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"Sunspots that matter: the effect of weather on solar technology adoption"

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Abstract

This paper tests for the effect of weather on solar technology adoption, taking advantage of the fact that sunshine is a direct input factor for solar electricity production. I find that a one standard deviation increase in monthly sunshine hours above the long-term average leads to an approximate 6.2 % growth in the residential solar market over a six-month period. I consider a range of potential mechanisms and find strong evidence for projection bias and salience as key drivers of my results. My findings show that there is an asymmetric response to positive and negative sunshine deviations from the long-term mean and that counties with a high vote share for the green party are particularly affected by these biases.

Keywords: projection bias; salience; technology diffusion; solar technology; energy policy.

JEL classification codes: D12, D91, Q42.

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1 Introduction

Climate change is one of the most pressing concerns for policy makers in the 21st century. Experts worldwide agree that a quick reduction in greenhouse gas emissions is needed.[1] One crucial sector in this process are energy and electricity markets and the transition from fossil fuels to renewable energy sources (RES). To incentivize private investment in RES, governments engage in costly support mechanisms. These policies often come in the form of investment or production subsidies and implicitly build on the assumption that decision-makers act rationally by evaluating private costs and benefits. Behavioral economics, however, has shown in different contexts that rationality is not necessarily a good assumption. When utility is context dependent and optimal decision-making involves the prediction of future utility levels, behavioral biases can lead to consumers mis-valuing costs and benefits, influencing their decision-making. In spite of the potentially large impact of behavioral biases on RES investment, this has only found little attention in the applied literature.

This paper studies the presence of behavioral deviations from the rational agent framework in the decision of a household to adopt a rooftop solar photovoltaics (solar PV) system. 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 fluctuations in weather, as it does not impact the long-term investment profitability. In contrast, I show that households respond to variations in sunshine. I test for a variety of competing mechanisms and find strong evidence that household decisions are over-influenced by factors in line with projection bias and salience. These insights are particularly relevant when it comes to costly policy support mechanisms aimed at increasing the uptake of public goods with positive externalities.

This paper is the first to provide causal evidence for projection bias and salience in the renewable energy investment context. This is especially relevant in this context given the significant amount of public resources spent on incentivizing technology adoption.[2] In line with the behavioral economics literature (Bordalo, Gennaioli, and Shleifer 2012, 2013, Loewenstein,

[1] United Nations Framework Convention on Climate Change, COP21 'Paris agreement', December 2015.

[2] In 2011 alone, total RES support in Germany accounted for 16.7 billion Euros. The largest individual share is solar PV technology, with 7.7 billion Euros.

O'Donoghue, and Rabin 2003), I provide empirical evidence that exogenous states, such as weather, can impact individual investment decisions. Furthermore, looking at county heterogeneity, I show that certain population groups are particularly affected, making them prominent candidates for targeting (Allcott, Knittel, and Taubinsky 2015, Costa and Kahn 2013, Gromet, Kunreuther, and Larrick 2013). If the objective of the policy-maker is to reach fast product diffusion, it is important to consider these biases when designing adoption campaigns.

I follow the theoretical literature on projection bias (Loewenstein, O'Donoghue, and Rabin 2003) and salience (Bordalo, Gennaioli, and Shleifer 2012, 2013) in durable goods purchase decisions to derive testable hypotheses for the case of solar PV investment. To empirically test for these hypotheses, I use administrative data on residential solar PV installations in Germany and high-resolution weather data. I focus on Germany, the world-market leader in solar PV deployment in 2011, as its institutional features are particularly well-suited for this analysis. First, the particular design of feed-in tariffs (FIT), the main support mechanism for renewable energy investment, guarantees comparable investment conditions for the time period 2000 to 2011 in an otherwise quickly changing market environment.[3] Second, given the long project horizon of 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 lag of approximately 9 weeks between the decision to adopt solar and the time the installation is completed and starts to produce electricity. Third, the adoption of a rooftop solar PV system involves a large financial commitment, comparable to the purchase of a car, which allows me to credibly exclude other mechanisms, such as short-lived mood fluctuations.

For my empirical analysis, I recover the long-term weather distribution for each county and define a weather shock as a weather realization one standard deviation above the long-term mean. My empirical identification takes advantage of the randomness of local weather as well as the

[3]While solar PV prices in Germany decreased by more than 50% in the time period 2006 to 2011, FITs adjustment led to comparable investment conditions over time. The presence of the unique policy instrument, FIT, allows potential solar PV customers to calculate their expected financial returns. Other important markets for residential solar PV, such as California, rely on a variety of inter-dependent policies, including the federal investment tax credit, accelerated depreciation, state incentives, and utility net-metering. Borenstein (2017) shows that private solar PV investment in California only recently led to positive returns on investment. Moreover, given net-metering policies, solar PV return depends on the design of the electricity block-tariff.

time gap between decision-making and completion of the installation. In my main specification, I regress solar PV market growth on current and lagged sunshine and other weather shocks, controlling for a rich set of county and time fixed-effects. In addition, I add data on county demographics, solar PV prices, as well as news on 'solar PV' and 'climate change', to test for competing mechanisms and county heterogeneity. Finally, I perform an online survey with German solar PV installers to provide additional market insights, in particular regarding customer key decision-variables, installation timing, and installer marketing outreach.

I find strong evidence that an exceptionally sunny month leads to additional solar PV installations with a two month lag, in line with the average installation timing. A sunshine shock implies a 6.2% growth of the residential solar PV market in a county, increasing the average number of installations from approximately 10 to 10.6. I allow for non-linear effects of sunshine and find that there exists a strong asymmetric response between positive and negative deviations from the long-term mean. Months with exceptionally low number of sunshine hours, lead to significantly fewer installations. In line with these findings, I show that other weather variables such as rain and cloud cover lead to similar results. On the other hand, temperature does not seem to impact technology adoption decisions. Finally, I show that 'green counties', with a large historic vote share for the green party, are particularly prone to additional adoption. Income and education, on the other hand, do not seem to play an important role in explaining the biases. These results suggest that political beliefs might play an important role in the response to policy interventions based on behavioral economic interventions.

My overall findings are both in line with projection bias and salience. According to projection bias, even small deviations from the long-term mean can impact investment decisions when households 'project' return expectations, based on current weather, into the future. On the other hand, a large deviation from the long-term sunshine mean makes the financial benefits related to solar PV investment more 'salient'. The presence of salience can furthermore lead to asymmetries in the response to sunshine deviations if perceptions of financial returns and investment costs are affected independently by positive and negative deviations. The data does not allow me to separate these channels. In the case of solar PV, sales are highly seasonal. For this reason, I am not able to test for projection bias and salience separately. I am able to rule out other possible mechanisms affecting investment decisions such as myopia, biased weather forecasts, and learning.

I perform several robustness tests of the main empirical results. In particular, I employ alternative weather data and run the analysis on sub-samples. Moreover, I provide evidence for robustness of the inference, employing standard errors that explicitly allow for spatial correlation and auto-correlation. Finally, by looking at the installation of wind turbines, a market that follows a similar investment dynamic, yet that is dominated by institutional investors, I exclude the possibility that RES investments are spuriously correlated with sunshine shocks.

In an attempt to rule out a variety of alternative mechanisms for my empirical results, I employ a distributed lag model to show that the main effect cannot be explained by inter-temporal substitution of solar PV purchases. Similarly, using data on both cloud coverage and rain, I exclude the possibility that households decide rationally, yet have strong preferences to leave their homes only in periods when it is not raining. While data on 'solar PV' news coverage is positively correlated with adoption, the main sunshine effect is not diminished. Finally, I consider the possibility of supply-side responses to short-term variations in weather. I do not find evidence that installers make strategic price promotions in periods of exceptional sunshine. In addition, the survey suggests that installers do not strategically adjust their marketing campaigns to short-term variations in weather.

The paper proceeds as follows. The introduction concludes with a discussion of the related literature. Section 2 gives additional details on the German solar PV market. Section 3 develops testable hypotheses for projection bias and salience in solar PV investment, while Section 4 describes the data. Sections 5 and 6 provide the main empirical strategy and results. Section 7 adds robustness and Section 8 discusses the findings further in light of competing mechanisms. Finally, Section 9 concludes.

Related Literature

This paper contributes to several strands of literature, first and foremost to the debate on rational consumer choice in the energy context. This discussion relates to the so-called 'energy-efficiency gap' (Allcott and Greenstone 2012, Jaffe and Stavins 1994). The energy-efficiency gap describes the idea that even though investment in energy efficient goods is privately beneficial, i.e. energy saving through the adoption of energy-saving appliances outweighs cost, technology uptake remains low. Several explanations have been given in the literature for this 'puzzle' including traditional market failures in line with imperfect information, inattention, or principal-agent issues. Alternatively, systematic behavioral biases in consumer decision-making and cognitive limitations in mental accounting may explain the presence of the energy-efficiency gap (Allcott, Mullainathan, and Taubinsky 2014, Gillingham, Newell, and Palmer 2009, Gillingham and Palmer 2014). The 'rationality' of consumer behavior in this context has been extensively tested in how much consumers 'undervalue' fuel economy when purchasing a vehicle (see for example Allcott and Wozny 2013, Anderson, Kellogg, and Sallee 2013, Busse, Knittel, and Zettelmeyer 2013, Greene 2010, Sallee, West, and Fan 2016), yet the literature has not come to a final agreement. This paper adds to this literature by providing first empirical evidence for projection bias and salience in an important energy investment decision.[4] The presence of behavioral agents can have important implications for effective policy design (Allan, Jaffe, and Sin 2014, Chetty 2015, Madrian 2014, Tietenberg 2009). In a case where investment is privately profitable and beneficial to society, low cost information campaigns can significantly increase technology adoption (Hortaçsu, Madanizadeh, and Puller 2017, Ito, Ida, and Tanaka 2016, Tiefenbeck, Goette, Degen, Tasic, Fleisch, Lalive, and Staake 2016).

Second, this paper contributes more broadly to the discussion on behavioral factors influencing technology diffusion, in particular concerning the adoption of solar PV technology. Estimating a dynamic discrete choice model of solar PV adoption in Belgium, De Groote and Verboven (2016) 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 (Bollinger and Gillingham 2012, Graziano and Gillingham 2015, Rode and Weber 2016). Evidence that household investment is particularly affected by projection bias and salience in 'green counties', suggests that there might be important inter-connections between these biases and peer effects.

Finally, testing for behavioral biases in field data remains challenging (DellaVigna 2009). The present paper builds on the literature on projection bias in other consumer domains, such as the

[4] Liao (2016) finds evidence that bad weather conditions can be related to a increased share of solar PV contract cancellations in the state of California and interprets her findings in line with projection bias. In contrast to her analysis, I focus on the 'sales effect' of exceptional sunshine. The institutional details in Germany lead to comparable investment conditions over time, which allows for a particularly credible test for deviations from rational choice.

purchase of winter cloths (Conlin, O'Donoghue, and Vogelsang 2007), college enrollment (Simonsohn 2010), car purchase (Busse, Pope, Pope, and Silva-Risso 2015), and health insurance (Chang, Huang, and Wang forthcoming), and provides evidence for behavioral biases in a large investment good, where weather (sunshine) can be directly linked to financial return expectations. This is the first paper to provide evidence that the interaction of behavioral biases can lead to asymmetric responses to positive and negative weather deviations from the long-term mean.

The work most closely related is Busse, Pope, Pope, and Silva-Risso (2015) that show that idiosyncratic variations in weather affect people's choice of vehicle types. In particular, they find that good weather over-influences the purchase of convertible cars, while bad weather increases purchases of 4-wheel-drive vehicles. Their setting relies on daily variations in weather. In contrast, the institutional context in the solar market, specifically the time gap between decision-making and completion of the installation, allows me rule out myopia and present bias. 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 weather evolution. Moreover, this paper extends the previous work by providing evidence on asymmetric responses to positive and negative deviations from the long-term sunshine mean and by showing that certain population sub-groups can be heterogeneously affected by behavioral biases.

2 Institutional Market Features

Germany has long been the world leader in solar PV technology deployment, accounting for more than 35% of the global operating capacity in 2011.[5] In spite of its relatively poor sunshine radiation, due to its geographic location, solar PV investment 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 to sell electricity at a fixed rate, above the retail price of electricity. FITs have been made available to residential solar PV investors with the introduction of the *Erneuerbare Energien Gesetz* (EEG) in 2000. The EEG involves an annual downward adjustment of

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

FIT to account for decreasing solar PV module prices. This 'degression rate' was set by the policy maker to keep the overall investment profitability comparable over time. Changes in the FIT rates only affect new installations and are announced several months before the actual adjustment. For residential investors it has been optimal to sell the full amount of electricity produced (at a high FIT), and to continue purchasing their electricity from retailers (at the residential electricity tariff).[6] Due to these incentives, solar PV investment has been mainly seen as a financial investment opportunity, with an internal rate of return of approximately 7-11%.[7]

During the period 2000 to 2011, there have been two amendments to the original EEG, that, however, did not change the overall investment incentives for residential customers. Only a major reform in 2012 changed FITs fundamentally, introducing mandatory on-site consumption and a more stringent downward revision of FIT rates. Even though the market for residential solar PV has grown importantly over the period 2000 to 2011, the share of solar energy in the German electricity mix remained at 3.1% in 2011. At the same time, there were no signs of market saturation and installed solar PV capacity continued to grow 29% in 2012.

A particularity of the solar PV market is that installations need to be handled by qualified installers and require site-specific planning. Solar supply in Germany is highly fragmented and dominated by local installer businesses.[8] In a survey with installers, I provide additional evidence that consumer's motivation to install solar PV is mainly financially motivated. At the same time, the survey reveals that most installers do not engage in costly marketing campaigns, and rather rely on word-of-mouth for customer acquisition. Most importantly, given the large investment character and individual planning of installations, there exists an average time gap of 9 weeks (median 8) from first customer contact to completion of the installation.[9] Appendix A provides additional details on the solar PV market in Germany, including FIT design and the installer

[6] In 2007, for instance, the FIT was 49.21 Eurocents per kilowatt-hour (KWh) electricity, while the average electricity rate for residential customers in Germany was 20.6 Eurocents per KWh, including all taxes and levies.

[7] The return depends on the exact location (solar irradiation), timing of the installation (FIT rate, cost), and the module's efficiency. Note that solar PV panels are usually maintenance free and require little follow-up investments. The most common replacements are electric inverters that have a life-expectancy of about 10 years.

[8] See for instance: Solar Installer Survey, Muehlhausen Consulting, 2014. Solar PV installation is often a complementary business to related activities, e.g. heating systems, water installations, and electric appliances.

[9] A similar time gap has been found by Seel, Barbose, and Wiser (2013) that survey installers in Germany and the US solar PV market.

survey.

Weather and the Profitability of Solar

Climate and weather 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 kWh to 1400 kWh per square meter and is higher in the South.[10] While thick cloud cover and shading can reduce significantly the electricity production from solar cells, other weather variations in temperature or intermittent clouds can have ambiguous effects on the performance of solar modules. These variations are, however, short-lived and have little impact on the average profitability of solar PV investment, which is entirely determined by long-term climatic conditions. I provide additional discussion regarding weather effects in Appendix B.

3 Behavioral Biases and Solar Investment

As short-term weather variations do not have a direct impact on future returns from solar PV investment, variation in sunshine should not affect the investment decisions of rational agents. However, as pointed out by a growing literature in behavioral economics (see literature surveys in DellaVigna 2009, Huck and Zhou 2011), many individual decisions might deviate from the standard economic model. If households forecast financial returns from solar PV investment based on current sunshine, their investment decisions might be overly influenced by the current state of weather in line with projection bias (Loewenstein and Schkade 1999, Loewenstein, O'Donoghue, and Rabin 2003). Similarly, in case an exceptional sunshine period draws consumers attention to certain product attributes, salience (Bordalo, Gennaioli, and Shleifer 2012, 2013) might affect consumer choice. This section elaborates further on projection bias and salience as sources for deviations from the neoclassical model in durable goods purchases and develops testable hypotheses

[10] Panel (a) of Figure B.1 depicts the average solar irradiation in Germany. Panels (b) - (d) of the same figure show actual weather averages for annual sunshine hours, mean temperature, and total annual precipitation in the time period 2000-2011.

for the particular case of solar PV investment.

3.1 Projection Bias

Following Loewenstein, O'Donoghue, and Rabin (2003), suppose that a person's instantaneous utility can be written as $u(c, s)$, where c is consumption good and s is the state that parameterizes the tastes of the decision maker. In case of a *simple projection bias*, people with current state s' form linear expectations about their future utility in state s. Thus, the person's predicted utility lies in between the true future tastes $u(c, s)$ and the current tastes $u(c, s')$ which implies that a person's behavior needs not to correspond to correct inter-temporal utility maximization.[11]

In the specific case of durable goods purchase, suppose furthermore 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 $\overline{\mu}$. The realization of μ_t is known at the beginning of the period and the durable good lasts M months. Without loss of generality, I assume that future utilities are not discounted. 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. Assume that the utility for the durable good is additively separable from utility of other goods and the current state is equal to the random variable, $s_t = \mu_t$. Then, in a one-time buying decision, *true* expected inter-temporal utility is given by

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

While in the presence of projection bias we have that

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

Clearly, $\mu_1 > \overline{\mu}$ implies $E_1[\widetilde{U_1}] > E_1[U_1]$ and vice versa. Thus, if the period 1 valuation is larger than the average valuation and the consumer 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

[11] *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. α = 0 implies correct prediction of future utility and α = 1 implies fully myopic habits.

sensitive to the valuation at the purchasing time. In the more realistic case of multiple buying decisions, the consumer can buy at most once in any period $t \in \{1,2,...\}$. A rational person would buy the good in period 1 or never, i.e. she buys if and only if $M\overline{\mu} - P \geqslant 0$. A high valuation $\mu_H > \overline{\mu}$, implies that $M\overline{\mu} + \alpha M(\mu_H - \overline{\mu}) - P > 0$, or in other words, projection bias can lead to impulse purchases in the case where the buying decision is highly irreversible. A low valuation, $\mu_L < \overline{\mu}$, on the other hand, implies that that no purchase is made, even though it would be generally beneficial to buy the product.

3.2 Salience

Salience (Bordalo, Gennaioli, and Shleifer 2012, 2013) 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 present paper, salience is related to sunshine, an exogenous weather variable, that varies over time and location, and which can make the (financial) investment potential of solar PV more salient. This type of salience is similar to the one discussed in Busse, Pope, Pope, and Silva-Risso (2015).

The definition of product attributes are important in the case of salience. If the main attribute is 'financial investment potential', then both positive and negative weather shocks might lead to an increased number of solar sales, as both weather types will make the perceived value of solar investment very different from the reference value (having the average levels of sunshine). This is probably inconsistent with the general intuition. Yet, defining two separate attributes, such as increased 'solar PV awareness' in exceptional rich sunshine periods, and 'perceived solar cost' in periods of exceptional poor sunshine means that responses to positive and negative deviations from the reference good do not need to be the same. As both product attributes can be independently affected, the two effects might lead to an asymmetric response in sunshine deviations from the long-term mean.

3.3 Testable hypotheses for solar PV investment

The durable goods character of solar PV makes it necessary for households to form return expectations and forecast these over the project horizon of 20 years when making their investment decision. The presence of FIT policies makes it easy to calculate the expected period profit of solar PV, as all electricity produced will be fed to the grid. As FIT rates are fixed over the investment horizon, the household must form expectations about the long-term electricity production of solar panels, which is directly linked to availability of sunshine and solar radiation. The net present value (NPV) is given by the discounted cash flow CF over the project horizon, times the expected electricity production $E_p(e)$. Formally, $NPV_p = \sum_{t=0}^{T} \delta^{t-1} CF_p \times E_p[e(sun, \cdot)]$, where CF is a function of the FIT rate and the installation cost, both defined at the period of investment, p. The expected electricity production $E_p[e(sun, \cdot)]$, depends on average solar radiation (sun), and other factors related to the efficiency of solar modules, the panel orientation towards the sun, etc. While information on long-term solar radiation is available to economic agents, behavioral agents might misinterpret the information contained in short term-weather events.[12]

As financial return expectations are directly affected by sunshine, behavioral agents intertemporal profit evaluations might be over-influenced by the current state of sunshine. In line with projection bias, agents project the current weather or their perceived profits into the future when making their purchase decision. Similarly, exceptional sunshine might remind consumers of the investment profitability or the cost of solar PV in line with salience. Both channels can lead to impulse purchases in the case of positive sunshine shocks, and to non-investment in exceptional poor sunshine conditions. While projection bias is related to a symmetric response in sunshine deviations from the long-term mean, the presence of salience might lead to asymmetries. I tests for the following hypotheses in the data:

[12]Information on long-term (global) solar radiation is available from different online data sources, such as the European Commission and the German Weather Service. Many installers provide households furthermore with a detailed NPV calculation when making their investment plan. Financial constraints do not play an important role in the case of solar PV investment in Germany due to the availability of interest-free loans offered by the bank for reconstruction, KfW.

1. Behavioral consumers will respond to idiosyncratic variations in sunshine, as sunshine impacts the perceived financial returns of solar PV investment.

2. Given the average timing from decision-making to completion of the installation, I expect the main effect two month after an exceptional sunshine period.

3. Both, positive and negative deviations from the long-term sunshine mean impact investment decisions. While projection bias suggests a symmetric response to positive and negative deviations, the presence of salience can lead to non-linearities.

4 Data

The primary data for this study is the universe of solar PV installations in Germany, which is 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 FITs. As investment in solar PV is highly unprofitable without this policy support, this dataset is likely to contain the universe of residential installations in Germany. In addition to the location, the data provides information on first grid connection (completion of the installation), as well as the size of the solar panel. The dataset consists of 580,000 residential solar PV installations with a capacity smaller or equal to 10 kW in the time period 2000-2011.[13] I aggregate all installations at county-month level and construct a balanced panel data set containing 57,888 observations (402 counties observed for 144 months). Figure 1 plots the cumulative number of solar PV installations in the last month of my sample, normalized by the potential market size, the number of residential buildings in the pre-sample period 1999. The map shows that installations have taken place all over Germany, even though there is important heterogeneity in terms of solar PV penetration.

I combine the installation data with detailed weather data from the German weather service (DWD). The main weather variables are derived from weather observations, that are based on around 400 weather stations in Germany. DWD uses a meteorological model to provide detailed spatial data on a one-kilometer (km) by one-km grid at the monthly frequency. This dataset

[13] From the raw dataset with approximately 600,000 installations, I drop obvious duplicates, i.e. observations with the same plant id. In addition, I drop any two installations that happen on the same day in the same zip code and are listed with equal capacity. Duplicates may emerge as a result of changes in network operator.

includes variables such as sunshine hours, temperature (mean, min, max), and precipitation for each point in the grid for every month. In addition to this 'gridded' data, I rely on a second weather data set, which provides direct observations from weather stations. For a total of 51 weather stations I observe daily measures of sunshine, temperature, rain, snow, and cloud cover ranging back to the 1970s. While sunshine, rain, and snow are cumulative measures, cloud cover is an index describing the percentage of visible clear sky. Relying on both 'gridded' weather data and station weather data provides useful robustness to my empirical analysis (Auffhammer, Hsiang, Schlenker, and Sobel 2013, Dell, Jones, and Olken 2014). I aggregate all weather data at the county-month level, using Geographic Information Systems (GIS) software.[14] Figure B.1 depicts the long-term solar radiation and the main weather variables for the period 2000 to 2011.[15]

Additional covariates allow me to control for time varying differences at county level and to test for heterogeneity of the main effect. County demographics come from the *German statistical agency* including data on population, household income, education, unemployment, agricultural surface, as well as the number of newly constructed residential and non-residential buildings. I also include vote participation and the voting shares for the green party in the federal elections 1998, 2002, 2005, and 2009. I complement this with data from Lexis Nexis, an online database covering major German newspapers. For that purpose, I downloaded all national news articles on 'solar PV' and 'climate change' and construct two monthly time series. In addition, I obtained data on solar PV prices for residential installations.[16] Finally, I conducted a survey with solar PV installers to obtain better insights into the customer-installer relationship. This data allows me to understand marketing and sales strategies of installers and more importantly, it provides me

[14]Each individual weather observation is assigned to a county if the centroid falls inside the county boundaries. I average across all data points in a given county to obtain the monthly weather averages. In the case of weather station data, I assign each county to its closest weather station.

[15]There exists an important trade-off in defining the appropriate spatial aggregation for my analysis: a more detailed weather aggregation would potentially increase the variation in local weather patterns, even though the weather maps in Figure B.1 suggest that this is not necessarily the case beyond the county level. On the other hand, a finer spatial aggregation implies an excess of observations with zero installations. Moreover, the use of county-level data allows me to add demographic and regional covariates to the analysis and to test for heterogeneous effects.

[16]Price data is based on installer bids from an online price comparison website for solar PV. Households 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. The author would like to thank *EuPD Research* for making this data available.

with information about the precise timing of solar PV installations, i.e. the time gap between first customer contact and completion of the installation. I discuss more details about the survey in Appendix A.2.

4.1 Definition of Weather Shocks

To test for the impact of exceptional weather on solar PV uptake, I construct weather shocks according to the following algorithm. First, I define the long-term weather distribution for sunshine, temperature, rain, etc. using the time period 1990 to 2011 in each county and for each month-of-the-year. Using this time period, the long-term averages are based on 22 observations for each county-month-of-the-year, e.g. January in Munich. As weather shows important year-to-year variation, it is important to consider a long time span when calculating the averages. In a second step, I define the discretized weather shocks as weather realizations that are one standard deviation above the long-term weather averages in a given region. Appendix B provides additional descriptives on the weather shocks. In addition to the discretized weather shocks, I test for non-linear effects to sunshine deviations from the long-term mean.

4.2 Descriptive Evidence

Table 1 presents summary statistics for the main weather variables, county demographics, and solar PV installations. Column 1 focuses on the entire sample, while columns 2 and 3 split the sample in high and low sunshine shock counties, according to the median of the average sunshine shock over the sample period.[17] The sample split reveals that there are considerably more solar PV installations in counties with a higher number of sunshine shocks, while the total number of sunshine hours in the two groups is the same. Furthermore, it highlights that the two subgroups are otherwise very similar in terms of observable characteristics. A higher number of solar PV installations in counties with more sunshine shocks can be seen as first descriptive evidence for the impact of exceptional sunshine on solar PV installations.

[17] Local variability in weather realizations combined with differences in the long-term weather distributions lead to differences in sunshine shock realizations. The mean of the sunshine shock variable is .203 (median of .201) with a standard deviation of 0.016.

Focusing on the time dimension, Figure 2 plots the unconditional mean of solar PV installations relative to the sunshine shock timing. The figure depicts the number of residential solar PV installations two months prior to a sunshine shock, in the month of a sunshine shock, and up to six months after for the group of counties that had a sunshine shock at time $t = 0$ and the group of counties that did not have a sunshine shock. While there are no detectable differences between the two groups two months prior to a sunshine shock, an exceptional sunshine month is related to more installations. This increase can be rationalized by supply side factors, e.g. rooftop access in the winter is feasible in exceptional sunny periods, yet not when it is snowing. More importantly, the figure shows a strong increase in installations at a two-month lag, in line with the average installation timing. These insights directly relate to hypotheses one and two, especially as later lags do not show an important difference in installations across the two groups. In order to advance towards a causal interpretation of these insights, the next section develops a regression framework that allows me to take into consideration sales and weather seasonality and to control for (un)observable county differences that might be related to solar PV uptake.

5 Empirical Strategy and Identification

5.1 Main regression model

To formally test for the impact of sunshine and other weather shocks on solar PV installations, I estimate the following regression model

$$\ln(y_{c,t}) = \alpha + \sum_{i=0}^{N} \beta_i weather_{c,t-i} + \sum_{j=1}^{3} \delta_{c,m_j} + \theta_y + \epsilon_{c,t} \tag{1}$$

where $y_{c,t}$ is the number of new residential solar PV installations in county c at month t divided by the potential market size (number of residential buildings in the pre-sample period 1999). The dependent variable can be interpreted as a proxy for solar PV growth.[18] $Weather_{c,t-i}$, is a vector of current and lagged weather variables. The specification includes up to 6 lags of sunshine, temperature, and precipitation weather shocks as defined in the previous section. As

[18]To be more precise, my main dependent variable is defined as: $\ln(\frac{solar_{c,t}+1}{buildings_{c,1999}})$, which is approximately normally distributed. I provide a histogram in Figure C.1.

different weather shocks might be correlated over time, I also test for the impact of individual shocks and weather levels. The regression includes county by month-of-the-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. These FEs are moreover allowed to vary with the three main FIT periods, δ_{c,m_j}, with $j \in$ {2000-04, 2005-09, 2010-11}. As the FIT reforms in 2004 and 2009 are related to changes in sales volatility of solar PV, it is important to allow the effects to vary over these periods (see Figure C.2). Finally, I control for changes in aggregate market conditions, such as solar PV prices and FIT levels, with a set of annual time dummies, θ_y. The total number of FEs in the main regression sums to 9,659. I cluster all standard errors at the county-level to allow the error term to be correlated within a given county over time.

Identification

To identify the causal impact of sunshine on solar PV adoption, I rely on randomness of local weather realizations with respect to the long-term averages. The fact that solar PV installations are highly seasonal makes it necessary to use a flexible set of time and county fixed-effects in my regression. Moreover, finding evidence for additional solar PV installations in an exceptional sunny period cannot be interpreted as a behavioral deviation from the neoclassical framework unless there is a time gap of at least one month, so that investors do not obtain a realized financial return from installing in an exceptionally sunny month. In a survey with local installers I confirmed that the average time gap between first customer contact and completion of the installation is 9 weeks (median 8 weeks). The time gap furthermore ensures that there is no contemporaneous correlation between current (and lagged) weather shocks and the error term, i.e. $E(weather_{c,t-i}, \epsilon_{c,t}) = 0$ for all $i \geqslant 0$.

5.2 Heterogeneous effects

In addition to main specification 1, I test whether certain demographic groups are heterogeneously affected by the bias. To do so, I divide the sample in two groups according to household income, share of tertiary education, and share of green voters. The division in 'high' and 'low' counties is determined according to the median. As household income may be endogenous to the adoption of solar PV panels once the share gets sufficiently large, I group the counties according to their income levels in the base year (2000). Similarly, as there might be concerns about reverse causality in the case of green voting behavior and the adoption of solar PV panels (Comin and Rode 2013), I rely on the federal elections in the pre-FIT period 1998 to define the groups. The main underlying assumption is that households self-select in similar neighborhoods in line with their own characteristics (referred to as homophily in the literature on social networks). While this measure is far from perfect, it will provide some useful insights for policy-design and targeting in the case of solar PV investment.

I choose to test for these variables as they are directly linked to solar technology adoption. Solar PV investment in Germany is mainly financially motivated and richer households, that are on average better educated, are more likely to adopt. Similarly, Costa and Kahn (2013) show that the response to behavioral policy interventions can vary importantly with political beliefs. In addition, I split the sample in high and low return counties, according to expected solar production in line with the long-term solar radiation to test if high/low return counties are particularly affected by the bias. Figure C.4 provides a visual inspection for the county division according to the main subcategories. For each of these variables, I run a separate regression, interacting the sunshine shock $sun_{c,t-i}$ with the dummy for the high group, D_h. Formally, I test for the following regression specification:

$$\ln(y_{c,t}) = \alpha + \sum_{i=0}^{N} \beta_i sun_{c,t-i} + \sum_{i=0}^{N} \beta_i sun_{c,t-i} \times D_h + \gamma D_h + \sum_{j=1}^{3} \delta_{c,m_j} + \theta_y + \epsilon_{c,t} \quad (2)$$

6 Results

6.1 Main results

Column 1 of Table 2 presents the main results, regressing solar PV uptake on current and lagged sunshine shocks, controlling for time and county-month-of-the-year FEs as introduced in the previous section. Columns 2 to 4 provide first robustness by including additional control variables, such as the lag of residential solar PV installations in each county, lagged sunshine hours, and lagged temperature (both in levels). Finally, column 5 replaces the annual FEs by more flexible county-year FEs. All specifications find a strong and highly significant impact of lag 2 of the sunshine shock. In line with the average installation timing, this means that a sunshine shock today will lead to more installations at a two month lag. The fact that the coefficient on lags 1 and 3 are positive and significant in some specifications (although smaller in magnitude) is in line with hypothesis two, as there is some variation in the installation timing. Lags 4 and 5, on the other hand, are typically negative and significant, indicating some harvesting-effects, i.e. a sunshine shock leads to some inter-temporal substitution of solar PV investment. Consumers might have decided to install a solar PV panel in the future, yet, the presence of a sunshine shock led them to contact their installer and to plan their installation. To address the importance of inter-temporal substitution of purchases, I sum the coefficients related to the distributive-lag model, similar to Busse, Pope, Pope, and Silva-Risso (2015), Deschenes and Moretti (2009), and Jacob, Lefgren, and Moretti (2007). I find an aggregate effect of .062 in the main specification in column 1. A Wald-test for the joint significance of the sum of coefficients yields a F-statistic of 5.01 (p-value of 0.026). The total aggregate effect indicates that a sunshine shock today leads to an approximate increase of 6.2% in solar PV growth over the six-month period following the shock. These results are in line with my hypotheses one and two, stating that behavioral consumers will respond to idiosyncratic variations in sunshine and that the main effect will be at a two-month lag, in line with the average installation timing. Finally, the high R-squared of about .8 indicates that the set of fixed effect is able to capture most of the seasonal and regional variation in solar PV uptake.

To test for hypothesis three, the non-linear effects of sunshine, I de-mean the sunshine hours for each county-month by its corresponding long-term mean, defined over the period 1990 to 2011. I construct 7 bins for these deviations from the mean. The bins are defined in 30 hour (h) intervals as 105-75 h less sunshine than the average month, 75-45 h less, etc. I then estimate model 1 including a separate dummy for each sunshine bin, including up to six lags of these. All estimates are relative to the historic average of sunshine hours in a given county ($\pm$ 15h), which is omitted from the regression.[19] The importance to test for non-linear responses in weather data has been documented in the previous literature (see for example Deschenes and Greenstone

[19]When creating the bins, I furthermore omit observations with less than -105 sunshine hours and more than +105 sunshine hours that represent less than 1% of the total sample. A histogram of demeaned sunshine hours is provided in Figure C.3.

2011, Zivin and Neidell 2014). Figure 3 plots the point estimates for each of the sunshine bins together with the 95% confidence intervals for lags 0 to 6: panel (a) for positive deviations and panel (b) for negative deviations from the long-term averages. There are several things worth noting: first, the positive bins in panel (a) replicate the main findings from Table 2. The figure also highlights that not only the very large deviations from the sunshine mean are driving the results, but also smaller deviations have a positive and significant effect at lag 2, which is followed by a small negative effect at lags 4 to 5. Second, both positive and negative deviations from the long-term sunshine mean have an impact on solar PV uptake. In fact, panel (b) suggests that negative sunshine deviations are quantitatively more important than positive ones, resulting in a large negative effect.

In the next step, I test for the impact of other weather shocks on solar PV uptake. For that purpose, I estimate the main regression model with weather shocks for sunshine, temperature, and precipitation.[20] I focus on the main effects at lags 0 to 4, as multiple weather shocks are likely to be correlated over time. Figure 4 plots the point estimates together with the 95% confidence intervals. The figure shows that controlling for other type of weather shocks does not alter the main effect of sunshine shocks on solar PV uptake. Moreover, as suggested by the non-linear effects of sunshine, a month with exceptionally high levels of precipitation leads to fewer installations. Temperature, on the other hand, has a zero effect for the main lags 2 to 4. However, I find that an exceptionally warm month leads to significantly fewer installations in the same period. This negative effect at impact can be explained by supply-side restrictions during exceptionally hot periods in the summer, that makes rooftop access unfeasible. To test for this assumption, I estimate the main regression model interacting contemporaneous temperature shocks with quarter-of-the-year dummies. The results, presented in Table C.1 show that the negative effect is mainly linked to the hottest month of the year (July, August, and September). This is particularly visible, when focusing on the average maximum temperature.[21]

[20]The weather shocks for temperature and precipitation are constructed in an analog way to sunshine shocks. Precipitation is measured as the average rainfall quantity in a month. Temperature is based on the mean temperature. For robustness, I experiment also with maximum temperatures. The results are not affected by this choice.

[21]The table employs temperature shocks based on mean temperature (columns 1 to 2) and maximum temperature (column 3). An alternative way to test for the presence of supply-side restrictions is to focus on adverse weather conditions in the winter months, such as snowfall that limits installer rooftop access. Figure C.7 provides evidence

6.2 County Heterogeneity

Table 3 presents the results for heterogeneity. The upper part of the table reports the main effect for lags 0 to 6 of the sunshine shocks, while the bottom part displays the interactions of the sunshine shock and lagged shocks with the dummy variable D_h indicating high income counties (column 1), counties with a high share of tertiary education (column 2), counties with a high share of green voters (column 3), and counties with high solar PV profitability (column 4). In addition to the interaction terms, the regression controls for contemporaneous levels of household income, share of tertiary education, unemployment rate, and percentage of agricultural surface. It is worth pointing out that the inclusion of additional control variables does not alter the main impact of sunshine shocks on solar PV uptake. Lag 2 of the sunshine shock remains highly significant in all four specifications with magnitudes aligned with the results presented in the previous section.

Focusing on the interactions for each of these subgroups, column 1 reveals that in high income counties a sunshine shock leads to additional installations at lags 1 to 2, while later lags are negative and significant. The overall effect is zero. This evidence is in line with salience and harvesting. As wealthy households do not require credit approval, their response time is shorter, spreading over the two month-period following a sunshine shock. Counties with a high share of tertiary education do not have an additional effects, which might be however related to noisiness in the education measure. On the other hand, testing for an additional effect in 'green counties', political orientation seems to play an important role in the way sunshine impacts solar PV investment decisions. While the main effect for sun shocks at lag 2 is reduced, the interaction term is highly significant and large in size. Adding up all lags, I find a total effect of 7.4%, while the main sunshine shock variable reduces to 2.5%. Green counties seem to be more susceptible to solar PV investment opportunities and exceptional sunshine has a strong additional sales effect. This could make green counties natural candidates for targeting, should the objective of the policy maker be fast product adoption. Another potential explanation for my finding is that solar PV installers know about the bias and target specifically sub-populations in line with weather. I elaborate on this possibility next. Column 4 of Table 3 tests for an additional effect for counties that have a high solar PV profitability. Counties with higher levels of solar radiation have a larger installation base and investment returns might be particularly salient in sunny periods. My findings do not

that snow has a negative effect on adoption at impact.

indicate any important differences across regions in response to sunshine shocks. This result can be explained by profitable investment conditions across Germany, given the national FIT policy.

6.3 Supplier response

As my main variable of interest is a market outcome, the overall effect of exceptional sunshine on solar PV installations could be affected both by a response in demand and supply. Solar PV installers may observe good weather periods and adopt marketing strategies to increase sales. To test for this possibility, I obtained detailed price data and performed a survey with installers. Price data is based on installer bids, which allows me to compare prices for similar installations in each quarter for the years 2010 and 2011. The original data contains 8,881 individual price bids for residential installations (system prices), which I aggregate at the county-quarter level. A histogram of the original data is given in Figure C.8. As I do not observe a sale for every county-quarter pair, I generate a second dataset, in which I interpolate missing observations using a flexible regression model that includes a nationwide price trend, county intercepts as well as separate effects for each state by half-year. Table 4 reports the main effects, regressing solar PV prices on lagged installations as well as current and lagged sunshine shocks for both the original sample and the interpolated data. The results indicate that the lagged number of solar PV installations have a negative impact on prices, which is in line with learning-by-doing in the solar PV industry (Bollinger and Gillingham 2014, Van Benthem, Gillingham, and Sweeney 2008). Focusing on the coefficients related to sunshine shocks, I do not find evidence that prices are lower in periods of exceptional sunshine or quarters thereafter.

In addition to price adjustments, installers might alter other components of their marketing mix. Evidence from the installer survey suggests that this is not the case. The survey highlights that most installers do not engage in costly marketing campaigns, but rather rely on word-of-mouth for customer acquisition (see Appendix A.2). While seasonality plays a role in sales, i.e. limited rooftop access during the winter, annual revision of the FIT schedule, there is no evidence that sales strategies are adjusted to short-lived variations in weather. It is worth pointing out that German solar PV installers are typically small in size and solar installation is often complementary to other business activities such as water, heating, or electrical appliances.

Even though I am not able to fully exclude the possibility that installers use good weather as a sales argument in their discussion with customers, the fact that customer acquisition follows word-of-mouth means that it is the households attention that needs to be drawn to solar PV in the first place. This observation, paired with the average time gap, makes it unlikely that my findings can be fully rationalized by supply-side factors.

7 Robustness

I perform a series of robustness checks for my main results. First, I verify that the main estimates are not affected by the choice of weather data. For that purpose, I reestimate model 1 with direct weather observations from weather stations. Weather station data is available for 51 stations ranging back to the 1970s.[22] I assign each county to its closest weather station and re-define the weather shocks according to this data. Column 1 in Table 5 presents the original sunshine shock variable for comparison, yet employs robust standard errors clustered at the larger weather station area (51 clusters), allowing for a wider degree of spatial correlation. The point estimates remain highly significant and are in line with my main results. Column 2 uses the sunshine shock definition based on weather station data and again finds a strong and significant effect at lag 2. Other lags are not significant. To minimize the measurement error for the sunshine shock variable, I estimate the model only with the subset of counties that have a weather station (column 3). Even though this exercise reduces considerably the number of observations, it provides a good robustness check, given the fact that weather-station location is independent of solar PV adoption and sunshine shocks. Again, the main effect remains highly significant for lag 2.

Second, columns 4 to 6 of Table 5 present robustness to a model with separate county FEs and month-of-the-year FEs that are allowed to vary with the three main FIT phases. While the standard errors in column 4 are clustered at weather station, column 5 employs Newey-West standard errors that explicitly account for autocorrelation and column 6 uses standard errors as in Conley (1999) that are consistent with both spatial correlation and autocorrelation. For these specifications, I set the autocorrelation parameter to 4 months and the distance cutoff for spatial correlation to 100 km. Independent of these modeling choices, the main effect for lag 2 remains significant.

[22] The location of these weather stations is depicted in Figure B.3.

Another issue with autocorrelated sunshine shocks was if households observed a shock today and could learn from it about future sunshine shocks. Figure 5 provides evidence that sunshine shocks are in deed surprises to consumers and not forecastable. For this purpose, I estimate model 1 with a full set of time indicator variables that are interacted with the sunshine shock. These indicator variables track the month of exceptional sunshine and the periods immediately preceding and following a shock.[23] The main effect is normalized with respect to the month preceding a sunshine shock, which is omitted from the regression. The plotted coefficients can be interpreted as the percent change in solar PV installations in county c relative to the month before a sunshine shock. The main effect at lag 2 is comparable in magnitude and significance, while I do not find evidence that the months immediately preceding a sunshine shock are different from zero.

Finally, I perform an additional test to show that sunshine shocks are not spuriously correlated with another type of RES investment that are dominated by institutional investors and that does not directly depend on sunshine: wind turbines.[24] I define the dependent variable for wind installations in line with solar PV and reestimate model 1 for the subset of counties that are suitable for wind turbines, i.e. having at least one wind installation in the period 2000-2011. This is the case for 310 counties. The regression controls for demographic covariates to account for this selection. Table 6, shows that solar PV installations follows the familiar pattern with this reduced sample. Wind installations, on the other hand, are not affected in the month of a sunshine shock and the four months thereafter. The appendix provides additional robustness concerning influential time periods, performing a sample split in Table C.2, and influential observations, excluding individual states from the regression in Figure C.11.

[23] I introduce a separate dummy for the history of sunshine shocks in each country, grouping periods with more than one year of lead or lag into an "early' and 'late' dummy. The Figure plots the sunshine shock coefficient for the most relevant period: three month prior to a sunshine shock and up to five month after the occurrence of a sunshine shock.

[24] Data on wind installations is available from the electricity network operator, 'netztransparenz.de'. Wind installations are subject to the same FIT policy (with lower rates), and their seasonal sales pattern strongly resembles that of solar PV installations (see Figure C.9).

8 Discussion

The previous sections have provided strong evidence for the causal impact of sunshine shocks on solar PV adoption that are 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, Huang, and Wang (forthcoming) 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 and Busse, Pope, Pope, and Silva-Risso (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.

The data at hand does unfortunately not allow me to fully disentangle the effects of salience and projection bias. Salience is usually defined with regard to the 'average good', or in this case regarding the long-term weather conditions. This implies that a consumer response to extreme sunshine deviations imply salience effects. Depending on the definition of consumer attributes, salience can lead to asymmetric responses in the case of positive and negative weather deviations from the long-term mean. Projection bias, on the other hand, predicts that the current levels of sunshine impact investment decisions, and that any deviations from the average impact product purchase decisions. As solar PV installations follow a highly seasonal sales path that is affected by average climatic conditions and FIT policy design, I am not able to directly test for these channels. Similar to Busse, Pope, Pope, and Silva-Risso (2015), I focus on the impact of exceptional weather (sunshine shocks) on purchase decisions. My finding that exceptional sunshine periods lead to more (less) solar PV investment can be seen as a sign for salience. Yet, finding evidence that also smaller deviations from the long-term sunshine mean lead to changes in investment behavior, is in line with projection bias. Even though I cannot fully distinguish between the two channels, I am able to rule out a series of alternative mechanisms for the empirical findings, which I will discuss in the remainder of this section.

Myopia & present bias: Consumer myopia (O'Donoghue and Rabin 1999, Laibson 1997) can lead to similar theoretical predictions as projection bias in the case of repeated consumer purchases. Yet, for the case of a one time purchase decision, this is not necessarily the case, especially as consumers do not receive financial returns in the month of their purchase. Evidence that an exceptional sunny month leads to additional installations at a two month lag is very difficult to reconcile with consumer myopia, given the high upfront investment cost of solar PV.[25] If consumers, on the other hand, present myopia in their profit expectations, myopia would be indistinguishable from projection bias.

Rain & cloud cover: Another potential concern is that individuals decide rationally about their investment, but it happens to be a rainy period and customers have strong preferences to leave their homes only in periods when it is dry. Using data on cloud cover helps me to eliminate this potential concern, as I can separate the effects of a covered sky from precipitation. I find that a high cloud cover impacts technology adoption, independent of rain (see Figure C.6).

News & information: Households might not respond to sunshine shocks themselves, but rather to information that becomes available in sunny periods. This would especially be a concern if news outlets are more likely to publish an article on solar PV or climate change in an exceptional sunny period. In order to test for this possibility, I obtained data on print media news coverage from the online database *Lexis Nexis* and created a monthly time series aggregating the number of articles that appear in the German press for 'solar PV' (990 entries), and 'climate change' (922 entries). The time series is plotted together with the series of new solar PV installations in Figure C.10. Table C.2 presents the main regression results, including data on news for solar PV (column 1), climate change (column 2), and both covariates (column 3). While both variables have a statistically significant impact on technology uptake, the main effect of sunshine shocks is robust to the inclusion of this potentially confounding factor. The news variables provides indirect evidence on the two-month time lag for installations. I find the largest magnitude at lag 2.

Learning: Another concern is that consumers might learn from exceptionally sunshine periods about future weather and climate conditions. However, as shown in Figure 5, sunshine shocks do not carry information on future sunshine events. Moreover, given data availability on long-term solar radiation, it is easy for rational agents to form expectations on average investment profitability. 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 might be for example more 'visible' on a sunny day. This type of learning, however, implies a

[25] De Groote and Verboven (2016) find that FIT policy leads to a general *undervaluation of future benefits* from solar PV adoption and interpret their finding in line with myopia. This paper, on the other hand, shows that sunshine shocks can lead to an important increase in solar adoption linked to an exaggeration of return expectations.

behavioral response that is very closely related to salience.

Climate change beliefs: Similarly, individuals beliefs about future climate might be affected by current weather conditions. The behavioral climate change literature (Deryugina 2013, Li, Johnson, and Zaval 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. As I do not find a significant effect of temperature on solar PV investment, climate change beliefs are not likely the main driver of my results.

Biased weather forecasts: One potential shortcoming of the data is that I am unable to distinguish between consumers having biased beliefs about future weather conditions and consumers having biased beliefs in their profit expectations. This is particularly 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 concerning preferences. The long time gap of about two-month between decision-making and installation makes it unlikely that investors believe that weather in two months time will be closely related to the weather today, given their past experience in weather seasonality in Germany. An alternative way to approach this possibility is to see by how much people are able to predict their local weather patterns. Krueger and Clement (1994) ask students in the United States to predict average high and low temperatures in their region for given days of the year and found that they are generally able to forecast the weather accurately. For the specific case of Germany, Burger-Scheidlin (2014) investigates the local weather perception of farmers related to climate change and long-term climatic evolutions. Her results indicate that farmers have an ample knowledge about how the weather should be at a given time of the year. Although one can assume that the general public has less 'inherited' knowledge, official weather information is available to both audiences.

9 Conclusion

This paper provides evidence that an important household investment decision, the installation of solar PV panels, is affected by behavioral economic phenomenon in line with projection bias and salience. Using administrative data on solar installations in Germany, I show that exceptionally sunny periods lead to an approximate 6.2% growth in the solar PV market in the six-month period following a sunshine shock. Furthermore, I show that there exists a strongly asymmetric response to positive and negative deviations from the long-term sunshine mean that can be explained by interactions of the two biases. Finally, I show that 'green counties', with a large historic share of green voters, are particularly affected by this sales effect. The overall findings cannot be rationalized by neoclassical theory with rational consumers yet are linked to projection bias and salience - two concepts closely related in the case of inter-temporal consumer purchase decisions.

Evidence for projection bias and salience in this high-stake investment decision implies that likely also other important consumer decisions are affected by behavioral biases. If consumers are prone to impulse purchases, a 'cooling-off period' combined with mandatory information disclosure is likely to increase consumer welfare (Loewenstein, O'Donoghue, and Rabin 2003). As pointed out by Busse, Pope, Pope, and Silva-Risso (2015), so far no clear recipe exists on how to de-bias consumers, which leaves an interesting field for future research.

On the other hand, given FIT subsidies, solar PV investment is both privately profitable and socially beneficial. If the objective of the policy-maker is to obtain a fast initial product diffusion, he might want to use these behavioral deviations from the neoclassical model to impact product uptake. Several lines of research have shown that policy formulation based on behavioral interventions can be successful (Allan, Jaffe, and Sin 2014, Chetty 2015, Madrian 2014). Alternatively, the finding of this study might help solar installers to communicate more effectively with potential customers, leading to additional product uptake at little or no cost. This is especially true if installers are able to target different population groups. Future research aiming at disentangling distinct behavioral channels through the use of randomized controlled trails would be beneficial to policy-targeting.

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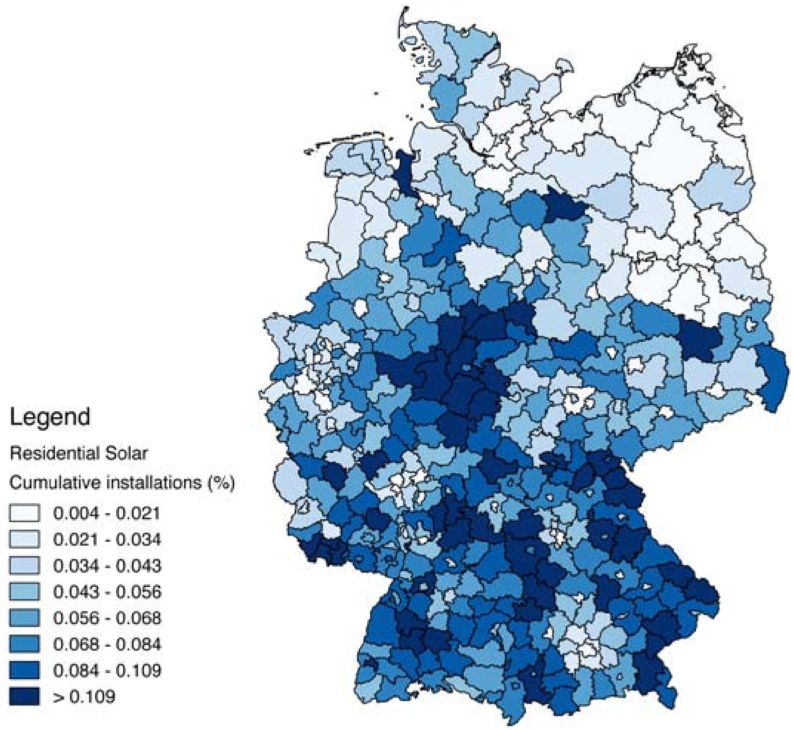
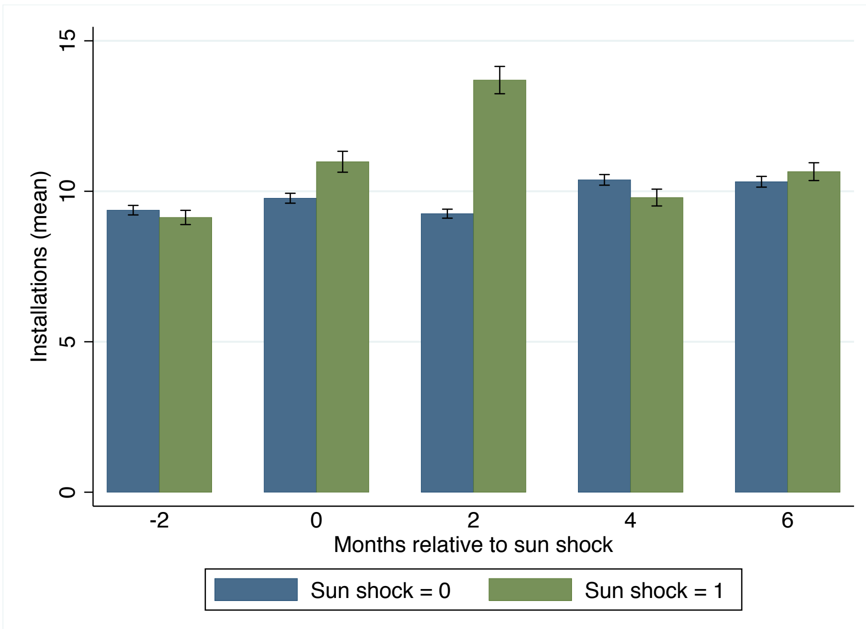
Figures & Tables

Figure 1: Solar installations in Germany, December 2011



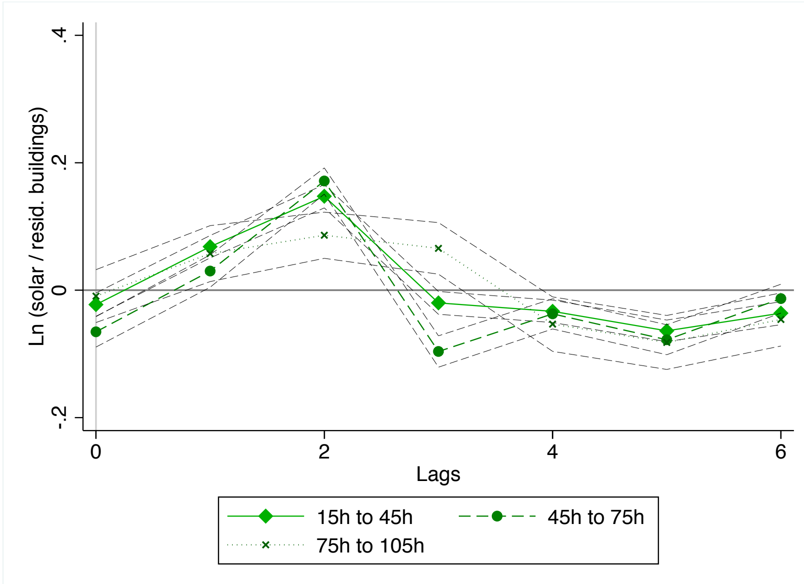
Note: Total number of residential solar PV installations ($\leqslant$ 10 kilowatt) in the period January 2000 to December 2011 normalized by the number of residential buildings in 1999. Unit of aggregation: counties. Darker areas represent higher solar PV penetration.

Figure 2: Solar installations and sunshine shocks

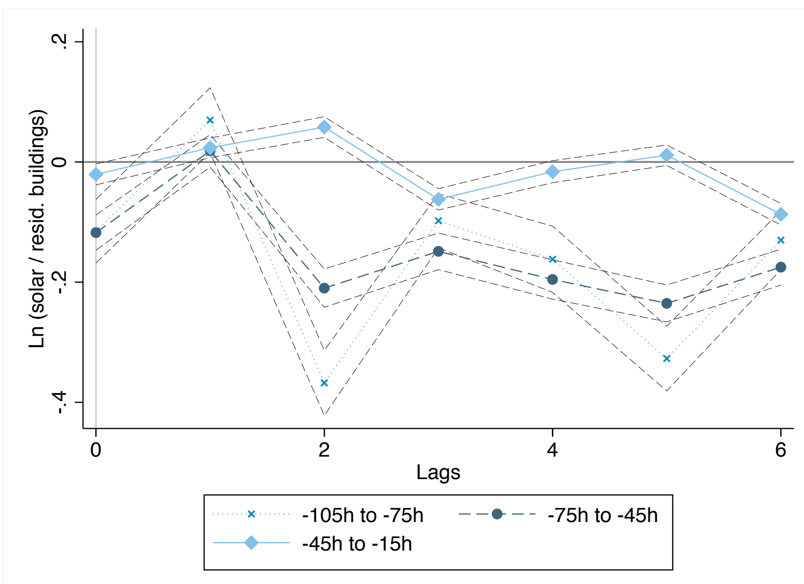


Note: The figure plots the average number of solar PV installations in counties with a positive sunshine shock at time period 0 in comparison to counties that have no sunshine shock in the same time period. The average number of installations is shown in two-month intervals, from 2 month prior to a sunshine shock (t=-2) to 6 month posterior to a sunshine shock (t =6).

Figure 3: Non-linear effects: de-meaned sunshine hours



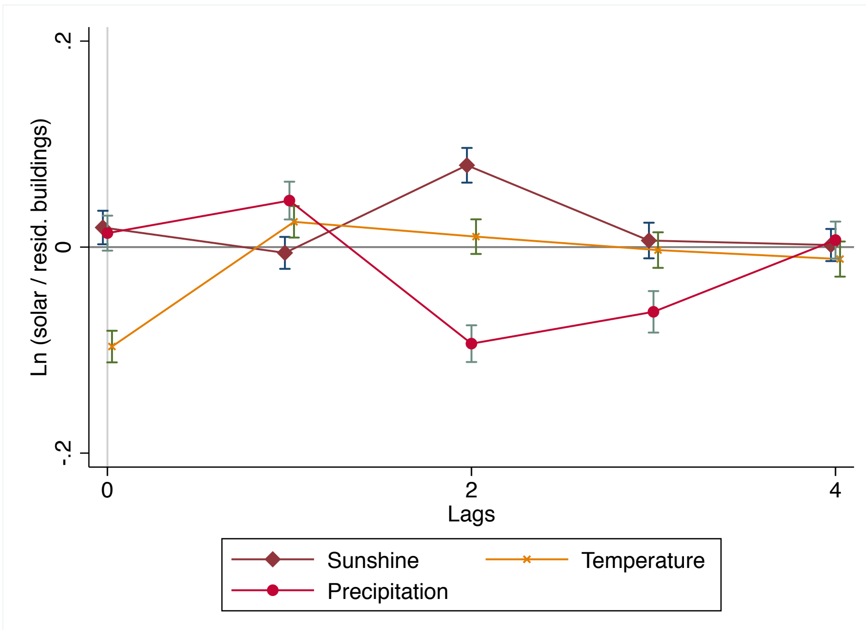
(a) Bins for positive deviations from the long-term mean



(b) Bins for negative deviations from the long-term mean

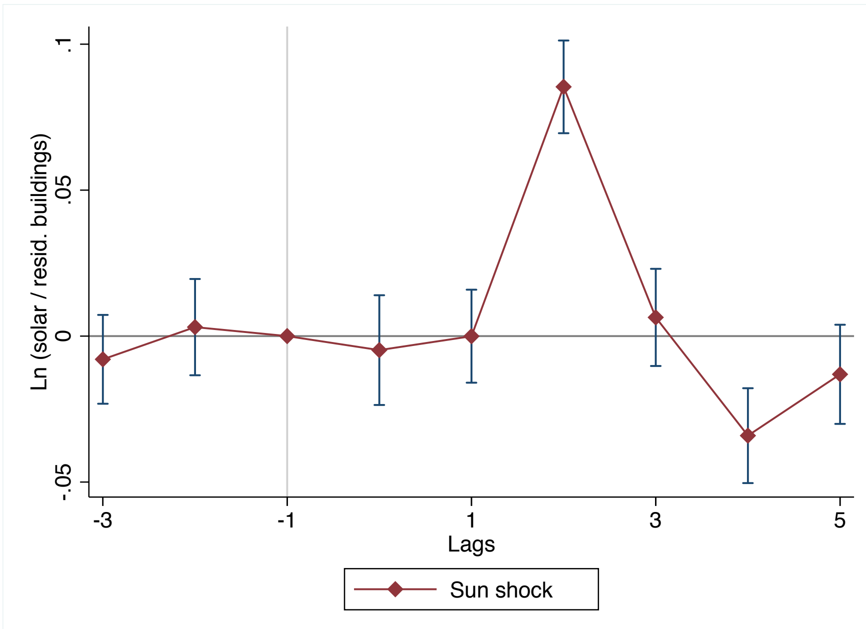
Note: The figure plots the coefficients and 95% confidence interval for a regression of the log of solar PV installations to residential buildings on bins for sunshine deviations from the long-term sunshine mean following regression model 1. Unit of observation: county-month. Each weather observation is demeaned by the long-term average in a given county-month-of-the-year. The corresponding histogram is provided in Figure C.3. All estimates are relative to the long-term mean category (+/- 15 sunshine hours), which is omitted from the regression. The results for positive (panel a) and negative (panel b) bins are split in two panels for ease of exposition. All standard errors are clustered at the county level.

Figure 4: Distinct weather shocks



Note: The figure plots the coefficients and 95% confidence interval regressing the log of solar PV installations to residential buildings on weather shocks for sunshine, temperature, and precipitation. Weather shocks are defined as weather realizations one standard deviation above the long-term weather mean. Unit of observation is county-month. The model follows main regression specification 1. All standard errors are clustered at the county level.

Figure 5: Predictability of sunshine shocks



Note: The figure plots the coefficients and 95% confidence interval regressing the log of solar PV installations to residential buildings on sunshine shocks interacted with monthly dummies. I introduce a separate dummy for the history of sunshine shocks in each country, grouping periods with more than 12 month of lead and lag in an 'early' and 'late' dummy. All results are relative to time period t-1, which is omitted from regression. The figure displays the sunshine shock coefficients for the period three month prior to a sunshine shock and up to five month posterior. The model includes year and county-month-of-the-year FEs as in specification 1. All standard errors are clustered at the county level.

Table 1: Summary statistics

	All	High sun shock	Low sun shock
Solar installations	10.02	11.53	8.71
	(18.28)	(20.02)	(16.52)
Sunshine hours	139.66	139.60	139.72
	(77.38)	(76.32)	(78.28)
Mean temperature, in degree C	9.45	9.32	9.56
	(6.62)	(6.62)	(6.62)
Population	204019	199232	208142
	(228264)	(271895)	(182422)
Household income pc, in Euros (2010)	18823	18964	18703
	(2304)	(2259)	(2335)
Vocational training, in %	62.50	62.78	62.26
	(6.04)	(5.59)	(6.38)
University degree , in %	8.43	8.35	8.50
	(3.93)	(4.01)	(3.86)
Unemployment rate , in %	9.77	8.83	10.57
	(4.62)	(4.16)	(4.85)
New residential buildings / population	0.18	0.19	0.16
	(0.11)	(0.11)	(0.10)
Agricultural surface , in %	0.47	0.50	0.44
	(0.16)	(0.15)	(0.16)
Green voters , in %	7.69	7.79	7.60
	(3.49)	(3.39)	(3.56)
Vote participation , in %	76.66	77.21	76.18
	(5.53)	(5.37)	(5.62)
Observations	57888	26784	31104
Counties	402	186	216

Note: Summary statistics for the period 2000-2011. Unit of observation is county-month. Column 1 refers to the full sample. Columns 2 and 3 split the sample according to the median of the sunshine shock in high (column 2) and low (column 3) sun shock counties. A sunshine shock is defined as a sunshine realization one standard deviation above the long-term mean in a given county-month-of-the-year. Standard deviations reported in parentheses.

Table 2: Main regression: sunshine shock

	(1)	(2)	(3)	(4)	(5)
Sun shock	−0.003	−0.003	−0.008	0.002	0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Lag sun shock	−0.004	−0.005	0.055***	0.016**	0.002
	(0.008)	(0.008)	(0.009)	(0.007)	(0.008)
Lag 2 sun shock	0.107***	0.107***	0.108***	0.113***	0.119***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Lag 3 sun shock	0.014*	0.013*	0.009	0.015**	0.025***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Lag 4 sun shock	−0.015**	−0.015**	−0.012*	0.008	−0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Lag 5 sun shock	−0.030***	−0.030***	−0.021***	−0.010	−0.029***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Lag 6 sun shock	−0.007	−0.006	−0.011	−0.005	−0.005
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	55476	55476	55476	55476	55476
R^2	0.794	0.794	0.795	0.796	0.859
Lag cumulative installations	N	Y	N	N	N
Lag sunshine hours	N	N	Y	N	N
Lag temperature	N	N	N	Y	N
Year FE	Y	Y	Y	Y	N
County-MoY FE	Y	Y	Y	Y	Y
County-Year FE	N	N	N	N	Y

Note: Dependent variable: log of solar PV installations to residential buildings. Unit of observation is county-month. Main model (column 1) controls for year fixed effects (FEs) and county-month-of-the-year FEs that vary with the three main FIT periods (2000-04, 2005-2009, 2010-11), resulting in a total of 9,659 FEs. Columns 2 to 4 include the lagged number of solar PV installations, lagged sunshine, and lagged temperature respectively as additional control variables. Column 5 replaces the yearly FE by a county $time$ year FE. Robust standard errors are clustered at the county level. $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***).

Table 3: Heterogeneous effects: county covariates

D_h	$\mathbb{1}(y_c \geqslant \overline{y})$	$\mathbb{1}(e_c \geqslant \overline{e})$	$\mathbb{1}(\nu_c \geqslant \overline{\nu})$	$\mathbb{1}(r_c \geqslant \overline{r})$
Sun shock	−0.003	−0.012	−0.008	0.004
	(0.009)	(0.010)	(0.010)	(0.010)
Lag sun shock	−0.022**	−0.019*	−0.022*	−0.041***
	(0.011)	(0.011)	(0.011)	(0.010)
Lag 2 sun shock	0.092***	0.102***	0.079***	0.095***
	(0.011)	(0.011)	(0.010)	(0.011)
Lag 3 sun shock	0.039***	0.013	0.029***	0.040***
	(0.011)	(0.010)	(0.011)	(0.010)
Lag 4 sun shock	−0.004	−0.017*	−0.005	−0.025**
	(0.009)	(0.009)	(0.009)	(0.010)
Lag 5 sun shock	−0.038***	−0.017	−0.041***	−0.041***
	(0.010)	(0.010)	(0.010)	(0.010)
Lag 6 sun shock	−0.011	−0.002	−0.007	−0.029***
	(0.010)	(0.010)	(0.010)	(0.010)
Sun shock × D_h	−0.000	0.020	0.008	−0.014
	(0.014)	(0.014)	(0.014)	(0.014)
Lag sun shock × D_h	0.038**	0.030**	0.035**	0.074***
	(0.015)	(0.015)	(0.015)	(0.014)
Lag 2 sun shock × D_h	0.031**	0.012	0.056***	0.024
	(0.015)	(0.015)	(0.015)	(0.015)
Lag 3 sun shock × D_h	−0.050***	0.003	−0.028*	−0.055***
	(0.014)	(0.015)	(0.015)	(0.014)
Lag 4 sun shock × D_h	−0.024*	0.004	−0.019	0.019
	(0.014)	(0.014)	(0.014)	(0.014)
Lag 5 sun shock × D_h	0.017	−0.027*	0.024	0.026*
	(0.015)	(0.015)	(0.015)	(0.016)
Lag 6 sun shock × D_h	0.007	−0.012	−0.002	0.038***
	(0.014)	(0.014)	(0.014)	(0.014)
Observations	55476	55476	55476	55476
R^2	0.796	0.796	0.796	0.796
Time FE	Y	Y	Y	Y
County-MoY FE	Y	Y	Y	Y

Note: Dependent variable: log of solar PV installations to residential buildings. Unit of observation is county-month. Each column interacts the sunshine shock with a separate dummy variable D_h indicating counties with high income (column 1), a high share of tertiary education (column 2), a high share of green voters (column 3), and high average solar radiation (column 4). D_h is defined with respect to the median: columns 1 to 2 considers the base-year (2000), while the vote share of the green party refer to the federal election in 1998. A county with high solar radiation in column 4 is identified regarding the long-term averages. The regression follows model 1 and includes additional control variables for tertiary education, household income, unemployment rate, and agricultural surface. Robust standard errors are clustered at the county level. $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***).

Table 4: Price effect of sunshine shocks

	Original data		Interpolated data	
	(1)	(2)	(3)	(4)
Lag solar installations	−0.008*	−0.007*		−0.009***
	(0.004)	(0.004)		(0.003)
Lag 2 solar installations	0.001	0.001		−0.001
	(0.007)	(0.007)		(0.005)
Sun shock		0.001	−0.005	−0.004
		(0.013)	(0.008)	(0.008)
Lag sun shock		0.015	0.014	0.013
		(0.013)	(0.009)	(0.009)
Lag 2 sun shock		0.010	−0.002	−0.003
		(0.019)	(0.011)	(0.011)
Observations	1835	1835	3104	3104
R^2	0.609	0.609	0.637	0.639
State-by-quarter FE	Y	Y	Y	Y

Note: Dependent variable: log price per KW of installed solar PV capacity (residential installations). Unit of observation is county-quarter, in 2010 and 2011. The regression controls for state by quarter fixed-effects. Columns 1 and 2 use the original sample, while columns 3 and 4 use an interpolated dataset that imputes missing prices for county-quarters with no reported sales using a flexible regression model that includes a nationwide price trend, county intercepts as well as price variation by state half-year. Robust standard errors are clustered at the county level. $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***).

Table 5: Robustness: weather data and inference

	(1)	(2)	(3)	(4)	(5)	(6)
Shock definition	Original	Weather station data		Original		
Standard errors	Cluster	Cluster	Cluster	Cluster	Newey-West	Conley
Sun shock	-0.003	0.007	0.029	-0.010	-0.010	-0.004
	(0.013)	(0.016)	(0.023)	(0.011)	(0.049)	(0.031)
Lag sun shock	-0.004	0.013	0.005	-0.003	-0.003	-0.020
	(0.015)	(0.014)	(0.021)	(0.012)	(0.072)	(0.027)
Lag 2 sun shock	0.107***	0.104***	0.074***	0.100***	0.100*	0.094***
	(0.014)	(0.016)	(0.022)	(0.011)	(0.052)	(0.026)
Lag 3 sun shock	0.014	0.016	0.046**	0.019*	0.019	0.017
	(0.012)	(0.018)	(0.022)	(0.011)	(0.044)	(0.025)
Lag 4 sun shock	-0.015	-0.004	0.011	-0.002	-0.002	0.004
	(0.014)	(0.016)	(0.021)	(0.013)	(0.041)	(0.024)
Lag 5 sun shock	-0.030**	-0.014	-0.015	-0.024**	-0.024	-0.020
	(0.012)	(0.012)	(0.021)	(0.011)	(0.051)	(0.023)
Lag 6 sun shock	-0.007	-0.009	-0.007	0.002	0.002	0.006
	(0.012)	(0.014)	(0.020)	(0.011)	(0.039)	(0.024)
Observations	55476	55476	6624	55476	55476	55476
R^2	0.794	0.793	0.788	0.665	-	-
Time FE	Y	Y	Y	Y	Y	Y
County-MoY FE	Y	Y	Y	N	N	N
Separate county & MoY FE	N	N	N	Y	Y	Y

Note: Dependent variable: log of solar PV installations to residential buildings. Unit of observation is county-month. Regression model in columns 1 to 3 controls for year FEs and county-month-of-the-year FEs. Columns 1 uses the original sunshine shock definition, while columns 2 and 3 employ weather station data to calculate the sunshine shock variable. Column 3 limits the sample to the subset of 51 counties with weather station. Columns 4 to 6 use a transformed regression model that relies on separate county FE and month-of-the-year FE. The total number of FE in this specification is 435. Columns 1 to 4 cluster at the weather station level, column 5 employs Newey-West standard errors and column 6 follows Conley (1999). The autocorrelation lag for these errors is set to 4 month. Spatial correlation is allowed to occur in a 100km radius. $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***).

Table 6: Sunshine shock and wind installations

	Solar	Wind
Sun shock	0.006	0.001
	(0.009)	(0.006)
Lag sun shock	−0.012	0.001
	(0.009)	(0.005)
Lag 2 sun shock	0.111***	0.008
	(0.008)	(0.006)
Lag 3 sun shock	0.016**	0.004
	(0.008)	(0.005)
Lag 4 sun shock	−0.008	−0.009
	(0.008)	(0.006)
Lag 5 sun shock	−0.034***	−0.012**
	(0.008)	(0.005)
Observations	43090	43090
R^2	0.811	0.760
Controls	Y	Y
Time FE	Y	Y
County-MoY FE	Y	Y

Note: Dependent variables: log of solar PV installations to residential buildings (column 1) and log of wind installations to residential buildings (column 2). Unit of observation is county-month. The sample is limited to counties that have at least one wind turbine in the period 2000-2011 (310 counties). The model includes year and county-MoY FEs as in specification 1 as well as contemporaneous control variables for tertiary education, household income, unemployment rate, and agricultural surface. Robust standard errors are clustered at the county level. $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***).

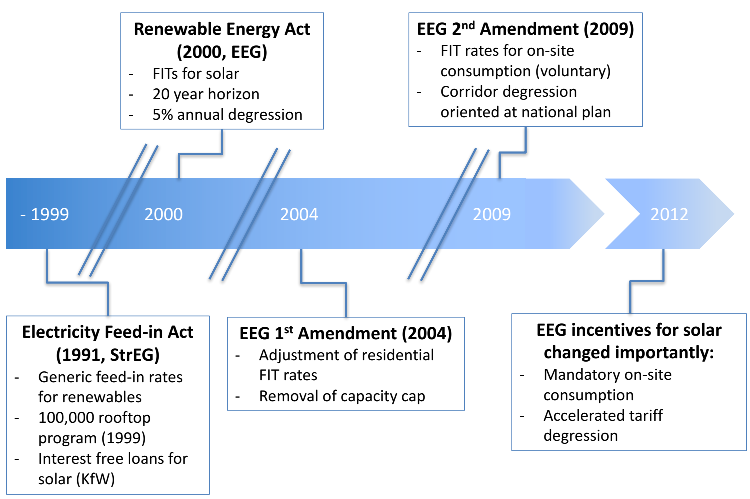
Appendix

A The German Solar Market

A.1 Overview

In spite of its small size and poor solar radiation, Germany has long been the global leader in installed solar PV capacity.[26] Most of this 'success' is attributed to the introduction of the *Erneuerbare Energien Gesetz* (EEG) in 2000 and the related feed-in tariffs (FIT) scheme that created a favorable investment environment for solar PV. Figure A.1 summarizes the main support policies. While FITs were already part of the 1991 electricity feed-in act, FIT rates were low and oriented towards hydro-electric power plants. The first important step towards residential investment in solar energy was taken in 1999 with the introduction of the so-called 100,000 rooftop program. This program had the objective to add a total of 300 Mega Watt (MW) of installed solar PV capacity to the electricity grid. It mainly operated through interest-free loans offered by the German bank for reconstruction (KfW). In 2000, the federal government introduced the EEG as part of a larger 'sustainability' incentive.

Figure A.1: FIT policy in Germany

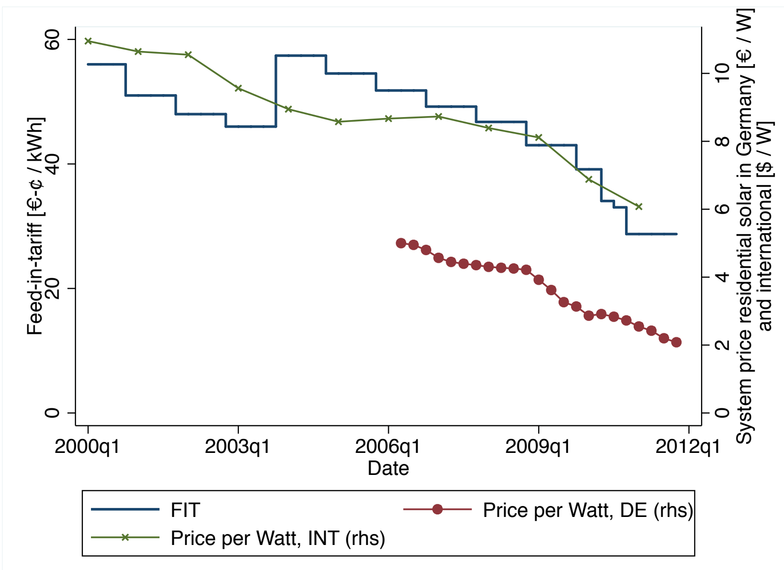


The EEG introduced a revised FIT scheme, offering additional incentives for private investments in solar PV. It guarantees investors access to the electric grid for a period of 20 years at a

[26] REN21 (2015), Global Status Report on Renewables.

fixed FIT above the retail price of electricity. The EEG also sets a fixed 'degression rate', the rate at which FITs decrease each year, in order to mimic market trends in cost developments. In the time period 2000 to 2011, there have been two amendments to the original EEG: the first, enacted in 2004, increased FIT rates for residential investors and removed the initially set capacity cap. The second, enacted in 2009, had the objective to make FIT more cost effective, offering reduced rates for on-site consumption. Yet, poor incentives led to little uptake of this new tariff option. Consequently, the 2009 reform did not affect the average profitability of solar PV and led to a record number of PV installations , both in 2010 and in 2011. The economic incentives for solar PV investment changed importantly in 2012, with the introduction of a more stringent FIT scheme.[27]

Figure A.2: FIT policy and solar PV prices



Note: Evolution of FIT tariffs and residential system solar PV prices.

Figure A.2 plots the evolution of FIT rates and solar PV prices over time. FITs are downward adjusted on the 31 of December of each year for new installations to account for price decreases in solar PV installations. Changes are previously announced and do not affect previous installations. The average solar PV system prices is plotted both for Germany (in Euros) and internationally (in $) to show trends in prices. The presence of FITs leads to highly comparable (and profitable) investment conditions in an otherwise quickly changing market environment.

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

For example, in the year 2007, the average price per installed kilowatt (KW) was 4440 Euros. A standard crystalline silicon panel produces around 830 KWh per year in the central German region of Frankfurt (taking into account an estimated system loss of 14%, PV GIS Calculator, European Commission). With the given FIT and a project horizon of 20 years, the investment results in an internal rate of return of about 7.7%. Individual return rates be considerably higher, depending on location, panel orientation towards the sun, and solar panel efficiency.

A.2 Solar Installer Survey

Solar supply in Germany is highly fragmented and dominated by local installers. I conduct an online survey with solar PV installers to obtain additional information on marketing and sales activities as well as information on the main consumer decision variables. The survey covers three main areas: motivation and decision variables affecting customer investment decisions, time gap in decision-making, and the impact of weather and climate on installer sales activities. I obtain solar PV installer email addresses through an automated web-scrape from an online directory of German solar PV installers. This section is based on 56 installers that responded to the online invitation to participate in the survey in August 2015. While the sampling rate is low (about 2%), the geographical representation of the installer sample mimics the one from my universe of installers.[28]

Even though the sample is unlikely to be fully representative of the German solar market, it provides useful insights on solar PV supply. My sample is mainly composed by professional solar installers (60% of respondents), electricians (12%), and heating & water installers (12%). Most of the companies are rather small in size with 1-5 employees (52%), while 20% have more than 20 employees. In addition, more than 50% of the respondents have been installing solar PV panels for at least 10 years and thus can provide credible information for changes in the solar PV business environment. In line with other Marketing surveys (see for example Muehlhausen Consulting, 2014), I find that installer markets are mainly local: 60% of businesses state that their main commercial activity is concentrated either in the same county or adjacent counties. The main insights from the online survey can be summarized by the following points:

1. Household investment decisions are affected by financial considerations.

[28]Additional data on the installer survey as well as the full questionnaire are available from the authors upon request.

2. Customers acquisition effort is low: installers mainly rely on word-of-mouth.

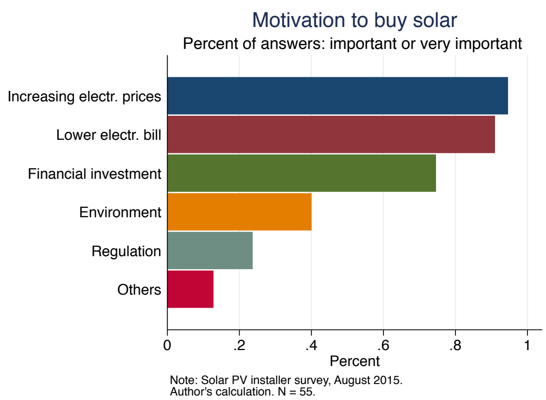
3. The average time gap from first customer contact to completion of the installation is 9 weeks.

4. There is no evidence that installers adapt their marketing strategies to short-term variations in weather.

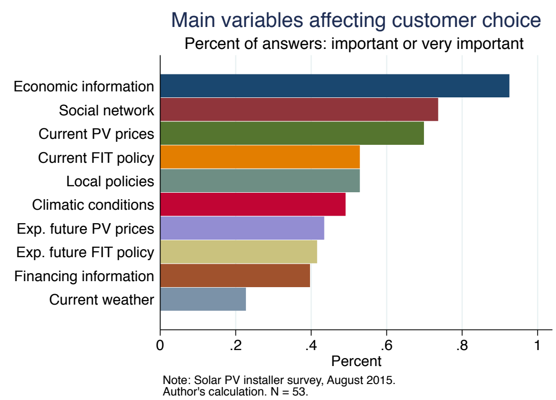
Panel (a) of Figure A.3 shows the percentage of installers that report that any of the listed variables are either 'very important' or 'important' for the customer motivation to purchase a solar PV panel (on a 1-7 Likert scale). The main motivations are financial. Environmental concerns are only considered to be important by about 40% of installers. Panel (b) of the same figure lists variables that affect the consumer decision to adopt a solar panel. Economic variables dominate the discussion together with information from social networks. Financing and weather, on the other hand, are not considered to be important influencing factors. Finally, panel (c) of the same figure lists the main marketing tools that are used by installers. I find that most installers rely on word-of-mouth (close to 70%) for customer acquisition. Events are used by roughly half of the sample. Other communication strategies, such as online advertisements, print media, or direct mailing are used by about 30-40%. Finally, as most of the installers are small in size it is not surprising that 75% of respondents do not have specific personnel involved in sales and marketing activities. This is in line with the fragmented nature of solar PV supply in Germany.

Finally, Figure A.4 plots the histogram for the average time gap between first customer contact and completion of the installation. The questionnaire invokes two separate questions regarding the average time length between first customer contact and contract signature and the time gap between contract signature and completion of the installation. The survey shows that on average it takes 5 weeks (median: 4 weeks) from first customer contact until contract signature. This time gap can be explained by individual planning of the installation (which often involves site visits), but also customers soliciting bids from competing installers, given the large financial stake. Once the contract is signed, on average it takes another 4 weeks (median: 4 weeks) to complete the installation. This time gap can be mainly explained by the actual work on the installation, as well as planning, permitting, and inspection. The total time gap is 9 weeks (median: 8 weeks), with an interquartile range from 6 to 10 weeks. These numbers are in line with an earlier survey

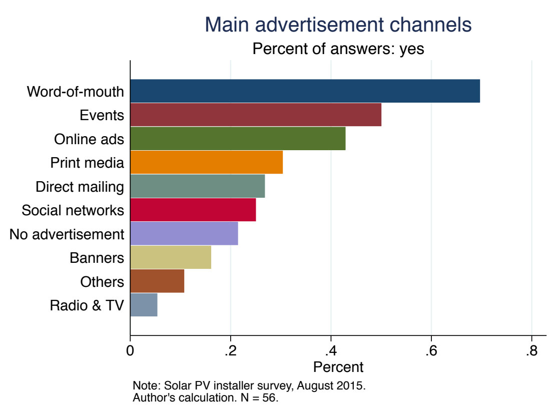
Figure A.3: Solar installer survey: main categories



(a) Customer motivation



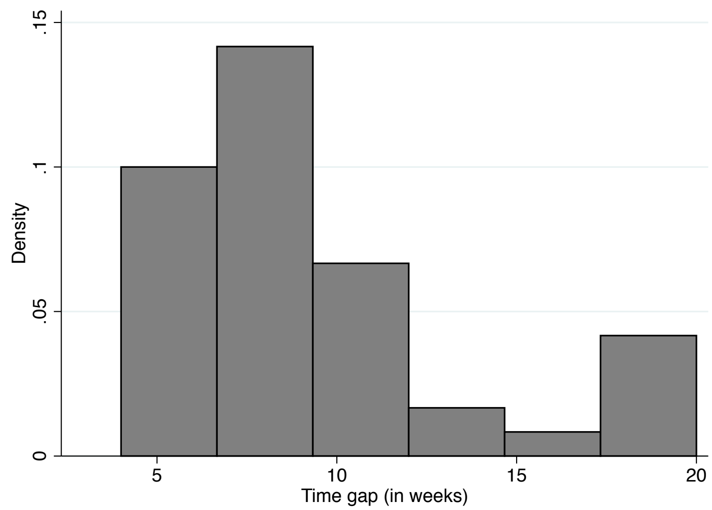
(b) Customer decision-making



(c) Installer: Main marketing channels

performed with German installers by Seel, Barbose, and Wiser (2013) that find that from the moment of contract signature it takes about 38 man-hours per system installation plus about 5-10 hours for permitting, interconnection and inspection, not considering additional site-specific planning, material availability, and installer workload.

Figure A.4: Solar Installer: timing



Note: Average time gap from customer decision-making to completion of the installation. Source: Solar installer survey (Own calculation), August 2015. N=45. Histogram cut at the 1st and 99th percentile.

B Weather & Solar PV Profitability

In addition to sunshine, different weather phenomena can impact the output of solar cells, at least in the short-run.[29] The main variables to consider are temperature and cloud cover:

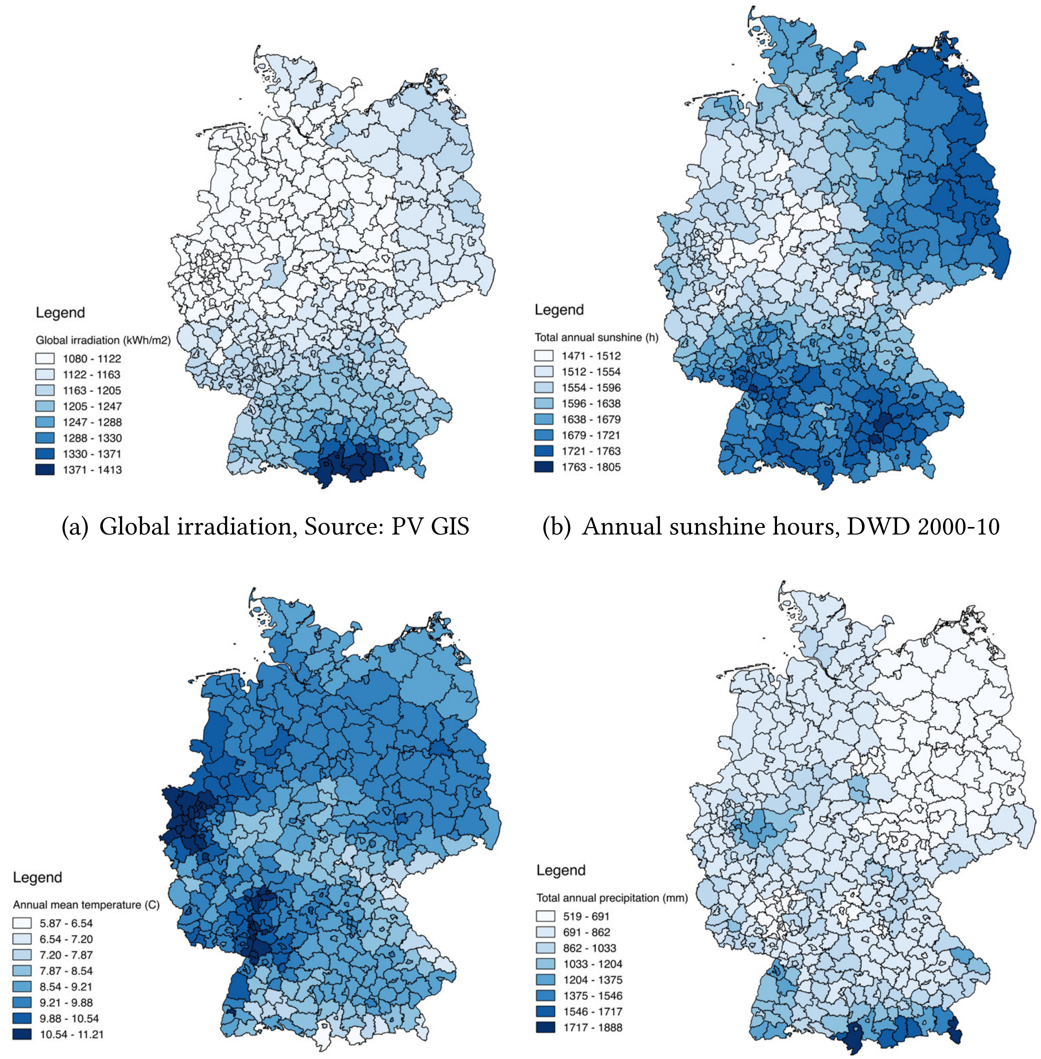
Temperature: High temperature can affect the performance of solar cells negatively. Both the electric current generated and its voltage are influenced by the operating temperature. However as the positive change in current is offset by a negative change in voltage, and given the fact that solar modules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

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

Other weather: Similarly, other weather events such as snow and ice can affect the quantity of sunlight absorbed by the solar PV panels, but their effects are typically short-lived and should not affect the average profitability of solar PV investments over the 20-year project horizon.

[29] See for example *EEPQRC (2011) guide on small scale rooftop solar PV systems.*

Figure B.1: Distribution of global solar radiation and weather variables



(a) Global irradiation, Source: PV GIS

(b) Annual sunshine hours, DWD 2000-10

(c) Annual mean temperature, DWD 2000-10

(d) Annual precipitations, DWD 2000-10

Weather Shocks

Figure B.2 depicts the mean of the sunshine shock variable over month (panel a) and years (panel b) of my sample period. Sunshine shocks are similarly likely to occur over individual months of the year, while there exists an important year-to-year variation. This year-to-year variation makes it necessary to condition on a long time horizon when defining the long-term weather averages. To test for autocorrelation of the sunshine shock at the county level, i.e. a sunshine shock today carries information on future sunshine shocks, Table B.1 provides summary statistic on the Portmanteau (Q) test statistic for white noise. I construct the test statistic for each county independently (for different lag structures) and present the percentage of counties where the null hypothesis of no autocorrelation can be rejected at the 1% and 5% significance level. Focusing on 6 and 12 lags, I find that autocorrelation of sunshine shocks is low.

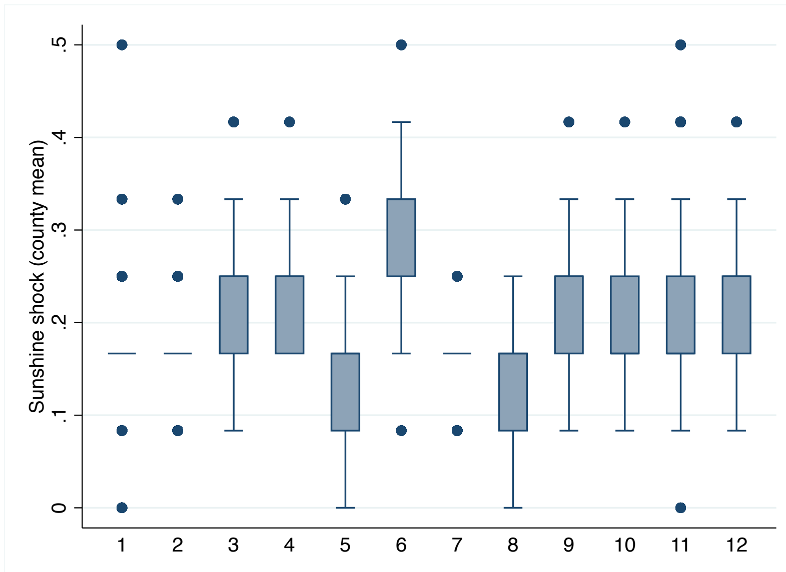
Table B.2 on the other hand looks at (global) spatial correlation of sunshine shocks. For each month of my sample, I calculate Moron's I test statistic and list the percentage of periods for which the null of no spatial autocorrelation can be rejected at the 1% and 5% significance level, assuming different spatial weighting matrices: "full" all counties can be correlated (weight = distance), "Q1" counties up to the 1st quartile can be spatially correlated (weight = distance), and "Q1 (0/1)" counties up to the median distance can influence the sunshine shock in a given county (weight = binary). The table suggests that spatial correlation of shocks is overall not of concern.

Table B.1: Portmanteau (Q-statistic) for white noise

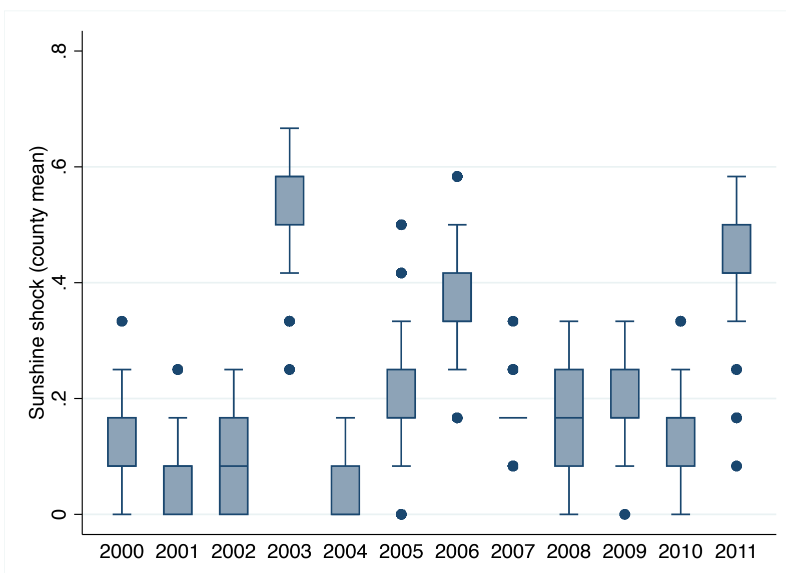
	Sunshine shock			
Q-statisitc	6 lags	12 lags	24 lags	40 lags
Percent counties with p<.01	.032	.007	.074	.102
Percent counties with p<.05	.089	.077	.209	.274

Note: A Q-(Portmanteau) statistic for white noise with different lag cut-offs are calculated for each county individually. The table presents the percentage of counties in which the white noise hypothesis can be rejected at the 1% and 5% level of significance respectively.

Figure B.2: Distribution of sunshine shocks



(a) Over: month



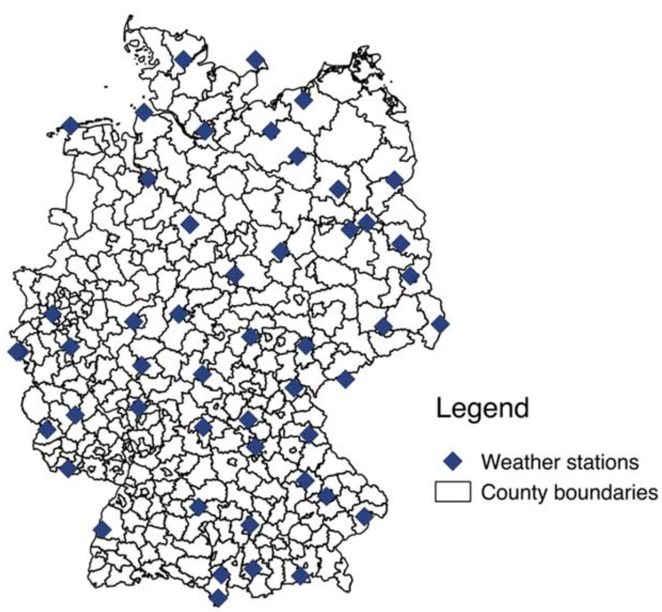
(b) Over: year

Table B.2: Moran's I on global spatial correlation

	Sunshine shock			Sunshine		
Moran's I	full	Q1	Q1 (0/1)	full	Q1	Q1 (0/1)
Percent counties with p<.01	.048	.061	.061	.021	.035	.062
Percent counties with p<.05	.067	.067	.133	.083	.076	.09

Note: The Moran I test statistic for global spatial correlation is calculated for each of the months in my sample, assuming different cutoffs for spatial correlation: column 1 allows all counties to be correlated, column 2 correlation up to the first quartile distance, and column 3 up to the first quartile distance with binary weights. The table presents the percentage of periods in which the null of "no spatial correlation" can be rejected at the 1% and 5% level of significance respectively.

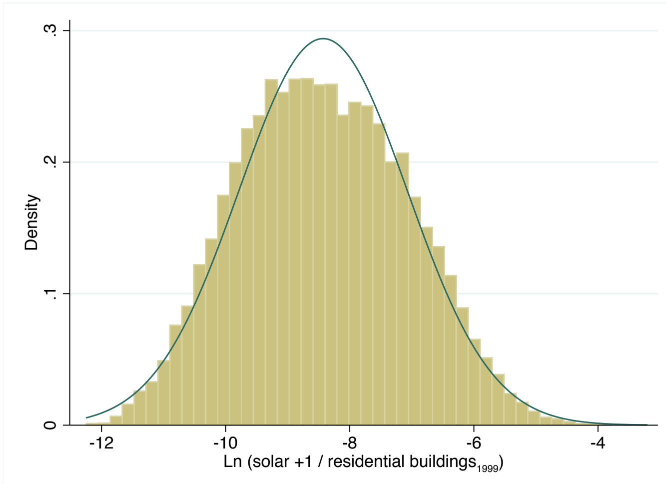
Figure B.3: Location of weather stations



Note: Locations of freely available weather stations with a historical record 1971-2011. Source: DWD, German Weather Service.

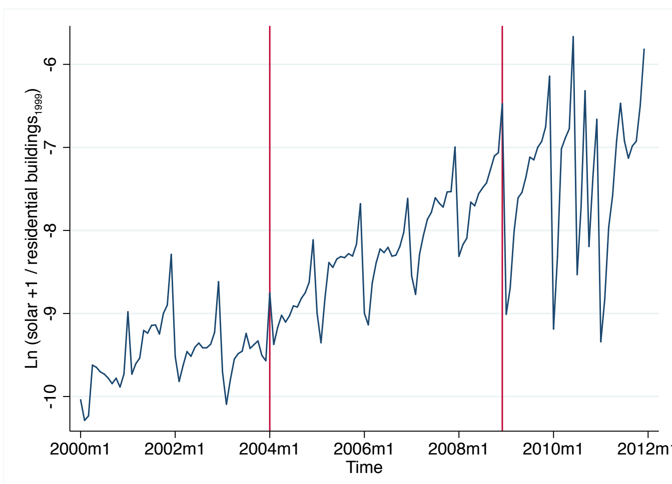
C Additional Figures & Tables

Figure C.1: Histogram: main dependent variable



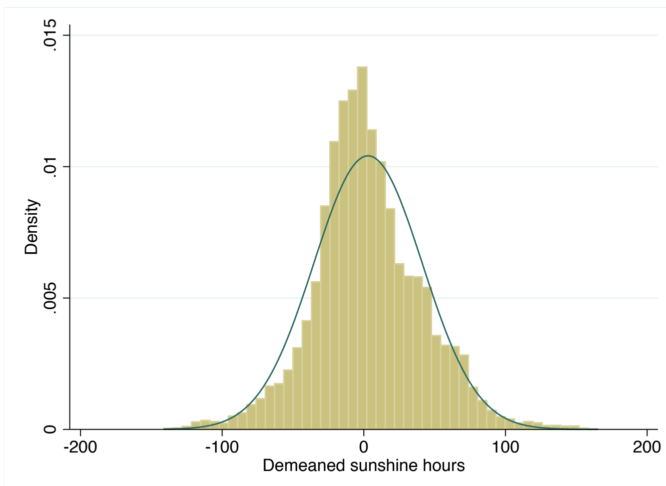
<u>Note:</u> Histogram of log of solar PV installations to potential market (residential buildings in 1999). Unit of observation is county-month, 2010-11. Normal distribution plotted for comparison.

Figure C.2: Main dependent variable over time



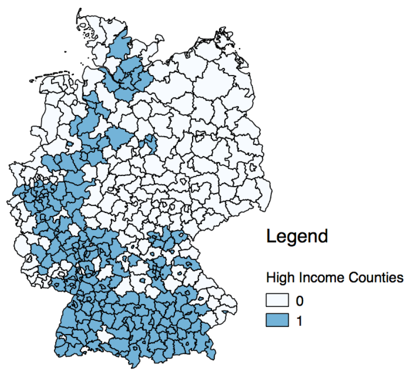
<u>Note:</u> Mean of log of solar PV installations to potential market (residential buildings in 1999) over the period 2000 to 2011. Unit of observation: month. Vertical lines indicate the 2004 and 2009 FIT reforms.

Figure C.3: Histogram: demeaned sunshine hours

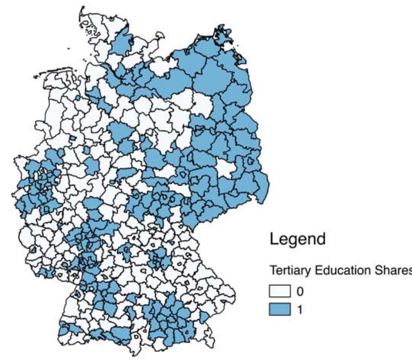


Note: Sunshine hours demeaned with respect to the long-term sunshine averages in each county-month-of-the-year. Unit of observation is county-month, 2010-11. Normal distribution plotted for comparison.

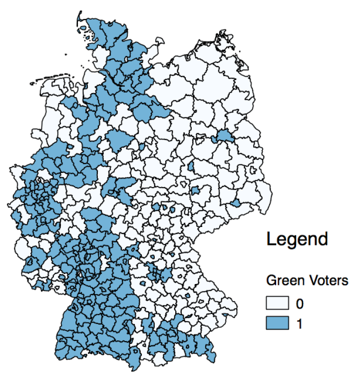
Figure C.4: Heterogeneity: county division



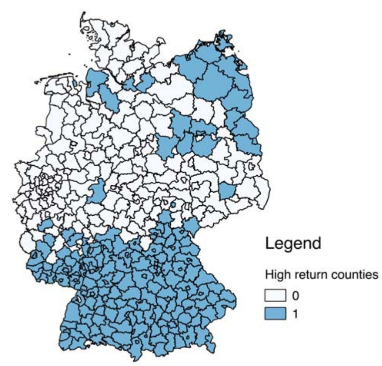
(a) Household income



(b) Tertiary education



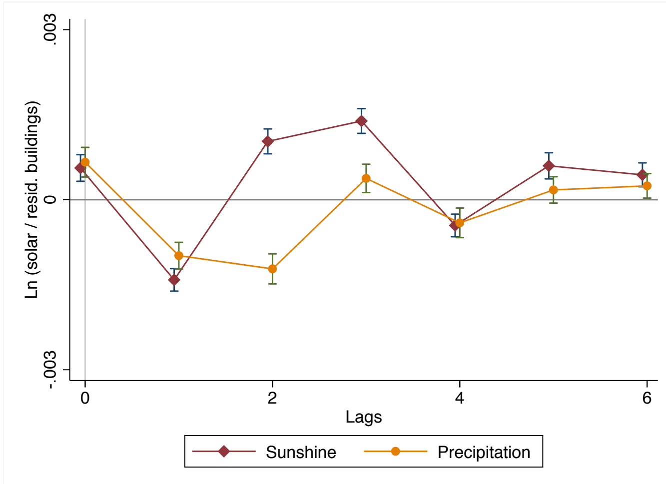
(c) Green voters



(d) Solar radiation

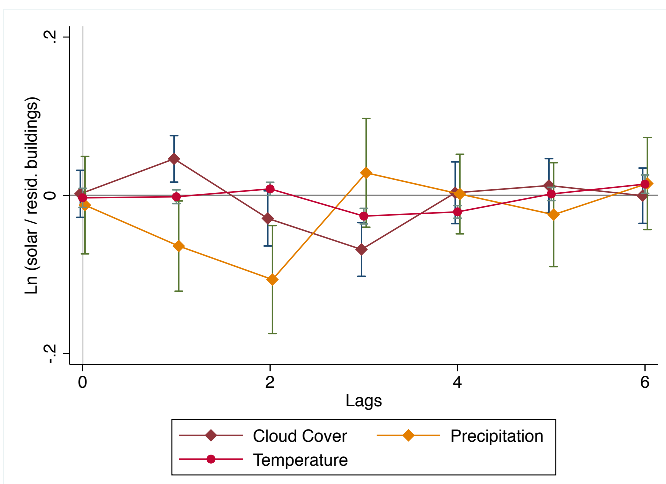
Note: Individual maps divide Germany in two regions according to the median household income (panel a), the median share of tertiary eduction (panels b), the median vote share of the green party (panel c), and the median solar radiation (panel d). While the division for income and education are made with respect to the base year (2000), the voting share is based on the 1998 federal elections, and the solar radiation is based on long-term averages.

Figure C.5: Weather levels



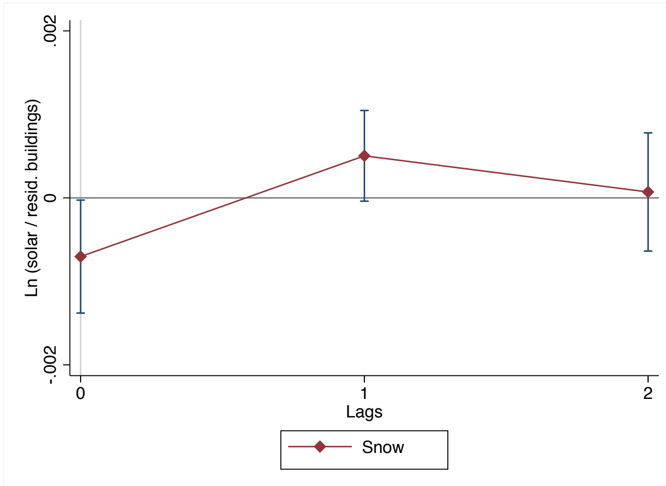
Note: The figure plots the coefficients and 95% confidence interval for a regression of the log of solar PV installations to residential buildings on sunshine hours and precipitation (in levels), following the main regression model 1. Unit of observation is county-month. Robust standard errors clustered at the county level.

Figure C.6: Weather shocks: weather station data



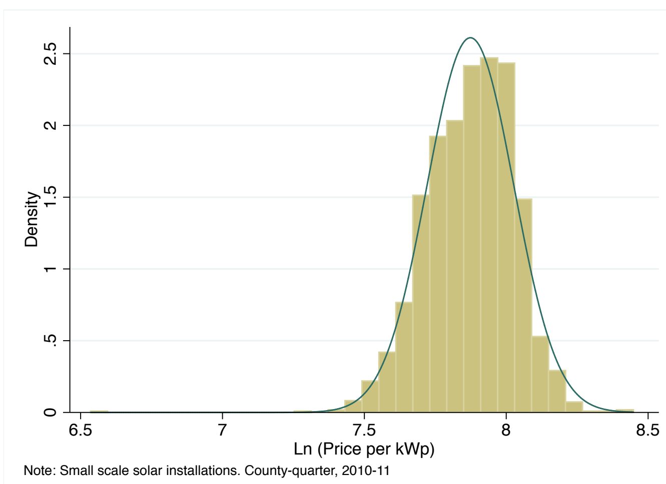
Note: The figure plots the coefficients and 95% confidence interval for a regression of the log of solar PV installations to residential buildings on weather shocks for temperature, precipitation, and cloud cover. Weather shocks calculated in an analog fashion to sunshine shocks. Cloud cover is measured as an index of blue sky. Unit of observation is county-month. Sample: counties with weather station, 2000-11, N= 6423. Robust standard errors clustered at the weather station.

Figure C.7: Snowfall: weather station data



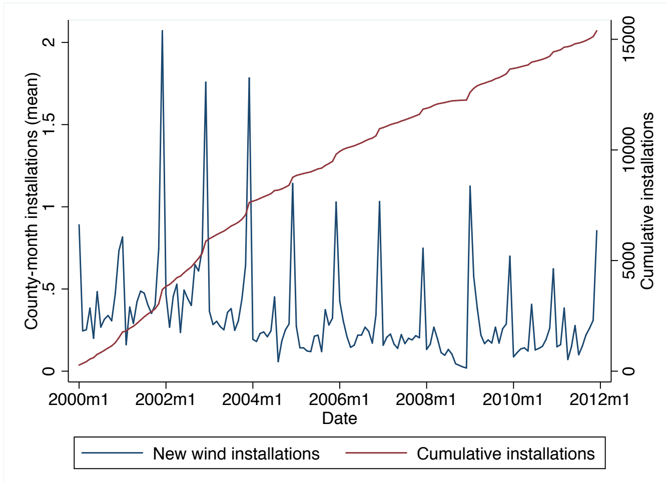
Note: The figure plots the coefficients and 95% confidence interval for a regression of the log of solar PV installations to residential buildings on snowfall (in levels). Unit of observation is county-month. Counties with weather station, 2000-11, N= 6768. Robust standard errors clustered at the weather station.

Figure C.8: Histogram: solar PV prices



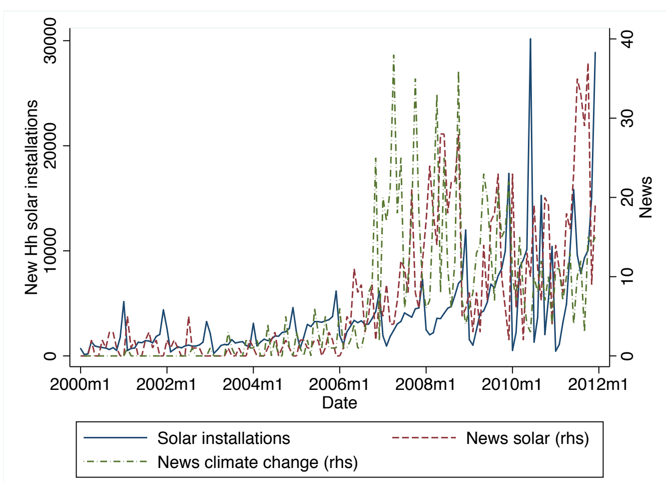
Note: Histogram of log solar PV prices (price per KW installed). Unit of observation is county-quarter, 2010-11. Normal distribution plotted for comparison.

Figure C.9: Wind installations



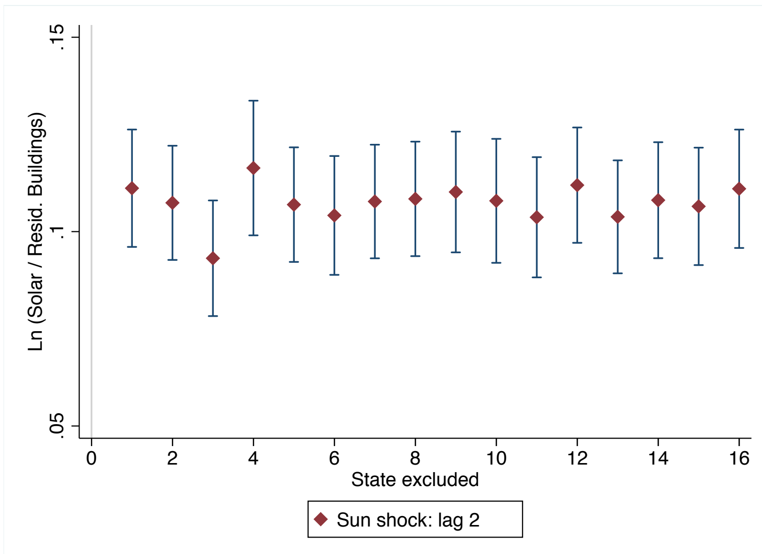
Note: Mean of wind installations and cumulative number of wind installations. Unit of observation: month.

Figure C.10: News coverage: solar PV & climate change



Note: Cumulative news on solar PV and climate change plotted together with number of residential solar PV installations. Unit of observation: month, 2000-11.

Figure C.11: Excluding state-by-state: lag 2



Note: The figure plots the coefficients and 95% confidence interval for a regression of the log of solar PV installations to residential buildings on sunshine shocks following the main regression model, excluding one federal state at a time. I plot the coefficients for lag 2 only. Robust standard errors clustered at the county level. States: 1: Brandenburg, 2: Berlin, 3: Baden-Wurttemberg, 4: Bavaria, 5: Bremen, 6: Hesse, 7: Hamburg, 8: Mecklenburg-Vorpommern, 9: Lower Saxony, 10: North Rhine-Westfalia, 11: Rhineland-Palatine, 12: Schleswig-Holstein, 13: Saarland, 14: Saxony, 15: Saxony-Anhalt, 16: Thuringia.

Table C.1: Contemporaneous temperature effects

	(1)	(2)	(3)
Mean temperature shock	−0.073***	−0.073***	
	(0.019)	(0.019)	
Mean temperature shock × quarter 2	0.056**	0.049**	
	(0.023)	(0.024)	
Mean temperature shock × quarter 3	−0.199***	−0.208***	
	(0.024)	(0.025)	
Mean temperature shock × quarter 4	0.090***	0.090***	
	(0.022)	(0.022)	
Max temperature shock			0.002
			(0.018)
Max temperature shock × quarter 2			−0.030
			(0.022)
Max temperature shock × quarter 3			−0.320***
			(0.023)
Max temperature shock × quarter 4			−0.015
			(0.022)
Sun shock		0.016**	0.029***
		(0.007)	(0.008)
Quarter 2	−0.008	−0.006	−0.003
	(0.023)	(0.023)	(0.023)
Quarter 3	−0.754***	−0.751***	−0.735***
	(0.034)	(0.034)	(0.034)
Quarter 4	−0.422***	−0.420***	−0.412***
	(0.041)	(0.041)	(0.042)
Observations	57888	57888	57888
R^2	0.807	0.807	0.807
Time FE	Y	Y	Y
County-MoY FE	Y	Y	Y

Note: Dependent variable: log of solar PV installations to residential buildings. Unit of observation is county-month. The regression follows model 1. Columns 1 and 2 interact current temperature shocks (based on mean temperature) with quarter of the year. Columns 3 uses a temperature shocks definition based on maximum temperature. Columns 2 and 3 furthermore control for contemporaneous sunshine shocks. Robust standard errors are clustered at the county level. p < 0.1 (*), p < 0.05 (**), p < 0.01 (***).

Table C.2: News coverage & sample split

	(1)	(2)	(3)	(4) $\leqslant 2005$	(5) > 2005
Sun shock	−0.011	0.009	−0.009	−0.012	−0.007
	(0.008)	(0.007)	(0.008)	(0.013)	(0.009)
Lag Sun shock	0.004	0.010	0.020**	0.053***	−0.020**
	(0.008)	(0.008)	(0.008)	(0.012)	(0.010)
Lag 2 Sun shock	0.099***	0.110***	0.104***	0.078***	0.097***
	(0.007)	(0.008)	(0.008)	(0.012)	(0.009)
Lag 3 Sun shock	0.015**	0.007	0.019***	0.011	0.007
	(0.007)	(0.007)	(0.007)	(0.012)	(0.009)
Lag 4 Sun shock	−0.013*	−0.009	−0.031***	−0.047***	0.048***
	(0.008)	(0.007)	(0.008)	(0.011)	(0.009)
Lag News solar	0.004***		0.009***		
	(0.001)		(0.001)		
Lag 2 News solar	0.018***		0.023***		
	(0.001)		(0.001)		
Lag 3 News solar	0.007***		0.007***		
	(0.001)		(0.001)		
Lag 4 News solar	−0.016***		−0.020***		
	(0.001)		(0.001)		
Lag News climate change		0.005***	0.001***		
		(0.000)	(0.000)		
Lag 2 News climate change		0.015***	0.018***		
		(0.000)	(0.001)		
Lag 3 News climate change		0.003***	0.007***		
		(0.000)	(0.001)		
Lag 4 News climate change		0.001***	−0.000		
		(0.000)	(0.000)		
Observations	55476	55476	55476	26532	28944
R^2	0.798	0.796	0.802	0.714	0.739
Time FE	Y	Y	Y	Y	Y
County-MoY FE	Y	Y	Y	Y	Y

Note: Dependent variable: log of solar PV installations to residential buildings. Unit of observation is county-month. The regression follows model 1. Columns 1 to 3 include additional time varying control variables that capture the number of news in German print media on ‘solar PV’ and ‘climate change’. Columns 4 and 5 split the sample according to the median period (December 2005). Robust standard errors are clustered at the county level. $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***).