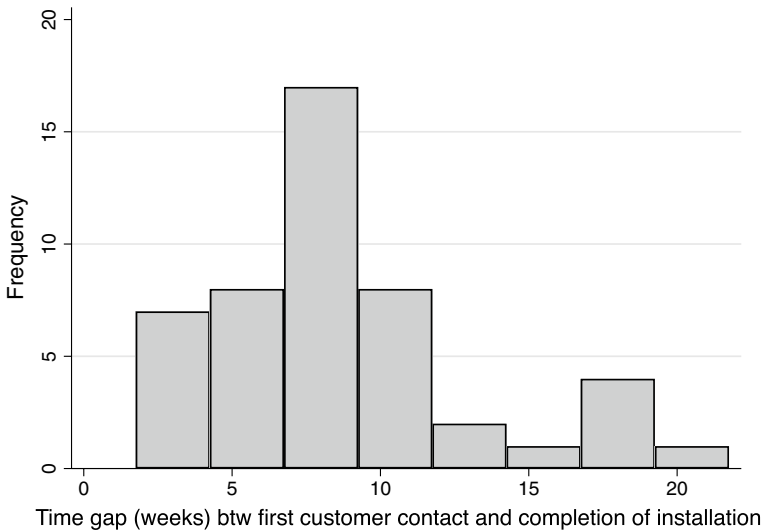


Fig. 1 Solar PV installation timing *Notes* Average time gap from first customer contact to completion of solar PV installation (N=49). Source: solar installer survey. See Online Appendix B.2 for details

To do so, I divide the de-meaned weather variables in equally sized bins and estimate a variation of regression model (1), where I include a separate dummy variable for each bin, $f(weather_{c,t=\tau})$. In specification (2), all coefficients can be interpreted with respect to the long-term averages, which is the omitted category.

$$y_{c,t} = \alpha + f(weather_{c,t=\tau}) + \delta_{c,m} + \theta_y + \epsilon_{c,t} \tag{2}$$

Finally, to study heterogeneous responses with regard to the average solar radiation (profitability) in a county, I use information on the long-term solar radiation and split the sample according to different cutoff rules (median, 25th percentile (pct), 10th pct, 5th pct) in counties with high and low average sunshine radiation and label them ‘high’ and ‘low’ return. In the regression, I interact the main sunshine variable with the dummy identifying ‘low return’ counties for the different definitions and otherwise follow Eq. (1).

Given the fixed nature of FiT, the financial profitability of solar PV investment is fully driven by the amount of electricity produced and thus the amount of sunshine received. If weather is mistakenly seen as a signal for investment profitability, exceptional sunshine in a region that on average receives little sunshine might be perceived differently than in an area that is very sunshine rich, i.e., in line with the definition of salience, the difference of the experienced weather to the average weather are more pronounced, and thus salience of the profitability and product awareness might be stronger.

In summary, even though in this empirical setting it is not possible to fully disentangle the two channels, the presence of non-linear responses to positive and negative weather deviations as well as heterogeneous effects allows me to show that both salience and projection bias are likely present. In Sect. 5, I elaborate on alternative mechanisms that could potentially explain the impact of sunshine on solar PV uptake.

Table 1 Weather deviations and solar PV uptake

	(1)	(2)	(3)	(4)	(5)	(6)
Sunshine	0.124*** (0.013)				0.116*** (0.014)	
Temperature		0.048*** (0.007)			0.013+ (0.008)	0.012 (0.009)
Precipitation			- 0.141*** (0.021)			
Cloudcover				- 0.253*** (0.034)		- 0.243*** (0.037)
SD of main weather variable	1.023	1.498	0.883	0.639	-	-
Semi-elasticity	0.047	0.026	- 0.046	- 0.059	-	-
Observations	287,832	287,832	287,832	287,576	287,832	287,576
R ²	0.276	0.276	0.276	0.276	0.276	0.276
Year FE	Y	Y	Y	Y	Y	Y
County-MoY FE	Y	Y	Y	Y	Y	Y

Dependent variable: Number of small scale (≤ 10 KW) solar PV installations. Unit of observation is county-week. Main weather variables are defined as average deviations from the long-term (1971–2013) mean, measured 6–12 weeks prior to solar PV completion date. Robust standard errors clustered at weather station in parenthesis. $p < 0.1$ (+), $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

4 Results

4.1 Main Results

Table 1 presents the first set of results, regressing solar PV installations in week t on the average weather deviations from the long-term mean 6–12 weeks prior to the installation date corresponding to the purchase period. Columns (1–4) present separate regressions for individual weather variables and Columns (5) and (6) use joint weather variables. In these last two specifications, I test jointly for sunshine and temperature as well as temperature and cloud cover, as correlation of these variables might be changing over the seasons.²⁹

Column (1) finds a positive and statistically significant effect (p -value < 0.001) of lagged sunshine during the purchase period on solar PV uptake. As the main weather variables are measured as average deviations from the long-term mean, an intuitive way of interpreting the coefficients is to express them in a standard deviations increase of the respective variable. According to my estimates, a one standard deviation (1.02 h) increase in the average de-measured sunshine during the purchase period will lead to 0.127 additional solar PV installations per week (0.124×1.02). This represents an increase of 4.7% when evaluated at the average number of weekly installations of 2.73, reported as semi-elasticity in Table 1.

Similarly, the table reports the point estimates and semi-elasticities for a one standard deviation increase in other key weather variable such as temperature, precipitation, and cloud cover. The largest absolute impact corresponds to cloud cover, equal to -5.9% . The effect of precipitation is similar to that of sunshine in Column (1), but with a negative sign, suggesting that these two weather variables might cancel out over time. I directly test for aggregate effects of these variables in Sect. 4.3 and find that the sunshine effect persists in aggregate data. Finally, temperature deviations have a small positive impact on solar PV installations. However, once controlling for sunshine or cloud cover in Columns (5) and (6), the effect of temperature is no longer statistically significant. Taken together, these findings point mainly to sunshine, or lack thereof, as the variable affecting residential solar PV uptake decisions.

4.2 Robustness for Main Findings

I check the robustness of my main findings concerning the inclusion of additional control variables, alternative fixed-effect structure, and functional form assumptions. Similarly, I vary the length of the purchase period and keep only counties within the median distance to the weather stations, to minimize potential measurement error. Finally, I perform sample splits to account for reforms of the *Renewable Energy Act*, and test for valid inference. The main results are robust to all of these checks. I elaborate briefly on the main implications here, but present the corresponding tables in the appendix.

One potential concern is that weather deviations during the purchase period might be correlated with other time-varying variables and contemporaneous weather. I show in Appendix Table 7 that the results are unaffected by the inclusion of additional control

²⁹ Sunshine and temperature are typically positively correlated throughout most of the year. Yet, this correlation can be negative in cold winter months. The reverse is true for temperature and cloud cover. Appendix Table 6 provides a correlation table for key weather variables over the sample period.

variables (population, newly constructed residential buildings, and household income) and contemporaneous weather (sunshine, temperature, and precipitation).

A related concern is that weather during the waiting period might impact product uptake as shown in Liao (2020). If a sunny period during the purchase time is followed by poor weather, this might lead to contract cancellations before the installation is completed. Yet, given the average profitability of investment discussed in Sect. 2.1, cancellations are less likely in the German setting.³⁰

Another concern is that my results depend on the definition of the purchase period and might be affected by measurement error in the weather data. Tables 8 and 9 provide robustness, using as alternative definition of the purchase period weeks 8–10 prior to the observed installation date and keep only the counties within the median distance to the weather station, respectively. All results remain robust. Moreover, as the main dependent variable in the regressions refers to the number of new solar PV installations, I perform a robustness check concerning the count-data nature of this variable, employing a log-transformed dependent variable (Table 10) and a non-linear count data model estimated by poisson pseudo-maximum likelihood (Table 11). I also show that the results are robust to an alternative FE structure (Table 12), where I employ state-year-quarter FEs. This flexible relationship allow for the possibility that mid-year FiT adjustments might impact solar PV uptake and that individual states follow distinct growth trajectories. Again, all these results are robust to these robustness checks.

Finally, I run the regression analysis for distinct time periods, given reforms of the *Renewable Energy Act* and changes in the underlying FiT regulation in 2004 and 2012 (Table 13). The main sunshine and cloud cover coefficients are unaffected by the choice of the sample period. Concerning inference, I test for spatial and temporal correlation in the error term in Table 14, where I employ HAC standard errors (Conley 1999).³¹ While the standard errors are larger in this specification, the main effects remain statistically significant at 5% for sunshine and at 1% for precipitation and cloud cover.

4.2.1 Causal Interpretation of the Findings

In order to provide additional evidence for a causal interpretation of my main findings, I take advantage of two distinct features of my data. First, I estimate Eq. (2) for large solar PV installations (> 500 KW). These type of solar PV plants are typically contracted by profit-maximizing investors, such as solar developers or electric utilities. I therefore do not expect to find similar behavioral responses to weather variables such as sunshine or cloud cover.³² The results, presented in Appendix Fig. 9, show that in this case there is no effect of weather on the uptake of these large solar PV plants.

³⁰ Thanks to generous FiT policies, solar PV investment has been generally profitable in Germany (Prol 2018), so regret decisions might be less common. While my data does not allow me to observe cancellations prior to completion of the installation, anecdotal evidence suggests that these are low. In California, about 12% of all contracts are cancelled (Liao 2020). This might be related to the fact that most residential solar PV investments led to negative expected returns prior to 2010 (Borenstein 2017).

³¹ I allow for up to 6 weeks of intertemporal correlation and spatial correlation for up to 300 kilometers (km). Germany's surface is approximately 600 × 800 km. The presence of mountain areas lead to regional and local weather patterns—see also Appendix Fig. 4.

³² For large installations, I do not observe the average lead time. In my analysis, I therefore assume a similar time gap of 6–12 weeks in line with the main specification. In case the lead time for large installations is longer, my regression still represents an important robustness check, to test for spurious correlation between weather and solar PV adoption.

Second, I exploit variation in the start and end dates of summer school holidays across federal states of Germany in a difference-in-differences setting similar to von Bismarck-Osten et al. (2022). German states have a standing tradition for differences in their summer holiday schedules to avoid overcrowding of travel infrastructure (see Appendix Table 15 vacation dates in 2013). I use these differences to show that when exceptional sunshine periods coincide with the main summer vacation period, they tend to have a smaller effect on solar PV installations. This is consistent with the fact that households travel during this period and are less likely to observe local weather patterns in their home region. As this effect might be also explained by the closure of installer businesses during the summer period, I test for the contemporaneous effect of sunshine on installations. The main hypothesis is that good weather does lead contemporaneously to more installations in case installer businesses are operating. This effect can be explained by installer rooftop access that is mostly possible during good weather periods, i.e., not during weeks with heavy rainfall or unstable weather conditions. The regression results are presented in Appendix Table 16. Column (1) shows that the interaction term for sunshine during the purchase period and summer vacation is negative and highly statistically significant, indicating that during this period, sunshine deviations lead to a smaller impact on solar PV uptake compared to regions where there are no vacations. Column (2) tests for contemporaneous sunshine and finds a positive and significant interaction effect between the two variables, in line with installer rooftop access that might only be possible during good weather periods. To summarize, these findings indicate that the results in Column (1) are most likely driven by a customer response to exceptional sunshine. I further elaborate on possible supply-side responses to weather deviations in Sect. 5.2.

4.3 Aggregate Impact of Sunshine on Solar PV Investment

While the analysis so far provides robust evidence for a causal link between short-lived weather deviations and residential solar PV uptake, it is not clear if these events translate to aggregate sales effects in case ‘harvesting’ is present, i.e., sunshine deviations might just lead to inter-temporal displacement of installations that would have occurred anyways. To test for this hypothesis, I focus on the effect of discretized sunshine shocks, defined as sunshine realization at least one standard deviation above the long-term mean, on solar PV uptake with monthly data aggregation.³³ I estimate a variation of equation (1) in which I replace the main weather variable with current and lagged measures of the sunshine shock variable, but otherwise include the same set of fixed-effects. To test for potential anticipation of sunshine shocks, I also include one lead into the regression equation. The results are depicted in Fig. 2.

I find that the sunshine shocks up to lag 2 are positively correlated with solar PV uptake. Further lags are typically negative or zero in line with some harvesting effects. To address the importance of inter-temporal substitution of purchases in line with harvesting, I sum the coefficients related to the distributive-lag model, similar to Busse et al. (2015) and Deschenes and Moretti (2009). Adding up the individual coefficients, I find that over the

³³ To aggregate weekly data at monthly frequency, I define a sunshine shock as a month in which at least two weeks qualify as exceptional in line with the standard deviation definition. This applies to 3.8% of observations. Online Appendix Fig. B.3 provides further background on the long-term (1971–2013) distribution of key weather variables as well as weather realizations for individual years in my sample.

seven months period an exceptional sunshine shock leads to an aggregate effect of 2.3 additional installations per month, which evaluated at the average number of monthly installations of 11.8 translates to a 19% increase. This large effect is clearly a combination of demand and supply-side factors.

However, given the average time gap from first customer contact to completion of the installations (see Fig. 1), I can be almost certain that sunshine shocks do not lead to additional solar PV demand and completion of the installation within the same month. Evaluating thus the impact of all lagged sunshine shocks, I find a similar increase in solar PV demand compared to my weekly analysis of 5.1%.³⁴ Taken together, these findings indicate that the total effect can be unlikely explained by harvesting and supply-side effects alone and that short-lived sunshine shocks can have an impact on aggregate solar PV uptake.³⁵ Finally, I also find no evidence that households can predict future sunshine shocks, as indicated by the zero effect for the lead that is close to zero and not statistically significant in Fig. 2.

4.4 Summary of Results

The previous sections have provided evidence on the causal impact of sunshine on solar PV adoption decisions in line with theoretical predictions of projection bias and salience. The size of the bias is comparable to previous papers that study projection bias in consumer decision-making, e.g. Chang et al. (2018) finds that a standard deviation increase in daily air pollution leads to a 7.2% increase in the number of insurance contracts sold that day. Busse et al. (2015) shows that a snow storm of approximately 10 inches will increase the fraction of four-wheel drive vehicles by about 6% over a period of two to three weeks. Similarly, in the solar PV context, Liao (2020) shows that a one standard deviation decrease in solar radiation is associated with a 7.1–9.8% increase in solar PV cancellations. The present study focuses on the sales effect of sunshine and related weather variables on solar PV adoption decisions. My findings indicate that exceptional sunshine during the purchase period translates into an approximate increase of 4.7% in solar PV installations in the short-run. When looking at aggregate effects by month, I confirm that weather shocks can lead to new installations. The next section discusses more closely the underlying mechanisms as well as alternative explanations that might lead to similar data patterns.

³⁴ To contrast these findings, I run the weekly analysis with current and lagged sunshine deviations and sunshine shocks (see Appendix Fig. 10). I find that the main impact of sunshine on solar PV uptake can be found at weeks (lags) 9 and 10, in line with the data from the installer survey. Moreover, I find a significant effect for the sunshine shock at impact, indicating that this measure might be more likely to pick up factors related to the feasibility of the solar PV installation, such as an exceptional sunny period in the winter months.

³⁵ As alternative strategy, I aggregate the data further at the annual frequency and leverage the differences in the exposure to sunshine shocks across countries to regress a binary variable for high 'exposure' (defined by either the median or the 75th percentile) on solar uptake. This effectively compares the impact of sunshine and precipitation in 'high' and 'low' exposure counties. I find that sunshine shocks lead to a larger effect compared to precipitation shocks and that this difference is robust to the definition of high exposure county, indicating that sunshine shocks can have an important impact on aggregate solar PV uptake. The detailed regression results are provided in Appendix Table 17.

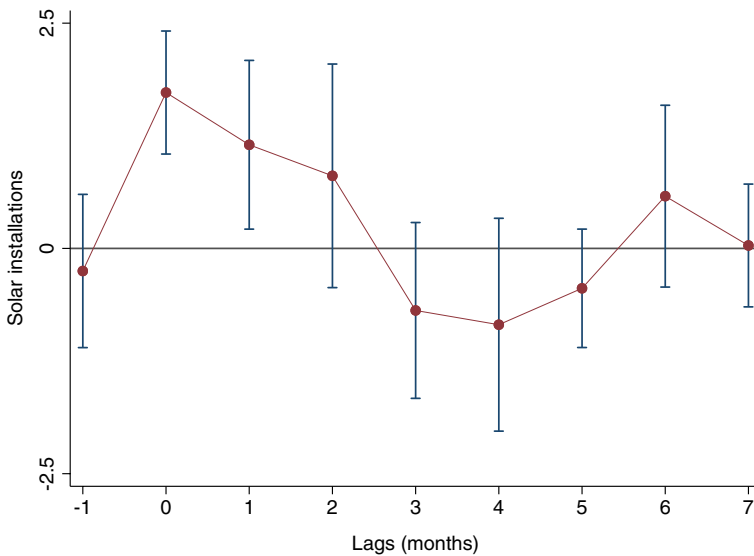


Fig. 2 Aggregate impact of sunshine, timing *Notes* Each marker represents the coefficient and the 95% confidence interval for a regression of residential solar PV installations on current and lagged sunshine shocks, defined as two weeks with sunshine realization one standard deviation above the long-term (1971–2013) mean. The regression model otherwise follows Eq. (1). Unit of observation: county-month. Robust standard errors are clustered by weather station

5 Discussion of Potential Mechanisms

5.1 Behavioral Channels

5.1.1 Heterogeneous Response to Sunshine Deviations

I begin by testing if the main sunshine effects differs across regions depending on the average financial return, using information on the long-term solar radiation. The findings are presented in Table 2. In Column (1), where ‘low return’ is defined as below the median, the interaction term is not significant. Interestingly, as I lower the cutoff to 25th, 10th, and 5th percentile, the coefficient on the interaction term becomes large and statistically significant. I interpret this as evidence that the signaling value of exceptional sunshine is likely higher in areas that on average receive less sunshine radiation and that in these counties, sunshine can lead to additional installations. Another possible explanation in finding a larger interaction effect for the ‘low return’ counties is that an exceptional sunshine period might lead to increased awareness of solar power and that this potentially expands the customer base. While this is especially true for ‘low return’ counties, the fact that the main sunshine effect is positive and significant across all columns indicates that changes in the customer base are likely not the main driver for my overall results.

Table 2 Heterogeneous response to sunshine deviations, investment profitability

	(1)	(2)	(3)	(4)
Sunshine	0.132*** (0.018)	0.113*** (0.014)	0.116*** (0.013)	0.119*** (0.012)
Sunshine × Low return: p50	- 0.015 (0.022)			
Sunshine × Low return: p25		0.044* (0.019)		
Sunshine × Low return: p10			0.079*** (0.022)	
Sunshine × Low return: p5				0.110*** (0.030)
Observations	287,832	287,832	287,832	287,832
R ²	0.276	0.276	0.276	0.276
Year FE	Y	Y	Y	Y
County-MoY FE	Y	Y	Y	Y

Dependent variable: Number of small scale (≤ 10 KW) solar PV installations. Unit of observation is county-week. Main weather variables are defined as average deviations from the long-term (1971–2013) mean, measured 6–12 weeks prior to solar PV completion date. Robust standard errors clustered at weather station in parenthesis. $p < 0.1$ (+), $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

5.1.2 Non-linear Effects

As mentioned in Sect. 3.2, non-linear effects are more consistent with salience than projection bias. I test for non-linear effects and show the results in Fig. 3. Each subfigure plots the coefficients and 95% confidence intervals for individual bins of the weather variable, e.g., de-meaned sunshine. The omitted category is the bin that contains zero, so the regression coefficients can be interpreted with respect to the historic averages. The mean values for each bin are reported in the horizontal axes. Focusing first on sunshine, on the top left panel, I find that large positive and negative deviations during the purchase period have a significant impact on solar PV uptake. Yet, positive deviations show larger effects than negative ones. For temperature, on the top right, I find that exceptionally cold temperatures lead to fewer adoptions, while I do not find any significant effects for positive deviations. Cloud cover and precipitation, on the other hand, show a mirror image of sunshine with higher cloud cover (precipitation) leading to less solar PV adoption.

These findings indicate that likely both projection bias and salience are at play. If households project solar PV profitability based on current weather into the future, their adoption decisions are overly influenced by the weather during the purchase period. Projection bias predicts that also smaller deviations from the long-term mean would impact adoption decisions, for which I find clear evidence in case of cloud cover and precipitation. I find evidence that both positive and negative deviations from the long-term mean might impact adoption decisions, leading to more and less uptake, respectively. The fact that these effects are non-linear indicate that other mechanisms such as salience and increased product awareness might be present for more extreme weather deviations.

5.2 Supply Versus Demand Response to Sunshine Deviations

As my analysis focuses on market-level outcomes, one concern is that exceptional sunshine can have an impact on solar PV installations through a supply side response. Solar PV installers may, for example, observe good weather periods and adopt marketing strategies to increase sales. I provide several indirect tests that this channel is not likely to explain the

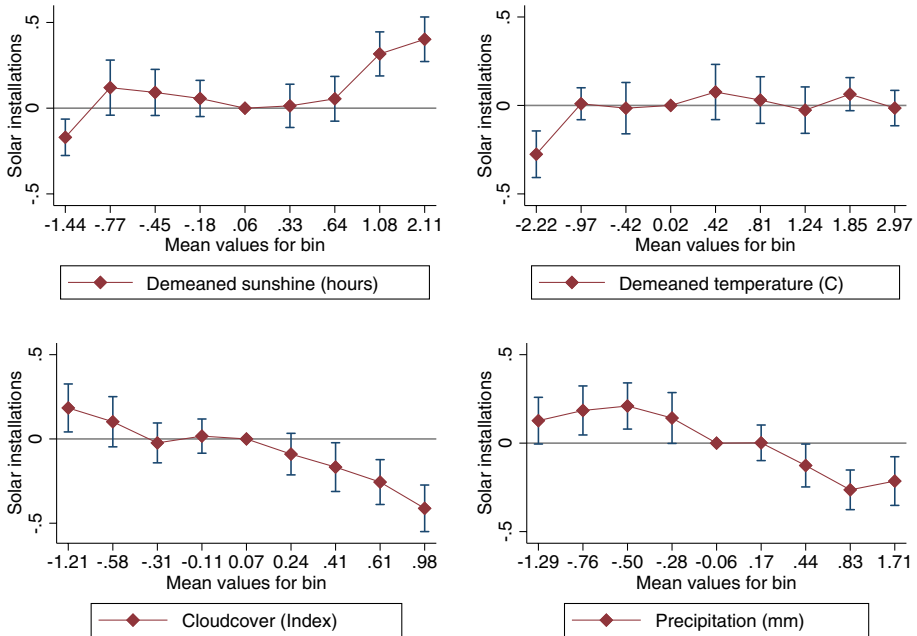


Fig. 3 Non-linear effect of weather on solar PV uptake *Notes* Each plot presents the coefficients and 95% confidence interval for a regression of residential solar PV installations on binned weather observations, defined as deviations from the long-term (1971–2013) averages during the purchase period. Unit of observation: county-week. Robust standard errors are clustered at weather station

main effects I find. First, I obtain additional data from online search behavior and find that exceptional sunshine during the purchase period is related to increased information search for the term ‘solar PV’ which may lead to increased solar PV adoption. Second, using detailed installer bid prices, I show that exceptional sunshine is not related to any price discounts. Finally, I collect primary data on solar PV installer marketing activities through an online survey to show that marketing campaigns are typically not adjusted to the weather.

To test for online search behavior, I use data from google trends concerning the search intensity for the terms ‘solar PV’ and ‘climate change’.³⁶ An increase in online search for the term ‘solar PV’ is a clear indication of consumer interest in solar PV panels. I also obtain the same series for the search term ‘climate change’ to test for a potential alternative mechanism, namely, households beliefs about how climate change affects solar PV profitability.³⁷ Following the same definition of the purchase period, I average the online search intensity at the time of decision making.³⁸ This timing alleviates potential endogeneity concerns regarding solar adoption and information search.

³⁶ Source: Google trends. This data is available at the monthly frequency from 2004 onwards. Online search intensity is reported as a normalized index ranging from 0 to 100 in each of the 16 federal state. I weight the individual series by the total search intensity (Germany-wide) over the sample period 2004–2013, to create a measure that is comparable across states.

³⁷ Solar PV installations might also directly affect the belief of households about climate change. Beattie et al. (2019) study the effect of residential solar PV installations on climate change beliefs in Australia and find that visible mitigation actions have a positive impact on belief in basic climate science.

³⁸ As this data is available at monthly frequency, I use the average online search intensity 2–3 months prior to the observed completion date of the solar installation, aligned with the sunshine deviations.

Table 3 Weather deviations and online information search

Dependent variable	(1)	(2)	(3)	(4)	(5)
Solar PV installations					Google: Solar PV
Sunshine	0.114*** (0.015)		- 0.372*** (0.083)		0.205*** (0.014)
Temperature		- 0.002 (0.009)		- 0.076+ (0.046)	
Sunshine × Google: Solar PV			0.009*** (0.001)		
Temperature × Google: Solar PV				0.002 (0.001)	
Google: Climate change	0.001 (0.002)	0.002 (0.002)			
Google: Solar PV	0.066*** (0.007)	0.067*** (0.007)	0.064*** (0.007)	0.066*** (0.008)	
Observations	203,814	203,814	203,814	203,814	203,814
R ²	0.336	0.335	0.336	0.335	0.731
Year FE	Y	Y	Y	Y	Y
County-MoY FE	Y	Y	Y	Y	Y

Dependent variable: Number of small scale (≤ 10 KW) solar PV installations. Unit of observation is county-week. Main weather variables are defined as average deviations from the long-term (1971–2013) mean, measured 6–12 weeks prior to solar PV completion date. Sample: 2004–2013. Google variables refer to the search terms from google trends for 'climate change' and 'solar PV', measured during the purchase period. Robust standard errors clustered at weather station in parenthesis. $p < 0.1$ (+), $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

The results are reported in Table 3. Columns (1) and (2) show the main sunshine and temperature regressions (similar to Table 1), controlling additionally for online information search for both terms ‘solar PV’ and ‘climate change’. While the main effect for sunshine is unaltered by the inclusion of these controls, the effect for temperature is close to zero and no longer statistically significant. Also, only the coefficient on google search ‘solar PV’ is statistically significant and of economic importance consistent with the idea that lagged search behavior on solar PV is related to adoption decisions.³⁹ To further elaborate on the interaction effects of sunshine and consumer search, Columns (3) and (4) interact the main sunshine and temperature variables with the google search term for ‘solar PV’ and find evidence that more online search in a sunshine rich period is related to increased solar PV uptake, while this is not the case for temperature. Finally, I directly test for the impact of sunshine deviations on the online search intensity for the term ‘solar PV’ in Column (5) and find that a standard deviation increase in sunshine (1.023 hours) is contemporaneously related to an increase in approximately 0.4% of the total search intensity, when evaluated at the average value of 50.67. The search intensity for the term ‘climate change’ is not statistically significant, indicating that climate change beliefs are likely not one of the main drivers for residential solar PV investment. Overall, these findings are in line with the hypothesis that exceptional sunshine relates contemporaneously to more information search for ‘solar PV’, which translates into a positive uptake of solar PV.

One alternative explanation is that there is a third variable, namely solar installer activity, that might drive online search behavior and installations during sunshine rich periods. To elaborate on this potential confounder, I regress solar PV prices on sunshine shocks to test if sunshine rich periods correlate with price discounts and additionally obtained data on installer marketing and sales activities. Price data is based on installer bids for residential customers from a large online solar PV platform, which allows me to compare prices for similar installations in each quarter for the years 2010 and 2011. The original data contains 8881 individual price bids, which I aggregate at the county-quarter level. A histogram of the price data is provided in Appendix Fig. 7, Panel (d). I provide additional information on the installer marketing activities in Online Appendix Sect. B.2, where I discuss the installer survey.

Given the quarterly frequency of the price data, I define sunshine shocks as a quarter with at least two weeks of exceptional sunshine (above the standard deviation of the long-term mean) and start by replicating the main results for solar PV adoption with quarterly data for the reduced sample 2010 and 2011. To account for different regional uptake over time, I include county-by-year fixed effects. The main results are reported in Table 4. Columns (1) and (2) show that sunshine shocks are positively correlated with solar PV installations in the same quarter. This finding is consistent with the monthly estimates presented in Sect. 4.3. Focusing on solar PV prices in Columns (3) and (4), I find that sunshine shocks in the same quarter are correlated with higher prices ($p < 0.1$). This might be explained by the fact that sunshine shocks lead to an increase in overall demand. My estimates show that a sunshine shock in Column (3) leads to an approximate increase of 2% in the average solar PV system price. Overall, these findings suggest that sunshine shocks are not correlated with installer price promotions, rather that increased demand during sunshine rich periods can lead to higher prices.

In addition to price adjustments, installers might alter other components of their marketing mix. However, evidence from the installer survey suggests that this is not the case.

³⁹ This fact is also in line with the installer survey that highlights that most customers contact an installer once they have decided to install solar PV. (see Panel (d) of Online Appendix B.2.

Most solar PV installers in Germany are small businesses that do not engage in large marketing campaigns, but rather rely on word-of-mouth for customer acquisition (see Online Appendix Panel (c) of Fig. B2). The survey also suggests that 75% of installers do not have specialized sales or marketing personnel and that most installers do not adapt their outreach activities to the season (65%) or to the weather (87%). Moreover, only 20% of respondents seem to engage in direct customer outreach activities.

Most important driving forces for installing solar PV are financial considerations with 75% of installers mentioning these factors to be important or very important in their discussion with potential customers. While the adjustment of the FiT schedule can lead to large increases in demand, two third of the respondents mention that the average time gap from first customer contact to completion of the installation does not change over the quarters of the year. I provide additional insights from the installer survey in Online Appendix Sect. B.2. Overall, the survey suggests that installers do not systematically use weather to increase marketing or outreach activities.

5.3 Alternative Explanations

5.3.1 Myopia and Present Bias

Consumer myopia (O'Donoghue and Rabin 1999; Laibson 1997) can lead to similar theoretical predictions as projection bias. However, in this context consumers do not receive financial returns at the time of their purchase. Evidence that an exceptionally sunny period leads to additional solar PV installations 6–12 weeks later is difficult to reconcile with consumer myopia given the high upfront investment cost of solar PV. Myopia could thus only rationalize the findings for very large discount rates or in case weather would be very persistent. The fact that I focus on deviations from long-term weather averages as well as sunshine shocks make this explanation less likely.

5.3.2 Learning

Another concern is that consumers might learn from exceptionally sunny periods about future weather and climate conditions. However, as shown in Fig. 2, sunshine shocks do not carry information for future sunshine events. Similarly, Online Appendix Fig. B.4 shows that long-term averages for sunshine and related weather variables are very comparable for the 30-years climate reference period 1961–1990 and the expanded period 1971–2013, which I use to determine the weather normals in my data.⁴⁰ Moreover, given data availability on average solar radiation, it is easy for rational agents to form expectations on average investment profitability in a setting with a FiT policy. 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. Solar PV might be, for example, more 'visible' on a sunny day (Bollinger et al. 2022; Rode and Müller 2021). This type of learning, however, implies a behavioral response that is very closely related to salience. As I do find that also smaller deviations from the long-term weather averages can impact adoption decisions (Fig. 3), the total effects cannot be likely fully explained by learning about the existence of the technology.

⁴⁰ The only variable that shows an increase over time is temperature, with higher mean temperatures for most weeks of the year.

Table 4 Price and quantity response to sunshine shocks

	(1)	(2)	(3)	(4)
	Solar installations		Price per KW	
Sunshine shock	29.845*** (8.286)	29.868** (10.959)	57.568+ (34.039)	76.446+ (45.976)
Lag sunshine shock		17.831 (11.369)		24.036 (36.600)
Mean of DV	96.873		2656.449	
Observations	1818	1568	1818	1568
R ²	0.520	0.553	0.720	0.713
County-Yr FE	Y	Y	Y	Y

Dependent variable (DV): Number of small scale ($\leq 10\text{KW}$) solar PV installations. Unit of observation is county-quarter. In line with the aggregate analysis, weather shocks are defined as two weeks with sunshine realization one standard deviation above the long-term (1971-2013) mean. Robust standard errors clustered at weather station in parenthesis. $p < 0.1$ (+), $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

Finally, the literature has highlighted the role of social learning and peer effects (Bollinger and Gillingham 2012; Gillingham and Bollinger 2021, see for instance) for solar PV adoption. Yet, the general result is that typically peer effects do not have an effect until the solar PV panels have been installed. Given the time window between purchase decision and completion of the installation, in case exceptional sunshine leads to new installations, these are second-order effects and would only show up weeks after the adoption triggered by sunshine. These additional effects might impact the long-run estimates in Fig. 2, but should not invalidate the direct effects of sunshine and related weather on uptake.

5.3.3 Climate Change Beliefs

Individual beliefs about future climate might be affected by current weather conditions. The behavioral climate change literature (Deryugina 2013; Li et al. 2011) has shown that current temperatures can have an impact on climate change beliefs. However, this literature points typically to a relationship between exceptional temperature and climate change beliefs. As I do not find a systematic effect of temperature on solar PV investment, and additionally I do not find any significant relationship between the online search for the term ‘climate change’ and solar PV adoption (Table 3), climate change beliefs do not seem to be the main driver for my results.

5.3.4 Biased Weather Forecasts

One potential shortcoming of the data is that I am unable to distinguish between consumers showing signs of projection bias and salience regarding future weather conditions or regarding profit expectations of solar PV. This is especially true in the context of German FiT policy, where the only uncertainty regarding the financial profitability is related to the future weather and climatic conditions. While this does not invalidate my overall findings, it is relevant when thinking about the external validity of the results, i.e. are these behavioral biases only present in the case of weather (individuals mis-predicting their local weather and climate) or when predicting financial returns more generally.

6 Conclusion

This paper provides evidence that an important household investment decision, namely the decision of a household to adopt solar PV panels, is affected by behavioral economic phenomena in line with projection bias and salience. Using administrative data on solar PV installations in Germany, I show that exceptionally high sunshine during the purchase period can lead to an approximate increase of 4.7% in solar PV installations in the short-run. I find evidence that both large and small deviations from the long-term weather mean affect adoption decisions. Furthermore, the responses to positive and negative deviations from the long-term mean are asymmetric and heterogeneous by the average profitability in the county. These are suggestive that both projection bias and salience are present in this context.

Market equilibrium outcomes, such as product adoption, involve both demand and supply responses. Thus, an important concern is that some of these effects are driven by supply-side factors. In this paper, I am able to incorporate additional data on solar PV prices, marketing and sales installer activities, and online search data. Using these, I provide evidence that supply-side factors are not likely a main driver of the observed weather responses.

This research highlights an important new channel in solar PV diffusion that might interact with other mechanisms, such as social learning and peer effects. My findings highlight that the weather can have an important impact on how individuals perceive the financial profitability of solar PV, ultimately affecting adoption decisions. Therefore, the effectiveness of information provision might be improved if aligned with the weather, i.e., information campaigns should not be run during particularly poor weather periods.⁴¹ This might be especially relevant in the context of solar PV adoption in the ongoing transition towards renewable energies, given ambitious climate change goals of national governments.⁴²

Appendix: Additional Figures and Tables

See Figs. 4, 5, 6, 7, 8, 9, 10 and Tables 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17.

⁴¹ In another context, Tiefenbeck et al. (2018) provide evidence on how to potentially overcome salience bias in energy-intensive behavior, using real-time feedback.

⁴² The German government recently announced an acceleration of the renewable energy expansion, with a new renewable energy target of 80% in total electricity consumption by 2030. See German Bundestag, 12 May 2022. Last accessed: 28 June 2022.

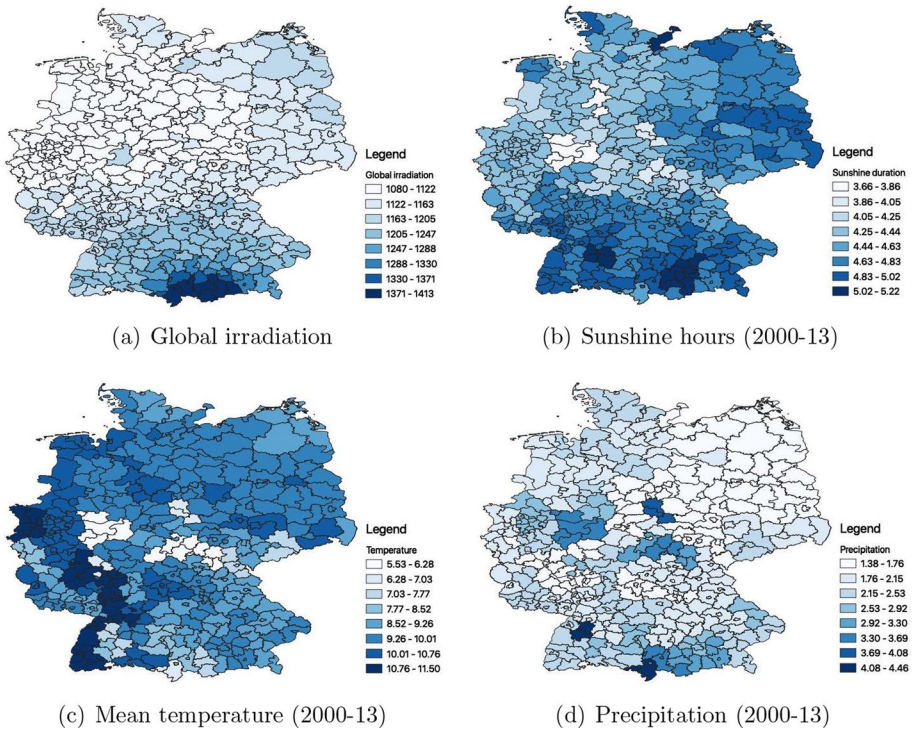


Fig. 4 Spatial distribution of weather and climatic variables *Notes* Panel **a** shows the the distribution of long-term solar radiation in Germany measured in kilowatthours (kWh) per square meter. Panels **b–d** show the distribution of actual weather variables over the sample period 2000–2013: average daily sunshine hours, average daily mean temperature (in degrees Celsius), and average daily precipitation (in millimeters), respectively. Darker areas represent higher values

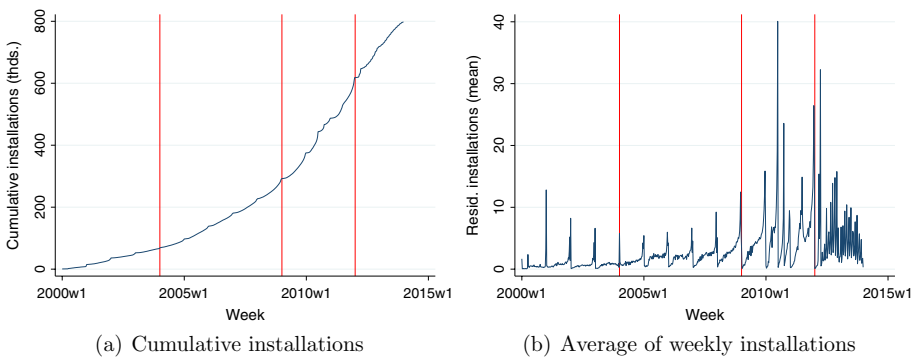


Fig. 5 Solar PV installations over time *Notes* Cumulative (Panel **a**) and average (Panel **b**) number of residential solar PV installations (≤ 10 KW) over the sample period 2000–2013. Unit of observation: week. Vertical lines indicate revisions of the *Renewable Energy Act* in 2004, 2009, and 2012

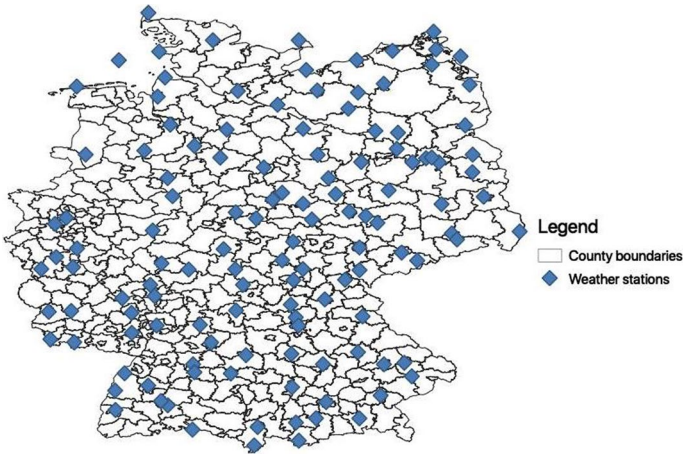


Fig. 6 Location of weather stations *Notes* Location of weather stations with a historical record 1961–2013 for daily sunshine hours. Source: German Weather Service (DWD)

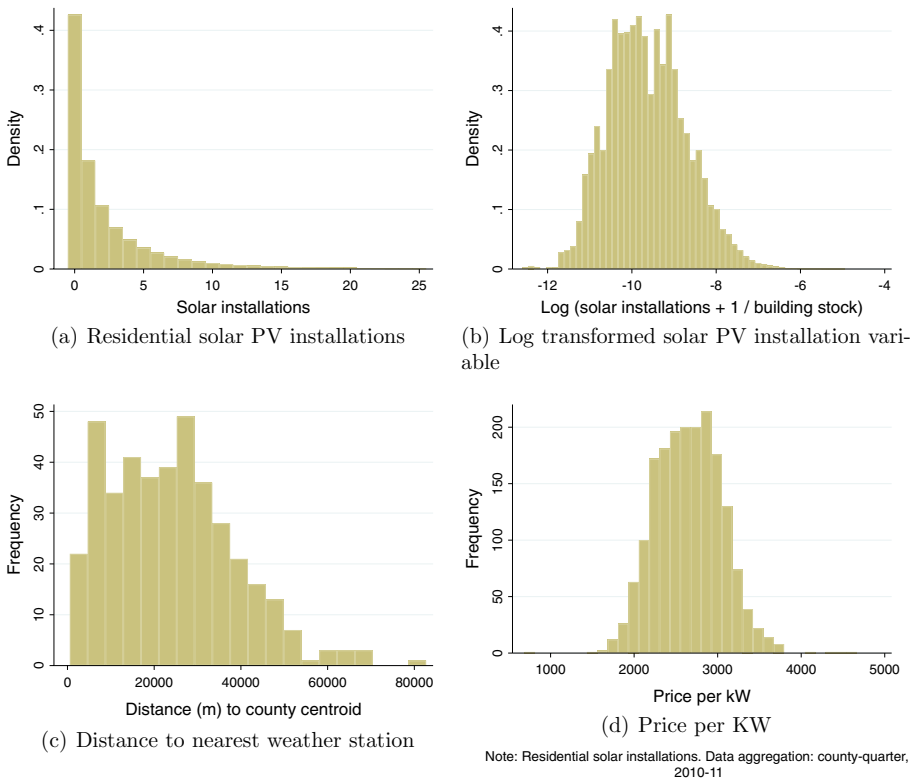


Fig. 7 Histogram of key variables *Notes* Distribution of key variables (2000–2013). Panel **a** displays the number of residential solar PV installations. Histogram cut at 99th percentile for ease of exposition. Panel **b** shows the log transformed solar PV investment normalized by the residential housing stock in 2000 ($\ln((\text{solar}+1)/\text{buildings})$). Panel **c** displays the distance to the closest weather station and Panel **d** the price per KW in the reduced sample period 2010–2011

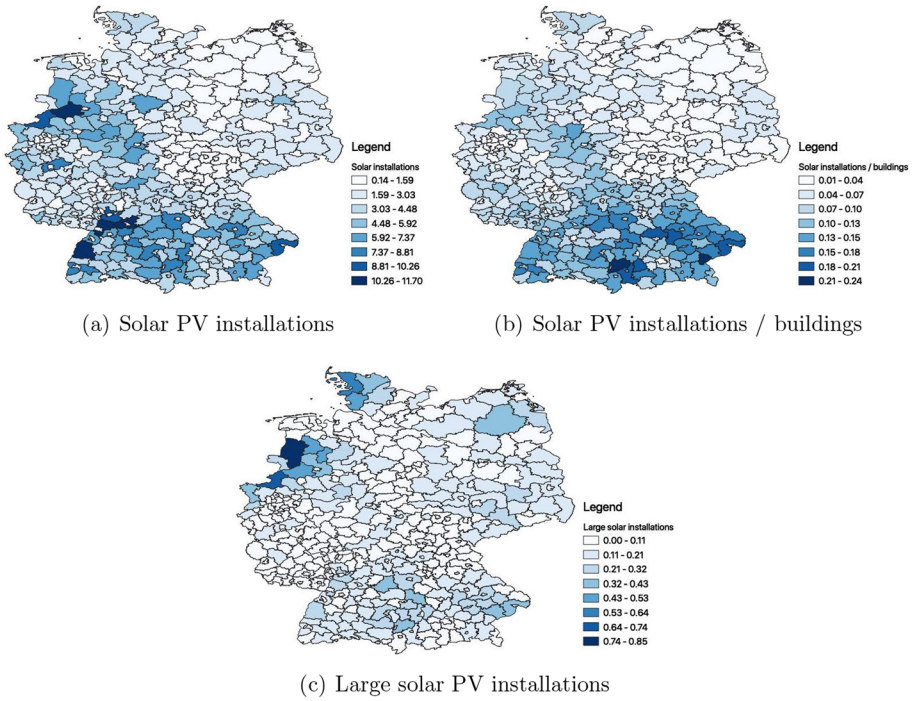


Fig. 8 Spatial distribution of solar PV installations *Notes* Panel **a** shows the average number of residential solar PV installations (≤ 10 KW) per week over the period 2000–2013. Panels **b** normalizes the number of installations by the residential housing stock in the year 2000. Panel **c** shows the average number of weekly solar installations of 'large' solar installations (≥ 100 KW)

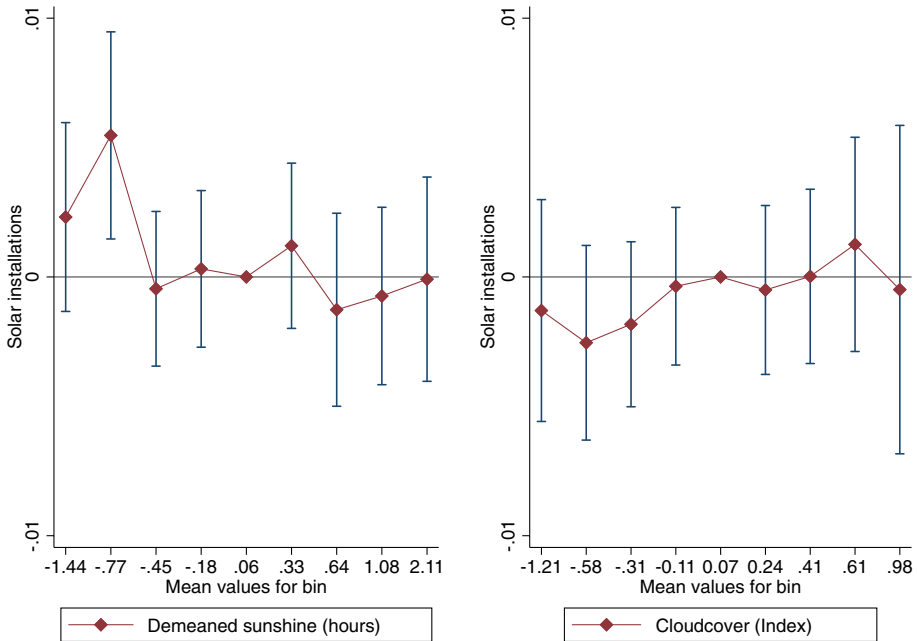
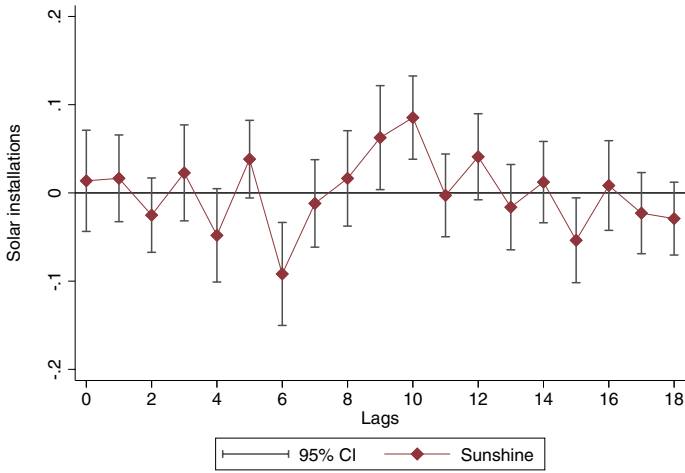
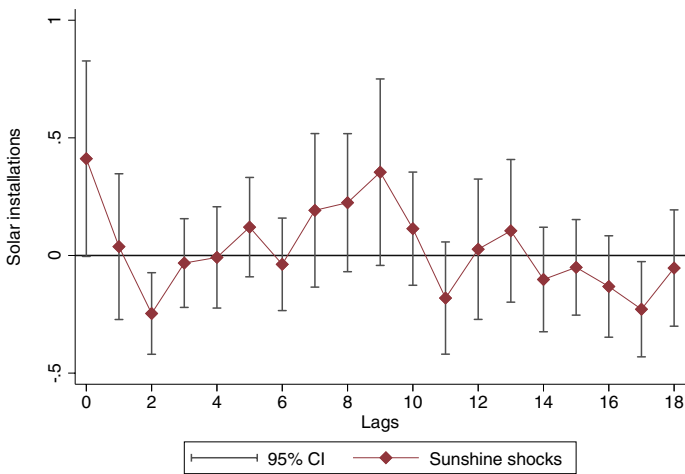


Fig. 9 Non-linear effects for large solar PV installations *Notes* Each plot presents the coefficients and 95% confidence interval for a regression of large solar PV installations (≥ 500 KW) on binned weather observations, defined as deviations from the long-term (1971–2013) averages, considering as purchase period 6–12 weeks prior to completion of the installation. Unit of observation: county-week. Robust standard errors clustered at weather station



(a) Sunshine deviations



(b) Sunshine shocks

Fig. 10 Impact of de-measured sunshine and sunshine shocks on solar PV uptake *Notes* Each marker represents the coefficient and the 95% confidence interval for a regression of residential solar PV installations on current and lagged sunshine. The regression model otherwise follows (1). In line with the main analysis, Panel **a** uses de-measured sunshine hours, while Panel **b** employs the discretized sunshine shock measure, defined as sunshine realization one standard deviation above the long-term (1971–2013) mean. Unit of observation: county-week. Robust HAC standard errors (Conley 1999) following the implementation by Hsiang (2010) account for autocorrelation up to 6 lags and a spatial correlation cutoff of 300 km, decaying linearly

Table 5 Summary statistics

	Mean	Std. dev.	Median	Min	Max
<i>Solar PV variables</i>					
Residential installations (≤ 10 KW)	2.726	(6.052)	1	0	470
All installations	4.893	(12.920)	1	0	780
Residential capacity (kW)	16.322	(37.734)	4.140	0	2808
All solar PV capacity (kW)	126	(2847)	7.540	0	1,469,605
<i>Weather variables</i>					
Distance to weather station (km)	23.877	(14.551)	22.938	0.532	82.734
Sunshine (hours)	4.594	(3.099)	4.100	0	14.786
Precipitation (mm)	2.145	(2.281)	1.500	0	34.314
Cloud cover (Index)	5.422	(1.408)	5.643	0	8
Mean temperature (Celsius)	9.487	(7.162)	9.686	- 16.100	29.757
<i>County covariates</i>					
Surface (km ²)	854	(638)	788	36	5470
Population (thds.)	203	(228)	149	34	3,460
New residential buildings	328	(294)	252	0	3313
Residential buildings (thds.)	44	(30)	37	6.579	317
Household income per capita (€ 2010)	19,038	(2571)	18,858	13,938	40,204
Vote share: green party (%)	7.917	(3.496)	7.271	2.277	28.675
Share of low education graduates (%)	31.148	(9.861)	29.694	9.611	90.112
Share of high education graduates (%)	27.504	(10.141)	26.581	0	70.323
Observations	292,656				

Summary statistics for the period 2000–2013. Unit of observation is county-week, but for county covariates that are reported annually with the exception of the vote share for the green party (federal elections 2002, 2005, 2009, and 2013). Weather variables reported as weekly averages of daily observations

Table 6 Correlation of de-meanded weather variables

	Sunshine	Temperature	Precipitation	Cloudcover
Sunshine	1.000			
Temperature	0.422	1.000		
Precipitation	- 0.487	- 0.082	1.000	
Cloudcover	- 0.822	- 0.350	0.443	1.000

Table 7 Main regression, controlling for contemporaneous weather and time-varying county

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Main weather effect during purchase period</i>						
Sunshine	0.127*** (0.014)				0.120*** (0.015)	
Temperature		0.046*** (0.007)			0.011 (0.007)	0.010 (0.008)
Precipitation			– 0.144*** (0.021)			
Cloudcover				– 0.257*** (0.034)		– 0.248*** (0.037)
<i>Contemporaneous weather controls</i>						
Sunshine	– 0.011* (0.005)	– 0.014** (0.005)	– 0.012* (0.005)	– 0.010* (0.005)	– 0.011* (0.005)	– 0.010* (0.005)
Temperature	0.018*** (0.003)	0.018*** (0.003)	0.019*** (0.003)	0.018*** (0.003)	0.018*** (0.003)	0.018*** (0.003)
Precipitation	– 0.020* (0.008)	– 0.016* (0.008)	– 0.019* (0.008)	– 0.020* (0.008)	– 0.020* (0.008)	– 0.020* (0.008)
SD of main weather variable	1.023	1.498	0.883	0.639	–	–
Semi-elasticity	0.048	0.025	– 0.047	– 0.06	–	–
Observations	279,584	279,584	279,584	279,328	279,584	279,328
R ²	0.283	0.283	0.283	0.283	0.283	0.283
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
County-MoY FE	Y	Y	Y	Y	Y	Y

Dependent variable: Number of small scale (≤ 10 KW) solar PV installations. Unit of observation is county-week. Main weather variables are defined as average deviations from the long-term (1971–2013) mean, measured 6–12 weeks prior to solar PV completion date. Contemporaneous weather controls include weekly averages of daily sunshine hours, mean temperature and precipitation amount. Additional control variables for population, number of newly constructed residential buildings, and household income per capita included. Robust standard errors clustered at weather station in parenthesis. $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

Table 8 Main regression, 8–10 weeks purchase period

	(1)	(2)	(3)	(4)	(5)	(6)
Sunshine	0.168*** (0.010)				0.171*** (0.011)	
Temperature		0.041*** (0.005)			– 0.006 (0.005)	0.004 (0.005)
Precipitation			– 0.033* (0.014)			
Cloudcover				– 0.310*** (0.023)		– 0.307*** (0.024)
SD of main weather variable	1.453	2.094	1.304	0.867	–	–
Semi-elasticity	0.09	0.031	– 0.016	– 0.099	–	–
Observations	288,636	288,636	288,636	288,378	288,636	288,378
R ²	0.277	0.276	0.276	0.277	0.277	0.277
Year FE	Y	Y	Y	Y	Y	Y
County-MoY FE	Y	Y	Y	Y	Y	Y

Dependent variable: Number of small scale (≤ 10 KW) solar PV installations. Unit of observation is county-week. Main weather variables are defined as average deviations from the long-term (1971–2013) mean, measured 8–10 weeks prior to solar PV completion date. Robust standard errors clustered at weather station in parenthesis. $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

Table 9 Main regression, limited to counties within median distance to weather station

	(1)	(2)	(3)	(4)	(5)	(6)
Sunshine	0.114*** (0.013)				0.109*** (0.015)	
Temperature		0.040*** (0.008)			0.007 (0.009)	0.008 (0.009)
Precipitation			– 0.131*** (0.023)			
Cloudcover				– 0.223*** (0.036)		– 0.217*** (0.040)
SD of main weather variable	1.022	1.501	0.874	0.647	–	–
Semi-elasticity	0.047	0.024	– 0.046	– 0.058	–	–
Observations	143,916	143,916	143,916	143,660	143,916	143,660
R ²	0.280	0.279	0.280	0.279	0.280	0.279
Year FE	Y	Y	Y	Y	Y	Y
County-MoY FE	Y	Y	Y	Y	Y	Y

Dependent variable: Number of small scale (≤ 10 KW) solar PV installations. Unit of observation is county-week. Main weather variables are defined as average deviations from the long-term (1971–2013) mean, measured 6–12 weeks prior to solar PV completion date. Sample limited to counties, whose distance to the nearest weather station is less than 23 km (median distance). Robust standard errors clustered at weather station in parenthesis. $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

Table 10 Main regression, transformed dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
Sunshine	0.015*** (0.002)				0.013*** (0.002)	
Temperature		0.007*** (0.001)			0.003* (0.001)	0.006*** (0.001)
Precipitation			– 0.018*** (0.003)			
Cloudcover				– 0.009* (0.004)		– 0.004 (0.004)
Observations	287,832	287,832	287,832	287,576	287,832	287,576
R ²	0.539	0.539	0.539	0.538	0.539	0.539
Year FE	Y	Y	Y	Y	Y	Y
County-MoY FE	Y	Y	Y	Y	Y	Y

Dependent variable: Log of small scale (≤ 10 KW) solar PV installations normalized by the residential housing stock in 2000 (see Panel (b) of Appendix Fig. 7). Unit of observation is county-week. Main weather variables are defined as average deviations from the long-term (1971–2013) mean, measured 6–12 weeks prior to solar PV completion date. Robust standard errors clustered at weather station in parenthesis. $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

Table 11 Main regression, non-linear model

	(1)	(2)	(3)	(4)	(5)	(6)
Sunshine	0.027*** (0.003)				0.040*** (0.004)	
Temperature		– 0.004 (0.003)			– 0.020*** (0.003)	– 0.013** (0.004)
Precipitation			– 0.018** (0.006)			
Cloudcover				– 0.029*** (0.008)		– 0.041*** (0.010)
Observations	287,767	287,767	287,767	287,511	287,767	287,511
Year FE	Y	Y	Y	Y	Y	Y
County-MoY FE	Y	Y	Y	Y	Y	Y

Dependent variable: Number of small scale (≤ 10 KW) solar PV installations. Unit of observation is county-week. Main weather variables are defined as average deviations from the long-term (1971–2013) mean, measured 6–12 weeks prior to solar PV completion date. Model estimated as non-linear regression applying a poisson pseudo-maximum likelihood (PPML). Individual coefficients are exponentiated and can be interpreted as incidence-rate ratios (normalized at zero). Robust standard errors clustered at weather station in parenthesis. $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

Table 12 Main regression, state-year-quarter FEs

	(1)	(2)	(3)	(4)	(5)	(6)
Sunshine	0.177*** (0.016)				0.214*** (0.018)	
Temperature		0.007 (0.009)			– 0.062*** (0.010)	– 0.044*** (0.011)
Precipitation			0.006 (0.023)			
Cloudcover				– 0.305*** (0.044)		– 0.339*** (0.048)
SD of main weather variable	1.023	1.498	0.883	0.639	–	–
Semi-elasticity	0.066	0.004	0.002	– 0.072	–	–
Observations	287,830	287,830	287,830	287,574	287,830	287,574
R ²	0.314	0.313	0.313	0.313	0.314	0.313
County FE	Y	Y	Y	Y	Y	Y
State-year-quarter FE	Y	Y	Y	Y	Y	Y

Dependent variable: Number of small scale (≤ 10 KW) solar PV installations. Unit of observation is county-week. Main weather variables are defined as average deviations from the long-term (1971–2013) mean, measured 6–12 weeks prior to solar PV completion date. Regressions include county (402) and state-year-quarter (894) FEs. Robust standard errors clustered at weather station in parenthesis. $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

Table 13 Main regression, limited sample according to major FiT revisions

	(1) Year ≤ 2011	(2)	(3) Year ≥ 2004	(4)
Sunshine	0.173*** (0.015)		0.171*** (0.015)	
Cloudcover		– 0.381*** (0.036)		– 0.355*** (0.037)
SD of main weather variable	1.031	0.627	1.016	0.651
Semi-elasticity	0.072	– 0.097	0.05	–0.066
Observations	246,024	245,872	209,040	208,784
R ²	0.303	0.303	0.327	0.327
Year FE	Y	Y	Y	Y
County-MoY FE	Y	Y	Y	Y

Dependent variable: Number of small scale (≤ 10 KW) solar PV installations. Unit of observation is county-week. Main weather variables are defined as average deviations from the long-term (1971–2013) mean, measured 6–12 weeks prior to solar PV completion date. Columns (1) and (2) limit the sample to the period 2000 to 2011, while Columns (3) and (4) use only data after 2004 in line with the main FiT reforms in 2004 and 2011. Robust standard errors clustered at weather station in parenthesis. $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

Table 14 Main regression, robust inference

	(1)	(2)	(3)	(4)	(5)	(6)
Sunshine	0.126* (0.051)				0.117 (0.060)	
Temperature		0.048 (0.033)			0.014 (0.039)	0.013 (0.037)
Precipitation			– 0.139** (0.053)			
Cloudcover				– 0.253** (0.081)		– 0.242** (0.093)
SD of main weather variable	1.023	1.498	0.883	0.639	–	–
Semi-elasticity	0.047	0.026	– 0.046	– 0.059	–	–
Observations	283,536	283,536	283,536	283,280	283,536	283,280
Year FE	Y	Y	Y	Y	Y	Y
County-MoY FE	Y	Y	Y	Y	Y	Y

Dependent variable: Number of small scale (≤ 10 KW) solar PV installations. Unit of observation is county-week. Main weather variables are defined as average deviations from the long-term (1971–2013) mean, measured 6–12 weeks prior to solar PV completion date. Robust HAC Standard errors (Conley 1999) following the implementation by Hsiang (2010) account for autocorrelation up to 6 lags and a spatial correlation cutoff of 300km, decaying linearly (Bartlett). $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

Table 15 Summer vacation dates by federal state (2013)

State	Vacation dates	Number of days
Baden-Württemberg	25.07–07.09	44
Bayern	31.07–11.09	42
Berlin	19.06–02.08	44
Brandenburg	20.06–02.08	43
Bremen	27.06–07.08	41
Hamburg	20.06.–31.07	41
Hessen	08.07–16.08	39
Mecklenburg-Vorpommern	22.06–03.08	42
Niedersachsen	27.06–07.08	41
Nordrhein-Westfalen	22.07–03.09	43
Rheinland-Pfalz	08.07–16.08	39
Saarland	08.07–17.08	40
Sachsen	15.07–23.08	39
Sachsen-Anhalt	15.07–28.08	44
Schleswig-Holstein	24.06–03.08	40
Thüringen	15.07–23.08	39

Table 16 Sunshine deviations and summer vacations

	(1)	(2)
Sunshine	0.164*** (0.016)	
Vacation × Sunshine	– 0.210*** (0.030)	
Vacation	– 0.082 (0.075)	– 0.133+ (0.075)
Contemporaneous sunshine		– 0.003 (0.005)
Vacation × Contemporaneous sunshine		0.074*** (0.011)
Observations	287,832	292,656
R ²	0.276	0.275
Year FE	Y	Y
County-MoY FE	Y	Y

Dependent variable: Number of small scale (≤ 10 KW) solar PV installations. Unit of observation is county-week. Main weather variables are defined as average deviations from the long-term (1971–2013) mean, measured 6–12 weeks prior to solar PV completion date. Contemporaneous sunshine is defined as sunshine in the week of the solar PV completion. Vacation is a dummy variable indicating the period of summer vacation in each of the 16 federal states. See Table 15 for exact dates in 1 year. $p < 0.1$ (+), $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

Table 17 Aggregate impact of sunshine and precipitation

Shock exposure	(1)	(2)	(3)	(4)	(5)	(6)
	Percentile 50			Percentile 75		
Sunshine shock	11.778*** (3.589)		11.655** (3.590)	15.777*** (4.037)		15.377*** (3.967)
Precipitation shock		– 8.710** (3.024)	– 8.599** (3.062)		– 12.520*** (3.774)	– 12.121*** (3.675)
Observations	5465	5465	5465	5465	5465	5465
R ²	0.792	0.791	0.792	0.792	0.792	0.793
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y

Dependent variable: Number of small scale (≤ 10 KW) solar PV installations. Unit of observation is county-year. Weather shocks are defined as weather realization one standard deviation above the long-term (1971–2013) mean. Column (1–3) divide the sample according to the median number of weather shocks in ‘high’ and ‘low’ exposure areas. Columns (4–6) according to the 75th percentile. Control variables include population, number of new residential buildings, household income per capita, as well as actual sunshine hours. Robust standard errors clustered at weather station in parenthesis. $p < 0.1$ (+), $p < 0.05$ (*), $p < 0.01$ (**), $p < 0.001$ (***)

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