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Diffusion of Solar Photovoltaic Energy: An Economic and Behavioral Perspective

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Martin PÉCLAT

Approved by the dissertation committee:

Prof Milad Zarin, University of Neuchâtel, thesis co-director

Prof. Andrea Baranzini, Haute école de gestion de Genève, thesis co-director

Prof. Nicole Mathys, University of Neuchâtel, president of the committee

Prof. Matthieu Glachant, MINES ParisTech (France)

Dr. Peter Cuony, Groupe E

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Faculté des sciences économiques
Avenue du 1er-Mars 26
CH-2000 Neuchâtel
www.unine.ch/seco

Contact:
Martin Péclat
martin.peclat@bluewin.ch
University of Neuchâtel, Institute of Economic Research
rue A.-L.Breguet 2, 2000 Neuchâtel, Switzerland

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IMPRIMATUR POUR LA THÈSE

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La Faculté des sciences économiques,
sur le rapport des membres du jury

Prof. Milad Zarin (co-directeur de thèse, Université de Neuchâtel)
Prof. Andrea Baranzini (co-directeur de thèse, HEG Genève)
Prof. Nicole Mathys (présidente du jury, professeure titulaire, Université de Neuchâtel)
Dr. Peter Cuony (responsable Solutions Smart Grid, Groupe E SA)
Prof. Matthieu Glachant (Centre d'économie industrielle, MINES Paristech)

Autorise l'impression de la présente thèse.

Neuchâtel, le 16 mars 2020

Annik Dubied

La doyenne
Annik Dubied

Abstract

The transition towards a greener economy requires a steady rise in the use of renewable energy sources. Solar energy is promising but comes with many challenges, two of which relate to this thesis. First, how to promote the deployment of photovoltaic (PV) technology? Second, how to cope with its intermittent power generation?

The first three chapters empirically investigate the impact of social contagion on the adoption of solar PV in Switzerland. Different approaches are used for the same purpose: uncovering the microeconomic and behavioral mechanisms that underlie social spillovers. Using unique georeferenced data and exploiting Swiss specificities, we are able to ascertain the role of both visibility and learning effects. That is, people are more likely to install solar panels if they see their neighbors doing so and if they can learn from their experience. The last chapter deals with the temporal mismatch between electricity supply and demand. Using a field experiment, we explore the possibility of modifying household consumption behavior to allow the integration of a greater share of intermittent solar energy.

One important implication of our findings is that current estimates of the cost-effectiveness of subsidies may be underestimated. For a full assessment, the virtuous circle generated by social spillovers should be taken into account. Overall, the results presented in this thesis call for innovative policy designs. Disseminating pro-environmental social norms at the local level and facilitating knowledge exchange between PV system owners and potential adopters, for instance, may prove relatively inexpensive measures to promote adoption. Encouraging households to redirect their consumption towards sunny hours through lower electricity prices could remove one of the obstacles to the widespread diffusion of solar PV.

Keywords Solar photovoltaics; Technology diffusion; Technology adoption; Social contagion; Peer effects; Subsidies; Demand response; Electricity demand
JEL codes D83; O33; Q41; Q42; Q55; R11; R12

Résumé

Diffusion de l'énergie solaire photovoltaïque : Une perspective économique et comportementale

La transition vers une économie plus verte requière une utilisation accrue des sources d'énergie renouvelables. L'énergie solaire est prometteuse mais s'accompagne de nombreux défis, dont deux sont abordés dans cette thèse. Tout d'abord, comment favoriser le déploiement de la technologie photovoltaïque (PV) ? Deuxièmement, comment faire face à sa production d'électricité intermittente ?

Les trois premiers chapitres étudient empiriquement l'impact de la contagion sociale sur l'adoption du PV solaire en Suisse. Différentes approches sont utilisées dans le même but: identifier les mécanismes microéconomiques et comportementaux qui sous-tendent le phénomène de contagion. En utilisant des données géo-référencées et en exploitant certaines spécificités suisses, nous sommes en mesure de déterminer le rôle des effets de visibilité et d'apprentissage. En d'autres termes, nous démontrons que les gens sont plus enclins à installer des panneaux solaires s'ils voient leurs voisins le faire et s'ils peuvent bénéficier de leur expérience. Le dernier chapitre traite de l'inadéquation temporelle entre l'offre et la demande d'électricité. À l'aide d'une expérience de terrain, nous examinons la possibilité de modifier le comportement de consommation des ménages pour permettre l'intégration d'une plus grande part d'énergie solaire variable.

Une implication importante de nos résultats est que les estimations existantes pourraient sous-estimer la performance des subventions. Pour une évaluation complète, il conviendrait de prendre en compte le cercle vertueux généré par la contagion sociale. Dans l'ensemble, les résultats présentés dans cette thèse appellent à concevoir des politiques innovantes. Par exemple, des mesures favorisant l'établissement de normes sociales pro-environnementales au niveau local et facilitant l'échange d'informations entre propriétaires d'installations PV et adoptants potentiels pourraient s'avérer peu coûteuses et efficaces pour stimuler l'adoption. Encourager les ménages à déplacer leur consommation vers les heures ensoleillées en modifiant le prix de l'électricité pourrait aussi lever l'un des obstacles à la diffusion à grande échelle du PV.

Mots-clés Solaire photovoltaïque; Diffusion des technologies ; Adoption des technologies; Contagion sociale ; Effets de pairs ; Subventions ; Réponse à la demande ; Demande d'électricité

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your precious advice. By always believing in me, you gave me confidence in the choices I made and allowed me to keep moving forward. I am so looking forward to our upcoming life as a married couple.

Short content

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General Introduction

1 Motivation

Solar photovoltaic (PV) panels convert the sun's radiation into electricity. From this ability stem environmental and economic benefits. First, electricity generation from solar energy is emission-free, making it a valuable option for climate change mitigation. Second, it improves energy security by lessening dependence on imports. Third, there is no shortage of space to install solar panels on the roofs or facades of buildings and this allows production to take place close to the end-consumer. Fourth, the solar industry generates jobs and wealth locally.

Policymakers worldwide have put in place subsidies to try to take advantage of these benefits. By the end of 2018, national or sub-national renewable energy support schemes were implemented in 111 countries (REN21, 2019). The cost of PV modules has dropped drastically over the last decades. In several countries, power generation from utility-scale PV installations is now cheaper than from conventional power plants, including fossil fuels (IRENA, 2019). The residential segment is also concerned, as the average price of rooftop solar installations has decreased by 63 to 81% in the main European markets (IRENA, 2017).

Despite widespread incentive programs and rising competitiveness, solar energy today represents only about 2.4% of global electricity generation (REN21, 2019). The installed PV capacity grows continuously, but at the same time the gap between the observed emission levels and those required to meet the Paris Agreement objective of keeping global temperature rise below 2 degrees Celsius continues to widen. Moreover, subsidies have recently come under criticism for their very high cost for climate change mitigation (Marcantonini and Ellerman, 2014; Marcantonini and Valero, 2015; Crago and Chernyakhovskiy, 2017) and many governments are phasing out subsidy programs.

In this context, a better understanding of the determinants of the adoption of solar PV energy might prove useful for developing alternative policy approaches.

One avenue for policymakers and practitioners could be to take advantage of social norms and information exchange between individuals. The literature has long shown the role of social networks in the diffusion of new technologies (e.g. Hägerstrand, 1952; Griliches, 1957; Mansfield, 1961). More recently, empirical studies have used micro-level data to show the importance of peer influence in adoption decisions of various technologies, such as modern irrigation systems (Genius et al., 2014), electric and hybrid vehicles (Narayanan and Nair, 2013), and menstrual cups (Oster and Thornton, 2012). The existence of social contagion effects in the adoption of residential solar PV is becoming increasingly documented (e.g. Bollinger and Gillingham, 2012; Noll et al., 2014; Graziano and Gillingham, 2015; Rode and Weber, 2016; Kosugi et al., 2019), but little is known about how they work in practice and who is affected. This thesis aims to contribute to the literature by studying in great depth the drivers of social contagion in the adoption of solar PV systems in Switzerland, through various approaches and for different agents.

A challenge related to the large-scale diffusion of renewable energies arises from the intermittent nature of their production. For solar PV, an intra-day imbalance can occur between household electricity consumption, which peaks in the evening, and solar energy production, which peaks in the middle of the day. The solutions generally applied to overcome this mismatch are to increase backup capacity with dispatchable power plants and to extend the grid. This thesis explores the potential of an alternative approach: adjusting the load demand by influencing electricity consumption behaviors.

2 Context

The empirical studies presented in this PhD thesis are conducted using Swiss data and a field experiment on Swiss households. Switzerland has a number of specific features that make it particularly attractive for the study of the determinants and challenges related to the diffusion of solar PV technology. This section provides a brief overview of the general context, focusing on the policy environment.

Switzerland's climate and energy policies

As a Member State to the United Nations Framework Convention on Climate Change having ratified the Kyoto Protocol (COP3), the Doha amendment (COP18), and the Paris Agreement (COP21), Switzerland is pursuing ambitious climate policies aimed at reducing its emissions. Under the Kyoto Protocol, the target was set at

8% greenhouse gas emissions abatement for the period 2008-2012 compared to 1990 levels. Under the Paris Agreement, Switzerland has pledged to halve its emissions by 2030, with respect to 1990. In 2019, following the publication of the latest report of the Intergovernmental Panel on Climate Change (IPCC), the Federal Council (Swiss government) decided to revise its long-term target upwards. The objective is to achieve carbon neutrality, i.e. zero net carbon emissions, by 2050.

Two federal laws oversee the achievement of commitments through a large variety of instruments and measures in various sectors (Baranzini et al., 2004). The CO_2 Act is the centerpiece of Swiss climate policy. In addition to measures to adapt to climate change, it provides for the implementation and coordination of all measures to reduce emissions in the areas of construction, transport and industry. Introduced in 1999, the CO_2 law was intended from the outset to lead to the adoption of a carbon tax covering all sectors and all emissions. After rejection in a popular vote in 2000, a carbon tax covering only heating and process fuels, but not transport fuels, was finally introduced in 2008.

The Energy Act contains the main measures relating to the energy sector. In accordance with the constitutional article dedicated to energy policy, its main goal is to guarantee a sufficient, diversified, safe, cost-effective and ecological energy supply. Since its introduction in 1999, the Swiss Energy Act has been amended several times in order to adapt to the objectives decided by the Swiss parliament and government. The latest amendment, approved by the Swiss voters in 2017, aims to reduce energy consumption, improve energy efficiency, phase out nuclear power and develop domestic renewable energy production. Regarding the latter, the objective is to reach at least 4,400 GWh in 2020 and at least 11,400 GWh in 2035, compared to about 2,700 GWh in 2018 (SFOE, 2019b).

A distinctive feature of Switzerland is its electricity generation sector, which is virtually carbon-free. At present, fossil fuels account for less than 3% of total generation, while hydro and nuclear represent about 60% and 30%, respectively. In 2007, while the construction of new nuclear power plants was still under discussion, the Swiss authorities set the target of increasing the share of renewable energies (excluding hydropower) in the production mix by 10% by 2030. The nuclear accident in Fukushima in 2011 has significantly reinforced the need to increase the share of renewable energies. Indeed, the new Energy Strategy 2050 developed by the Swiss government in the aftermath of the disaster has banned any new construction of nuclear power plants. As hypdropower is already widely exploited, the use of renewable energy sources appears to be the safest way to guarantee energy security and supply, while avoiding the construction of gas or coal-fired power plants that would jeopardize Switzerland's climate objectives.

Subsidies for solar PV in Switzerland

Given the limited coverage of the Swiss carbon tax and the ambitious climate agenda in terms of emissions targets, Swiss authorities introduced in 2008 a feed-in tariff to promote the adoption of renewable energy technologies. This production-based subsidy, called "cost-covering remuneration for feed-in to the electricity grid", aims to ensure the profitability of electricity production from renewable energy sources by guaranteeing sufficiently high revenues. By registering in the scheme, owners of solar, wind, geothermal, biomas and small hydro power plants benefit from a fixed payment guarantee for each kilowatt-hour injected into the grid over a given period. At the time the feed-in tariff was launched, new solar PV installations received guarantees of payments for a period of 25 years with a tariff ranging between CHF 0.49 and 0.90 per kWh, putting Switzerland on a par with Germany and France. To provide equivalent returns on investment, the exact level of the fixed tariff is established on the basis of reference installations and depends on the installation date and technical characteristics. Registrations are open to all owners of PV systems built in 2006 or after and with an installed capacity larger than 2 kilowatt-peak (kWp). Hence, the scheme does not only support the adoption by residential owners, but by commercial owners as well.

The Swiss feed-in tariff is exclusively financed by an electricity surcharge paid by Swiss electricity consumers. Demand for solar exceeded policymakers' expectations, leading promised subsidies to exceed the revenues collected through the electricity surcharge. Although policymakers adjusted upward the electricity surcharge several times, such adjustments were not sufficient to close the gap, leading to the establishment of a waiting list.

To reduce the waiting time, the Swiss government introduced an alternative instrument, a "one-off investment grant", which is available only for solar PV installations. Starting from 2014, this investment subsidy became the only option for installations with a peak capacity below 10 kW, whereas installations between 10 and 30 kW could choose whether to apply for the feed-in tariff, and be added to the waiting list, or apply for the investment subsidy. Installations above 30 kW could only apply for the feed-in tariff, so that no policy change occurred for this subgroup. Under the investment subsidy, the contribution amounts to a maximum of 30% of the price of a reference installation and is paid shortly after the completion date.

While the Swiss feed-in tariff is set to be abolished in 2022, the investment subsidy is currently planned to be in force until 2030. These two instruments strongly contributed to the deployment of PV technology in Switzerland. From a few thousands of installations in 2008, the number of PV systems has increased to reach approximately 85,000 in 2018. According to the latest available data (SFOE, 2019a), the total installed PV capacity in Switzerland at the end of 2018 was 2,168 MW, an increase of 14% compared to the previous year. However, the proportion of electricity consumed in Switzerland that is generated from solar energy, 3.4% in 2018, remains modest. As a comparison, this share reaches 8.2% in 2019 in Germany, one of the European leaders in this respect (Wirth and Schneider, 2019).

3 Theoretical background on peer effects

The importance of peers in the processes of adoption and diffusion of new technologies is documented in numerous studies across a variety of literatures. To explain why and how social influence occurs, past studies invoke concepts from the disciplines of economics, as well as psychology and sociology. This section provides an overview of the theoretical framework relevant to the first three chapters of this PhD thesis, which deal with the functioning and implications of social influence in the deployment of solar PV.

In the economic, marketing, and diffusion of innovations literatures, *peer effects*, sometimes also termed *social contagion*, refer to the influence that the behavior of group members exert on the attitudes, values and behaviors of individuals within the group (Wolske et al., 2020). In the context of this PhD thesis, the study of peer effects therefore consists of examining the influence of existing adopters of solar technology on the adoption behavior of their peers who have not yet adopted. Peer effects encompass all channels through which peer-adopters intervene in the decision-making process leading to the installation solar panels.[1] Contextual effects, i.e. any other peer-independent factors influencing the choice of individuals, are therefore excluded from this definition. From a policy perspective, identifying true causal peer effects is important because, unlike contextual factors, they involve a multiplier effect (Richter, 2013).

Given the strong negative relationship between distance and social influence (Hägerstrand, 1952), empirical studies within the energy domain commonly define the peer group based on geographical proximity (Wolske et al., 2020). Some re-

[1] As noted by Narayanan and Nair (2013), negative peer effects leading to a rejection of a technology may also exist.

searchers in this literature therefore use the terms ‘neighborhood effects’ or ‘spatial peer effects’ to refer to social contagion. This terminology has the advantage of emphasizing that the influence of peers who are geographically distant but socially close is excluded, and also that the peer group should not be thought of as individuals who necessarily know each other personally.

Diffusion of innovation

The idea that social influence is a key determinant of technology uptake underlies the *diffusion of innovations* (DOI) theory developed since the mid-1900s (Hägerstrand, 1952; Griliches, 1957; Mansfield, 1961; Rogers, 2003; Arndt, 1967; Bass, 1969). This theoretical framework seeks to define the elements that explain why, how and how quickly, innovations spread within and across social groups. In a central contribution in the DOI literature, Rogers (2003) defines diffusion as “the process by which an innovation is communicated through certain channels over time among the members of a social system”. Although Rogers does not use the specific terms ‘peer effects’ or ‘social contagion’ in his work, this definition reflects that these topics are indeed intrinsically linked to the subject matter covered in the field of DOI research. It is therefore not surprising that most of the recent studies on the determinants of the adoption of new (energy) technologies draw on DOI theory to explain the role of social factors.

The inclusion of social spillover effects in DOI models contributed to explain two well-known and frequently observed features of the diffusion patterns of new technologies in time and space: an S-shaped curve of adoption and a geographical clustering of adopters.

The explanation offered by DOI theory for the temporal pattern of diffusion (an acceleration phase followed by a deceleration phase) relies on the presence of different types of individuals, each having distinctive attitudes towards innovations (Rogers, 2003). While early adopters tend to be naturally eager for innovation and well integrated into the social system, the late majority is more risk-averse and enjoys a lower degree of opinion leadership. The former are therefore generally perceived as reliable sources of information, to which the latter are more receptive (Rogers, 2003).

Spatial clustering in technology adoption may result from many factors, but localized social spillovers are a particularly consistent explanation. Geographic proximity makes interpersonal communication more likely and strengthens social ties, thereby facilitating the exchange of information (Hagerstrand et al., 1967; Baptista, 1999). Moreover, several studies demonstrate that some knowledge is tacit and hardly codifiable, and can therefore be exchanged primarily via social interactions (Audretsch and Feldman, 1996; Breschi and Lissoni, 2001; Ponds et al., 2007).

In addition to the characteristics of potential adopters and available communication channels, the DOI literature argues that the attributes of a particular innovation, as perceived by individuals, determine its specific deployment trajectory. According to Rogers' classic characterization, there are five attributes that impact the rate of adoption of a new technology. Its *relative advantage* over the status quo, or in comparison to other alternatives. Its degree of *compatibility* with existing values and norms, as well as with available infrastructure. Its *complexity* in acquisition and use. Its *triability*, i.e. the extent to which it can be experimented with but not definitively implemented. And finally, its *observability*, which refers to the possibility of witnessing the results of adoption by others.

This breakdown into attribute categories provides insights into why peer effects may be relevant in the adoption process of solar PV technology. On the one hand, the high visibility of solar panels—it is easy to see their presence in the neighborhood—and their compliance with social norms—installing is generally associated with climate-protective behavior—could positively influence the adoption rate. According to Rogers, these characteristics enhance the strength of the social spillovers effects. On the other hand, the diffusion of solar PV may suffer from its lack of triability—it is impossible to try it without adopting it—and its apparent complexity—a long-term financial investment involving many administrative steps. Although disadvantageous for speed of deployment, these attributes could increase the need to learn from the experience of other similar peers nearby (Palm, 2017).

Underlying mechanisms

Empirical evidence on how seeing other PV installations and talking to their owners can influence the decision-making process is scarce. From a theoretical perspective, however, scholars have envisioned a multitude of mechanisms that may comprise peer effects. A common distinction is between the inner workings that are *passive* and those that are *active* (Rai and Robinson, 2013; Rai et al., 2016; Palm, 2017). Passive peer effects encompass all processes where social contagion arises from the mere observation of peers' behavior, whereas active peer effects involve direct interpersonal communications. As this thesis deals with solar PV, a highly visible technology, we prefer to use a more straightforward terminology that distinguishes between *visibility effects* (i.e. the passive component of peer effects) and *learning* *effects* (i.e. the active component).

Seeing passively PV systems in the neighborhood may induce a change in behavior, and eventually lead to adoption, for several reasons. A frequently mentioned rationale is that it raises awareness and interest in this still fairly emerging technology. As a result of the visual stimulus, individuals may be prompted to actively seek information about the benefits of adopting, either from general sources or directly from their neighbors (Rai and Robinson, 2013; Brudermann et al., 2013a; Palm, 2017). The influence of witnessing solar panels may also materialize in a more direct way. The presence of PV systems nearby may convey a signal about the profitability and desirability of the PV technology. In addition, as psychologists have long pointed out, humans have a natural tendency to imitate the behaviour of their peers (see e.g. Asch, 1956). Such imitative behavior can stem from observational learning (Bandura and Walters, 1977)—following others' decision may be beneficial as it demonstrates the feasibility and desirability of installing solar panels—and from social norms (Cialdini and Goldstein, 2004)—individuals want to conform to what they believe to be common and socially accepted.

Talking actively with the owners of PV installations is assumed to be the second main route through which peer effects operate. Similarly to seeing solar panels, word-of-mouth with neighbors may arouse curiosity and openness about the technology among potential adopters. Such effects acting upstream of the decision-making process could prove particularly important in the case of solar PV, where the market is typically fragmented and organized around small local providers without significant marketing resources (Mazzarol, 2011; Palm, 2017). According to the technology adoption literature, however, the main effects of word-of-mouth are to address informational barriers by reducing learning costs and uncertainty that prospectors face when considering investing in solar PV. Indeed, decision-making can be complex, or may appear to be so, as it requires forward-looking calculations to estimate energy savings and their value, and technical expertise to compare alternative PV systems. Obtaining feedback from trustworthy neighbors who have already adopted, whether through spontaneous face-to-face discussions or at dedicated public events, could therefore be particularly valuable. This could help, in particular, to reassure people about the reliability of the installation and to check whether the announced benefits correspond to reality (Wolske et al., 2020). In addition, the installation of solar panels requires knowledge about the procedures for connection to the electricity grid, about the administrative steps for obtaining building permits and subsidies, and about the reliability of a given PV installer. As this knowledge is typically local and tacit (e.g. Owen et al., 2014; Palm, 2016; Neij et al., 2017), word-of-mouth with neighbors may be the only way to obtain it. It may also be the most effective way, as interpersonal contact allows relevant and missing information to be gathered directly (Rai and Robinson, 2013; Rai et al., 2016).

4 Overview

The four chapters of this PhD thesis cover two topics related to the diffusion of solar PV technology. The first topic, discussed in the first three chapters, deals with the phenomenon of social contagion in the adoption of solar PV. The main objective is to highlight the determinants of and barriers to social spillovers. The second topic, covered in chapter 4, analyses one of the solutions to the temporal imbalance between solar energy generation and electricity consumption, namely demand-side management.

Chapter 1 aims to assess the magnitude and drivers of social contagion effects in the adoption of solar PV. Since the seminal paper of Bollinger and Gillingham (2012), the role of peer effects in PV adoption decisions has been ascertained in various contexts (e.g. Noll et al., 2014; Graziano and Gillingham, 2015; Rode and Weber, 2016; Kosugi et al., 2019). However, this emerging literature provides only limited insights into the microeconomic mechanisms underlying social contagion. In addition, existing empirical studies have so far focused exclusively on household adoption, without investigating whether other agents may be influenced by their peers. In this chapter, we address these gaps by exploiting a very large dataset containing information on virtually all PV systems in Switzerland. We complement this rich dataset with building characteristics in order to highlight the effect of visibility, which, together with word of mouth, is a channel through which social contagion is assumed to operate.

Our results confirm that social contagion is a localized and short-term phenomenon: adoptions are mainly influenced by the nearest and most recent PV systems. We contribute to the literature by showing that such effects are not limited to household adoptions. Businesses also react to the presence of pre-existing installations in the neighborhood, especially when they are owned by other businesses. Furthermore, we show that most visible installations—as proxied by solar panels capacity, roof pitch and building height—generate more social spillovers.

Chapter 2 further investigates the functioning of social spillovers by relying on barriers to their deployment. While social contagion is typically measured by examining whether adoption is stronger where the installed based is large—this is what we do in chapter 1—, this chapter develops an original approach of looking at whether adoption is weaker in regions where spillovers are obstructed. This may be the case in the presence of cultural borders. Indeed, residents living close to a border may benefit less from social interactions with PV owners located on the other side, which may hamper the exchange of information on the technology. In this chapter, we evaluate whether the proximity to the language border between the French and German-speaking parts of Switzerland implies lower levels of PV adoption.

Descriptive analysis show a divergence in the rate of adoption between municipalities located very close to the border and those located further away. We are able to attribute this effect to the language border by showing that the divergence intensified after the introduction of a nationwide feed-in tariff. The impact on PV uptake is significant. Our results suggest that there would have been about 20% more adoption in the absence of any barrier. In municipalities where a high proportion of the population speaks the language on the other side, however, we observe a lower impact of the border.

Chapter 3 tackles the conventional wisdom that subsidies can only have an impact where and when they are implemented. Through social contagion, subsidies may have a positive impact on PV adoption even after they are discontinued, and also beyond jurisdictional boundaries. The current literature does not account for such indirect effects (Hughes and Podolefsky, 2015; Crago and Chernyakhovskiy, 2017), and may therefore underestimate the cost-effectiveness of subsidies for solar PV. In this chapter, we leverage temporal and spatial variation in sub-national subsidies in Switzerland to evaluate their direct and indirect impact.

We first show that cantons implementing subsidies experience significantly higher adoption levels than cantons that do not. This finding is then used as a starting point to analyze cross-boundaries effects. We find that municipalities in cantons that never implemented any financial incentive for PV, but located near the border of a canton that did, benefited from higher adoption with respect to municipalities located further away from the border. Consistently with the patterns observed for social contagion, this cross-border effect decreases with distance. It also persist over time, albeit less and less strongly, even after the discontinuation of the subsidy in the neighboring canton.

Chapter 4 abandons the topic of social contagion to address the question of how to cope with increasing intermittent solar production. While the demand for electricity consumption is highest in the evenings, solar generation is typically abundant in the afternoons. This temporal mismatch between supply and demand can be an obstacle to the widespread diffusion of solar energy. The main aim of this chapter is to quantify the extent to which households are willing to shift their consumption towards peak production periods when encouraged to do so by a change in the electricity tariff. This study differs from most previous contributions, which have mainly focused on quantifying the possibility of reducing consumption during peak consumption hours (see, for instance, the review of Buchanan et al., 2015).

Using a field experiment conducted on Swiss households, we show that time-of-use tariffs can lead to a sustainable increase in the share of electricity consumption during typically sunny hours. Yet, this increase mainly results from energy conservation in the evenings. Moreover, we find that very low financial incentives levels are sufficient, but that households need to clearly foresee the financial savings they may obtain from undertaking actions in order to significantly adapt their consumption habits.

Chapter 1

What drives social contagion in the adoption of solar photovoltaic technology?

This chapter is based on a working paper (Baranzini et al., 2017a) written with Andrea Baranzini (Haute école de gestion de Genève, HES-SO // University of Applied Sciences and Arts Western Switzerland) and Stefano Carattini (Georgia State University). This research was financially supported by the Swiss Federal Office of Energy (SFOE), grant number SI/501305-01. We thank Ariel Dinar, Anne-Kathrin Faust, Kenneth Gillingham, Rolf Wüstenhagen, and the participants at various conferences for very useful comments on a previous version of this paper.

This paper was presented by Martin Péclat at the Annual Congress of the Swiss Society of Economics and Statistics (SSES), Lausanne (Switzerland), June 2017, at the 23rd Annual Conference of the European Association of Environmental and Resource Economists (EAERE), Athens (Greece), June 2017, and at the 12th Conference of the European Society for Ecological Economics (ESEE), Budapest (Hungary), June 2017.

Abstract
Increasing the use of renewable energy is central to address climate change. Recent research has suggested the existence of social contagion in the adoption of solar photovoltaic (PV) panels. While the existing literature has focused on residential adoption only, we extend the analysis to private firms and farms, and use the technical characteristics of the solar panels, to inform on the underlying mechanisms. To this end, we exploit a unique large dataset providing detailed information on about 60,000 solar installations in Switzerland, including their specific location at the street-number level, information on the type of solar installations and the building characteristics, and couple it with rich socioeconomic data at the municipality and neighborhood level. We find that households' decisions to adopt the solar technology are dependent on pre-existing adoption, and in particular on spatially close and recent installations. Firms' and farms' solar PV adoptions react to neighboring PV panels, although to a lesser extent than households. Furthermore, companies are more influenced by panels installed by other companies, compared to panels installed by households. Our results suggest that both learning and visibility effects are important drivers of social contagion.

Keywords Social contagion; Peer effects; Solar PV; Renewable energy; Technology adoption

JEL codes D83; O33; Q42; R11; R12

1 Introduction

Reducing greenhouse gas emissions and preventing dangerous interferences with the climate system is among the top challenges of this century. Governments committed under the Paris Agreement to drastically reduce their emissions, and now face the challenge of turning pledges into effective policies. Economists have long advocated the use of carbon pricing as central instrument of a climate policy package (Goulder and Parry, 2008; Aldy and Stavins, 2012; Baranzini et al., 2017b), yet the number of countries pricing carbon in a generalized way remains insufficient (World Bank, Ecofys and Vivid Economics, 2016). In the meanwhile, subsidies for renewable energy have come under critique for their very high cost (Marcantonini and Ellerman, 2014; Marcantonini and Valero, 2015; Crago and Chernyakhovskiy, 2017) and regressive effects (Borenstein, 2017).

Recent work suggests the existence of an additional policy approach: the use of social norms. People seem indeed to follow local social norms even in global dilemmas (Carattini et al., 2019) and the culture of cooperation that helps solving many social dilemmas seems to be also helpful in driving climate-friendly behavior (Carattini et al., 2015). Social norms have been shown to work and provide lessons on how to achieve social objectives such as reducing smoking or drinking (Nyborg et al., 2016). They also play an important role in the adoption of residential solar photovoltaic (PV) panels (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Rode and Weber, 2016; Kosugi et al., 2019) and of hybrid cars (Narayanan and Nair, 2013; Heutel and Muehlegger, 2015), in particular through social contagion and the visibility of pro-environmental behavior (Sexton and Sexton, 2014; Carattini et al., 2019).

More in detail, using data for 85'046 residential PV systems in California and an original identification strategy, Bollinger and Gillingham (2012) are the first to demonstrate the existence of peer effects in the adoption of PV systems. They show that one extra installation at the zip-code level increases the probability of adoption in the zip code by 0.78 %. Graziano and Gillingham (2015) confirm this result using geocoded data at the street level for Connecticut and show that most recent installations may have stronger peer effects. Rode and Weber (2016) produce similar results exploiting the large number of solar panels adopted in Germany. These papers have started a brand new literature, raising a multiplicity of fundamental questions. How do peer effects work in practice? Do they apply in the same way to all types of solar panels? Do they emerge only for residential adopters, does contagion also work for firms, and between households and firms? Our paper sheds new light on the microeconomic mechanisms driving social contagion in the adoption of solar PV. While the literature has so far focused on residential solar PV adoption only, we also examine the behaviour of firms and farms. In addition, we investigate in detail how the magnitude of social spillovers is impacted by visible features and surrounding environment of the PV installations.

In this paper, we analyze the adoption of PV panels in Switzerland. Our analysis is based on a rich dataset containing very detailed geographic and technical information on 59,819 PV systems, covering adoptions made over the years 2006-2015. We also possess details on the specific installed capacity and type of mounting-system of the panels. Our dataset allows us to exploit the identification strategy of Bollinger and Gillingham (2012) with the precise spatial approach of Graziano and Gillingham (2015). For each new owner, we know both the time of decision to adopt the solar panel and the time of installation, as well as its location at the finest level, the street-number. For each location, we have extensive socioeconomic data, measured with regular frequency. In this way, we address the main threats to identification, i.e. self-selection of households into specific geographical areas (homophily), and correlated unobservables and simultaneity.

Our approach works as follows. We model the number of new PV adoptions in a municipality during a quarter as a function of the average installed PV systems around them, using different radii to take into account the effect of distance. For each geocoded PV installation in the database, we count the number of pre-existing installations, at the time of the decision to adopt. By exploiting the lag between the time of the decision to adopt and the time of installation, we apply the identification strategy of Bollinger and Gillingham (2012), crucial to address the issue of simultaneity, or reflection (Manski, 1993). We address the remaining two issues, homophily and confounding from correlated unobservables, by enriching the model with municipality-specific and quarter-specific fixed effects, as well as interaction dummies between cantons, the administrative units composing the Swiss federal state, and quarters. In addition, we incorporate socio-economic controls and detailed location characteristics to account for spatial and temporal heterogeneity. Finally, we extend our analyses to neighborhoods, to test the robustness of our results to potential within-municipality homophily.

As expected, we find that distance is an important determinant of social contagion: PV systems installed further away show persistently lower impact on the adoption of new PV systems than the nearest ones. In line with Graziano and Gillingham (2015), we find that the oldest nearby installations have a lower impact in the adoption choice than the most recently built PV systems. Furthermore, for each vintage, social contagion effects tend to weaken, as the market becomes more mature. Besides providing new evidence about the influence of spatially close, pre-existing PV systems on the adoption decisions of residential owners, our analysis reveals that firms and farms also react to neighboring PV panels, although to a lesser extent than households do. On average, an extra PV installation within 1 km increases the number of residential adoptions in the municipality by 0.11 installations per quarter, and by 0.09 for commercial adoptions. Further, we investigate the variation of social spillovers with ownership and technical characteristics of the solar panels. Our results show that, everything else equal, social contagion is primarily due to similar ownership, i.e. firms (farms) are mainly influenced by the nearby firm-owned (farm-owned) installations. Furthermore, we observe that large PV systems impact adoptions more heavily than smaller ones. In addition, we find that adoptions are more heavily stimulated by more visible installations, where we measure visibility based on the mounting type (building-integrated versus building-attached PV systems), the building location, and the pitch and height of the roof. Hence, we conclude that both learning and visibility effects operate in the diffusion of solar PV technology in Switzerland.

This paper contributes to the nascent literature studying the role of social contagion in the adoption of clean technologies by providing a better understanding of the drivers behind social contagion. First, we identify social contagion effects not only for residential customers but also for commercial customers, which in our results is related to similar ownership. Second, we identify, by combining multiple approaches, the effect of visibility of pro-environmental behavior on others' adoption. Third, we identify weakening social contagion effects in recent period, which we associate to a more mature market. Fourth, we bring the analysis of social contagion to a finer level and show that our results are robust to such additional specifications. More broadly, we contribute to a large economic literature on learning and imitation in the adoption of new technologies (e.g. Foster and Rosenzweig, 1995; Axsen et al., 2009; Conley and Udry, 2010; Oster and Thornton, 2012; Narayanan and Nair, 2013; Genius et al., 2014).

Our results provide insights for practitioners and policymakers alike. Leveraging social contagion could indeed represent a valuable option for many governments and even more so for those that are currently planning to phase out subsidies to solar energy. In the United States, solar panel installers and grass-root organizations have started undertaking specific initiatives to leverage social contagion, such as curbside signs communicating the presence of a solar panel in the nearby home or demonstration sites, group pricing for neighbors, and solar ambassadors (Bollinger and Gillingham, 2012; Kraft-Todd et al., 2018; Bollinger et al., 2019). However, an effective implementation of such strategies requires information on which agents are affected by social contagion and on how installation characteristics affect them. By investigating the variation of peer effects at a higher level of detail, our study provides guidance and support for the use of targeted initiatives leveraging peer effects for both residential and commercial adoption. These initiatives should not only focus on households' incentives for conspicuous conservation (Sexton and Sexton, 2014), but also on accelerating learning across businesses, for instance through clusters and industry-specific umbrella organizations. Learning-driven social contagion among firms is likely to depend more on the generosity of the current subsidy system, whereas social contagion in the adoption of residential installations is likely to survive to changing financial incentives, to the extent that it is driven by pro-social and pro-environmental motives.

2 Context

As a Member State to the United Nations Framework Convention on Climate Change having ratified the Kyoto Protocol (COP3), the Doha amendment (COP18), and the Paris Agreement (COP21), Switzerland is pursuing ambitious climate policies aimed at reducing its emissions. Under the Kyoto Protocol, the target was set at 8 % greenhouse gas emissions abatement for the period 2008-2012 compared to 1990. Under the Paris Agreement, Switzerland pledged a 50 % reduction in emissions by 2030, with respect to 1990. Two federal laws oversee the achievement of commitments through a large variety of instruments and measures in various sectors (Baranzini et al., 2004). The Energy Act of 1999 provides the main measures related to the energy sector and thus directly determines the policies supporting the PV technology. The CO_2 Act of 1999 provides the main framework to deal with climate change, and was expected since the outset to lead to the adoption of a carbon tax covering all sectors and emissions. However, following the rejection of three tax designs in a 2000 ballot (Thalmann, 2004), Switzerland renounced at the time to price carbon and adopted voluntary agreements at the sectorial level. A carbon tax was eventually introduced in 2008, but covering only heating and process fuels, and not transport fuels.[1]

[1] The initial tax rate was set at CHF 12 per ton of CO_2. Given that emissions had not decreased enough to meet the objectives in the CO_2 Act, the tax rate was raised four times in the following

Given the limited coverage of the Swiss carbon tax, and the ambitious climate agenda in terms of emissions targets, an aggressive feed-in tariff called "cost-covering remuneration for feed-in to the electricity grid" (CRF) was introduced in 2008 to promote the adoption of renewable energy[2]. At the time the scheme was launched, new solar PV installations received guarantees of payments over a period of 25 years for each kWh injected into the grid. Tariff rates have ranged between 0.49 and 0.90 Swiss francs per kWh, putting Switzerland on a par with Germany and France. The tariff may be slightly different across installation types to provide equivalent returns on investment, a feature that we exploit in our empirical analyses. Registrations are open to all owners of PV systems built in 2006 or after and with an installed capacity larger than 2 kilowatt-peak (kWp).[3] Hence, the scheme does not only support the adoption by residential owners, but by commercial owners as well.

The CRF strongly contributed to the deployment of PV technology in Switzerland (see Figure 1). From a few thousands installations in 2008, the number of PV systems has increased to reach approximately 60,000 in 2015. Overall, the total PV capacity remains however modest, with only 1'394 MWp installed by the end of 2015 (SFOE, 2016). In 2015, PV-generated electricity in Switzerland corresponded to 1.92 % (1.12 TWh) of final electricity consumption, a low figure compared to the 6.8 % in 2015 in Germany, the European leader in terms of PV capacity (Wirth and Schneider, 2015).[4] Even so, and in spite of the decision taken after the Fukushima accident to slowly phase out nuclear power, the Swiss government is planning to phase out subsidies to solar energy by 2022.

3 Empirical approach and data

3.1 Installed base

The idea that agents might care about the adoption decisions of others is deeply rooted in the theory of technology diffusion developed since the 1950s. Social con-

years and since 2018 is at CHF 96 per ton of CO_2. A small number of large firms are exempted from the carbon tax, but submitted to the Swiss Emission Trading Scheme (Krysiak and Oberauner, 2010). 1 Swiss franc (CHF) close to parity with the US dollar at the time of writing.

[2]Since 2014 a "one-off investment grant" has also been introduced with similar purposes. Our data focus however almost exclusively on CRF-led deployment.

[3]kWp corresponds to the nominal power (capacity) of a PV installation. It measures the peak amount of power the PV installation produces under standard testing conditions.

[4]The average PV capacity factors, defined as the ratio of actual electricity production to the maximum possible electricity output, are relatively comparable in the two countries. For 2015, it was 9.65% in Switzerland (SFOE, 2016) and approximately 10.7% in Germany (own calculations based on BMWi, 2016 data).

nections, which allow the information on the existence of a technology to spread across consumers or firms, are regarded as a crucial component of new adoptions (Griliches, 1957; Mansfield, 1961). It became quickly apparent that the geographic proximity is an important dimension of diffusion, which may also depend on the visibility of a technology (Rogers, 2003; Griliches, 1957; Mansfield, 1961).

Social contagion in the adoption of solar panels is expected to work through both word-of-mouth (learning) and visibility (imitation).[5] The former is supposed to act primarily upon the learning costs and the uncertainty that households face when considering the option of an investment in solar PV. Indeed, adopting a PV system demands a relatively high individual involvement, since it is probably a decision that is taken only once in a lifetime (Jager, 2006). Decisions regarding adoption of a PV system are complex because they involve forward-looking calculations such as estimating energy savings and their value, and technical competencies to compare alternative PV systems. Moreover, expected costs and benefits related to adoption are usually highly dependent on the level of solar radiation, the procedures for the connection to the electricity grid, the acquisition of building permits, or to the reliability of a given PV installer. Yet, this type of knowledge is typically very local (e.g. Owen et al., 2014; Palm, 2016; Neij et al., 2017). As a consequence, in their decisions about solar PV, individuals often look for other adopters to obtain information about the benefits of this technology, especially from owners in their neighborhood (Brudermann et al., 2013b; Rai et al., 2016). Imitation works in the same way. Potential adopters tend to refer to the behaviour of their neighbours. If they have chosen to adopt, this provides a reassuring signal about the feasibility and benefits of installing solar panels. Individuals may also have a preference to stay in tune with the local social norm and thus adopt pro-environmental behavior, especially when this is sufficiently spread and visible (Carattini et al., 2019).

To explore the role of social contagion in the diffusion process, the empirical literature usually relies on the so-called ‘installed base’ of a technology, i.e. the cumulative number of adopters at a particular moment in time on a given territory, as the central explanatory variable of new adoptions (cf. Bass, 1969).

Using the installed base to measure social spillovers can, however, be a challenging task. There are three threats that could confound a causal estimation of past

[5] A few survey-based studies that seek to identify the components of social contagion use a different terminology (Rai and Robinson, 2013; Rai et al., 2016; Palm, 2017). Learning effects, which involve active discussions with the owners of PV installations, are referred to as *active peer effects* and visibility effects, which involve the mere observation of PV systems, are referred to as *passive peer effects*. Further details are provided in the general introduction of this PhD thesis.

adopters' effect on current adoption behavior.[6] The first issue is spatial sorting related to the self-selection of households into specific geographical areas (homophily). This issue may arise if households come to live in a particular region for the same reason that may make them more likely to adopt the technology under scrutiny, potentially leading to an overestimation of the social contagion effect. The second issue relates to correlated unobservables. If some location characteristics simultaneously influence the behavior of all potential adopters in a region, this may result in a correlation between the number of past adopters and the installation rate, which should not be attributed to social contagion. Finally, a notorious issue in the identification of social contagion is the reflection problem (Manski, 1993). Reflection, or simultaneity, refers to a situation wherein individual decisions in a group or municipality are influenced by the behavior of others in the group, and conversely. This phenomenon potentially leads to an inconsistent assessment of the causal installed base effect, unless it is possible to address the source of endogeneity and determine who is influencing whom in the relations among peers.

The first two issues are typically addressed using fixed effects in estimations. In particular, the inclusion of spatial fixed effects allows controlling for unobserved time-invariant heterogeneity between regions. Time fixed effects are also frequently used to capture broader factors varying in time such as changes in the levels of government subsidies or technology maturity. Finally, potential differentiated time evolution across regions should be accounted for by incorporating interaction effects between regions and time.[7] These interactions target potential regulatory changes at the subnational level, related to urban planning or other local policies that may have an impact on the adoption of solar panels.

The issue of reflection is more complex to deal with. In their seminal paper, Bollinger and Gillingham (2012) propose an innovative strategy based on the existence of a time lag between the moment at which a new adopter decides to purchase a solar panel and the moment at which the installation is completed. This new adopter might have been influenced by other adoptions around her, yet she is arguably not in position to influence others as long as the installation is not completed, and visible to neighbors, and she starts experiencing its potential benefits.

This identification strategy presumes that it is possible to precisely measure

[6] See Bollinger and Gillingham (2012) for a mathematical exposition of each of these issues.

[7] To this end, we include interaction terms between the 26 Swiss cantons and every year-quarter in our estimations. The estimates are only slightly reduced when also controlling for municipality-times-year interactions. Given the high cost in degrees of freedom, we do not include the latter interactions terms in our preferred specification, but do include them for robustness purposes in Table B.14.

the presence of PV installations that might affect the adoption decisions in each given location. We achieve this by computing the individual installed base for each installation in the database. We define the individual installed base as the number of already in-service PV systems surrounding the installation of interest. More precisely, for each new adopter, we count the number of PV installations that (i) are located within a given crow-fly distance and that (ii) have been completed prior to the day of the adoption decision. These spatial and temporal constraints are designed to capture the relevant installations for social contagion while exploiting the time lag between the decision to adopt the solar panel and the date of installation and connection to the grid, à la Bollinger and Gillingham (2012).[8]

Our approach of the installed base has three major advantages compared to using the existing stock of adopters in a municipality or a zip code, as it is the case in the literature on technology diffusion in the absence of very detailed spatial data. First, the usage of geocoded data at street number-level allows assessing the effect of distance with much more accuracy.[9] Second, social contagion effects that take place across administrative boundaries are not ignored, since even the PV systems located in a different municipality or zip code are taken into account in the computation of the installed base. Finally, the temporal dimension is also more meticulously considered at the individual level: we record the neighboring completed installations at the exact day of decision, instead of only the ones in-service at period *t-1*.

Most of our analyses are conducted with installed bases that measure the preexisting PV installations within a circle of 1 km radius. However, to investigate how distance may affect the strength of social contagion, we also generate disc-shaped installed bases that surround an inner circle. The inside and outside radii of each disc are set so that the area is always a constant multiple of the previous disc or

[8]In our data, the median time lag between the PV purchasing decision and the installation is 126 days. This time lag is similar to the "simultaneity time window" of 120 days used in Graziano and Gillingham (2015) as a substitute for the exact time lag, which is not observable in their data. Note that a small fraction of installations in our dataset have been completed prior to their registration in the CRF, in particular during the period 2006-2008. In these cases, we approximate the adoption date by subtracting the median time lag that we observe in our data from the completion date. In any case, including or not these observations does not affect our estimates neither qualitatively nor quantitatively. Furthermore, we also conducted robustness tests adding an additional, conservative lag on top of the actual lag observed in our data. Our results are unchanged, as shown in Table B.1 for additional lags of 3, 6, and 12 months. All additional estimations are available by the authors upon request.

[9]We geocoded the addresses using HERE API to obtain the X and Y coordinates for each PV installation in the sample. For about 89% of our installations, we obtained the exact geographic location at the street-level number. Our results would be unchanged if only these observations were to be used in the estimations. The remaining installations could be geocoded at the street level. Only 0.38% of the total installations could not be geocoded, not even at the zip-code or at the municipality level. The latter 227 installations were not considered in the final sample.

circle. Hence, the radii can be computed as:

$$r_d = \sqrt{\frac{1}{m+1}\sum_{i=0}^{d} m^i} \tag{1}$$

where d is the disc number (d=0 corresponds to the inner circle) and m is the area multiplier.[10] By fixing a sufficiently high area-multiplier factor, this procedure allows to precisely measure the effect of neighbors at small distances while at the same time keeping track of those located much further away.

To investigate how time may affect the strength of social contagion, we compare the effects of installations completed in the last 6, 12, 24 or more months prior to adoption. Finally, to address our main research questions, we divide the individual installed bases into characteristic-specific installed bases, each of which focuses on neighboring installations with a specific characteristic or a combination thereof. We consider the following groups of characteristics: ownership, PV capacity, type of mounting system, roof pitch, roof height, and geographical isolation. For each characteristic, the sum of the different characteristic-specific installed bases is always equal to the complete installed base. In this way, our analyses consider separately the effect of each characteristic, while never omitting any PV system.

We construct the main independent variables of our model by combining the various installed bases at the municipality level, the finest level at which it is possible to access detailed socioeconomic control variables for the entire country. Following the procedure developed by Graziano and Gillingham (2015), we compute the spatiotemporal variables capturing the mean of the installed bases of all new adopters in municipality i of canton c during a quarter t ($Average\ PV_{i,c,t}$) as follows:

$$Average\ PV_{i,c,t} = \frac{1}{\Delta PV_{i,c,t}} \sum_{k=1}^{\Delta PV_{i,c,t}} Installed\,base_k \tag{2}$$

where $\triangle PV_{i,c,t}$ is the number of new PV systems installed in the municipality i during the quarter t and $Installed\,base_k$ is the individual installed base of the adopter k. This methodology provides an efficient way of measuring the average potential influence of neighboring PV installations, because it preserves the individual level properties despite the spatial and temporal aggregation. That is, we use municipalities boundaries only for data aggregation, and not for the measurement of neigh-

[10] Note that we can obtain the same radii with the following formula: $r_b = r_0 \times \sqrt{\sum_{i=0}^{b} m^i}$, where r_0 is the choice of radius for the inner circle. However, the notation proposed in Equation (1) has the advantage of always providing a 1 km oustside radius for the first band (r_1=1 km), regardless of the multiplier chosen.

boring installations. From the individual installed bases we create a municipality-specific vector containing all the spatiotemporal variables ($Average\ PV_{i,c,t}$), which may be defined according to the installation characteristics available in our dataset. All observations are used, and the panel is always balanced.

To further isolate any potential confounding effect of homophily, we run additional specifications at the neighborhood level. For municipalities whose neighborhoods boundaries are defined, we therefore compute $AveragePV_{i,c,t}$ at the neighborhood level based on Equation (2), where subscript i corresponds to a neighborhood rather than a municipality.

3.2 Econometric model

In our empirical estimation, we explain the number of new adoptions of solar PV ($\Delta PV_{i,c,t}$) in a municipality i of canton c during the quarter t as a function of the spatiotemporal installed base, while controlling for a large set of socioeconomic, political, housing and meteorological data. More specifically, our specification has the following form:

$$\Delta PV_{i,c,t} = \alpha + \beta Average\ PV_{i,c,t} + \gamma C_{i,c,t} + \phi_i + \lambda_{c,t} + \varepsilon_{i,c,t} \tag{3}$$

where $Average\ PV_{i,c,t}$ is a vector of selected spatiotemporal variables. This vector contains the main explanatory variables of interest and allows, depending on the specification, to consider separately the neighboring PV installations according to their distance, time since completion or characteristics. $C_{i,c,t}$ is a vector of control variables capturing the potential effect of time-varying heterogeneity, ϕ_i represents municipality-specific fixed effects controlling for time-invariant unobserved heterogeneity, and $\lambda_{c,t}$ represents interaction fixed effects between cantons and quarters to account for correlated unobservables with a differentiated time evolution across regions (e.g. local policies). $\varepsilon_{i,c,t}$ is the i.i.d. error term, clustered at the municipality level.[11]

In alternative specifications, we lower the level of aggregation to the neighborhood level. For municipalities for which neighborhood level data are available, the variables in Equation (3) are therefore defined at the neighborhood level.

[11] Clustering at the municipality level accounts for correlation within municipalities. For sensitivity purposes, we also run specifications with year-quarter clusters (one-way clustering by time) and municipalities and year-quarter clusters (two-way clustering by space and time). Results are reported in Table B.2 in the Appendix. Our main estimates remain highly statistically significant even with this conservative approach, despite some slight increase in the standard errors.

In line with Angrist and Pischke (2008), and to avoid issues related with the incidental parameter problem, we estimate the model using the standard balanced panel fixed effect linear regression method. Our estimations always rely on a fully balanced panel dataset. As a result, $\Delta PV_{i,c,t}$ and $Average\ PV_{i,c,t}$ take the value 0 when there is no adoption in a municipality during a particular quarter.

Solar PV installation data

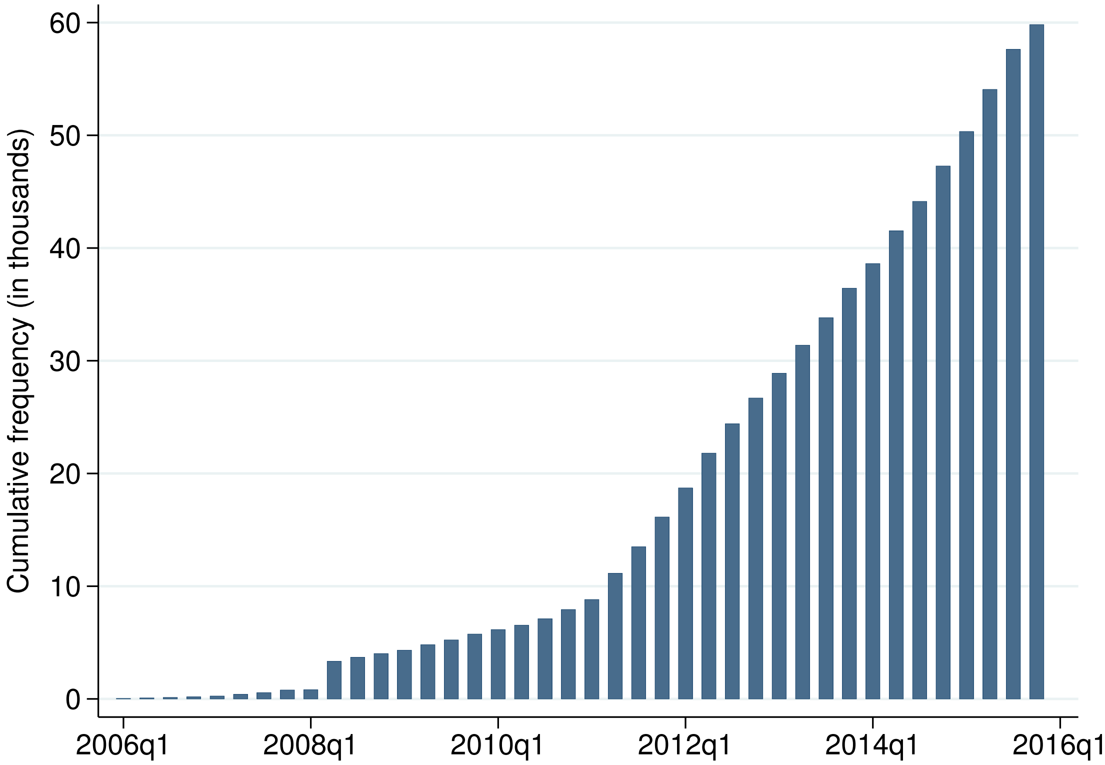
The main data source for our empirical analysis is a rich and detailed database provided by the Swiss Federal Office of Energy (SFOE) containing information on 60,046 solar PV systems adopted in Switzerland in the decade between January 2006 and December 2015. Since we were not able to geocode 227 addresses, our final sample includes 59'819 PV installations. SFOE has been tracking since the beginning of the CRF in 2008 all owners of solar panels applying to the federal subsidy, which also include installations from 2006 and 2007.[12] Since the rise of solar capacity in Switzerland really occurred after the introduction of the feed-in tariff in March 2008, our analysis captures the most important period of diffusion of solar panels (see Figure 1).[13] Figure A.1 in the Appendix illustrates the spatial dimension of our data. It reports the cumulative number of adoptions per municipality by the end of 2015.

The database includes three variables of critical importance for the identification of social spillovers in the adoption of solar PV. For each installation, we know the address at the street-number level, the date of registration, and the date of completion. Furthermore, the database provides an additional set of unique information on the characteristics of each installation. In particular, we know for each PV system the type of ownership, as well as crucial technical characteristics, such as the installed capacity (in kWp) and the type of installation. As shown in Table 1, about 44 % of the PV systems are owned by households. Existing studies refer to those owners

[12]Installations completed after 2006 can apply for the CRF, but subsidies are only granted over a period of 25 years since the date of completion and are not paid retroactively.

[13]All installations above 2 kWp built after January 1st 2006 are eligible for a federal subsidy for injecting electricity into the grid, regardless of the type of owner. We use for our analysis both completed and operational PV systems, the large majority, as well as projects of PV installations, for which the owner has already taken the decision to purchase and registered for the subsidy, but which are not yet installed (at the time our data were collected). Note that the latter owners may not be in position to spur social contagion, yet their own decision might have been influenced by others' adoption and is therefore of interest. That is, these installations appear on the left-hand side only. Note that in the Swiss case, the time-lag between the decision to register for the subsidy and the completion date is due to both technical aspects and a delay in the response of the federal administration in attributing the subsidy. Dropping uncompleted installations from the left-hand side does not affect our estimates neither qualitatively nor quantitatively.

Figure 1: Cumulative number of adoptions, per quarter



Note: This figure shows the adoption of solar panels in Switzerland. The CRF was introduced in May 2008. The figure displays the first part of the canonical S-shaped adoption curve, with a number of early adopters, even before 2008, and a market acceleration following the implementation of the CRF.

only. 28 % of installations are owned by firms and 4 % by farmers. The remaining is composed of installations owned by utilities, public buildings, and owners that have not been classified in any of these categories by SFOE (type unknown).

Our database also distinguishes between three types of installations, which are relevant for the definition of the subsidy rate. Table 1 shows that around three quarters of the installations are building-attached (BAPV), i.e. applied on the existing building structure. The second most common type is building-integrated systems (BIPV, 23 %). In this case, solar panels do not only serve for electricity production, but also replace a conventional building material. That is, PV systems are considered to be building-integrated if a structure of the building would not fulfill its original function (weather protection, thermal insulation or safety barrier) were the solar panels to be removed. BIPV systems can be installed on facades or steep roofs. Finally, some installations are ground-mounted (GRPV). The scarcity of this latter category in Switzerland (about 700 installations, corresponding to approximately 1% of the sample) prevents us from analyzing them specifically.[14]

Finally, we have information about the peak capacity (in kWp) of the PV systems. Since the efficiency of all models of solar panels is relatively similar, this variable constitutes a good proxy for the size of the installations. Following the categories used by SFOE in the attribution of the federal subsidies, we assigned each PV installation to one of the four following categories: under 10 kWp (about half of the installations), from 10 to 29.9 kWp (28%), from 30 to 99.9 kWp (14%) and over 100 kWp (9%).

Table 1: Distribution of PV installations by ownership, type and capacity categories

	<10 kWp		10-29.9 kWp		30-99.9 kWp		>100 kWp		Total	
Ownership	*N*	% (row)	*N*	% (row)	*N*	% (row)	*N*	% (row)	*N*	% (column)
Households	17,007	(64.15)	7,784	(29.36)	1,131	(4.27)	591	(2.23)	26,513	(44.32)
Firms	7,677	(45.17)	4,293	(25.26)	3,016	(17.75)	2,009	(11.82)	16,995	(28.41)
Farms	105	(4.59)	831	(36.32)	849	(37.11)	503	(21.98)	2,288	(3.82)
Other & undefined	4,615	(32.91)	3,957	(28.22)	3,468	(24.73)	1,983	(14.14)	14,023	(23.44)
Total	29,404	(49.15)	16,865	(28.19)	8,464	(14.15)	5,086	(8.50)	59,819	(100.00)
	BAPV		BIPV		GRPV				Total	
Ownership	*N*	% (row)	*N*	% (row)	*N*	% (row)			*N*	% (column)
Households	20,479	(77.24)	5,781	(21.80)	253	(0.95)			26,513	(44.32)
Firms	12,914	(75.99)	3,847	(22.64)	234	(1.38)			16,995	(28.41)
Farms	1,552	(67.83)	719	(31.42)	17	(0.74)			2,288	(3.82)
Other & undefined	10,449	(74.51)	3,370	(24.03)	204	(1.45)			14,023	(23.44)
Total	45,394	(75.89)	13,717	(22.93)	708	(1.18)			59,819	(100.00)
	<10 kWp		10-29.9 kWp		30-99.9 kWp		>100 kWp		Total	
Type	*N*	% (row)	*N*	% (row)	*N*	% (row)	*N*	% (row)	*N*	% (column)
BAPV	22,770	(50.16)	12,302	(27.10)	6,266	(13.80)	4,056	(8.94)	45,394	(75.89)
BIPV	6,292	(45.87)	4,397	(32.06)	2,119	(15.45)	909	(6.63)	13,717	(22.93)
GRPV	342	(48.31)	166	(23.45)	79	(11.16)	121	(17.09)	708	(1.18)
Total	29,404	(49.15)	16,865	(28.19)	8,464	(14.15)	5,086	(8.50)	59,819	(100.00)

Note: All data are provided by the SFOE and are based on the subsidy scheme's administrative register. BAPV stands for building-attached photovoltaics, BIPV stands for building-integrated photovoltaics, and GRPV stands for ground-mounted photovoltaics. The category "Other and undefined" includes solar panels installed on public buildings, or by utilities. It also includes installations with missing values for the ownership category.

Buildings data

To complement the information on the characteristics of PV installations, we combine the PV database with two additional geo-referenced databases containing in-

[14]Note that given its particular territory and high density, large solar farms are uncommon in Switzerland.

formation on the attributes of each building.

The first database is the Building and Dwelling Statistic (BDS) of the Swiss Federal Statistical Office (FSO). The BDS covers virtually all residential buildings, as well as most commercial and industrial buildings. This database is very comprehensive. Only rudimentary structures such as sheds, detached garages or cabins are not registered. The BDS contains data on the number of floors of all buildings, which we use as an indicator of the building height. The BDS also allow us to measure whether a building is surrounded by other buildings, which could have implications for the visibility of a solar installation. In detail, we measure the "geographical isolation" of a building by counting the number of buildings surrounding it, in a given radius. We access 2015 data from the BDS.

The second database is a unique solar cadastre recently developed by the Swiss Federal Office of Energy (SFOE), in cooperation with the Federal Office of Meteorology and Climatology (MeteoSwiss) and the Federal Office of Topography (swisstopo). The cadastre assesses the potential of buildings for solar energy sources based on several criteria, including the pitch angle. For all buildings in the cadastre, we have access to the area, the inclination angle, and the yearly irradiance of each of the surfaces that make up the roof. Since our geographic PV data do not allow to identify the exact roof surface(s) on which the solar panels are installed, we create an aggregate measure of the roof pitch, for each building. This measure is an area-weighted average of the slopes (in degrees) of all the PV-suitable roof surfaces of a building.[15]

We merge the PV and buildings databases based on geographic coordinates. Each building-mounted PV installation for which we know the exact point location is assigned to the closest building. We assume that the closest building is the one on which the solar panels are installed only if the distance that separates them, according to our computation, is smaller than 15 meters. As shown in Table A.2 in the Appendix, which provides descriptive statistics of the building attributes, this procedure allows us to determine the height, isolation, and pitch for about 73%, 88% and 74% of the PV installations, respectively.[16] We use the buildings characteristics to classify the PV installations in different categories. Two classifications are used

[15]Following the guidelines of this very specific dataset, roof surfaces with yearly irradiance below 800 kWh/m^2 are excluded from the computations. These surfaces are categorized as "low potential" and are unlikely to host a solar installation.

[16]The solar cadastre is only available for a sub-sample of 1,640 municipalities among the 2242 in our database (see footnote 17). Our analyses of roof characteristics therefore only cover a part of Switzerland, which includes about 80% of PV installations. As shown in column (1) of Table 6 in the Appendix, this reduction in the sample size does not affect our baseline results.

for the roof pitch. The first distinguishes flat roofs from steep roofs and the second between roofs with a pitch below 24 degrees and those with a pitch above 24 degrees (24 degrees being the median value). With regard to height, the installations are classified according to their height in relation to the average building, either in the municipality or within a radius of 100 meters. Each time, we distinguish between installations on buildings that are higher and lower than the average building. Finally, we determine the level of isolation based on the number of buildings within 100 meters of the PV systems. The threshold we use is 18, which is the median number observed over all installations.

Municipality level data

Adoptions of the solar PV technology may depend on several socioeconomic, demographic, meteorological and built environment factors. For Switzerland, the narrowest geographical level at which data are available for the entire country is the municipality, and data are typically provided on an annual basis. We hence collect the relevant variables and, for each of them, we create a panel dataset at the municipality level for every year of the period 2006-2015.[17]

Table 2 summarizes these variables. A first set of variables that we include in our model to capture time-varying heterogeneity relates to the characteristics of the population and in particular to a set of variables that, according to the literature, may affect adoption: age, income, level of unemployment, green preferences (cf. Dharshing, 2017 for a recent analysis). We measure green preferences (*green voting)* by summing the electoral scores of the Green Party of Switzerland and the Green Liberal Party of Switzerland at the federal elections of the Swiss National Council. These are the two main, and only, green parties of Switzerland. The second set of variables measures contextual factors that may be linked to the feasibility and profitability of PV installations. Capturing building features is of particular relevance in this type of study. Besides the building level data described above, we also generate municipality-specific proportions. We measure the proportion of buildings in each municipality for the following four categories: detached houses, apartment

[17]Every year a number of municipalities is involved in mergers. To facilitate the matching between the different databases and periods, we use the boundaries of the 2,289 municipalities that existed in Switzerland as of April 10, 2016, as the reference spatial units. That is, we build a balanced panel dataset that includes the same 2,289 municipalities over ten years by spatially aggregating the values for the municipalities that merged during the period. However, most of our estimations do not consider 47 municipalities, which never experienced any PV adoption, by the end of 2015. Hence, the final sample is composed of 2,242 municipalities. Our results remain unaffected if these additional 47 municipalities were included.

Table 2: Municipality level data: summary statistics

Variables	Mean	Std. Dev.	Min.	Max.	Source
Population characteristics					
% population aged <30	33.59	4.19	8.39	57.21	FSO
% population aged 30-44	20.60	3.12	4.35	46.01	FSO
% population aged 45-64	29.21	3.44	0.00	51.74	FSO
% population aged 65-100	16.60	4.15	0.22	42.38	FSO
% tax payers with income CHF <14.9 k	2.45	5.81	0.00	61.98	FTA
% tax payers with income CHF 15-29.9k	13.25	4.39	0.00	65.05	FTA
% tax payers with income CHF 30-49.9k	29.65	7.35	0.00	61.82	FTA
% tax payers with income CHF 50-74.9k	27.14	4.39	0.00	49.02	FTA
% tax payers with income CHF >75k	27.50	11.35	0.00	72.00	FTA
# of unemployed individuals	59.19	280.47	0.08	9,048.92	SECO
Green voting (in %)	9.82	5.47	0.00	72.22	FSO
Contextual factors					
% detached houses	60.11	13.71	0.00	96.40	FSO (BDS)
% apartment buildings	21.07	10.25	0.00	99.99	FSO (BDS)
% buildings with residential/commercial use	14.16	9.72	0.00	85.71	FSO (BDS)
% commercial/industrial buildings	4.66	2.86	0.00	33.50	FSO (BDS)
Average # of rooms per dwelling	4.11	0.43	2.16	5.63	FSO (BDS)
Average area per dwelling	111.82	15.86	57.39	187.19	FSO (BDS)
Solar radiation (in W/sqm)	146.10	9.62	121.30	190.45	MeteoSwiss
N		22,420			

Note: Our models include all control variables listed in this table, except *% population aged <30*, *% tax payers with income CHF >14.9 k* and *% detached houses* that are reference variables. All variables have annual values at the municipality level. Summary statistics are computed over all years (2006 to 2015) for all municipalities having at least one PV installation (2,242 municipalities). Age data have been linearly extrapolated for the years 2006 to 2009, income data for the year 2015, building and dwelling data for the years 2006 to 2008. Green voting data have been linearly interpolated for the years in between two elections, which take place every four years (last in 2015). For privacy reasons, unemployment data cannot be accessed for 139 municipality-years because the absolute number of unemployed individuals is less than 5. In those cases, we replaced the missing values by 2.5. Our estimations are fully robust to alternative ways to address missing values in control variables. FSO stands for Federal Statistical Office, FSO (BDS) for the Building and Dwelling Statistic of the FSO, FTA for Federal Tax Administration, SECO for State Secretariat for Economic Affairs. MeteoSwiss is the Federal Office for Meteorology and Climatology.

buildings, buildings with apartment and other use, and buildings used only for commercial or industrial purposes. We also calculate the average number of floors of each building, and the characteristics of the dwellings (average area and number of rooms). These variables may be relevant as they can affect the energy consumption of residential and commercial owners. Finally, we also consider solar radiation (in W/m^2) as a control variable, knowing that exposure to solar radiation is crucial for solar panels to be effective, and the higher the exposure, the higher the expected return on investment. In contrast to the BDS data, these variables are available for all municipalities in our sample.

Neighborhood level data

Neighborhood level data are available for the 17 largest Swiss municipalities, as shown in Figure A.2 in the Appendix. For each of them, we collect the same socioeconomic and contextual variables as those that we use at the municipality level.[18] We provide summary statistics for the control variables at the neighborhood level, as well as information on the sources, in Table A.3 in the Appendix.

4 Empirical results

4.1 Baseline model

The influence of spatially close neighbors on the adoption of the PV technology is captured in the model by the coefficient β. We estimate the baseline model including all solar panels in our dataset and provide evidence on the existence of peer effects in the adoption of the PV technology in Switzerland. We also investigate how distance and time between PV installations impact the magnitude of social contagion.

Table 3 provides our baseline results. Column (1) presents the results using all PV installations in our dataset. We observe that all coefficients related to the installed bases are positive and statistically significant at the 1% level. That is, a higher average number of nearby installations increases the number of adoptions in the municipality. For the average municipality, any additional installation in a radius of about 300 meters increases the number of adoptions in the municipality by about 0.06 installations per quarter.

A closer look at the discs reveals that, the closer the existing installations, the stronger the effects on new adoptions. Table 3 shows that coefficients related to PV installations further away are systematically lower than the ones capturing installations that are closer to the adopter. This finding is in line with previous studies on social contagion in the diffusion of PV technology, suggesting that social contagion is a localized phenomenon, whose effects are strong in a limited geographical

[18] We use the boundaries of the neighborhoods as defined by the FSO in 2006. These boundaries remained unchanged throughout the observation period. Our final panel dataset is thus balanced and contains 303 neighborhoods over ten years. However, similar to what we do at the municipality level, our estimations at the neighborhood level focus only on the 279 neighborhoods that experienced at least one PV adoption by the end of 2015.

Table 3: Baseline specifications including all PV adoptions for the years 2006-2015

	(1) Complete	(2) 6 months	(3) 12 months	(4) 24 months
Average PV, 0-0.333 km	0.0571^{***}			
	(0.0146)			
Average PV, 0-0.333 km, last *period* only		0.1759^{***}	0.1194^{***}	0.0795^{***}
		(0.0325)	(0.0235)	(0.0181)
Average PV, 0-0.333 km, except last *period*		0.0174	0.0094	0.0207
		(0.0163)	(0.0181)	(0.0217)
Average PV, 0.333-1 km	0.0568^{***}			
	(0.0074)			
Average PV, 0.333-1 km, last *period* only		0.1639^{***}	0.1036^{***}	0.0741^{***}
		(0.0225)	(0.0155)	(0.0102)
Average PV, 0.333-1 km, except last *period*		0.0346^{***}	0.0358^{***}	0.0373^{***}
		(0.0075)	(0.0087)	(0.0108)
Average PV, 1-2.848 km	0.0077^{***}			
	(0.0021)			
Average PV, 1-2.848 km, last *period* only		0.0423^{***}	0.0280^{***}	0.0176^{***}
		(0.0072)	(0.0049)	(0.0032)
Average PV, 1-2.848 km, except last *period*		0.0009	−0.0010	−0.0038
		(0.0029)	(0.0033)	(0.0044)
Average PV, 2.848-8.062 km	0.0040^{***}			
	(0.0003)			
Average PV, 2.848-8.062 km, last *period* only		0.0177^{***}	0.0128^{***}	0.0080^{***}
		(0.0016)	(0.0011)	(0.0007)
Average PV, 2.848-8.062 km, except last *period*		0.0016^{***}	0.0005	−0.0003
		(0.0004)	(0.0006)	(0.0008)
Constant	3.0504^{*}	2.3566	2.4196	2.8499^{*}
	(1.2826)	(1.2498)	(1.2547)	(1.2629)
Controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Canton × year-quarter FE	Yes	Yes	Yes	Yes
# Observations	89,680	89,680	89,680	89,680
R^2	0.3540	0.3692	0.3689	0.3634

Note: Standard errors in parentheses, clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Radii of the inner circle and disc installed bases are computed based on Equation (1) with an area-multiplier m of 8 (see Sub-Section 3.1).
The dependent variable is the number of new PV system adoptions in a municipality-year quarter. The number of observations corresponds to N=2,242 municipalities time T=40 quarters. Municipalities are distributed accross 26 cantons. Columns (2) to (4) split the full spatiotemporal installed bases between the PV installations completed in the last 6, 12 or 24 months prior to adoption and the installations completed prior to these periods.

area, and decrease as distance increases. For comparison, Graziano and Gillingham (2015) find weaker social contagion effects for neighbors located more than 0.5 miles away, and even more so for households located 1 mile away or more. Using a different methodology, Rode and Weber (2016) find very localized spillovers, vanishing completely, at least in statistical terms, after 1 km. Similarly to Graziano and Gillingham (2015), our coefficients remain significant beyond the 1 km threshold, even though, at longer distances as in the 2.848-8.062 km range, they become very small (e.g. 0.004) and not economically meaningful.

Columns (2) to (4) of Table 3 show that the oldest nearby installations have a lower impact on the adoption decisions than the most recently built PV systems, and in some cases no significant impact at all when located further away. To obtain this result, we divide each band into two samples, based on the time since completion: for a given distance, one sample captures the most recently installed PV systems, and the other the remaining installations. When defining recent installations as installations completed in the last 6 months (column (2)), we find that the coefficient at 0.333 km is 0.18, while it falls at 0.02 for the PV systems installed more than 6 months prior to adoption. This means that one additional PV system in the previous six months results on average in 0.18 new adoptions per quarter and its effect is on average approximately ten times larger than for all remaining older installations. The coefficient falls to 0.12 (0.08) when considering the last 12 (24) months as the period defining recent installations. That is, the larger the time frame considered when specifying the recent installations, the weaker the peer effects. In this respect, we stress that the effect of an installation dissipates relatively rapidly.

Even when taking into account the different vintages, we find that the strength of peer effects decreases with distance, as in Graziano and Gillingham (2015). As far as imitation is concerned, the intuition is that new installations are more likely to catch people's attention. As far as learning is concerned, with a relatively fixed pool of neighbors, the opportunity for sharing is also fixed, and after some time, most prospective PV buyers in a given social network are likely to have received their information.

Figure B.1 and Table B.3 in the Appendix investigate how social contagion effects evolve over time. In Figure B.1, we estimate the models of columns (1) and (2) of Table 3 for different sub-periods in our sample. To ensure that inference is based on a sufficient number of observations, we focus in each estimation on a rolling four-year period. As in other estimations below, we use only one radius, defined at 1 km. For each period, Figure B.1 displays the estimated coefficients (and confidence intervals) using all surrounding installations, within the radius, for the computation of the spatiotemporal variables, regardless of the date of connection to the grid (cf. column (1) in Table 3); those that have been connected to the grid for less than 6 months; and those that have been connected to the grid for more than 6 months (cf. column (2) in Table 3). Figure B.1 shows that the importance of social contagion for new adoptions decreases over time. We attribute this pattern to the fact that the Swiss solar market is becoming more mature, and solar panels more mainstream. Table B.3 confirms the time-diminishing patterns of social contagion by using interactions between the complete spatiotemporal variable and either a continuous time indicator (column (1)), or a dummy variable for each year (column (2)). According to column (1), the impact of an additional PV installation in the installed base decreases on average by 0.01 points every quarter. This reduction is highly statistically significant. Column (2) corroborates this finding and, consistently with Figure B.1, confirms that social spillovers are decreasing in a relatively linear fashion. This result is in contrast with Bollinger and Gillingham (2012), who find an increase in strength of social contagion around the end of their sample (2001-2011). Their explanation is, however, compatible with our findings. According to Bollinger and Gillingham (2012), the increase in their coefficients is to be attributed to specific initiatives aimed at leveraging social contagion, in particular by SolarCity. SolarCity, a subsidiary of Tesla, Inc., is one of the leading residential solar installer in the US. One of its marketing campaigns, introduced in 2008, specifically relies on the exchange of information at the local level about the benefits of solar technology. The initiative, called the SolarCity Ambassador Program, provides a reward for the company's customers who successfully convince their neighbors or relatives to install solar panels on their roofs. Similar programs promoting PV adoption through community-level social learning and social norms have been implemented by authorities, installers or electricity utilities (see e.g. Bollinger et al., 2019; Gillingham and Bollinger, 2017; Bollinger et al., 2016). We are however not aware of any such initiative having taken place in Switzerland. This difference points to interesting avenues for future research, analyzing how social contagion effects may vary depending on whether any initiatives are undertaken to leverage them.

Besides providing evidence for the presence, and evolution, of social contagion effects, our results reveal some interesting correlations between the adoption of solar panels and some population characteristics and contextual variables. We report in Table B.4 in the Appendix the coefficients for the control variables. We discuss here the most relevant correlations for the socioeconomic variables green votes, income and age. The share of voters supporting green parties is found to have a positive and strongly significant impact in the adoption of solar panels. Following the seminal paper by Deacon and Shapiro (1975), several studies have highlighted the role of political preferences, and more specifically green preferences, on the demand for environmental quality, e.g. Kahn (2007) on commuting modes, annual gasoline consumption, and vehicle choice in California or Thalmann (2004) and Bornstein and Lanz (2008) on energy tax ballots in Switzerland. Sexton and Sexton (2014) find with data for the states of Colorado and Washington that in areas with particularly strong green preferences the market share of Priuses has been growing compared to other hybrid cars. The authors attribute this result to the strong green signal that Priuses can provide, given its unique design, and to the higher value of this signal in green areas. As in Graziano and Gillingham (2015), income does not have a clear positive and statistically significant impact on the number of adoptions. We find that a higher proportion of upper-middle-class households (income between CHF 50,000 and 75,000) may drive stronger adoption, but the effect of the poorest and richest classes remains statistically insignificant. Note also that including median or mean income instead of income classes does not bring any more explanatory power. At the same time, we observe an inverse-U relationship for age, suggesting that wealth (or permanent income) may matter more than current income measured by the official statistics. Other factors, such as the ability to plan for the long-run, may also enter the household utility function. Concerning contextual factors, we note that solar radiation does not have an impact on adoption in our data, neither in a contemporaneous way (as in Table B.4) nor with a lag (cf. Lamp, 2016).

4.2 Uncovering the mechanisms

We address in this section the main research questions of this paper: Whose adoption is the most affected by past adoptions? Which type of installation is the most influential for future adoption? And more generally, what are the main drivers behind social contagion? We focus on the variation across our measures of social spillovers for several features and technical characteristics of the PV installations in our dataset. We start by deepening the examination of the effects on social contagion of panels of varying size, already undertaken by Bollinger and Gillingham (2012), by relying on power categories. We then extend our analyses to the role ownership and mounting type. Our analyses of the mounting type point to a potential role for the visibility of an installation. We further investigate this role by looking at the inclination of the solar panels (roof pitch), the height of the roof (number of floors) and the isolation of the PV installation (number of buildings in proximity).

For simplicity, we consider the influence of all installations within a 1 km radius for the remainder of this study. The effect of distance, and of installations' age, remains, however, valid also for the specifications used here.

Table 4: Main specifications focusing on size

	(1) All adopt.	(2) <10 kWp adopt.	(3) 10-29.9 kWp adopt.	(4) 30-99.9 kWp adopt.	(5) >100 kWp adopt.
Average PV, <10 kWp	0.127^{***}	0.106^{***}	0.085^{***}	0.091^{***}	0.078^{***}
	(0.009)	(0.006)	(0.006)	(0.008)	(0.009)
Average PV, 10-29.9 kWp	0.070^{***}	0.031^{*}	0.073^{***}	0.075^{***}	0.065^{***}
	(0.018)	(0.013)	(0.013)	(0.016)	(0.014)
Average PV, 30-99.9 kWp	0.271^{***}	0.208^{***}	0.202^{***}	0.219^{***}	0.212^{***}
	(0.040)	(0.027)	(0.021)	(0.031)	(0.027)
Average PV, >100 kWp	0.234^{***}	0.171^{***}	0.200^{***}	0.150^{**}	0.141^{***}
	(0.045)	(0.039)	(0.037)	(0.050)	(0.031)
Constant	2.942^{*}	1.941^{**}	0.207	-0.173	0.110
	(1.280)	(0.748)	(0.386)	(0.229)	(0.179)
Controls	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes
Canton × year-quarter FE	Yes	Yes	Yes	Yes	Yes
# Observations	89,680	89,680	89,680	89,680	89,680
R^2	0.3280	0.3314	0.3561	0.2882	0.2920

Note: Standard errors in parentheses, clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
The dependent variable is the total number of new PV system adoptions (column (1)), and of a particular size only (columns (2) to (5)), in a municipality-quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius. Installed bases are generated based on installation size.

Size Here we are interested in assessing whether installations with larger capacity lead to stronger social contagion, knowing that capacity may be a good proxy for both size and productivity. The intuition is the following. Larger installations may be more profitable, but are also riskier, increasing the return to learning from word-of-mouth. At the same time, everything else equal, larger installations are likely to be more visible and thus imitation may also be higher. Hence, both effects may drive higher social contagion with larger installations. We examine below whether both effects are at play in our context.

Table 4 presents our estimations by separating the installed base according to the power categories: under 10 kWp, between 10 and 30 kWp, between 30 and 100 kWp, and over 100 kWp. We use the exact same specifications as in Table 3, with the dependent variable being the total number of new adoptions or the total number of new adoptions of a given size.

Column (1) in Table 4 suggests that the largest installations (peak capacity > 30 kW) in the installed base generate stronger social contagion effects than smaller ones. This finding confirms empirically the hypothesis stated in Bollinger and Gillingham (2012), i.e. that large solar panels are more visible and therefore drive more additional adoptions. The remaining columns look at whether contagion is stronger between installations with similar capacities. Interestingly, we find that installations of a given size do not drive disproportionately more adoptions of the same size, suggesting that learning effects, if any, have the primary effect of encouraging adoption of solar technology rather than directing the choice towards a particular size.

Table 5: Main specifications focusing on type

	(1) All adopt.		(2) BAPV		(3) BIPV	
Average PV, BIPV	0.194^{***}	(0.018)	0.187^{***}	(0.013)	0.174^{***}	(0.018)
Average PV, BAPV	0.113^{***}	(0.007)	0.055^{***}	(0.005)	0.110^{***}	(0.007)
Constant	2.906^{*}	(1.282)	-0.122	(0.405)	2.329^{*}	(1.056)
Controls	Yes		Yes		Yes	
Municipality FE	Yes		Yes		Yes	
Canton × year-quarter FE	Yes		Yes		Yes	
# Observations	89,680		89,680		89,680	
R^2	0.3267		0.2925		0.3261	

Note: Standard errors in parentheses, clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

The dependent variable is the number of PV system adoptions of all types (column (1)), of the BAPV type (column (2)), and of the BIPV type (column (3)), in a municipality-quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius.

Type The analysis of installation size indicates that learning and imitation effects may be contributing to social contagion, but it does not confirm that at least one or the other is at play. To investigate further the drivers of social contagion, we make use of several characteristics of the PV installations that are likely to influence their visibility. As a first step, we exploit the the fact that our dataset gives information on the type of installation, BAPV or BIPV. We expect BIPV to drive stronger contagion. Given that BIPV installations are more frequently installed on steep roofs, they are likely to be more visible, since they are more exposed to the view of passersby than rooftops.

Following the same protocol, we also look at whether installations of a given type are more likely to be influenced by other installations of the same type, especially through learning, which should be stronger when type-specific.

We address this question in two steps. First, we look at the effect of each type of installation on all new adoptions. Column (1) of Table 5 shows that, everything else equal, BIPV systems are more influential than BAPV systems. The coefficient of interest for BIPV systems is almost twice as big (0.194) as the one for BAPV systems (0.113). Second, we look at what installations are more likely to be influenced by what type. In columns (2) and (3) we find that BIPV installations lead to higher adoption of solar panels of both types, BAPV and BIPV. That is, contagion from BIPV to BAPV is stronger than from BAPV to BAPV.

All these results point to a potentially strong visibility effect. To further explore this question, we look in what follows at roof pitch, building isolation, and building height.

Roof pitch, building isolation, and building height To further investigate whether more visible PV installations generate stronger social contagion, we consider various attributes of the buildings on which PV systems are installed, which could influence their visibility. The first attribute is the pitch of the roof, which determines the inclination of the solar panels. Hence, we expect social contagion to be positively correlated with the angle of the roof, through visibility effects. The second attribute is related to the height of the building: the taller the building, the less visible the solar installations from the streets. However, solar installations could still be seen from the upper floors of the surrounding buildings. To account for this, we calculate the relative height of every building equipped with solar PV systems with respect to nearby buildings. More precisely, we measure the relative height of each building as the difference in the number of floors compared to the average number of floors of all buildings within a radius of 100 meters. We expect that PV systems installed in buildings surrounded by taller buildings are more visible and thus generate stronger social contagion. The third attribute that we use to assess the effect of visibility is a measure of its geographical isolation. Whether a solar installation can be seen by passersby, and not only by the most proximate neighbors, depends on whether its view is obstructed by other buildings. For instance, solar panels on a detached house may remain largely unnoticed if other buildings, especially taller buildings, separate the house from the main street. Overall, we expect the steepest, lowest, and most isolated roofs to generate stronger social contagion, through the mechanisms related to visibility.

We test these hypotheses by applying our standard strategy, leveraging our baseline model with a 1 km radius with installed bases that are separated according to the different categories of each building attribute. As explained, we restrict our analyses to 1,640 municipalities.

Tables 6, 7, and 8 report our main results for roof pitch, building height, and building isolation, respectively. All estimates are consistent with our priors. Building characteristics associated with higher visibility show stronger social contagion coefficients.[19]

When looking at the roof pitch, we run two separate estimations. First, we distinguish between flat roofs, i.e. with a 0° pitch, from steep roofs. The estimation results are provided in column (2) of Table 6. Second, we distinguish between roofs above and below the median pitch. The estimation results are provided in column (3) of Table 6. As expected, we find weaker social contagion for flat roofs. Also, we find that half of the PV installations, those with the steepest roofs, drive approximately 30% more adoptions than the remaining half.

Table 7 investigates the impact of the relative height of the building. We find that the coefficient capturing the effect of solar panels installed on smaller buildings than their neighbors' is larger than the coefficient for the buildings that are higher than their neighbors. PV on lower buildings than their surroundings are more visible than those on higher buildings, and thus drive more social contagion.

Finally, in Table 8, we differentiate the impact of PV installations according to their degree of isolation. More precisely, we measure separately the influence of PV installations that have, for a given radius, a below-median number of neighboring buildings, and those with an above-median number. Results show that social contagion is stronger when the existing PV installations are isolated. We attribute this

[19]Estimation results report stronger contagion from PV installations with an undefined pitch, height or isolation than from PV installations included in a particular category. We attribute this result to the fact that the likelihood of being included in the undefined category is higher for large capacity and geographically isolated PV installations. The main reason is that the coordinates of the buildings in the BDS indicate the main entry of the building, whereas our coordinates for the PV installations, in general, indicate the center of the building. Hence, when merging the two databases, the likelihood that such distance exceeds our threshold of 15 meters is greater for large buildings than smaller buildings (see Section 3.2 for more details on the merging procedure).

Table 6: Main specifications focusing on roof pitch

	(1) All adopt.	(2) All adopt.	(3) All adopt.
Average PV	0.127^{***} (0.006)		
Average PV, steep roof (>1°)		0.120^{***} (0.009)	
Average PV, flat roof (<1°)		0.085^{**} (0.026)	
Average PV, pitch>24°			0.133^{***} (0.012)
Average PV, pitch<=24°			0.099^{***} (0.011)
Average PV, undefined pitch		0.196^{***} (0.025)	0.196^{***} (0.025)
Constant	4.056^{*} (1.960)	3.903^{*} (1.952)	3.911^{*} (1.955)
Controls	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Canton × year-quarter FE	Yes	Yes	Yes
# Observations	66,400	66,400	66,400
R^2	0.3332	0.3343	0.3345

Note: Standard errors in parentheses, clustered at the municipality level. *p<0.05, **p<0.01, ***p<0.001.
The dependent variable is the number of PV system adoptions by a particular type of owner, in a municipality-quarter. The number of observations corresponds to N=1,660 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius.
The median roof pitch, 24°, is calculated over the 34,717 PV installations in our dataset for which we could identify the corresponding building with a sufficient level of certainty.
The "undefined pitch" category includes all PV installations for which we could not identify the corresponding building (see section 3.2).

result to the fact that solar installations on relatively isolated buildings can be seen from further away, as their view is less obstructed by other buildings.

Tables B.5 and B.6 in the Appendix combine the different attributes in pairs. The results show that, even after taking into account the (relative) height of buildings, the most inclined solar panels, and those installed on the most isolated buildings, have a greater influence on potential adopters. This confirms that our visibility indicators are complementary, and that more visible PV system bring higher social contagion.

However, such detailed information on the characteristics of buildings may not always be available. Even for Switzerland, where the dataset is maintained by a public agency, not all municipalities are covered. Hence, using mounting type as a

Table 7: Main specifications focusing on roof height

	(1) All adopt.	(2) All adopt.
Average PV, smaller than average building in 100m radius	0.120^{***} (0.012)	
Average PV, higher than average building in 100m radius	0.094^{***} (0.014)	
Average PV, smaller than municipality average		0.133^{***} (0.010)
Average PV, higher than municipality average		0.066^{***} (0.014)
Average PV, undefined height	0.227^{***} (0.017)	0.229^{***} (0.017)
Constant	2.982^{*} (1.278)	2.890^{*} (1.277)
Controls	Yes	Yes
Municipality FE	Yes	Yes
Canton × year-quarter FE	Yes	Yes
# Observations	89,680	89,680
R^2	0.3283	0.3290

Note: Standard errors in parentheses, clustered at the municipality level. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.
The dependent variable is the number of PV system adoptions by a particular type of owner, in a municipality-quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius.
The "undefined height" category includes all PV installations for which we could not identify the corresponding building (see section 3.2).

proxy for visibility may still provide several advantages. To support this strategy, we examine whether BIPV are more likely installed on steep roofs, and less likely to be installed on flat roofs, as compared to BAPV. Our hypotheses are confirmed. As reported in Figure A.3 in the Appendix, only 2% of BIPV systems are installed on roofs with an angle lower or equal to 1%, whereas this proportion jumps to 14% for BAPV systems. The average roof pitch is 26° for building-integrated systems and 22° for building-attached systems. In what follows, we combine ownership, size, and type. Type is used as the main proxy for an installation's visibility, given the larger number of observations and the support provided by the analysis of roof pitch.

Ownership Given that our dataset includes the individual level categorical variable "owner", we are able to assess whether social contagion is a driver of adoptions only among households or also for legal persons such as firms and farms.

We proceed, again, in two steps. We first look at the effect of all pre-existing solar panels, regardless of their owner, on the adoption of solar panels by owner type. That is, we look at what type of owner is most influenced by an existing pool of solar installations. Columns (1) to (3) of Table 9 present the coefficients of

Table 8: Main specification focusing on isolation

	(1) All adopt.
Average PV, below median # of buildings within 100m	0.185*** (0.010)
Average PV, above median # of buildings within 100m	0.098*** (0.007)
Average PV, undefined isolation	0.230*** (0.029)
Constant	2.851* (1.268)
Controls	Yes
Municipality FE	Yes
Canton × year-quarter FE	Yes
# Observations	89,680
R^2	0.3294

Note: Standard errors in parentheses, clustered at the municipality level. *p<0.05, **p<0.01, ***p<0.001.
The dependent variable is the number of PV system adoptions by a particular type of owner, in a municipality-quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius.
The median number of buildings within a 100 meter radius is 17. This average number is calculated over the 52,832 PV installations for which we know the exact location.
The "undefined isolation" category includes all PV installations for which we could not identify the corresponding building (see section 3.2).

interest. Column (1) reports the results for the influence of existing installations on households' adoption. In line with Table 3 and the literature, which has so far focused on residential installations only, we find a positive impact. The aggregate results of Table 3 are, however, not only driven by the behavior of households. Interestingly, we find in columns (2) and (3) that the decision of firms and farms to adopt solar PVs is also impacted by pre-existing nearby PV systems, although to a lesser extent than for households. In these specifications the installed bases included pre-existing installations of all types. The next step consists in observing whether owners of a given type are influenced in the same way by each pre-existing installation, or whether they are more likely to be influenced by the behavior of owners of the same type, that is, their peers.

Social contagion effects are expected to operate through word-of-mouth and imitation, and for both channels, social contagion could be stronger for narrower definitions of peers. Think of the effect of talking with existing adopters: learning is likely

Table 9: Main specifications focusing on ownership

	(1) Household adopt.	(2) Firms adopt.	(3) Farms adopt.	(4) Household adopt.	(5) Firms adopt.	(6) Farms adopt.
Average PV	0.112***	0.093***	0.091***			
	(0.004)	(0.005)	(0.009)			
Average PV, same *owner*				0.085***	0.205***	0.329***
				(0.010)	(0.013)	(0.092)
Average PV, other *owners*				0.131***	0.026**	0.087***
				(0.006)	(0.008)	(0.009)
Constant	3.167***	−0.522	0.080	3.186***	−0.464	0.066
	(0.949)	(0.339)	(0.118)	(0.957)	(0.334)	(0.118)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Canton × year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	89,680	89,680	89,680	89,680	89,680	89,680
R^2	0.4397	0.2487	0.2805	0.4413	0.2668	0.2843

Note: Standard errors in parentheses, clustered at the municipality level. ***p < 0.01, **p < 0.05, *p < 0.1
The dependent variable is the number of PV system adoptions by a particular type of owner, in a municipality-quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius. Columns (4) to (6) split the complete spatiotemporal installed bases between the PV installations owned by an owner of the same type of the adopter, and the PV installations owned by owners of a different type.

to work better when one learns from a similar situation. Not only should the information gathered by talking to a similar peer be more relevant, but it should also be more persuasive. Firms are therefore more likely to be influenced by learning from neighboring firms, and farmers are more likely to be influenced by learning from other farmers. Imitation is also more likely to work among close peers. Seeing a PV system in the neighborhood probably sends a more persuasive signal, and generates a more influential social norm, if the agent who installed it is comparable.

We test this hypothesis by computing a new set of installed bases: one spatiotemporal variable accounts for same-owner installations, and another accounts for all remaining installations. As shown in columns (5) and (6) of Table 9, much stronger contagion is found for firms and farms when similar ownership is considered. For example, column (5) indicates that one additional firm-owned installation in the average installed base at 1 km creates as much influence on firm adoptions as eight installations of the remaining types of owners. This difference is even more important for adoptions by farms, as shown in column (6). Interestingly, we also note that, although firm decisions are mainly affected by other firm behavior, non-firm neighbors are still relevant for explaining firm adoptions. That is, the adoption of other actors in the economy, households in particular, influences the adoption by firms. One explanation may be that the household level of adoption in a given location provides a signal to firms that their customer base is going green, which may induce them to adopt PV technology for marketing and social responsibility reasons.

Somewhat surprisingly, social contagion is not stronger for households when we consider only adoptions by other households. This result suggests that households are, everything else equal, more likely to be influenced by installations owned by non-households. Since, however, installation characteristics may change across owner types, we extend our analyses to interactions between ownership and installation size. We also look at the interaction between ownership and installation type, also because the strength of each channel, learning or imitation, may vary depending on the agent involved. Finally, we look at the interaction between ownership, installation type and size.

In what follows, we combine ownership, size, and type. Type is used as the main proxy for an installation's visibility, given the larger number of observations and the support provided by the analysis of roof pitch.

Size and ownership Are households more influenced by non-household neighbors than by their peers simply because non-household PV installations are larger? Table B.7 in the Appendix focuses on the contagion from existing installations of different sizes to new adoptions by households only.

As in Table 9, households are influenced by owners of other types more than they are by other households, but this holds true only for small installations, the large majority in our sample. While the difference between the effect of residential and commercial installations on residential adoption is relatively small, it does suggest the existence of a potential additional role for visibility. Visibility may not only provide a signal of greenness but, in particular as far as commercial adoption is concerned, also a signal of profitability. Since commercial adoption may be driven to a lesser extent by pro-environmental motivations, relatively small installations by (potentially small) private firms may provide a particularly strong signal of profitability. With larger installations, social spillovers become also larger, as expected, and contagion from residential installations become more important than contagion from commercial installations. With larger installations, this somehow counter-intuitive result disappears, and the relative effect of residential installations compared to commercial installations becomes larger. It is plausible that as the size of the installations increases, households may turn to their peers for learning, and commercial investments look increasingly different from residential investments.

Type and ownership Our results so far suggest that BIPV installations lead to stronger contagion for any type of photovoltaics than BAPV installations. They also suggest that firms (farms) are more likely to be influenced by the behavior of other firms (farms). This result is not confounded by differences in the size of installations.

Table B.8 in the Appendix examines the interaction between ownership and installation type. We proceed as usual in two steps. Columns (1) to (3) confirm that BIPV installations have larger influence on new adoptions than BAPV installations. This holds true for all types of owners. While one may be surprised that firms and farms are also influenced by the visibility of BIPV installations, private firms do care about social trends and norms and install solar panels to signal their greenness to their customers, as often reported in the news. More visible installations may to some extent also provide a signal in terms of profitability, to which prospective commercial customers may be particularly receptive. Finally, we find again in columns (4) to (6) that firms and farms are more likely to be influenced by firms and farms, respectively, also when taking into account the difference in installation types.

Size and type We proceed in the same way for type and size (cf. Table B.9 in the Appendix). BIPV installations drive stronger contagion also when taking into account differences in capacity, except for some large installations, which may be very visible regardless of their type. We also confirm that the larger the installation, the larger the social contagion effects, even when installation types are taken into account. The same results apply to all owner types.

Size, type and ownership In order to conclude that both visibility and word-of-mouth play crucial roles in the social contagion of the PV technology, we estimate the model by controlling at the same time for ownership, type and size. This is the last step necessary to confirm our set of results.

None of our general findings is contradicted by the new evidence provided in Table B.10 in the Appendix. Note, however, that as the installed bases become smaller and smaller, inference results from a relatively small number of observations, which implies less reliability. This leads two coefficients to become negative, yet not statistically different from zero, and several others to be imprecisely estimated. Even so, Table B.10 provides comforting evidence supporting our general set of stylized facts: (1) the bigger the solar panel, the stronger the contagion; (2) the more visible the solar panel, the stronger the contagion; (3) the more similar the owner type, the stronger the contagion.

4.3 Alternative specifications

Non-linear models In this section we test the robustness of our results by considering several alternative estimators to OLS and by investigating the effect of including additional fixed effects to the baseline specification. For the sake of clarity, we conduct these tests using the complete installed bases within a 1 km radius only. We also investigate the sensitivity of our baseline results when varying the aggregation of distance.

Three estimators can be used as alternatives to the linear fixed effects model used throughout this paper. The first is the first difference estimator (FD). Similarly to spatial fixed effects models, FD allows controlling for time-invariant unobserved heterogeneity across spatial units. The second and third alternative estimators are the negative binomial (NB) and Poisson regression models. NB and Poisson account for the count data character of our dependent variable. NB is generally preferred over Poisson if the dependent count variable is over-dispersed, which is the case in our data (see e.g. Cameron and Trivedi). The average number of adoption per municipality-quarter is 0.67, and the variance is 2.60. However, unlike Poisson models, NB may suffer from the incidental parameter problem common to most non-linear models in presence of fixed effects (see e.g. Greene, 2018).

Table B.11 in the Appendix reports the results for the three different estimators. Every estimation includes the same set of control variables and fixed effects as in our baseline specification. The only exception is, as expected, the FD model, wherein municipalities fixed effects are replaced by the first difference transformation. All coefficients are positive and statistically significant, supporting our main estimations. The coefficient from the FD regression can be directly compared with that in our baseline OLS regression. As column (1) shows, OLS and FD provide very similar results.

Alternative discs In what follows we test the robustness of our results to another dimension. Here, we focus on the radii used to define the discs over which we compute the installed bases. In our baseline estimations, we set the radii so that the three discs have an area equal to 8 times that of the previous disc or circle (see Section 3.1). In Table B.12 in the Appendix, we test different area multipliers. The reported estimates show that our results for the effect of distance are unchanged when using multipliers of 3, 5, 6, and 9.

As noted by Rode and Weber (2016), imposing discs to have the exact same area as the inner circle, i.e. a multiplier of 1, has the advantage of allowing a better comparability between the coefficients. However, it also implies discs whose width quickly becomes narrow, making the assessment of the effect of distance more difficult and less accurate. In Table B.13 in the Appendix, we thus estimate our model with a relatively large inner circle of 1, 2 or 3 km radius and a unique disc with the same area. As expected, we observe stronger social contagion from nearby PV installations located in the inner circle than from those located further away in the surrounding disc. Adding additional same-area discs would provide generally consistent results, although the coefficient for a given band is no longer systematically smaller than the coefficient of the previous band.

Additional fixed effects We perform additional robustness tests by introducing additional fixed effects aimed at controlling for any residual homophily. Table B.14 in the Appendix shows that adding municipality by year fixed effects only marginally decreases the coefficient of interest, from 0.127 to 0.123. This result supports our main findings.

4.4 Analyses at the neighborhood level

In this section, we present a set of analyses based on the neighborhood level data presented in Section 3. These analyses aim at tackling any residual homophily, and potential changes in observables that vary over time at the very local level. To this end, we proceed by disaggregating our data at the neighborhood level whenever data are available. Neighborhood level data are available for the 17 largest Swiss municipalities, as shown in Figure A.2 in the Appendix. These 17 cities are subdivided into 279 neighborhoods. For each of them, we collect the same socioeconomic and contextual variables as those that we use at the municipality level. We provide summary statistics for these control variables, as well as information on the sources, in Table A.3 in the Appendix.

To analyze the results from our analyses at the neighborhood level, we proceed as follows. First, we estimate our baseline estimation for the 17 cities for which we could access neighborhood level data. The estimation results are provided in column

(1) of Table B.15. The objective of this estimation is to provide a comparison for the following estimations. In column (1), all control variables and fixed effects are defined at the municipality level. Our main effect persists even with this smaller, selected sample. Next, we add fixed effects at the neighborhood level. We do so in column (2). We only observe a relatively small decrease in the size of our coefficient of interest when adding fixed effects at the neighborhood level. In the following step, we add time-varying control variables at the neighborhood level. We do so in column (3). Again, in line with expectations, we observe a decrease in the coefficient of interest. However, such decline is, again, very moderate. Hence, we conclude that gains of conducting social contagion analyses at the neighborhood level is rather small. In other words, social contagion analyses at the municipal level are, if anything, only marginally biased. This finding supports the existing literature, which virtually entirely relies on fixed effects and confounding variables defined at the municipal or zip code level.

Note that adding to our baseline estimation the 10,720 additional observations that we obtain by replacing 17 cities with 279 neighborhoods, observed over 40 year-quarters would not affect our baseline results.[20] With 10,720 additional observations, the coefficients decreases slightly from 0.127 to 0.118. This result is provided, for completeness, in column (4) of Table B.15.

5 Conclusions

In this paper, we analyze the drivers of social contagion in the diffusion of solar photovoltaic technology. Besides confirming the existence of social contagion in the adoption of solar panels, we contribute to a very recent literature by providing novel evidence on the microeconomic mechanisms driving social contagion in the adoption of solar PV. In particular, while the literature has so far focused on residential solar PV adoption only, we also examine the behavior of firms and farms, and investigate in detail the impact of PV characteristics such as size and type on the magnitude of social spillovers, with a particular focus on the installation's visibility.

We exploit a very rich panel dataset containing geographical location and technical information on 59,819 PV systems adopted in Switzerland over the period 2006-2015. With precise geographical information, we are able to identify the lo-

[20] In six of the 17 cities, the neighborhoods do not cover the entire municipality territory. Our panel dataset therefore contains 2,510 spatial units, including 2225 municipalities, 279 neighborhoods and 6 units corresponding to the remaining territories of the cities. For these latter six spatial units, which contain only 141 PV installations, we use the control variables at the municipality level.

cation of each solar panel at the street level and measure social spillovers across municipality boundaries. Following Bollinger and Gillingham (2012), our identification strategies relies on the temporal lag between the time of purchase and the time of installation, coupled with a large set of detailed controls available yearly at the municipal level. For each PV installation, we compute the individual installed bases, i.e. the number of nearby pre-existing installations at the time of adoption. In order to unveil the underlying mechanisms of social contagion, we consider various characteristics of the pre-existing installations. We focus on ownership and differentiate between residential adoptions, and adoptions by firms and farms. We focus on size, and assess how social contagion may be dependent on the size of the installation. Finally, we focus on the type of mounting system, roof pitch, building isolation, and building height to investigate whether more visible installations increase the probability of adoption.

We find that households are not the only agents reacting to pre-existing adoptions. Social contagion is also a driver of adoptions in the private sector. A closer analysis reveals that social spillovers are stronger among owners of the same category, i.e. nearby firms-owned (farms-owned) installations weight more heavily on firms (farms) adoption decisions. Furthermore, we observe that more visible PV systems, i.e. those on steep roofs, low buildings and in areas with low obstruction, generate more influence among potential adopters in the neighborhood. The role of visibility is confirmed by using data on roof pitch, building height, and building isolation. By considering simultaneously the role of ownership, size and type, we provide evidence that both visibility and word-of-mouth are important drivers of social contagion. We also confirm, with higher precision and detail than in previous studies, that social contagion is a very localized and short-term phenomenon, whose strength declines with distance and time. These results remain valid throughout the paper, including in the estimations focusing on specific PV characteristics.

The results of our study have several implications for practitioners and policymakers alike, especially in a context in which subsidies for renewable energy are under pressure, and "first-best" policies such as carbon taxes still face strong opposition from the general public and part of the economy. In this paper, we provide evidence on how social contagion works, orienting potential interventions to leverage it. These interventions would be the most successful, and potentially the most cost-effective, if targeted to the different agents involved in the market, in particular differentiating between residential and commercial customers. Measures could focus on creating new opportunities for learning and sharing, as well as on increasing the visibility of all vintages of existing installations, either physically or online.

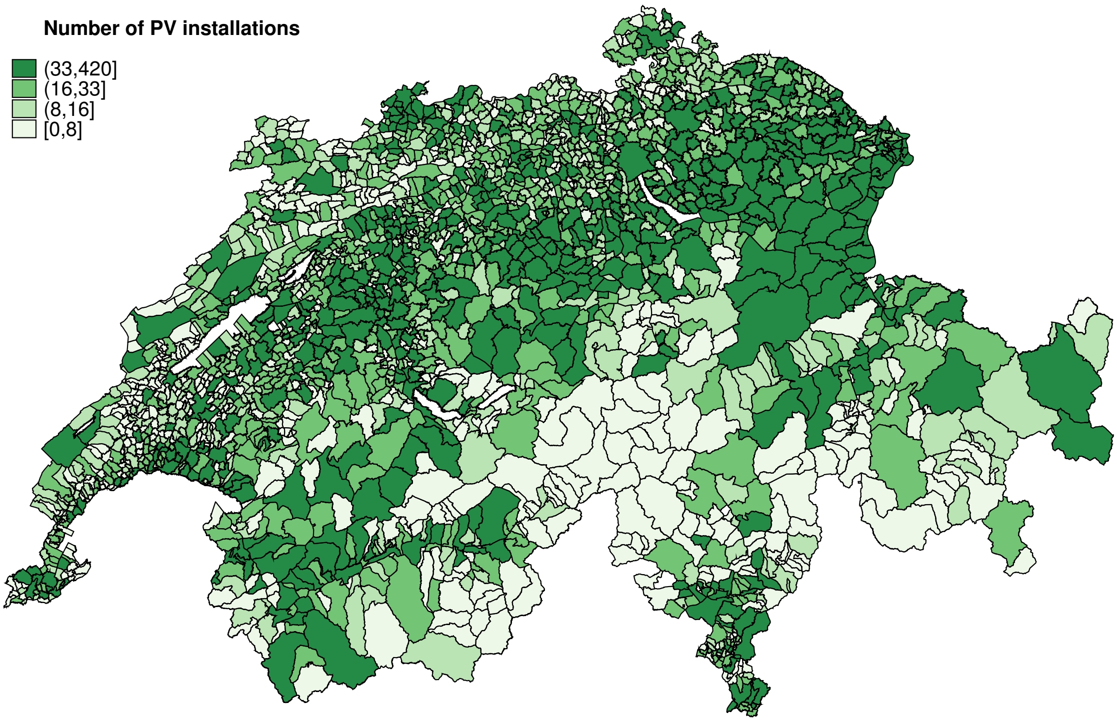
Appendix A: Additional descriptive statistics

Table A.1: Summary statistics of the dependent variables used in the models

Variables	Mean	SD	Min	Max	Observations
All adoptions	0.667	1.61	0	46	89,680
Households	0.296	0.97	0	33	89,680
Firms	0.190	0.72	0	37	89,680
Farms	0.026	0.21	0	16	89,680
BAPV	0.506	1.36	0	42	89,680
BIPV	0.153	0.53	0	21	89,680
<10kWp	0.328	0.93	0	29	89,680
10-29.9kWp	0.188	0.67	0	26	89,680
30-99.9kWp	0.094	0.44	0	22	89,680
>100kWp	0.057	0.31	0	17	89,680

Note: The dependent variables measure the number of adoptions in a municipality during a particular year-quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons.

Figure A.1: Number of PV installations per municipality, by the end of 2015



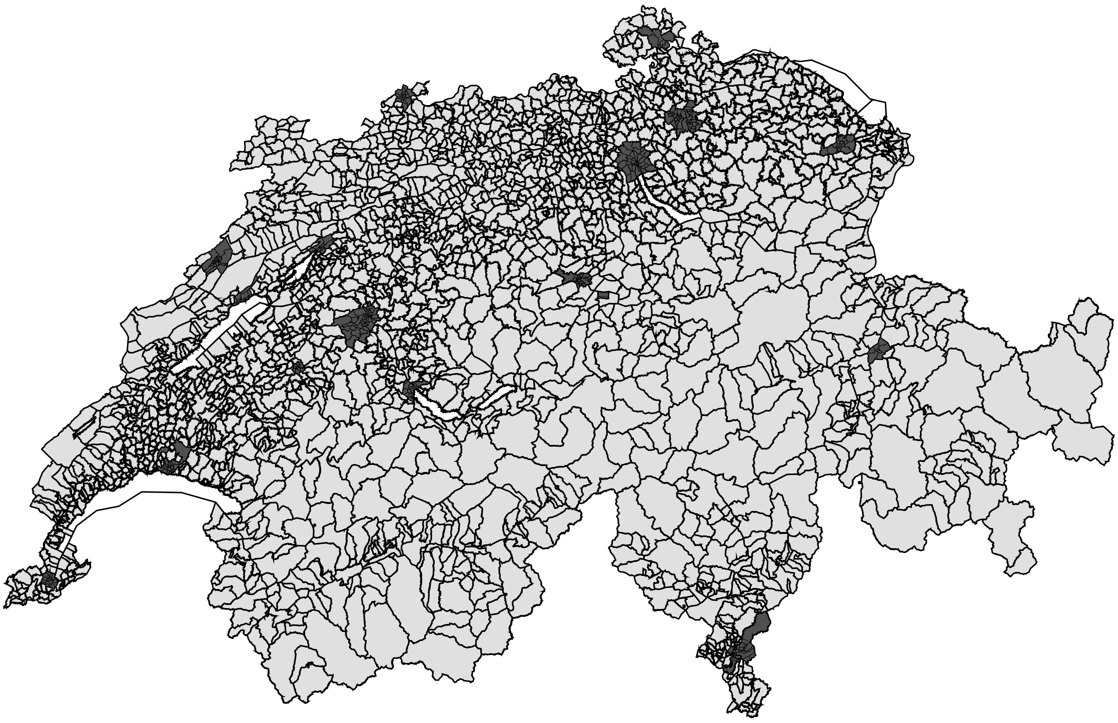
Note: This map shows the number of PV installations in the Swiss municipalities in 2015. Source: Swiss Federal Office of Energy (SFOE) and Swiss Federal Office of Topography (swisstopo).

Table A.2: Distribution of PV installations by type, roof pitch, building isolation, and building height

	BAPV		BIPV		GRPV		Total	
Roof pitch (flat/steep)	N	% (row)	N	% (row)	N	% (row)	N	% (col.)
Flat roof (<=1°)	3,791	(95.13)	194	(4.87)	0	(0.00)	3,985	(8.53)
Steep roof (>1°)	23,044	(74.98)	7,688	(25.02)	0	(0.00)	30,732	(65.75)
Undefined pitch	8,722	(72.55)	2,741	(22.80)	559	(4.65)	12,022	(25.72)
Total	35,557	(76.08)	10,623	(22.73)	559	(1.20)	46,739	(100.00)
Roof pitch (median)	N	% (row)	N	% (row)	N	% (row)	N	% (col.)
Pitch<=24°	13,618	(81.04)	3,187	(18.96)	0	(0.00)	16,805	(35.95)
Pitch>24°	13,217	(73.79)	4,695	(26.21)	0	(0.00)	17,912	(38.32)
Undefined pitch	8,722	(72.55)	2,741	(22.80)	559	(4.65)	12,022	(25.72)
Total	35,557	(76.08)	10,623	(22.73)	559	(1.20)	46,739	(100.00)
Height (in relation to 100 m average)	N	% (row)	N	% (row)	N	% (row)	N	% (row)
Lower than 100m average	20,460	(76.34)	6,340	(23.66)	0	(0.00)	26,800	(44.80)
Higher than 100m average	12,836	(77.09)	3,814	(22.91)	0	(0.00)	16,650	(27.83)
Undefined # of floors	12,098	(73.91)	3,563	(21.77)	708	(4.33)	16,369	(27.36)
Total	45,394	(75.89)	13,717	(22.93)	708	(1.18)	59,819	(100.00)
Height (in relation to mun. average)	N	% (row)	N	% (row)	N	% (row)	N	% (col.)
Lower than municipality average	21,097	(76.86)	6,353	(23.14)	0	(0.00)	27,450	(45.89)
Higer than municipality average	12,199	(76.24)	3,801	(23.76)	0	(0.00)	16,000	(26.75)
Undefined # of floors	12,098	(73.91)	3,563	(21.77)	708	(4.33)	16,369	(27.36)
Total	45,394	(75.89)	13,717	(22.93)	708	(1.18)	59,819	(100.00)
Isolation	N	% (row)	N	% (row)	N	% (row)	N	% (col.)
Below median # of buildings within 100m	19,705	(74.31)	6,504	(24.53)	310	(1.17)	26,519	(44.33)
Above median # of buildings within 100m	20,817	(79.11)	5,252	(19.96)	244	(0.93)	26,313	(43.99)
Undefined isolation	4,872	(69.73)	1,961	(28.07)	154	(2.20)	6,987	(11.68)
Total	45,394	(75.89)	13,717	(22.93)	708	(1.18)	59,819	(100.00)

Note: PV data, including the type of mounting system of the PV panels, are provided by the SFOE and are based on the subsidy scheme's administrative register. BAPV stands for building-attached photovoltaics, BIPV stands for building-integrated photovoltaics, and GRPV stands for ground-mounted photovoltaics. We computed the roof pitch categories based on the solar cadastre provided by the SFOE, MeteoSwiss and swisstopo. Since the solar cadaster does not cover the entire Swiss territory, we could determine the pitch for only 78% (46,739) of all PV installations (59,819). We computed the number of floors and isolation categories based on the BDS provided by the FSO.

Figure A.2: Municipalities divided into neighborhoods



Note: Dark grey areas represent the 17 largest municipalities of Switzerland (in terms of population) whose territory is divided into neighborhoods. These cities are: Basel, Berne, Biel/Bienne, Chur, Fribourg, Geneva, Köniz, La Chaux-de-Fonds, Lausanne, Lugano, Lucerne, Neuchâtel, Schaffhausen, St. Gallen, Thun, Winterthur, and Zurich. Light grey areas show the other municipalities. Blank areas are either lakes or foreign enclaves. Source: GEOSTAT, Swiss Federal Statistical Office (FSO) and swissBOUNDARIES3D 2016, Swiss Federal Office of Topography (swisstopo).

Table A.3: Neighborhood level data: summary statistics

Variables	Mean	Std. Dev.	Min.	Max.	Source
		Population characteristics			
% pop. aged <30	32.34	4.98	0.00	78.50	FSO
% pop. aged 30-44	23.67	4.85	0.00	43.69	FSO
% pop. aged 45-64	26.07	4.38	0.00	77.78	FSO
% pop. aged 65-100	17.91	5.35	0.00	37.73	FSO
% tax payers with income <CHF 14.9 k	1.22	1.36	0.32	7.28	FTA
% tax payers with income CHF 15-29.9k	14.18	2.33	8.80	19.98	FTA
% tax payers with income CHF 30-49.9k	29.32	3.73	20.56	38.26	FTA
% tax payers with income CHF 50-74.9k	28.14	2.30	21.38	32.27	FTA
% tax payers with income CHF >75k	27.13	4.42	17.76	38.46	FTA
# of unemployed individuals	1,529.81	1,185.14	3.00	5,176.08	SECO/Cantons
Green voting (in %)	17.71	6.02	0.00	31.53	FSO/Cantons
		Contextual factors			
% detached houses	31.57	22.70	0.00	89.97	FSO (BDS)
% apartment buildings	41.47	17.11	0.00	83.16	FSO (BDS)
% builings with apart. and other use	18.52	15.11	0.00	70.27	FSO (BDS)
% commercial/industrial buildings	8.44	10.76	0.00	100.00	FSO (BDS)
Av. # of rooms per dwelling	3.36	0.55	2.09	5.33	FSO (BDS)
Av. area per dwelling	88.20	18.01	58.15	184.80	FSO (BDS)
Solar radiation (in W/sqm)	142.67	8.07	124.53	167.29	MeteoSwiss

Note: This table lists all control variables used in Table B.15, for the neighborhood level only. This table also lists the reference variables *% population aged <30*, *% tax payers with income CHF <14.9 k* and *% detached houses*. All variables have annual values at the neighborhood level. Summary statistics are computed over all years (2006 to 2015) for all neighborhoods having at least one PV installation (279 neighborhoods).

FSO stands for Federal Statistical Office, *FSO (BDS)* for the Building and Dwelling Statistic of the FSO, *FTA* for Federal Tax Administration, *SECO* for State Secretariat for Economic Affairs. *MeteoSwiss* is the Federal Office for Meteorology and Climatology. The source *Cantons* indicates that the data are produced by the relevant canton statistical office.

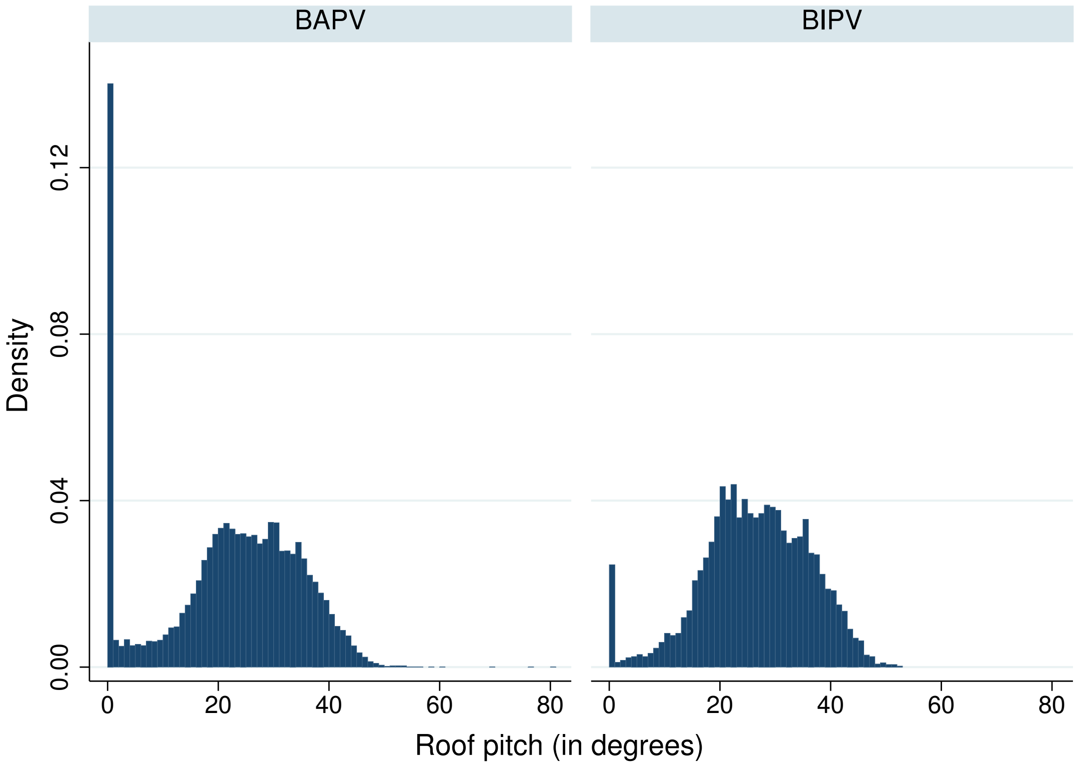
Data for age classes have been linearly extrapolated for the years 2006 to 2009. The data are also missing for a few neighborhoods and years. That is, municipality level data have been used for all the neighborhoods in Chur, for three neighborhoods in Thun, for one neighborhood in Lugano, and for all neighborhoods during the years 2010 to 2014 in Neuchâtel. Age data have been linearly intrapolated for the year 2014 in the neighborhoods of Köniz.

Unemployment data are available only at the district level (groups of 2 to 4 neighborhoods) in Zurich. Hence, in Zurich, we use the same annual district level values for all neighborhoods in a district. In Geneva, data are only available at the neighborhood level for the years 2014 and 2015. We hence use the 2014 values for the years 2006 to 2013. Since other cities do not produce or do not provide unemployment data at the levels other than the municipality, we use for them municipality level data.

Green voting data have been linearly interpolated for the years in between two elections, which take place every four years (last in 2015). We were able to access neighborhood level data on green voting for Zurich, Geneva, and Lugano. In Zurich, the data only exist at the district or two districts level (groups of 2 to 7 neighborhoods). In Lugano, the data only exist for approximately half of the neighborhoods (depending on the year). Data do not exist at the neighborhood level for other cities either because the voters can vote in the polling station of their choice or because the boundaries of the electroral precincts do not superimpose with those of the neighborhoods. In both cases, it is not possible to precisely assign the ballots to a particular neighborhood.

The only control variable for which we do not have neighborhood level data is income. Neither the federal nor the cantonal tax administrations produce data at a finer level than the municipality.

Figure A.3: Histogram of roof pitch of PV installations, by type



Note: Roof pitch (angle, in °) is the area-weighted average of the pitches of all PV-suitable roof surfaces of a building. The left (right) panel shows the distribution of the roof pitch for buildings equipped with BAPV (BIPV) installations. Source: SFOE, swisstopo, MeteoSwiss.

Appendix B: Additional empirical results

Table B.1: Alternative specification: conservative lags

	(1) 0 month	(2) 3 months	(3) 6 months	(4) 12 months
Average PV, *lag*	0.127^{***}	0.133^{***}	0.139^{***}	0.155^{***}
	(0.005)	(0.005)	(0.006)	(0.007)
Constant	3.083^{*}	3.218^{*}	3.290^{*}	3.297^{*}
	(1.289)	(1.310)	(1.323)	(1.350)
Controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Canton × year-quarter FE	Yes	Yes	Yes	Yes
# Observations	89,680	89,680	89,680	89,680
R^2	0.3259	0.3182	0.3126	0.3045

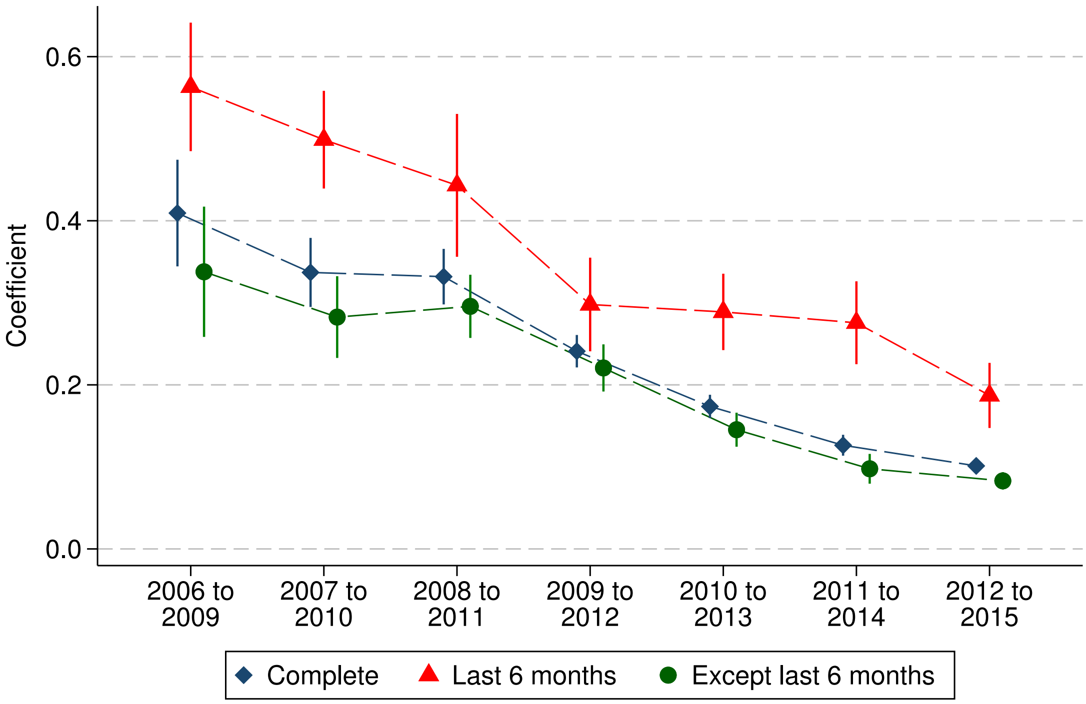
Note: Standard errors in parentheses, clustered at the municipality level. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.
The dependent variable is the number of new PV system adoptions in a municipality-year quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons.
Spatiotemporal variables are computed based on individual installed bases within a 1 km radius. In column (1), the installed bases are computed according to our standard approach, which takes into account the observed lag between the date of the decision to adopt and the date of installation. In columns (2), (3) and (4), additional lags of respectively 3, 6 and 12 months are added when computing the installed bases.

Table B.2: Additional estimations: municipality and/or time clustering

	(1) One-way clustering of SE by municipality		(2) One-way clustering of SE by year-quarter		(3) Two-way clustering of SE by municipality and year-quarter	
Average PV, 1km	0.127^{***}	(0.005)	0.127^{***}	(0.012)	0.127^{***}	(0.015)
% pop. aged 30-44	0.006	(0.005)	0.006^{**}	(0.002)	0.006	(0.006)
% pop. aged 45-64	-0.015^{**}	(0.005)	-0.015^{***}	(0.003)	-0.015^{*}	(0.006)
% pop. aged 65-100	-0.037^{***}	(0.008)	-0.037^{***}	(0.003)	-0.037^{***}	(0.010)
% tax payers with income CHF 15-29.9k	0.010	(0.006)	0.010^{**}	(0.003)	0.010	(0.007)
% tax payers with income CHF 30-49.9k	0.011	(0.006)	0.011^{***}	(0.003)	0.011	(0.007)
% tax payers with income CHF 50-74.9k	0.013^{*}	(0.006)	0.013^{***}	(0.003)	0.013	(0.008)
% tax payers with income CHF >75k	0.006	(0.006)	0.006	(0.003)	0.006	(0.008)
# of unemployed individuals	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Green voting (in %)	0.013^{**}	(0.005)	0.013^{***}	(0.002)	0.013^{*}	(0.006)
% apartment buildings	-0.006	(0.006)	-0.006^{*}	(0.002)	-0.006	(0.007)
% builings with apart. and other use	0.042^{***}	(0.010)	0.042^{***}	(0.006)	0.042^{**}	(0.013)
% commercial/industrial buildings	0.000	(0.009)	0.000	(0.004)	0.000	(0.012)
Av. # of rooms per dwelling	-0.560	(0.288)	-0.560^{***}	(0.119)	-0.560	(0.302)
Av. area per dwelling	-0.012	(0.006)	-0.012^{***}	(0.002)	-0.012	(0.008)
Solar radiation (in W/sqm)	0.000	(0.003)	0.000	(0.003)	0.000	(0.004)
Constant	3.083^{*}	(1.289)	3.098^{***}	(0.727)		
Municipality FE	Yes		Yes		Yes	
Canton × year-quarter FE	Yes		Yes		Yes	
# Observations	89,680		89,680		89,680	
R^2	0.3259		0.3259		0.4851	

Note: Standard errors in parentheses. Stantard errors are clustered on municipalities in column (1), on year-quarters in column (2), and on municipalities and year-quarters in column (3). $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.
The dependent variable is the number of new PV system adoptions in a municipality-year quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons.

Figure B.1: Baseline specifications for the evolution of social contagion over the years 2006-2015



Note: This figure shows how the estimated coefficients for social contagion evolve over time. Spatiotemporal variables are computed using a 1 km radius. “Complete” indicates estimations using all surrounding installations, regardless of the date of connection to the grid. “Last 6 months” indicates estimations using all surrounding installations that have been connected to the grid for less than 6 months. “Except last 6 months” indicates estimations using all surrounding installations that have been connected to the grid for more than 6 months. Bars indicate confidence intervals at 95%.

Table B.3: Baseline specifications for the evolution of social contagion over the years 2006-2015

	(1) All adopt.		(2) All adopt.	
Average PV	0.475^{***}	(0.023)		
Average PV × Quarter (continuous)	-0.010^{***}	(0.001)		
Average PV × year=2006			0.732^{*}	(0.308)
Average PV × year=2007			0.709^{***}	(0.094)
Average PV × year=2008			0.597^{***}	(0.094)
Average PV × year=2009			0.308^{***}	(0.026)
Average PV × year=2010			0.250^{***}	(0.022)
Average PV × year=2011			0.334^{***}	(0.021)
Average PV × year=2012			0.225^{***}	(0.011)
Average PV × year=2013			0.161^{***}	(0.008)
Average PV × year=2014			0.128^{***}	(0.007)
Average PV × year=2015			0.108^{***}	(0.005)
Constant	3.364^{**}	(1.286)	3.288^{*}	(1.288)
Controls	Yes		Yes	
Municipality FE	Yes		Yes	
Canton × year-quarter FE	Yes		Yes	
# Observations	89,680		89,680	
R^2	0.3399		0.3413	

Note: Standard errors in parentheses, clustered at the spatial unit level. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.
The dependent variable is the number of new PV system adoptions in a municipality-year quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons.
Spatiotemporal variables are computed based on individual installed bases within a 1 km radius.

Table B.4: Baseline specifications including all PV adoptions for the years 2006-2015

	(1) Complete		(2) 6 months		(3) 12 months		(4) 24 months	
Average PV, 0-0.333 km	0.057^{***}	(0.015)						
Average PV, 0-0.333 km, last *period* only			0.176^{***}	(0.032)	0.119^{***}	(0.024)	0.080^{***}	(0.018)
Average PV, 0-0.333 km, except last *period*			0.017	(0.016)	0.009	(0.018)	0.021	(0.022)
Average PV, 0.333-1 km	0.057^{***}	(0.007)						
Average PV, 0.333-1 km, last *period* only			0.164^{***}	(0.023)	0.104^{***}	(0.016)	0.074^{***}	(0.010)
Average PV, 0.333-1 km, except last *period*			0.035^{***}	(0.008)	0.036^{***}	(0.009)	0.037^{***}	(0.011)
Average PV, 1-2.848 km	0.008^{***}	(0.002)						
Average PV, 1-2.848 km, last *period* only			0.042^{***}	(0.007)	0.028^{***}	(0.005)	0.018^{***}	(0.003)
Average PV, 1-2.848 km, except last *period*			0.001	(0.003)	−0.001	(0.003)	−0.004	(0.004)
Average PV, 2.848-8.062 km	0.004^{***}	(0.000)						
Average PV, 2.848-8.062 km, last *period* only			0.018^{***}	(0.002)	0.013^{***}	(0.001)	0.008^{***}	(0.001)
Average PV, 2.848-8.062 km, except last *period*			0.002^{***}	(0.000)	0.001	(0.001)	−0.000	(0.001)
% pop. aged 30-44	0.010^{*}	(0.005)	0.011^{*}	(0.005)	0.011^{*}	(0.005)	0.011^{*}	(0.005)
% pop. aged 45-64	−0.008	(0.005)	-0.009^{*}	(0.005)	-0.009^{*}	(0.005)	−0.009	(0.005)
% pop. aged 65-100	-0.033^{***}	(0.007)	-0.032^{***}	(0.007)	-0.032^{***}	(0.007)	-0.032^{***}	(0.007)
% of tax payers with income CHF 15-29.9k	0.009	(0.006)	0.008	(0.006)	0.008	(0.006)	0.008	(0.006)
% of tax payers with income CHF 30-49.9k	0.010	(0.006)	0.010	(0.006)	0.010	(0.006)	0.010	(0.006)
% of tax payers with income CHF 50-74.9k	0.014^{*}	(0.006)	0.013^{*}	(0.006)	0.013^{*}	(0.006)	0.014^{*}	(0.006)
% of tax payers with income CHF >75k	0.006	(0.006)	0.005	(0.006)	0.005	(0.006)	0.005	(0.006)
# of unemployed individuals	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Green voting	0.014^{**}	(0.005)	0.013^{**}	(0.004)	0.013^{**}	(0.004)	0.014^{**}	(0.005)
% apartment buildings	−0.009	(0.006)	−0.009	(0.006)	−0.010	(0.006)	−0.009	(0.006)
% builings with apart. and other use	0.043^{***}	(0.009)	0.043^{***}	(0.009)	0.043^{***}	(0.009)	0.043^{***}	(0.009)
% commercial/industrial buildings	0.007	(0.009)	0.006	(0.009)	0.005	(0.009)	0.005	(0.009)
Av. # of rooms per dwelling	-0.644^{*}	(0.281)	-0.627^{*}	(0.275)	-0.629^{*}	(0.275)	-0.632^{*}	(0.279)
Av. area per dwelling	−0.010	(0.006)	−0.009	(0.006)	−0.009	(0.006)	−0.009	(0.006)
Mean solar radiation (in W/sqm)	−0.000	(0.003)	0.004	(0.003)	0.003	(0.003)	−0.000	(0.003)
Constant	3.050^{*}	(1.283)	2.357	(1.250)	2.420	(1.255)	2.850^{*}	(1.263)
Municipality FE	Yes		Yes		Yes		Yes	
Canton × year-quarter FE	Yes		Yes		Yes		Yes	
# Observations	89,680		89,680		89,680		89,680	
R^2	0.3540		0.3692		0.3689		0.3634	

Note: Standard errors in parentheses, clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Radii of the inner circle and discs installed bases are computed based on Equation (1) with an area-multiplier m of 8 (see Sub-Section 3.1).
The dependent variable is the number of new PV system adoptions in a municipality-year quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons. Columns (2) to (4) split the complete spatiotemporal installed bases between the PV installations completed in the last 6, 12 or 24 months prior to adoption and the installations completed prior to these periods.

Table B.5: Main specifications focusing on pitch and height

	(1) All adopt.		(2) All adopt.	
Average PV, smaller than average building in 100m radius, steep roof (>1°)	0.138***	(0.019)		
Average PV, smaller than average building in 100m radius, flat roof (<=1°)	0.079	(0.045)		
Average PV, higher than average building in 100m radius, steep roof (>1°)	0.095***	(0.018)		
Average PV, higher than average building in 100m radius, flat roof (<=1°)	0.061	(0.051)		
Average PV, smaller than average building in 100m radius, pitch>24°)			0.184***	(0.021)
Average PV, smaller than average building in 100m radius, pitch<=24°)			0.087***	(0.020)
Average PV, higher than average building in 100m radius, pitch>24°)			0.065**	(0.022)
Average PV, higher than average building in 100m radius, pitch<=24°)			0.123***	(0.027)
Average PV, undefined pitch and/or # of floors	0.176***	(0.019)	0.175***	(0.019)
Constant	3.943*	(1.957)	3.872*	(1.953)
Controls	Yes		Yes	
Municipality FE	Yes		Yes	
Canton × year-quarter FE	Yes		Yes	
# Observations	66,400		66,400	
R^2	0.3342		0.3349	

Note: Standard errors in parentheses, clustered at the municipality level. *p<0.05, **p<0.01, ***p<0.001.
The dependent variable is the number of PV system adoptions by a particular type of owner, in a municipality-quarter. The number of observations corresponds to N=1,660 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius.
The median roof pitch, 24°, is calculated over the 34,717 PV installations in our dataset for which we could identify the corresponding building with a sufficient level of certainty.
The "undefined pitch and/or # of floors" category includes all PV installations for which we could not identify the corresponding building (see section 3.2). Estimation results report stronger contagion from PV installations with an undefined height and/or pitch than from those included in a particular category. We attribute this result to the fact that the likelihood of being included in the undefined category is higher for large capacity and geographically isolated PV installations. The main reason is that the coordinates of the buildings in the BDS indicate the main entry of the building, whereas our coordinates for the PV installations, in general, indicate the center of the building. Hence, the likelihood that such distance exceeds our threshold of 15 meters is greater for large buildings than smaller buildings.

Table B.6: Main specification focusing on isolation and height

	(1) All adopt.
Average PV, below median # of buildings within 100m, smaller than average building in 100m radius	0.178*** (0.019)
Average PV, below median # of buildings within 100m, higher than average building in 100m radius	0.168*** (0.023)
Average PV, above median # of buildings within 100m, smaller than average building in 100m radius	0.105*** (0.015)
Average PV, above median # of buildings within 100m, higher than average building in 100m radius	0.074*** (0.018)
Average PV, undefined isolation and/or height	0.219*** (0.018)
Constant	2.932* (1.268)
Controls	Yes
Municipality FE	Yes
Canton × Year FE	Yes
# Observations	89,680
R^2	0.3297

Note: Standard errors in parentheses, clustered at the municipality level. *p<0.05, **p<0.01, ***p<0.001.
The dependent variable is the number of PV system adoptions in a municipality-quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius.
The median number of buildings within a 100 meter radius is 17. This average number is calculated over the 52,832 PV installations for which we know the exact location.
The "undefined isolation and/or height" category includes all PV installations for which we could not identify the corresponding building (see section 3.2). Estimation results report stronger contagion from PV installations with an undefined isolation and/or height than from those included in a particular category. We attribute this result to the fact that the likelihood of being included in the undefined category is higher for large capacity and geographically isolated PV installations. The main reason is that the coordinates of the buildings in the BDS indicate the main entry of the building, whereas our coordinates for the PV installations, in general, indicate the center of the building. Hence, the likelihood that such distance exceeds our threshold of 15 meters is greater for large buildings than smaller buildings.

Table B.7: Main specification focusing on size and ownership

	(1) Household adopt.
Average PV, <10 kWp, household	0.079*** (0.013)
Average PV, <10 kWp, other owners	0.132*** (0.010)
Average PV, 10-29.9 kWp, household	0.087** (0.033)
Average PV, 10-29.9 kWp, other owners	0.085*** (0.017)
Average PV, 30-99.9 kWp, household	0.362*** (0.086)
Average PV, 30-99.9 kWp, other owners	0.191*** (0.035)
Average PV, >100 kWp, household	0.323* (0.146)
Average PV, >100 kWp, other owners	0.189*** (0.039)
Constant	3.159*** (0.954)
Controls	Yes
Municipality FE	Yes
Canton × year-quarter FE	Yes
# Observations	89,680
R^2	0.4434

Note: Standard errors in parentheses, clustered at the municipality level. *p<0.05, **p<0.01, ***p<0.001.
Dependent variable is the number of PV system adoptions by all owner types (column (1)), and only by households (column (2)), in a municipality quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius. Installed bases are generated based on installation size and ownership.

Table B.8: Main specifications focusing on type and ownership

	(1) Household adopt.	(2) Firms adopt.	(3) Farms adopt.	(4) Household adopt.	(5) Firms adopt.	(6) Farms adopt.
Average PV, BIPV	0.175***	0.178***	0.234***			
	(0.016)	(0.024)	(0.026)			
Average PV, BAPV	0.099***	0.077***	0.058***			
	(0.006)	(0.007)	(0.011)			
Average PV, BIPV, same *owner*				0.105***	0.270***	0.510***
				(0.027)	(0.037)	(0.137)
Average PV, BAPV, same *owner*				0.086***	0.187***	0.274**
				(0.013)	(0.015)	(0.100)
Average PV, BIPV, other *owners*				0.207***	0.071**	0.228***
				(0.022)	(0.027)	(0.026)
Average PV, BAPV, other *owners*				0.110***	0.020*	0.055***
				(0.008)	(0.009)	(0.010)
Constant	3.007**	−0.563	0.022	3.064**	−0.490	0.010
	(0.941)	(0.334)	(0.116)	(0.947)	(0.332)	(0.115)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Canton × year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	89,680	89,680	89,680	89,680	89,680	89,680
R^2	0.4415	0.2517	0.3047	0.4428	0.2679	0.3081

Note: Standard errors in parentheses, clustered at the municipality level. *p<0.05, **p<0.01, ***p<0.001. Dependent variable is the number of PV system adoptions by a particular type of owner in a municipality quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius. In columns (1) to (3), installed bases are generated based on installation type. In columns (4) to (6), installed bases are generated based on installation type and ownership.

Table B.9: Main specifications focusing on size and type

	(1) All adopt.	(2) Household adopt.	(3) Firms adopt.	(4) Farms adopt.
Average PV, BIPV, <10 kWp	0.193***	0.167***	0.162***	0.168***
	(0.021)	(0.019)	(0.026)	(0.030)
Average PV, BAPV, <10 kWp	0.113***	0.097***	0.069***	0.019
	(0.011)	(0.010)	(0.009)	(0.013)
Average PV, BIPV, 10-29.9 kWp	0.183***	0.181***	0.155**	0.275***
	(0.036)	(0.031)	(0.059)	(0.052)
Average PV, BAPV, 10-29.9 kWp	0.045*	0.056**	0.032	0.096***
	(0.021)	(0.018)	(0.020)	(0.021)
Average PV, BIPV, 30-99.9 kWp	0.214***	0.185***	0.363**	0.433***
	(0.065)	(0.052)	(0.121)	(0.065)
Average PV, BAPV, 30-99.9 kWp	0.289***	0.230***	0.204***	0.197***
	(0.045)	(0.041)	(0.036)	(0.040)
Average PV, BIPV, >100 kWp	0.250*	0.322***	0.284*	0.482***
	(0.112)	(0.092)	(0.123)	(0.098)
Average PV, BAPV, >100 kWp	0.240***	0.158***	0.199***	0.246***
	(0.049)	(0.040)	(0.054)	(0.066)
Constant	2.752*	2.921**	−0.658*	−0.005
	(1.272)	(0.938)	(0.329)	(0.113)
Controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Canton × year-quarter FE	Yes	Yes	Yes	Yes
# Observations	89,680	89,680	89,680	89,680
R^2	0.3292	0.4441	0.2558	0.3244

Note: Standard errors in parentheses, clustered at the municipality level. *p<0.05, **p<0.01, ***p<0.001. The dependent variable is the number of PV system adoptions by all types of owners (column (1)) or by a particular type of owner (columns (2) to (4)), in a municipality-year quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius. Installed bases are generated based on installation size and ownership.

Table B.10: Main specifications focusing on size, type, and ownership

	(1) Household adopt.		(2) Firms adopt.		(3) Farms adopt.	
Average PV, BIPV, same *owner*, <10 kWp	0.101**	(0.033)	0.248***	(0.031)	0.600	(0.530)
Average PV, BAPV, same *owner*, <10 kWp	0.081***	(0.015)	0.195***	(0.017)	−0.246	(0.399)
Average PV, BIPV, other *owners*, <10 kWp	0.200***	(0.028)	0.017	(0.031)	0.166***	(0.030)
Average PV, BAPV, other *owners*, <10 kWp	0.111***	(0.011)	−0.017	(0.011)	0.020	(0.013)
Average PV, BIPV, same *owner*, 10-29.9 kWp	0.094	(0.050)	0.246*	(0.096)	0.098	(0.269)
Average PV, BAPV, same *owner*, 10-29.9 kWp	0.084*	(0.041)	0.112*	(0.045)	0.138	(0.190)
Average PV, BIPV, other *owners*, 10-29.9 kWp	0.240***	(0.034)	0.113	(0.080)	0.282***	(0.053)
Average PV, BAPV, other *owners*, 10-29.9 kWp	0.049**	(0.018)	0.053	(0.030)	0.094***	(0.022)
Average PV, BIPV, same *owner*, 30-99.9 kWp	0.243*	(0.106)	0.601**	(0.221)	0.404*	(0.175)
Average PV, BAPV, same *owner*, 30-99.9 kWp	0.422***	(0.118)	0.217***	(0.062)	0.417**	(0.160)
Average PV, BIPV, other *owners*, 30-99.9 kWp	0.161**	(0.056)	0.215*	(0.094)	0.432***	(0.068)
Average PV, BAPV, other *owners*, 30-99.9 kWp	0.203***	(0.039)	0.177***	(0.046)	0.180***	(0.041)
Average PV, BIPV, same *owner*, >100 kWp	0.838***	(0.201)	0.345*	(0.165)	0.614*	(0.284)
Average PV, BAPV, same *owner*, >100 kWp	0.198	(0.174)	0.168*	(0.066)	0.110	(0.479)
Average PV, BIPV, other *owners*, >100 kWp	0.314***	(0.090)	0.218	(0.183)	0.466***	(0.084)
Average PV, BAPV, other *owners*, >100 kWp	0.171***	(0.041)	0.327***	(0.082)	0.238***	(0.065)
Constant	3.019**	(0.942)	−0.608	(0.325)	−0.010	(0.113)
Controls	Yes		Yes		Yes	
Municipality FE	Yes		Yes		Yes	
Canton × Year FE	Yes		Yes		Yes	
# Observations	89,680		89,680		89,680	
R^2	0.4458		0.2749		0.3256	

Note: Standard errors in parentheses, clustered at the municipality level. *p<0.05, **p<0.01, ***p<0.001.
The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius.

Table B.11: Alternative estimations with first difference, negative binomial, and Poisson

	(1) FD	(2) NB [Coeff.]	(3) NB [IRR]	(4) Poisson [Coeff.]	(5) Poisson [IRR]
Average PV, 1km	0.132***	0.063***	1.065***	0.042***	1.043***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
Constant	0.014	−3.965	0.019	−3.703	0.025
	(0.013)	(2.337)	(0.044)	(2.359)	(0.058)
Controls	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	Yes	Yes	Yes	Yes
Canton × year-quarter FE	Yes	Yes	Yes	Yes	Yes
# Observations	87,438	89,680	89,680	89,680	89,680
R^2	0.1477				

Note: Standard errors in parentheses, clustered at the municipality level. *p<0.05, **p<0.01, ***p<0.001.
The dependent variable is the number of new PV system adoptions in a municipality-year quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons.
FD stands for First Difference and NB for Negative Binomial
Columns (3) and (5) report the NB and Poisson regression results in terms of incidence rate ratios (IRR), which are obtained by exponentiating the coefficients in columns (2) and (4).

Table B.12: Alternative specifications: alternative discs

	(1) $m = 3$	(2) $m = 5$	(3) $m = 6$	(4) $m = 9$
Average PV, 0 - r_0 km	0.082***	0.070***	0.064***	0.058***
	(0.011)	(0.013)	(0.014)	(0.014)
Average PV, r_0 - r_1 km	0.055***	0.055***	0.057***	0.057***
	(0.008)	(0.008)	(0.008)	(0.007)
Average PV, r_1 - r_2 km	0.025***	0.013***	0.010***	0.007***
	(0.005)	(0.003)	(0.003)	(0.002)
Average PV, r_2 - r_3 km	0.018***	0.008***	0.006***	0.003***
	(0.002)	(0.001)	(0.001)	(0.000)
Constant	3.075*	3.144*	3.069*	3.023*
	(1.283)	(1.287)	(1.286)	(1.282)
Controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Canton × year-quarter FE	Yes	Yes	Yes	Yes
# Observations	89,680	89,680	89,680	89,680
R^2	0.3437	0.3487	0.3507	0.3554

Note: Standard errors in parentheses, clustered at the municipality level. ***p < 0.01, **p < 0.05, *p < 0.1
Radii r_b of the inner circle and disc installed bases are computed based on Equation (1) using the area-multiplier m specified in the column header (see Sub-Section 3.1).
The dependent variable is the number of new PV system adoptions in a municipality-year quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons.

Table B.13: Alternative specifications: alternative discs with same area

	(1) All adopt.	(2) All adopt.	(3) All adopt.
Average PV, 0-1 km	0.092^{***} (0.005)		
Average PV, 1-1.414 km	0.076^{***} (0.007)		
Average PV, 0-2 km		0.042^{***} (0.003)	
Average PV, 2-2.828 km		0.019^{***} (0.003)	
Average PV, 0-3 km			0.021^{***} (0.002)
Average PV, 3-4.243 km			0.012^{***} (0.002)
Constant	3.110^{*} (1.281)	3.083^{*} (1.297)	3.271^{*} (1.319)
Controls	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Canton × year-quarter FE	Yes	Yes	Yes
# Observations	89,680	89,680	89,680
R^2	0.3328	0.3397	0.3422

Note: Standard errors in parentheses, clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Outside radii of the disc installed bases are calcultated with $r_1 = \sqrt{2} \times r_0$, where r_0 is the inner circle radius.
The dependent variable is the number of new PV system adoptions in a municipality-year quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons.

Table B.14: Alternative specifications: municipality-year fixed effects

	(1) All adopt.	(2) All adopt.
Average PV, 1 km	0.127*** (0.005)	0.123*** (0.004)
Controls	Yes	Yes
Municipality FE	Yes	No
Canton × year-quarter FE	Yes	Yes
Municipality × Year FE	No	Yes
# Observations	89,680	89,680
R^2	0.3259	0.6811

Note: Standard errors in parentheses, clustered at the municipality level. *p<0.05, **p<0.01, ***p<0.001.
The dependent variable is the number of new PV system adoptions in a municipality-year quarter. The number of observations corresponds to N=2,242 municipalities times T=40 quarters. Municipalities are distributed accross 26 cantons.

Table B.15: Neighborhood level data: main estimations

	(1) All adopt.	(2) All adopt.	(3) All adopt.	(4) All adopt.
Average PV, 1 km	0.088***	0.084***	0.082***	0.118***
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	35.254	39.418	16.998	1.909
	(33.971)	(34.550)	(29.367)	(0.984)
Controls (Mun. level)	Yes	Yes	No	No
Controls (Neighb. level)	No	No	Yes	No
Controls (Spatial unit level)	No	No	No	Yes
Municipality FE	Yes	No	No	No
Neighborhood FE	No	Yes	Yes	No
Spatial unit FE	No	No	Yes	Yes
Canton × year-quarter FE	Yes	Yes	Yes	Yes
# Observations	11,400	11,400	11,400	100,400
R^2	0.3270	0.2996	0.2972	0.3167

Note: Standard errors in parentheses, clustered at the spatial unit level. *p<0.05, **p<0.01, ***p<0.001.
Dependent variable is the number of new PV system adoptions in a spatial unit-year quarter. The number of observations corresponds to N=# of spatial units times T=40 quarters. N=279 neighborhoods in models (1) to (3) and N=2,510 (2,225 municipalities + 279 neighborhoods + 6 territories of cities not covered by neighborhoods) in model (4). Spatial units are distributed accross 12 cantons in models (1) to (3) and across 26 cantons in model (4).

Chapter 2

Social interactions and the adoption of solar PV: Evidence from cultural borders

This chapter based on a working paper (Carattini et al., 2018b) written with Stefano Carattini (Georgia State University) and Andrea Baranzini (Haute école de gestion de Genève, HES-SO // University of Applied Sciences and Arts Western Switzerland). This research was financially supported by the Swiss Federal Office of Energy (SFOE), grant number SI/501305-01. We thank Jeroen van den Bergh, Roger Fouquet, Bruno Lanz, Milad Zarin and the participants at various conferences for very useful comments on a previous version of this paper.

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Abstract
Social spillovers are considered a key feature of technological diffusion. In presence of cultural barriers, social spillovers may, however, be hampered. In this paper, we exploit exogenous cultural borders and a policy shock to investigate the role of social spillovers in the adoption of solar photovoltaic (PV) technology. With data on about 19,000 solar PV systems, we assess whether proximity to a language border implies a lower rate of PV adoption. The results confirm that the cultural border hinders social spillovers. Following the implementation of a nationwide feed-in tariff fundamentally changing the financial profitability of solar PV, we find a divergence in the rate of adoption between municipalities located very close to the border, and others located further away. This effect is, however, moderated by the proportion of inhabitants speaking the language of the other side of the border as main language at home. The effects measured in this paper are persistent over time, and consistent with the role of localized social spillovers in the adoption of clean technologies. The number of "missing" PV adoptions resulting from the language border is non-negligible, as the border leads to 20% less PV adoptions.

Keywords Solar PV; Technology diffusion; Social contagion; Cultural barriers
JEL codes D83; O33; Q42; R11; R12

1 Introduction

Technological progress is among the key determinants of economic prosperity (e.g. Solow, 1956). Technological progress requires a combination of innovation, leading to the development of new technologies, and diffusion, leading new technologies to be adopted by households and firms. Facilitating the diffusion of technologies is, hence, as important as developing new ones. Social spillovers are considered a crucial element in the adoption of new technologies, as formalized, several decades ago, by Hägerstrand (1952), Griliches (1957), Mansfield (1961), Arndt (1967), Bass (1969), Rogers (2003).

Technological progress is also key for achieving sustainability. Mitigating climate change, in particular, requires a rapid shift to low-carbon technologies. Energy from fossil sources should be replaced by energy from renewable sources. Understanding how the adoption of renewable energy spreads is crucial to guide policymaking in the effort to tackle climate change. The adoption of the solar photovoltaic (PV) technology represents an especially interesting case. The large potential of solar energy relies on the fact that standard households and businesses can adopt it. With solar energy, each household can become a microgenerator. While residential installations tend to have a relatively limited capacity, in the order of 5 to 10 kW peak, taken together, a myriad of installations can have a strong impact on the composition of the energy mix. More than 1.6 million installations exist now in Germany, about 1.2 million in the United States, and nearly 1 million in the United Kingdom. A relatively small country like Switzerland has more than 60,000 installations. The high rate of adoption in some countries is related to the implementation of very generous financial schemes supporting the adoption of solar energy. However, increasing evidence points to strong spatial differences, within countries, in the rate of adoption. To contribute to explain this pattern, an emerging literature has analyzed the role of social spillovers in the adoption of solar energy (e.g. Bollinger and Gillingham, 2012; Noll et al., 2014; Graziano and Gillingham, 2015; Rode and Weber, 2016). This literature considers two main drivers of social spillovers. First, a solar installation requires a non-negligible investment, which also entails some degree of risk. Learning from other adopters is expected to influence the probability that one adopts as well. Word-of-mouth is, hence, considered a plausible channel for social spillovers. Second, adopting solar energy may be considered as a very visible form of climate-friendly behavior. People may be more likely to go green when they see others, locally, going green (Carattini et al., 2019). Imitation is, hence, considered another plausible channel for social spillovers.

So far, the literature on social spillovers in the adoption of solar energy has mainly focused on measuring the magnitude of these spillovers, and how they vary with time and distance (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Rode and Weber, 2016). Relatively little attention has been given to the drivers of social spillovers (see, however, Baranzini et al., 2017a). No attention has been given, to the best of our knowledge, to the analysis of barriers to social spillovers. Important barriers to social spillovers may, however, exist. Cultural barriers are an obvious, although neglected, candidate for this analysis.

Specifically, there is one cultural barrier that has been exploited in the economic literature because of its very suitable empirical properties (see Eugster and Parchet, 2013). This is the language border between the French-speaking and the German-speaking parts of Switzerland. This is a sharp border, which only partly overlaps jurisdictional or natural borders. People are homogeneously distributed across the border. Its origin goes back in time to the Middle Age. Since then, its geographical definition has only slightly changed and large segments have remained virtually identical.

In this paper, we investigate whether the language border between the French-speaking and the German-speaking parts of Switzerland has an impact on the adoption of solar PV. To this end, we exploit the combination of this sharp spatial discontinuity and a policy shock related to the implementation of a nationwide feed-in tariff. We find 20% less adoptions in proximity to the border. This figure is consistent across specifications. Hence, the language border leads to a non-negligible quantity of "missing" installations. This effect is very localized. The effect of the border tends to vanish once extending the analysis to a radius of 15 km or more. Interestingly, we do not find any discontinuity at the border. That is, the effect of geographic proximity to the cultural border is much stronger than the effect, if any, of culture itself. The effect of the border is, however, mitigated by the fraction of people who are fluent with the language of the other side. When this fraction is sufficiently high, the border has no effect on solar adoption.

This paper contributes to the literature on technological diffusion by providing unique evidence on the effect of an exogenous cultural border on technological adoption. It also contributes to the literature on the economics of renewable energy. It confirms previous evidence on the importance of social spillovers for the adoption of solar energy and supports initiatives to leverage them. It also shows how powerful cultural barriers can be in hampering the adoption of a clean technology. While the border exploited in this paper is especially sharp, spatial sorting, across dimensions such as ethnicity, race, political orientation, or religion, is common in many contexts. Each community border may also act as a barrier to social spillovers, which could potentially be addressed with well-designed interventions.

The remainder of this paper is organized as follows. Section 2 introduces the literature on social spillovers, with a particular emphasis on solar PV. Section 3 presents the data sources and outlines our empirical strategy. Section 4 reports our empirical results. Section 5 concludes.

2 Background

2.1 Social interactions and the adoption of (clean) technologies

The role of social networks in the adoption of new technologies has long been recognized in the social science literature. Since the 1950s, the theory of technology diffusion posited that the adoption of innovations and technologies is related, at least in part, to the process of individuals sharing information with their neighbors (Hägerstrand, 1952; Griliches, 1957; Mansfield, 1961; Rogers, 2003; Arndt, 1967; Bass, 1969). The inclusion of social contagion effects in diffusion models contributed to explain two well-known and frequently observed features of the diffusion of new technologies in space and time: geographical clustering and an S-shaped curve of adoption.

A more recent literature has taken advantage of the availability of micro-level data to identify empirically the role of localized social spillovers in technology adoption decisions. The presence of peer influence has been identified, in particular, in the adoption of agricultural technologies (Foster and Rosenzweig, 1995; Conley and Udry, 2010; Genius et al., 2014), electric and hybrid vehicles (Axsen et al., 2009; Narayanan and Nair, 2013), or menstrual cups (Oster and Thornton, 2012). The existence of social contagion in the adoption of residential solar PV is becoming increasingly documented. It has been measured in the United States (Bollinger and Gillingham, 2012; Rai and Robinson, 2013; Noll et al., 2014; Graziano and Gillingham, 2015), Germany (Rode and Weber, 2016) and Switzerland (Baranzini et al., 2017a). Social spillovers are expected to work through both social learning (word-of-mouth) and social norms (imitation). The former relates mainly to the information asymmetry, and uncertainty, that agents face when considering investing in solar PV. The decision to adopt a (green) technology, but also the actual purchase on the market, require specific know-how that is eminently local. Social interactions allow this locally-relevant knowledge to diffuse among peers. The latter effect, imitation, stems from the motivation of individuals to stay in tune with the norm and thus adopt pro-environmental behavior when this is sufficiently spread and visible (see Carattini et al., 2019). It may also result from the fact that the presence of solar panels in the neighborhood stimulates interest in the PV technology and conveys a signal about its benefits.

The literature on social spillovers in the adoption of solar panels has provided a set of stylized facts that is consistent with both channels. First, social spillovers tend to represent a very localized phenomenon. Social spillovers tend to decay very rapidly with distance (Graziano and Gillingham, 2015). Rode and Weber (2016) find that social spillovers take place within a radius of about 1 km. That is, only close neighbors influence potential adopters. This result is confirmed by Baranzini et al. (2017a), who find that the effect of installations located further than 3 km is very weak and economically no longer meaningful. Second, recent vintages tend to have stronger influence on potential new adoptions (Graziano and Gillingham, 2015; Baranzini et al., 2017a). Baranzini et al. (2017a) show that adoptions that are 12 months old or less lead on average to twice as many additional adoptions than older vintages. That is, the probability that an installation leads to additional installations decreases with time since completion. Third, everything else equal, larger installations are associated to stronger spillovers (Bollinger and Gillingham, 2012; Baranzini et al., 2017a). Fourth, installations that are more visible are more likely to lead to further adoptions than less visible ones. Baranzini et al. (2017a) exploit the difference between building-attached and building-integrated installations to show that, everything else equal, the most visible type of installation leads to more adoptions, and not only of the same type, but also of the other type. Fifth, the strength of social spillovers may, everything else equal, increase or decrease over time, depending on the underlying market dynamics. Bollinger and Gillingham (2012) find stronger social spillovers towards the end of their period of analysis, which goes from 2001 to 2011. The authors attribute this increase in strength to initiatives undertaken by local actors aimed precisely at encouraging the exchange of information across neighbors and from previous adopters to potential adopters. In contrast, Baranzini et al. (2017a) find weaker social spillovers towards the end of their period, which goes from 2006 to 2015. They attribute this pattern to market saturation.

This paper focuses in particular on elements favoring, or obstructing, social contagion. Social learning has been receiving increased attention in recent times (e.g. Golub and Jackson, 2010; Bloch et al., 2018; Wolitzky, 2018). Research designs combining field experiments with social network analysis have contributed to our understanding of the fundamental role of social interactions for the diffusion of new technologies (e.g. Duflo and Saez, 2003; Beaman and Magruder, 2012; Banerjee et al., 2014; Dupas, 2014; Alatas et al., 2016; Breza and Chandrasekhar, 2018). Social learning allows information to spread, and beliefs to be updated. Specific factors may facilitate information spreading, such as geographical and social proximity (e.g. Fafchamps and Gubert, 2007). Information transmission probabilities may decay with social distance, as examined in Banerjee et al. (2012). Individuals are also more likely to trust individuals who are socially proximate (e.g. Binzel and Fehr, 2013).

In the context of environmental behavior, the role of social norms has been widely studied (see Farrow et al., 2017 for a review of empirical studies and Nyborg, 2018 for a mostly theoretical overview). An important reference in this literature is Nyborg et al. (2006). Building on the previous work by Brekke et al. (2003), Nyborg et al. (2006) formalize a model of socially contingent moral motivation in which, in a given period, an individual's decision to adopt a given green good depends on the social norm, i.e. how many people around her have adopted in the previous period. In the model, the assumption of perfect information about other people's behavior is relaxed, and replaced by a noisy signal. In this case, individuals estimate the presence of the green good based on availability heurestics (Tversky and Kahneman, 1973). It follows that people observing fewer instances of adoption, of the green good, around them, are likely to estimate a lower social norm and, thus, following the model of socially contingent moral motivation, are also less likely to adopt themselves. Conversely, advertisement campaigns can bias beliefs upward, by leading individuals to think that a given good is more widespread than it actually is.

3 Empirical approach and data

3.1 Data

Our main source of information is a rich dataset maintained by the Swiss Federal Office of Energy (SFOE) and containing the exact location, at the street-number level, of virtually all solar panels in Switzerland connected to the grid and installed between 2006 and 2015. The owners of the installations are mainly households, but also firms, farms, and utilities. Among other technical characteristics and administrative information, the database provides the exact address of 59,819 solar PV systems. We geocode all addresses to obtain the exact spatial coordinates (see Baranzini et al., 2017a for additional details on this dataset). Importantly, for each installation, we also know when the decision to order the PV system was taken and when the installation was completed.[1]

Adoption of the solar PV technology may depend on several socioeconomic, demographic, meteorological, and built environment factors. For Switzerland, the narrowest geographical level at which information on socioeconomic variables is available is the municipality, and data are typically provided on an annual basis. In our analyses, described below, we include a first set of variables related to population characteristics to control for spatial and time-varying heterogeneity. Following the literature, we collect data on socio-economic characteristics related to the adoption of solar installations, such as age, income, level of unemployment, and green preferences (see Dharshing, 2017 for a recent analysis). We measure green preferences (green voting) by summing the electoral scores, at the federal elections of the Swiss National Council, of the two green parties active in Swiss politics, the Green Party of Switzerland and the Green Liberal Party of Switzerland.

The second set of variables measures contextual factors that may be linked to the feasibility and profitability of PV installations. We use variables characterizing the type of building and solar irradiance. Building characteristics are of particular relevance, although in existing studies those data are often unavailable. We access a large register containing individual information on all buildings and dwellings in Switzerland, divided into the following four categories: detached houses, apartment buildings, buildings with apartment and other use, and buildings used only for commercial or industrial purposes. Information is also available for the average number of floors of each building, and on the characteristics of the dwellings (average area and number of rooms). These variables may affect the energy consumption of residential and commercial owners. We compute the mean annual solar irradiance (in W/m^2) at municipality level based on a raster dataset. Exposure to solar irradiance is crucial for solar panels to be effective, and the higher the exposure, the higher the expected return on investment. The summary statistics, and sources, for the variables included in this paper are provided in Table A.1 in the Appendix.

[1] Our dataset may include some observations for which the installation had not yet been completed at the time the data were released. Excluding these observations would not change our results.

3.2 Identifying borders

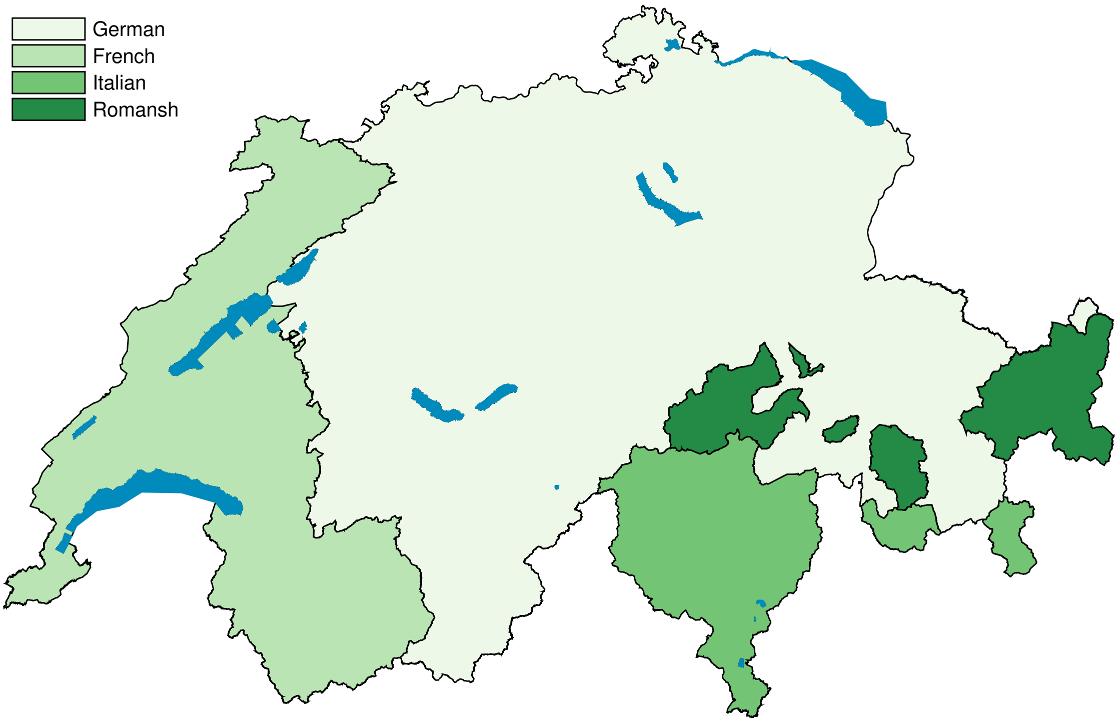
Switzerland has four national languages that are traditionally spoken in different and relatively homogeneous regions of the country. According to the 2015 structural survey of the Swiss Federal Office of Statistics (FSO), 63% of the 8.13 million inhabitants of Switzerland declared to speak German (or a variety of Swiss German) as main language at home, 23% French, 8% Italian, and less than 1% Romansch. The boundary between French- and German-speaking parts is the most suitable for our research question, because it crosses Switzerland from North to South for about 270 km along regions with a large variability of population density and topography. Importantly, about half the length of the French-German border is located within bilingual cantons (Fribourg, Bern and Valais), which allows us to focus on the language border, while keeping institutional features constant.

The definition of boundaries between German, French, and Italian speaking regions goes back in time to the Middle Age. Language borders have remained remarkably stable over time. Sharp discontinuities have existed for the past centuries and are still observable these days. The discontinuity at the boundary between French- and German-speaking parts is particularly sharp. The fraction of German- (French-) speaking residents in municipalities located within less than 5 km from the border falls (rises) from an average of 90% (6%) on the East to 14% (80%) on the West. Another interesting characteristic of this language border is that inhabitants are homogeneously distributed on both sides. Natural barriers are absent from most of the boundary, despite the presence of an important mountain range in the area, the Alps. This is the result of Alpine summits being distributed, in Switzerland, along an East-West line.

As shown on Figure 1, the German-Italian, German-Romansch and Italian-Romansch borders are shorter and lack territorial continuity. In addition, these borders superimpose more frequently with cantonal boundaries and are located in mountainous, sparsely populated areas, with the highest summits usually defining the border. Finally, most inhabitants of the Romansh-speaking areas use German in every-day life.

To perform our analysis of the impact of the border on PV adoption, we first need to precisely identify the location of the language border. Then, we compute the distances of each PV installation to the border. For reasons of political sensitivity, no official source provides precise geographical data on the location of language borders in Switzerland. To define the language border we thus combine two datasets and proceed in a standard way. The first dataset, provided by the FSO, contains

Figure 1: Linguistic regions of Switzerland



Note: This map shows the four linguistic regions of Switzerland according to the language spoken by the majority of the population of each municipality. Blue areas are either lakes or foreign enclaves. Source: Structural Survey 2010-2014, Swiss Federal Statistical Office (FSO) and swissBOUNDARIES3D 2016, Swiss Federal Office of Topography (swisstopo).

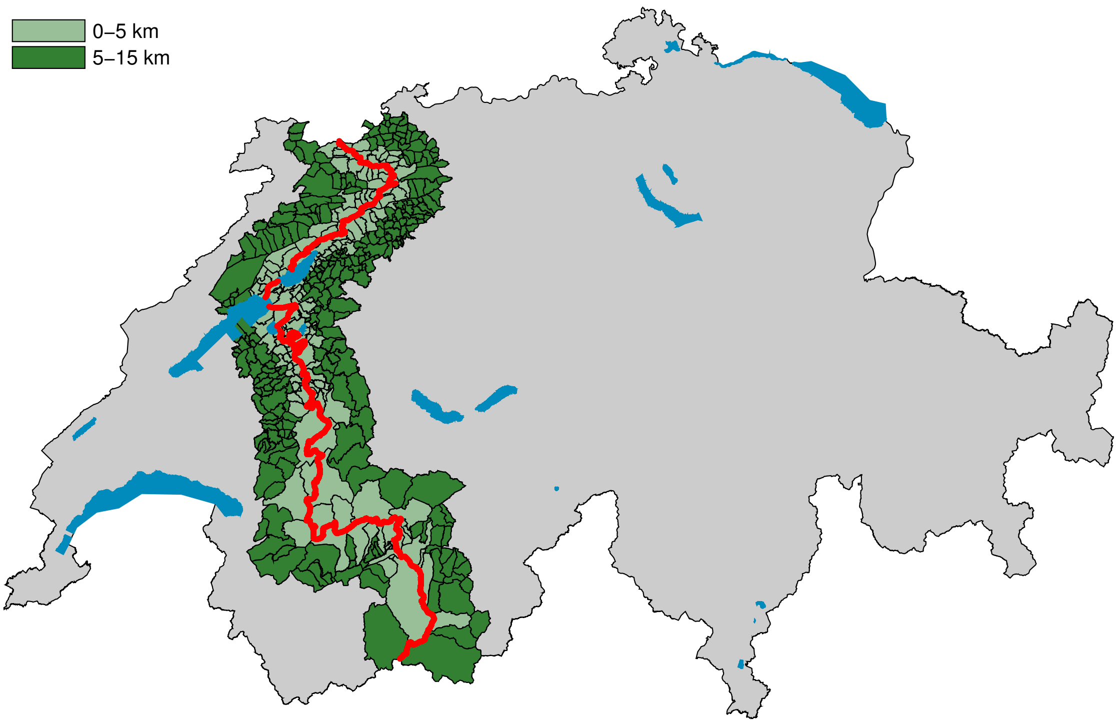
data on the most widely used national language at home by permanent residents. We use municipal data for 2016, municipalities representing the finest level at which this information is available. The second dataset is produced by the Swiss office of topography (swisstopo), and includes georeferenced data of municipalities' boundaries. Based on these data, we identify municipalities as either French- or German-speaking. After having identified all pairs of contiguous municipalities whose main language are different from each other (one French- and one German-speaking), we generate the language border as the line generated by the shared borders of these municipalities.[2] For more precision, we increase the resolution of swisstopo's spatial data to have at least one geographical point every 50 meters along the language border.

Having established the spatial separation between the two linguistic regions, we can compute the distances between the location of each PV installation and the clos-

[2]There are three German-speaking enclaves located in the French-speaking part. To have a unique and continuous language border, we consider these three municipalities as French-speaking. Excluding these observations would not affect our results.

est border point. We aggregate these measures at the municipality level to obtain the mean Euclidean distance to the border for all PV installations located within a municipality.[3] Starting from a total of 2,289 Swiss municipalities, we select 733 municipalities whose PV installations are located on average within 25 km from the language border. This leaves us with 18,960 PV installations. To better capture the effect of interest, in our analyses below we focus especially on 436 (159) municipalities located within 15 (5) km from the border (see Figure 2), for a total of 10,533 (3,265) PV installations.

Figure 2: French-German language border and surrounding municipalities



Note: The red line shows the language border between the French- (West) and the German-speaking (East) parts of Switzerland. Light green areas represent the municipalities whose PV installations are located on average less than 5 km away from the border. Dark green areas show the municipalities whose PV installations are located on average between 5 and 15 km away from the border. Blue areas are either lakes or foreign enclaves. The rest of the map (in grey) represents all remaining Swiss municipalities. Source: Structural Survey 2010-2014, Swiss Federal Statistical Office (FSO) and swissBOUNDARIES3D 2016, Swiss Federal Office of Topography (swisstopo)

[3]Our results remain unaffected if we use, for each municipality, a single measure of distance to the border, either from the municipality's geometric centroid (based on our own computation) or from its center (based on GEOSTAT data, Swiss Federal Statistical Office (FSO)).

3.3 Empirical approach

We are interested in whether the language border acts as a barrier to social spillovers in the adoption of solar PV. If that is the case, we should observe, everything else being equal, less solar installations in proximity to the border. To address this question, we use a multilayered empirical strategy.

Our first empirical approach to measure the impact of the language border on solar PV adoption relies on standard cross-sectional regressions. We explain the total number of adoptions in municipality i (PV_i) as a function of the average distance to the border of all PV installations in the municipality i ($Distance_i$), while controlling, as described above, for a large set of demographic, socioeconomic, political, meteorological and building characteristics (X_i). More specifically, our specification has the following form:

$$PV_i = \alpha + \beta Distance_i + X_i'\gamma + \epsilon_i \tag{1}$$

If the language border limits the extent of social spillovers, we should expect a positive β coefficient. Everything else equal, the further we go from the language border, the higher the level of adoption. The objective of this first analysis is to determine whether there is a common pattern that is compatible with the language border being an obstacle to social spillovers. There is no ambition, at this stage, to deliver causal estimates on the effect of the border.

To further investigate if the presence of a language barrier may result in lower social spillovers, we test whether the release of important information on solar PV has a differentiated impact depending on the distance from the language border. To this end, we exploit the quasi-natural feature of the implementation, in 2008, of a countrywide feed-in tariff (FIT), which changed dramatically the profitability of solar installations in Switzerland.[4] With the FIT, the remuneration for each kWh injected into the electricity grid jumped from CHF 0.15 to CHF 0.49-0.90,[5] depending on the type and capacity of the PV installation. Given the historical roots of the language border, and the fact that the FIT is defined at the federal level, we can leverage the exogenous interaction between these two elements. The theoretical prediction from the literature on social contagion in the adoption of clean technologies would suggest that the FIT creates new valuable opportunities

[4] We use 2008 as treatment date because this is when the news of the feed-in tariff spread. This news received intense media coverage in Switzerland. Before 2008, very little information circulated on any federal plan to subsidize solar PV. Our results would remain unaffected if we were to add a 6-month lag and use July 2007 as treatment date.

[5] 1 Swiss franc (CHF) close to parity with the US dollar at the time of writing.

to learn from others, and observe new installations, as it creates a major shock on the profitability of solar installations. If we are in presence of social spillovers, and if the language border hampers these, we would expect the ex-post rate of solar adoption to be lower in proximity to the border than elsewhere. Along the lines of a difference-in-differences approach, we test this hypothesis with the following specification:

$$\Delta PV_{it} = \alpha_i + \beta FIT \times distance_{it} + X_{it}'\gamma + \mu_t + \epsilon_{it} \tag{2}$$

where ΔPV_{it} is the number of new adoptions in a municipality i during the year t and ϵ_{it} is the i.i.d. error term, clustered at the municipality level. The main coefficient of interest is given by $FIT \times distance_{it}$, which is an interaction term between the mean distance to the border and a categorical variable that takes value one after the implementation of the FIT, and zero otherwise. We also include a vector of control variables (X_{it}) to capture the potential effect of time-varying heterogeneity, municipality-specific fixed effects, α_i, to capture potential time-invariant unobserved heterogeneity, and year-specific time dummies, μ_t, to capture time-varying factors potentially affecting the adoption rate over the whole region.[6]

The sharpness of the language border also provides the ideal framework for a regression discontinuity design (RDD), as exploited in Eugster and Parchet (2013). Hence, we also proceed with an RDD. In our context, the objective of the RDD is twofold. First, it allows us to test whether there is any difference in adoption between the French- and the German-speaking parts of Switzerland, due to a difference in culture. More specifically, we are interested in whether there is any discontinuity in the adoption of solar PV at the language border. Distance from the border is the running variable in our RD approach. For French-speaking municipalities, in the West, distance is coded negatively (we multiply by minus 1). Second, the RDD allows us to test whether there is any effect of distance from the language border on the adoption of solar PV on either side, thus complementing the approach described by equation (2). More specifically, we are interested in whether there is a downward (upward) relationship between distance to the border and the adoption of solar PV in the French-speaking (German-speaking) Switzerland.

[6] OLS is used in all specifications. Fixed effects are justified by a χ^2 (27) of 184.51 (p > $\chi^2(27) = 0.0000$) in the Hausman test for model (1) of Table 2. The Hausman test supports the use of a fixed-effect model also in all other specifications. For each control variable in X_{it}, we test whether its level in 2008, and its evolution between 2008 and 2015, is related to distance to the language border. No specific pattern is identified. The same applies to the distribution of installers, measured in 2018 (see Figure A.1).

4 Empirical results

4.1 Cross-sectional evidence

We start our analysis of the role of linguistic barriers by exploring how the proximity to the language border affects the number of PV adoptions. In proximity to the border, unless they are fluent in both languages, individuals are likely to receive information from, and be influenced by, only one side of the border, the one that shares the same language. If the language border slows down information spreading, we should observe less PV systems close to the border. Our exploratory cross-sectional model investigates the role of distance to the border by focusing on municipalities that are located within different distances (5, 10, 15, 20, and 25 km) on both sides of the language border. The dependent variable is the number of existing adoptions as of December 31, 2015.

Table 1 confirms our intuition that, everything else equal, PV systems are more widespread in distant municipalities than in the ones near the border. That is, we find positive and statistically significant coefficients for distance in models (1) to (4).[7] The interpretation of the coefficients is as follows: each additional kilometer away from the border increases the number of solar PV adoptions by β units per municipality, on average, installed between 2006 and 2015. The coefficient for column (1), for instance, suggests that the region within 5 km from the border experiences a lower level of adoption quantifiable in about 2 less PV adoptions per municipality per kilometer. A closer look at the magnitude of the coefficients for distance across the models of Table 1 reveals that the border effect is a localized phenomenon that decreases with distance. Each time the area of analysis is widened by 5 km on both sides of the border, the coefficient for distance shrinks. From 25 km (column (5)) and beyond, our model no longer captures any distance effect (at least in statistical terms), as the effect observed for the closest municipalities is diluted in the mass of distant, unaffected, municipalities. As described above, our specifications in Table 1 account for spatial heterogeneity by including several population characteristics and contextual factors. We report the coefficients for our control variables in Table A.3 in the Appendix. Signs and magnitudes for these variables are in line with the literature. To facilitate the interpretation of the border effect, we also estimate the models

[7]Approximately half the length of the language border is located within bilingual cantons (Bern, Fribourg, Valais), and the other half overlaps with cantonal borders. To ensure that the effect is not driven by institutional differences across cantons, we have also estimated a model including only municipalities near "purely linguistic" sections of the border. We find a similar pattern with this smaller sample.

by transforming the dependent variable *(PV)* in natural log form.[8] Therefore, the coefficients represent semi-elasticities, i.e. percentage changes in the number of PV systems related to a one-unit change in the distance to the border. As reported in Table A.2 in the Appendix, the semi-elasticity estimates range from 0.017 to 0.110 when including all municipalities up to 20, and 5 km, from the border, respectively. All else equal, this suggests that, as we approach the border in the last 5 km, we would expect about 11% less PV installations for each extra kilometer.

Table 1: Effect of distance to the language border on PV adoptions

	5 km	10 km	15 km	20 km	25 km
	(1)	(2)	(3)	(4)	(5)
Distance	1.898^{**}	0.710^{**}	0.656^{***}	0.407^{***}	0.070
	(0.942)	(0.335)	(0.212)	(0.127)	(0.089)
Constant	-84.209	-16.129	-57.760	31.174	9.632
	(74.512)	(50.824)	(47.369)	(48.861)	(40.930)
Controls	Yes	Yes	Yes	Yes	Yes
N	159	302	436	576	733
R^2	0.5672	0.5365	0.5948	0.5575	0.6380

Note: Heteroskedasticity-consistent standard errors in parentheses. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.
The dependent variable is the total number of PV system adoptions in a municipality by the end of 2015.

4.2 Causal evidence

The evidence provided in the previous section suggests that there are less solar adoptions in proximity to the language border. To assess whether this is due to the border acting as a barrier to social spillovers, we estimate the effect of the implementation of the Swiss FIT on the adoption of solar panels. Our hypotheses are as follows. First, we expect the FIT to lead to more adoptions, as it makes solar energy financially much more attractive. Second, if the language border acts as a barrier to social spillovers, we should observe a divergence in the rate of adoption between regions close to the border and regions located further away, once the

[8] Virtually all municipalities in our dataset have at least one installation. There is one municipality that does not meet this criterion. Since the logarithmic transformation is not possible in this case, this municipality is not included in the estimations.

FIT is implemented. That is, we expect the rate of adoption to increase in both regions in proximity to the border and regions located further away, but we expect a significantly higher increase in the latter than the former. This is because the FIT represents a shock to the solar market, which is expected to reinvigorate social spillovers.

As described above, we test these hypotheses by exploiting the exogenous location of the language border and its interaction with the implementation of the FIT, in a panel setting. In the spirit of difference-in-differences with heterogeneous effects, we look at the effect of a variable taking value one after 2008, when the FIT is implemented, interacted with a variable measuring distance from the border. The dependent variable is the annual number of PV adoptions by municipality. If the FIT, as treatment, has a homogeneous effect on the Swiss territory, we should not find any effect of the interaction (time dummies capture the direct effect of the FIT). If, on the contrary, the effect of the FIT varies with respect to the distance from the border, then we should find a positive and significant effect of the interaction. The further we move from the border, the more adoptions we should observe. In this case, we may also expect the effect of the language border to be stronger in its immediate proximity. Extending the area under observation should decrease the magnitude of the coefficient. To assess whether the stylized fact identified in the previous section is related with the implementation of the FIT, and not with pre-existing conditions, we also run a placebo test for the period pre-FIT.

Table 2 reports the results of our panel approach. We look, initially, at the entire period, from 2006 to 2015, and at all municipalities within 5 km from the language border. We remind that the FIT started in 2008. Column (1) reports the coefficient of this first estimation. We find that our interaction term is positive, in line with our expectations, and statistically significant. Since the implementation of the FIT, municipalities closer to the border experience substantially lower adoption. The number of “missing” PV systems is non-negligible. One kilometer closer to the border implies 0.24 less adoptions per municipality per year, or about 2 installations per municipality per kilometer over the period 2008-2015. Column (2) extends the sample to municipalities located further away from the language border, up to 15 km. As expected, the effect of the interaction term decreases, as municipalities located further away from the border suffer less from the barrier to social spillovers that the border represents. Precision increases, with the number of observations. Note that, in line with our intuition, the interaction effect vanishes completely when very distant municipalities are included in the model. Additional estimations, not reported here, suggest that when the sample is extended to include municipalities as far as 30 km from the border, the average effect of the interaction goes virtually to zero. This confirms the very localized character of the border effect.

Columns (3) to (6) are dedicated to the placebo test. Since data are available for only two years prior to the implementation of the FIT, the only option for a placebo test is 2007. A placebo test would thus cover 2006 and 2007. To ensure comparability, in columns (3) and (4) we run the same models of columns (1) and (2), respectively, while restricting the sample to two years only, i.e. one before, and one after, the true date of implementation of the FIT. We find that the coefficients in columns (3) and (4) are of the same order of magnitude of those in columns (1) and (2), although slightly smaller. That is, the language border leads to "missing" adoptions right after the implementation of the FIT. With time, the effect of missing social spillovers leads to more "missing" adoptions per year. Hence, we observe the snowball effect of social spillovers. Although the marginal benefits from social learning is higher in proximity to the border, this region does not catch up with the rest of the sample. As before, extending the area from 5 to 15 km around the border results in smaller coefficients for distance, given the localized character of the border effect.

Now that our interaction term has been estimated for a sample of two years, we can run a placebo test and compare coefficients. Columns (5) and (6) provide the estimates for the placebo test, which artificially considers the FIT to have been launched in 2007. In both columns, the coefficients are statistically insignificant, and less than 10% of the estimates for the true date of implementation.

Using the coefficient for the interaction between distance and the implementation of the Swiss FIT, we can estimate in Table 3 the total number of "missing" PV adoptions, over the period of analysis, for the average municipality. We proceed as follows. For each specification, we first report the coefficient estimated in Table 2, which gives us the average number of "missing" PV adoptions per kilometer per year. For the specification focusing on the first 5 km from the border, this coefficient is 0.244. We then multiply this coefficient by 8, which represents the total duration, in our sample, of the FIT (2008 to 2015). Over the period with FIT, for the specification focusing on the first 5 km from the border, we obtain about 2 "missing" PV adoptions per km. Taking the average distance, 2.5 km for this specification (and 7.5 for the specification extending the range to 15 km), we can compute the number of "missing" PV adoptions for the average municipality. This number is between 5 and 6, depending on the specification. That is, the presence

Table 2: Interaction between the implementation of the Swiss FIT and distance to the language border

	2006-2015		2007-2008		2006-2007	
	5 km	15 km	5 km	15 km	5 km	15 km
	(1)	(2)	(3)	(4)	(5)	(6)
FIT 2008 × Distance	0.244**	0.101***	0.216***	0.054***		
	(0.098)	(0.029)	(0.073)	(0.017)		
Placebo FIT 2007 × Distance					0.016	0.003
					(0.033)	(0.006)
Constant	22.542	−10.866	9.890	−22.292	−0.538	−9.902
	(18.175)	(15.144)	(42.239)	(32.082)	(23.253)	(12.720)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,590	4,360	318	872	318	872
R^2	0.3506	0.3509	0.3466	0.3631	0.3773	0.1620

Note: Heteroskedasticity-consistent standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01.
The dependent variable is the number of new PV system adoptions in a municipality-year.
FIT 2008 × Distance is an interaction term between the distance to the border and a dummy variable that takes value 1 for all years since the implementation of the FIT in 2008, and 0 otherwise.

of the language border implies an average "loss" of 5 to 6 PV adoptions per municipality during the years 2008 to 2015. In comparison to the average number of PV adoptions per municipality in Switzerland (26.68), this number represents a loss of approximately 20%.

To assess the total effect of the language border, we multiply the average number of "missing" PV adoptions per municipality by the number of municipalities covered by each specification. The last column of Table 3 shows that the border, in conjunction with the implementation of the FIT, has led to a loss of about 780 PV adoptions in the area within 5 km from the border. This number reaches 2,600 when considering all municipalities within 15 km from the border. These numbers confirm our previous findings about the reduction in the number of adoptions caused by the border: the estimated losses within 5 and 15 km from the border represent approximately 20% of the total number of PV adoptions that would have taken place in the absence of any cultural barrier (i.e the sum of "missing" and existing adoptions). Following from Table 3, we observe in rows (3) and (4) that the effect of the border is already strong in 2008. The effect of the language border is related to a loss of about 200 installations already in 2008, which also represents approximately 20% of the estimated total.

Table 3: Number of "missing" PV adoptions

			Per municipality			All municipalities
Model	km	Period	Per km and year	Per km	Total	Total
(1)	5	2006-2015	0.244	1.952	4.88	775.92
(2)	15	2006-2015	0.101	0.808	6.06	2642.16
(3)	5	2007-2008	0.216	0.216	0.54	85.86
(4)	15	2007-2008	0.054	0.054	0.41	176.58

Note: The fourth column reports the coefficients from Table 2. They correspond to the average number of "missing" PV adoptions per municipality, kilometer, and year. The estimate in the fifth column is obtained by multiplying the estimate of the fourth column times the number of years after the introduction of the FIT, up to 2015. The sixth column displays the average number of "missing" PV adoptions per municipality. The last column displays the total number of "missing" PV adoptions.

Figure 3 illustrates the results of the RDD. Consistently with our previous analyses, the outcome variable is, here, the total number of adoptions, per municipality, over the period 2008-2015, in the region within 15 km from the border. We observe two facts. First, there is virtually no jump in adoptions in proximity to the border. Second, as expected, adoption of the solar PV technology decreases when approaching the border, on each side.[9] These two facts not only confirm our previous results on the effect of the language border, but also suggest that the effect of the cultural barrier is much stronger than the effect, if any, of culture itself.

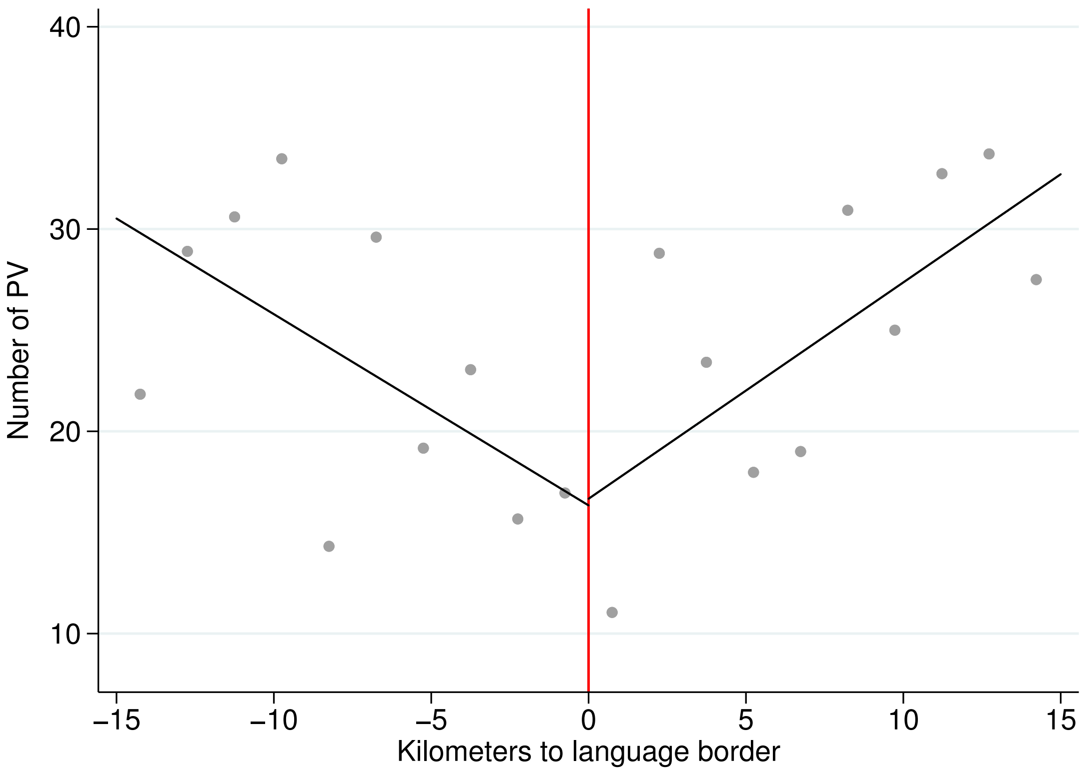
Table 4 quantifies the effects illustrated by Figure 3. Column (1) of Table 4 shows that the discontinuity in culture is associated with no significant change in the rate of adoption of solar PV. Columns (2) and (3) measure the slope of adoption, as a

[9] As a robustness test, to ensure that the depression we observe at the border is not driven by municipalities' size, we also conducted the analysis using density of solar PV adoptions per inhabitants at the municipality level. Our findings remain unchanged. Our results are also robust to the use of several bandwidth selectors identified in the literature. Figure A.2 and Table A.5 in the Appendix report the RDD results using the two main definitions of optimal bandwidths in Calonico et al. (2016), which minimize either the mean squared errors (MSE) or the coverage error-rate (CER). In our case, the optimal bandwidths range between 11.487 and 16.894 km. These distances are close to the 15 km that we use throughout the paper. Furthermore, standard statistical tests confirm that the coefficients for distance obtained with any optimal bandwidth are sufficiently close, statistically speaking, to the coefficients obtained with a bandwidth of 15 km. Hence, for simplicity, we present our results based on a distance of 15 km from the border. Figure A.2 and Table A.5 in the Appendix also present the results for bandwidths of 5 km. In all cases, the choice of the bandwidth has no implication for the findings in this section. Figures 3 and A.2 show fitted values from linear regressions. Fitted values from second-degree polynomial regressions would provide similar results.

function of distance from the border, for the Western (French-speaking) and Eastern (German-speaking) side, respectively. The coefficients for distance confirm that the language border results in missing adoptions. They also confirm that the border exerts a similar influence on adoption on both sides. The coefficients of columns (2) and (3) are statistically the same, once considered the inversion of sign introduced by our coding strategy.[10]

No control variables are included in the estimations reported in Table 4. Including our standard set of control variables would lead to the same coefficients, in statistical terms. Either way, our estimates are relatively close to the previous finding of 0.808 missing adoptions per municipality per kilometer (see model (2), fifth column, in Table 3).

Figure 3: Adoptions after the implementation of the FIT and border discontinuity



Note: Distance is coded negatively for French-speaking municipalities and positively for German-speaking municipalities. Each dot on the figure represents a bin, in this context the average number of PV adoptions per municipality, during the period 2008 to 2015, for distance bandwidths of 1.5 km. This figure uses all observations within 15 km from the border.

[10]The null hypothesis that coefficients are equal cannot be rejected (*p-value*=0.8187). The statistical equality of the coefficients for each side of the border also holds when focusing on the municipalities within 5 km from the border (*p-value*=0.5584) as well as within MSE-optimal (*p-value*=0.2678) and CER-optimal bandwidths (*p-value*=0.9902).

Table 4: Interaction between the implementation of the Swiss FIT and distance to the language border: regression discontinuity and slopes

	RD	West	East
	(1)	(2)	(3)
RD estimate	0.329		
	(3.959)		
Distance		-0.945^{**}	1.069^{***}
		(0.406)	(0.361)
Constant		16.338^{***}	16.667^{***}
		(2.873)	(2.725)
N	436	188	248
R^2		0.0198	0.0362

Note: Heteroskedasticity-consistent standard errors in parentheses. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. The dependent variable is the number of PV system adoptions in a municipality during the period 2008 to 2015 (after the introduction of the FIT). *Distance* is coded negatively for French-speaking municipalities and positively for German-speaking municipalities. This table uses all observations within 15 km from the border

4.3 Heterogeneous effects

In what follows, we further investigate the mechanisms behind the effect of the language border, by considering the language skills of the municipalities' population. As shown in section 4.2, the implementation of the FIT leads to a relative depression in the number of PV adoptions close to the border, in comparison with the other regions. Until now, we treated all municipalities with the same average distance to the border in the same way. However, people in some municipalities may be fluent in the language of the other side of the border. In Switzerland, about 20% of the population frequently uses at least two national languages. For these people, the border should represent less of an obstacle to social spillovers. Hence, fluency with the other language may moderate the effect of the border. That is, the effect of the border should be smaller for municipalities with a higher fraction of people fluent in both French and German.

To test this moderating effect, we proceed as follows. First, we analyze the distribution, within municipalities, of people speaking, at home, the language of the other side of the border, i.e. French in the German-speaking region, and German in the French-speaking region (see Figure 4). Given this distribution, we divide the sample into two subsamples, one including municipalities with a share of individuals speaking the language of the other side that is below the median, and one that is above the median. We then repeat the same approach used for Table 2, and look at the interaction term for both subsamples.

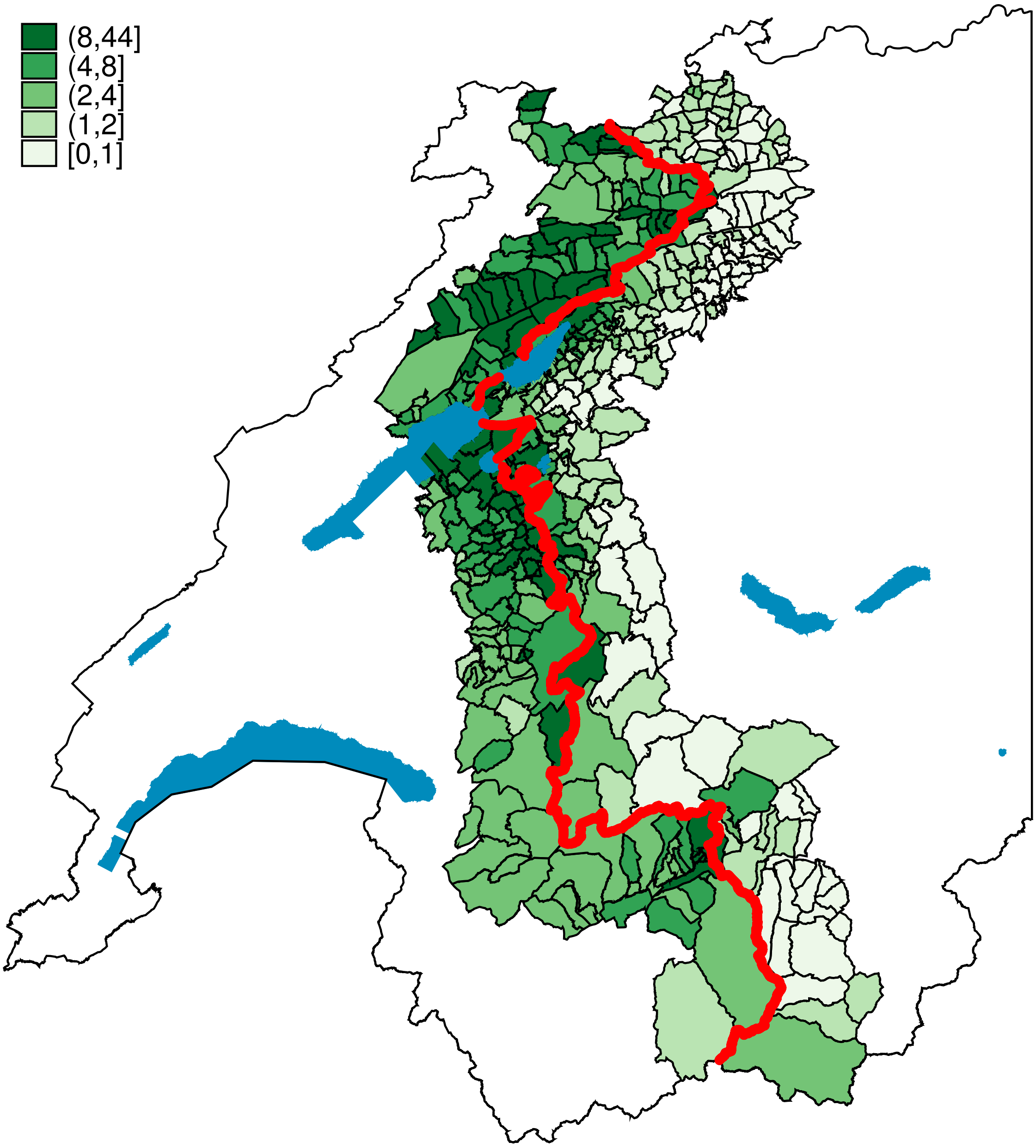
Table 5 provides our estimates. As before, we consider two geographical areas: municipalities within 5 km from the border, and municipalities within 15 km from the border. For each range, we compare odd and even columns. In odd columns, the overall level of fluency in the other language is lower. As expected, the effect of the language border is stronger in odd columns. In even columns, the effect of the border is statistically not different from zero. This suggests that mainly municipalities with a level of multilingualism below the median drive the effect of the border analyzed above. In terms of magnitude, the coefficients in odd columns are at least four times larger, regardless of the specification. We conclude that, the effect of the language border that we observed in the previous analyses is, indeed, driven by the language boundary acting as a barrier to social spillovers. It should be noted that our findings regarding the distance remain valid for these specifications: all coefficients are larger at 5 km than at 15 km.

In the same spirit of the RDD implemented in section 4.2, we now analyze the magnitude of the depression in the number of solar PV adoptions in proximity to the border, based on the level of multilingualism of each municipality. If the effect of the language border depended on the ability to communicate with individuals on the other side, we should observe steeper slopes, on both sides of the border, for municipalities with a below-average level of fluency with the language of the other side. To address this question, we proceed as follows. As in Table 5, we analyze separately the level of adoption in proximity to the border for municipalities with a level of fluency below, and above, the median. As before, we consider all adoptions after the implementation of the Swiss FIT in municipalities within 15 km from the border.[11]

Figure 5 illustrates our results. In line with our intuition, the fitted line is much steeper in plot (a), with a below median-share of population speaking the language

[11]The smaller number of observations on each side of the border, after the separation of the municipalities in two groups based on the median fluency, makes the results rarely statistically significant with bandwidths smaller than 15 km. However, regardless of the level of fluency, we always observe a negative slope for French-speaking municipalities and a positive slope for German-speaking municipalities with bandwidths of 5, 11.487, 15 and 16.894 km. Except for the 5 km bandwidths, the RD estimations also point to no evidence of a jump in the rate of adoption between the two sides of the border.

Figure 4: Percentage of people speaking the language of the other side of the border, as main language at home



Note: Green shaded areas represent the municipalities whose PV installations are located on average less than 15 km away from the border. The red line shows the language border between the French- (West) and the German-speaking (East) parts of Switzerland. White areas represent more distant municipalities and blue areas represent lakes. Source: Swiss census 2000, Swiss Federal Statistical Office (FSO) and swissBOUNDARIES3D 2016, Swiss Federal Office of Topography (swisstopo).

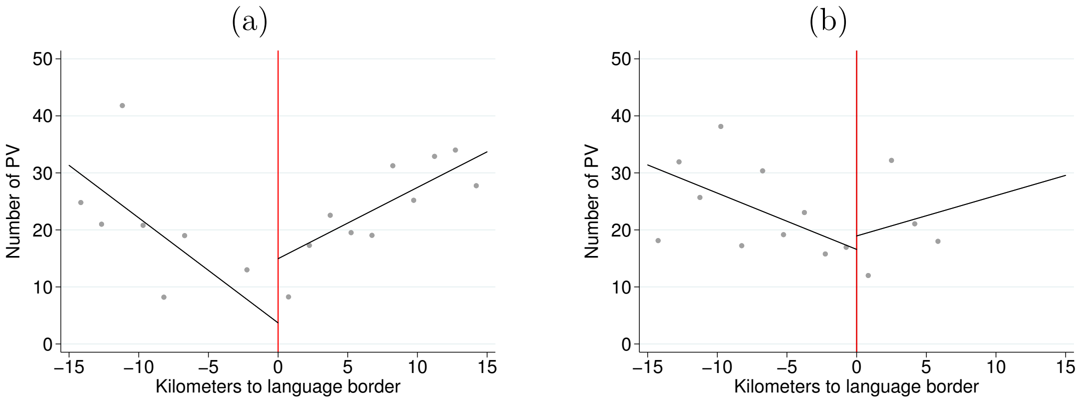
of the other side, than in plot (b), with an above median share. As before, the jump at the cultural border is not stastically significant in both plots (a) and (b).

Table 5: Implementation of the Swiss FIT, distance to the language border, and fluency in the other language

	5 km		15 km	
	Below median	Above median	Below median	Above median
	(1)	(2)	(3)	(4)
FIT 2008 × Distance	0.301**	0.082	0.095**	0.021
	(0.132)	(0.143)	(0.044)	(0.043)
Constant	−21.068	38.823*	−39.685*	−5.284
	(22.676)	(22.674)	(20.439)	(23.209)
Controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	800	790	2,180	2,180
R^2	0.2264	0.1634	0.1976	0.1696

Note: Heteroskedasticity-consistent standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. The dependent variable is the number of new PV system adoptions in a municipality-year. *FIT 2008 × Distance* is an interaction term between the distance to the border and a dummy variable that takes value 1 for all years since the implementation of the FIT in 2008, and 0 otherwise. The estimations include PV adoptions for the years 2006-2015 in municipalities up to 5 km and 15 km away of the border. Odd-numbered models include municipalities with a below-median percentage of people who speak the language of the other side as main language at home, and even-numbered models include municipalities with an above-median percentage.

Figure 5: Adoptions after the introduction of the FIT and border discontinuity, by fluency in the language of the other side



Note: Distance is coded negatively for French-speaking municipalities and positively for German-speaking municipalities. Each dot on the figure represents a bin, in this context the average number of PV adoptions per municipality, during the period 2008 to 2015, for distance bandwidths of 1.5 km. These plots use observations within 15 km from the border. Plot (a) only includes municipalities with a below-median percentage of people who speak the language of the other side as main language at home, and plot (b) only includes municipalities with an above-median percentage.

5 Conclusions

In this paper, we exploit exogenous cultural borders and a policy shock to investigate the role of social spillovers in the adoption of solar PV. More specifically, we assess whether proximity to language borders implies lower rates of adoption, and whether this effect is moderated by fluency in the language of the other side of the border.

Literature shows that social spillovers are an important driver of technology adoption in general, and of solar PV in particular. Previous studies have also highlighted the localized nature of social spillovers. However, social spillovers may be hampered by the presence of cultural barriers. That is, residents of municipalities adjacent to a language border may benefit less from social interactions with PV owners located on the other side, which may reduce the exchange of information on the technology. In presence of a cultural barrier, the pool of individuals from which to learn, at a given distance, may be smaller, limiting the power of social spillovers to address information asymmetry and reduce uncertainty on investments in solar energy.

Switzerland offers the ideal framework to analyze the effect of cultural borders on the adoption of solar PV. Language groups live in geographically distinct regions. The French-German boundary runs from North to South, only in part overlapping natural barriers, and superimposing with institutional borders for less than half of its length. The origin of this boundary goes back to the Middle Age. The location of this border is exogenous to the implementation of federal policies promoting the adoption of solar PV. In 2008, Switzerland introduced a countrywide feed-in tariff for electricity generated from solar PV systems. By deeply modifying the profitability of PV installations, the new support scheme created a major shock to the solar PV market. We exploit the combination of these two factors to identify the role of cultural borders in affecting social spillovers and the adoption of a clean technology.

Descriptive analyses show that the language border hampers the diffusion of solar PV. All else being equal, we observe a positive correlation between the number of adoptions in a municipality and the mean distance of these installations from the border. That is, compared to regions further away from the border, we find a relative depression in the uptake of solar PV in proximity to the border. We further investigate the causal origin of this spatial pattern. In the spirit of difference-in-differences, we explore the effect of the language border on the adoption of solar PV after the implementation of a feed-in tariff. We confirm that the language border leads to a divergence in uptake. Municipalities located in the proximity to the border experience a lower rate of adoption than others located further away. The number of "missing" installations represents about 20% of the average adoptions per municipality per year. A placebo test confirms that this pattern emerges with the implementation of the feed-in tariff. This effect is, however, moderated by the fluency in the language of the other side of the border of a municipality's population. The effect of proximity to the border disappears in municipalities whose population is in large part familiar with the language of the other side.

This paper contributes to an important strand of literature on the role of social spillovers in the adoption of new technologies. It also contributes to an emerging literature analyzing social spillovers in the particular case of solar PV. Consistently, our evidence calls for social interventions aimed at providing opportunities for networking with and learning from PV owners and installers, to foster the adoption of solar PV in presence of information asymmetry and uncertainty.

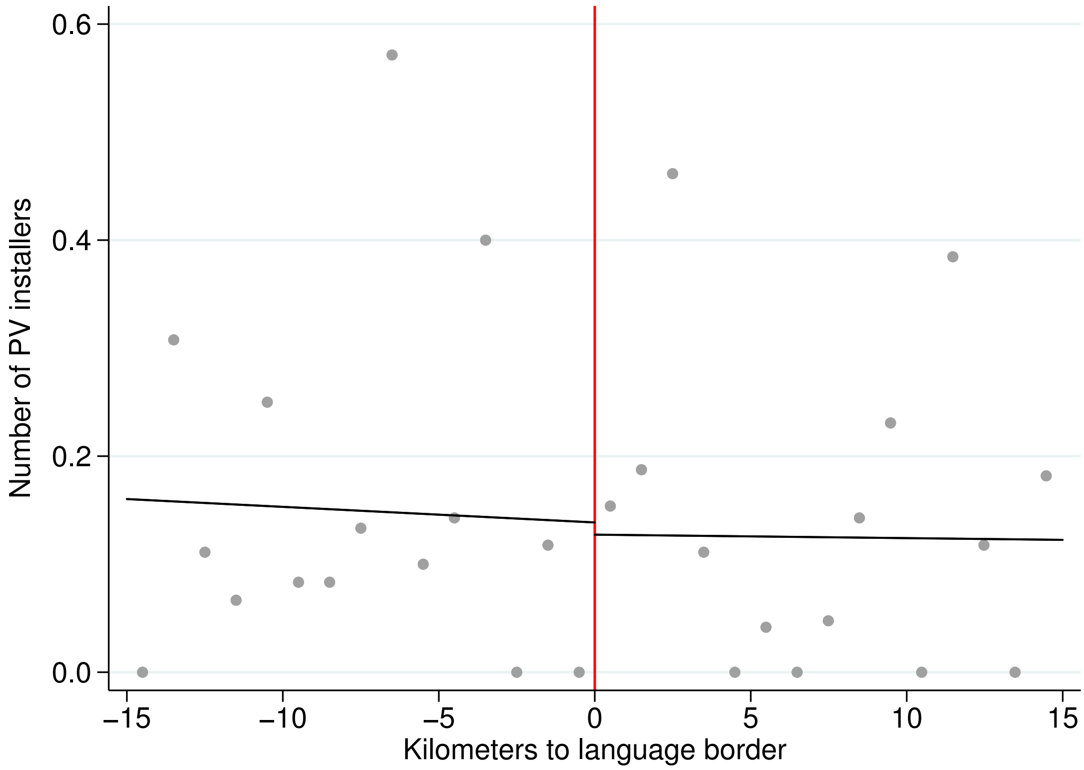
Appendix

Table A.1: Summary statistics of control variables

Variables	Mean	Std. Dev.	Min.	Max.	Source
Population characteristics					
Population	2,946.64	8,798.96	34	169,916	FSO
% pop. aged <30	33.27	4.15	14.84	57.21	FSO
% pop. aged 30-44	20.23	3.08	4.65	46.01	FSO
% pop. aged 45-64	29.34	3.54	0.00	51.74	FSO
% pop. aged 65+	17.17	3.95	2.11	37.30	FSO
% tax payers with income CHF <14.9k	2.55	6.43	0.00	54.73	FTA
% tax payers with income CHF 15-29.9k	13.71	4.22	0.00	65.05	FTA
% tax payers with income CHF 30-49.9k	31.10	6.74	0.00	61.54	FTA
% tax payers with income CHF 50-74.9k	27.94	4.24	0.00	49.02	FTA
% tax payers with income CHF >75k	24.69	8.96	0.00	67.86	FTA
# of unemployed individuals	50.27	181.30	0.08	3,713.25	SECO
Green voting (in %)	9.07	4.90	0.00	29.53	FSO
Contextual factors					
Density (inhabitants/ha)	3.11	5.43	0.02	71.24	Own calculations
% detached houses	61.42	13.14	0.00	90.20	FSO (BDS)
% apartment buildings	19.60	9.36	0.00	70.37	FSO (BDS)
% buildings with residential/commercial use	14.37	9.67	0.00	85.71	FSO (BDS)
% commercial/industrial buildings	4.61	2.80	0.00	33.50	FSO (BDS)
Average # of rooms per dwelling	4.07	0.38	2.16	5.07	FSO (BDS)
Average area per dwelling (in sq meters)	109.32	14.08	57.39	152.19	FSO (BDS)
Solar irradiance (in W/sqm)	147.16	9.86	128.72	190.45	MeteoSwiss
N			7,330		

Note: All variables are observed, yearly, at the municipality level. Summary statistics are computed over all years (2006 to 2015) for all municipalities within 25 km from the border (733 municipalities). Given the presence of missing values, data for age have been linearly extrapolated for the years 2006 to 2009, income data for the year 2015, and building and dwelling data for the years 2006 to 2008. Green voting has been linearly interpolated for the years in between two elections, which take place every four years (last in 2015). For privacy reasons, unemployment data cannot be accessed for a few municipality-years when the absolute number of unemployed individuals is less than 5. In those cases, we replaced the missing values by 2.5. Our estimations are fully robust to alternative ways to address missing values in control variables. FSO stands for Federal Statistical Office, FSO (BDS) for the Building and Dwelling Statistic of the FSO, FTA for Federal Tax Administration, SECO for State Secretariat for Economic Affairs. MeteoSwiss is the Federal Office for Meteorology and Climatology.

Figure A.1: PV installers and distance to the language border



Note: Distance is coded negatively for French-speaking municipalities and positively for German-speaking municipalities. Each dot on the Figure represents a bin, in this context the average number of PV installers per municipality, for distance bandwidths of 1 km. Fitted lines are computed on observations within 15 km from the border. PV installers are firms active in the installation of solar PV installations. Source: Members' register of Swissolar, the umbrella organization of the Swiss solar industry. Register accessed in May 2018.

Table A.2: Effect of distance to the language border on PV adoptions (semi-elasticity)

	5 km (1)	10 km (2)	15 km (3)	20 km (4)	25 km (5)
Distance	0.110**	0.039**	0.030***	0.017***	0.006
	(0.044)	(0.017)	(0.009)	(0.006)	(0.004)
Constant	0.424	1.594	1.173	5.033**	5.499***
	(3.840)	(3.119)	(2.279)	(2.196)	(1.991)
Controls	Yes	Yes	Yes	Yes	Yes
N	158	301	435	575	732
R^2	0.5542	0.4088	0.4626	0.3767	0.3646

Note: Heteroskedasticity-consistent standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. The dependent variable is the logarithmic transformation of the total number of PV system adoptions in a municipality by the end of 2015.

Table A.3: Effect of distance to the language border on PV adoptions: with coefficients for control variables

	5 km (1)	10 km (2)	15 km (3)	20 km (4)	25 km (5)
Distance	1.898** (0.942)	0.710** (0.335)	0.656*** (0.212)	0.407*** (0.127)	0.070 (0.089)
Population	0.008*** (0.002)	0.006** (0.003)	0.009*** (0.002)	0.004** (0.002)	0.005*** (0.001)
% pop. aged 30-44	−0.071 (0.533)	−0.012 (0.356)	−0.082 (0.363)	−0.885** (0.410)	−1.105*** (0.375)
% pop. aged 45-64	−0.756* (0.389)	−0.462 (0.281)	−0.464* (0.247)	−0.879*** (0.266)	−1.168*** (0.220)
% pop. aged 65+	−0.174 (0.298)	0.286 (0.226)	−0.045 (0.220)	−0.184 (0.227)	−0.353* (0.214)
% tax payers with income CHF 15-29.9k	0.657 (0.481)	0.089 (0.302)	−0.145 (0.294)	−0.045 (0.281)	−0.097 (0.268)
% tax payers with income CHF 30-49.9k	0.799** (0.336)	0.388 (0.256)	0.422** (0.203)	0.622*** (0.204)	0.807*** (0.206)
% tax payers with income CHF 50-74.9k	0.353 (0.314)	0.048 (0.267)	−0.153 (0.216)	0.063 (0.213)	0.058 (0.189)
% tax payers with income CHF >75k	1.292** (0.515)	0.643* (0.366)	0.620* (0.319)	1.119*** (0.285)	1.022*** (0.232)
# of unemployed individuals	−0.243*** (0.077)	−0.112 (0.119)	−0.190** (0.082)	−0.092 (0.069)	−0.108* (0.062)
Green voting (in %)	−0.072 (0.390)	0.298 (0.324)	0.405 (0.284)	0.273 (0.220)	0.504** (0.240)
Density (inhabitants/ha)	−0.721 (0.451)	−0.585 (0.566)	−0.713 (0.484)	−0.001 (0.423)	−0.217 (0.462)
% apartment buildings	−0.277 (0.299)	0.141 (0.235)	0.027 (0.164)	0.006 (0.148)	0.011 (0.133)
% buildings with residential/commercial use	−0.120 (0.138)	−0.015 (0.102)	−0.008 (0.102)	−0.102 (0.100)	−0.211** (0.092)
% commercial/industrial buildings	0.194 (0.473)	−0.078 (0.466)	−0.531 (0.343)	−0.429 (0.305)	−0.261 (0.279)
Average # of rooms per dwelling	2.004 (8.182)	−2.607 (6.844)	3.942 (6.249)	−3.471 (5.893)	−1.002 (4.690)
Average area per dwelling	−0.402 (0.260)	−0.062 (0.168)	−0.140 (0.140)	−0.261* (0.146)	−0.234* (0.121)
Solar irradiance (in W/sqm)	0.592* (0.301)	0.116 (0.168)	0.392** (0.169)	0.172 (0.181)	0.330** (0.157)
Constant	−84.209 (74.512)	−16.129 (50.824)	−57.760 (47.369)	31.174 (48.861)	9.632 (40.930)
N	159	302	436	576	733
R^2	0.5672	0.5365	0.5948	0.5575	0.6380

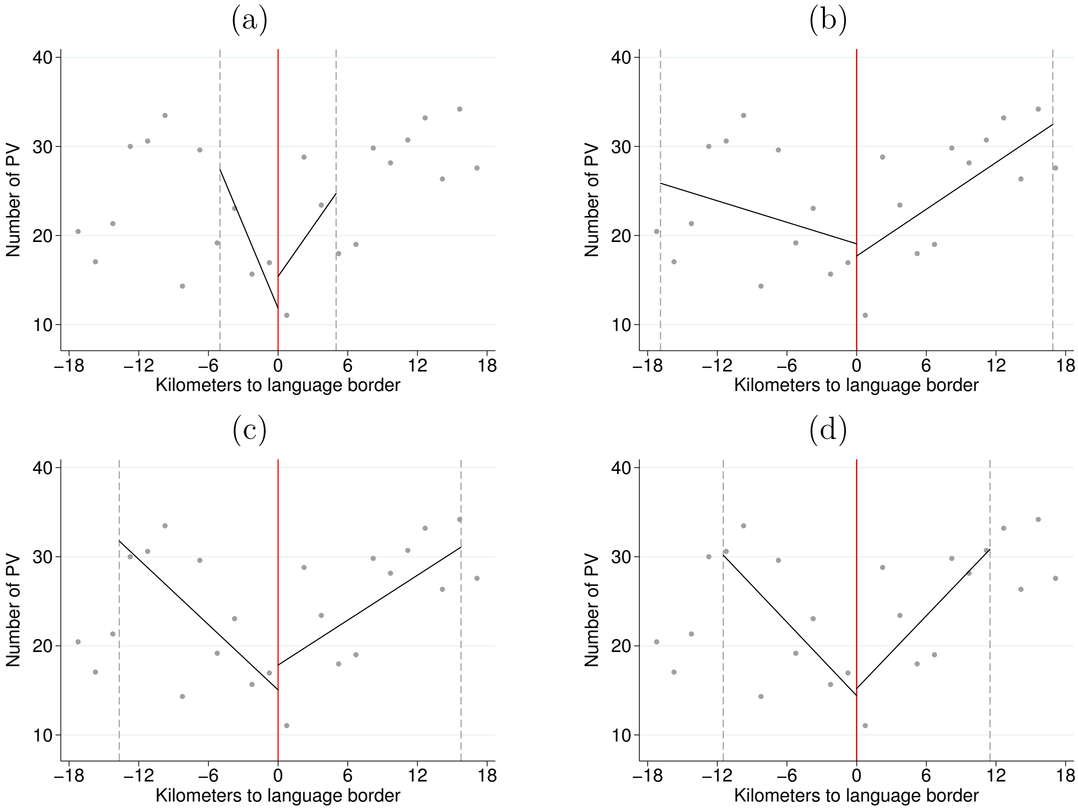
Note: Heteroskedasticity-consistent standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. The dependent variable is the total number of PV system adoptions in a municipality by the end of 2015.

Table A.4: Interaction between the implementation of the Swiss FIT and distance to the language border: with coefficients for control variables

	2006-2015		2007-2008		2006-2007	
	5 km (1)	15 km (2)	5 km (3)	15 km (4)	5 km (5)	15 km (6)
FIT 2008 × Distance	0.244^{**} (0.098)	0.101^{***} (0.029)	0.216^{***} (0.073)	0.054^{***} (0.017)		
Placebo FIT 2007 × Distance					0.016 (0.033)	0.003 (0.006)
Density (inhabitants/ha)	-1.338^{*} (0.718)	−1.632 (1.290)	0.304 (1.119)	−2.169 (1.651)	−1.245 (0.889)	−0.655 (0.622)
Population	0.005^{***} (0.001)	0.007^{***} (0.002)	0.000 (0.002)	0.006^{*} (0.003)	0.005^{**} (0.002)	0.003^{***} (0.001)
% pop. aged 30-44	−0.110 (0.084)	0.000 (0.065)	-0.387^{*} (0.196)	−0.002 (0.170)	0.078 (0.090)	−0.024 (0.079)
% pop. aged 45-64	-0.140^{*} (0.079)	−0.059 (0.054)	−0.131 (0.196)	−0.000 (0.152)	0.079 (0.067)	−0.033 (0.068)
% pop. aged 65+	-0.222^{**} (0.089)	−0.095 (0.072)	-0.540^{*} (0.289)	−0.068 (0.229)	−0.016 (0.079)	−0.033 (0.081)
# of unemployed individuals	−0.005 (0.007)	0.003 (0.010)	-0.038^{*} (0.022)	-0.043^{**} (0.017)	−0.011 (0.007)	−0.005 (0.006)
Green voting (in %)	0.082^{*} (0.048)	0.076 (0.055)	0.092 (0.113)	0.045 (0.076)	0.037 (0.070)	0.047 (0.044)
% tax payers with income CHF 15-29.9k	0.049 (0.089)	−0.002 (0.064)	−0.065 (0.137)	−0.071 (0.054)	-0.074^{*} (0.043)	-0.039^{*} (0.022)
% tax payers with income CHF 30-49.9k	0.081 (0.081)	0.048 (0.061)	−0.022 (0.132)	−0.024 (0.056)	−0.068 (0.043)	-0.039^{*} (0.023)
% tax payers with income CHF 50-74.9k	0.042 (0.083)	0.023 (0.065)	−0.019 (0.143)	0.002 (0.065)	−0.080 (0.049)	−0.034 (0.024)
% tax payers with income CHF >75k	0.096 (0.077)	0.041 (0.064)	−0.013 (0.140)	−0.006 (0.072)	-0.100^{**} (0.050)	-0.049^{**} (0.024)
% apartment buildings	0.133 (0.153)	0.025 (0.095)	0.221 (0.349)	0.080 (0.247)	0.086 (0.136)	0.166^{*} (0.087)
% buildings with residential/commercial use	−0.119 (0.151)	0.188 (0.119)	−0.430 (0.559)	0.166 (0.330)	-0.382^{*} (0.228)	-0.315^{**} (0.146)
% commercial/industrial buildings	0.404^{*} (0.233)	0.030 (0.100)	−0.311 (0.841)	−0.538 (0.367)	0.358^{**} (0.180)	0.368^{**} (0.160)
Average # of rooms per dwelling	-4.738^{*} (2.766)	0.713 (2.397)	−3.241 (9.463)	1.745 (7.310)	−2.000 (4.375)	2.757 (3.159)
Average area per dwelling	−0.022 (0.057)	-0.113^{**} (0.057)	0.207 (0.234)	−0.005 (0.168)	0.050 (0.075)	−0.007 (0.071)
Solar irradiance (in W/sqm)	−0.057 (0.050)	0.032 (0.034)	0.040 (0.070)	0.076^{**} (0.038)	0.015 (0.024)	0.005 (0.011)
Constant	22.542 (18.175)	−10.866 (15.144)	9.890 (42.239)	−22.292 (32.082)	−0.538 (23.253)	−9.902 (12.720)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,590	4,360	318	872	318	872
R^2	0.3506	0.3509	0.3466	0.3631	0.3773	0.1620

Note: Heteroskedasticity-consistent standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. The dependent variable is the number of new PV system adoptions in a municipality-year. *FIT 2008 × Distance* is an interaction term between the distance to the border and a dummy variable that takes value 1 for the period after the introduction of the feed-in tariff in 2008, and 0 otherwise.

Figure A.2: PV adoptions after the introduction of the FIT based on distance to the language border, using different bandwidths



Note: Distance is coded negatively for French-speaking municipalities and positively for German-speaking municipalities. Each dot on the figures represents a bin, in this context the average number of PV adoptions per municipality, during the period 2008 to 2015, for distance bandwidths of 1.5 km. Fitted lines in plot (a) are computed on observations within 5 km from the border. Fitted lines in other plots use the main optimal bandwidth selectors proposed in Calonico et al. (2016). Plots (b) and (c) use mean squared error (MSE)-optimal bandwidths, with one common bandwidth of 16.894 km on either sides of the border in plot (b) and two distinct bandwidths of 13.673 (French-speaking municipalities) and 15.757 km (German-speaking municipalities) in plot (c). Plot (d) uses coverage error-rate (CER)-optimal bandwidth, which is 11.487 km. As expected, slopes become generally flatter with larger bandwidths.

Table A.5: Interaction between the implementation of the Swiss FIT and distance to the language border: regression discontinuity using different bandwidths

	Manual	MSE-optimal	MSE-optimal	CER-optimal
	5 km	16.894 km	West: 13.673 km East: 15.757 km	11.487 km
	(1)	(2)	(3)	(4)
RD estimate	3.551	−1.368	2.784	0.794
	(5.581)	(3.787)	(4.010)	(4.658)
N	159	493	434	343

Note: Heteroskedasticity-consistent standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. The dependent variable is the number of PV system adoptions in a municipality during the period 2008 to 2015 (after the introduction of the FIT). Distance is coded negatively for French-speaking municipalities and positively for German-speaking municipalities. Column (1) includes all observations within 5 km from the border. Other columns use the main optimal bandwidth selectors proposed in Calonico et al. (2016). Columns (2) and (3) use mean squared error (MSE)-optimal bandwidths, with one common bandwidth of 16.894 km on either sides of the border in column (3) and two distinct bandwidths of 13.673 (French-speaking municipalities) and 15.757 km (German-speaking municipalities) in column (c). Column (4) uses coverage error-rate (CER)-optimal bandwidth, which is 11.487 km.

Chapter 3

Local subsidies for solar energy, cross-boundary effects, and effects beyond discontinuation

This chapter is based on a section of a report written with Stefano Carattini (Georgia State University) for the Swiss Federal Energy Office (Baranzini et al., 2019). We thank Andrea Baranzini for his very helpful feedback and remarks throughout the writing of the paper. We also thank Nicolas Borzykowski, Adeline Scherantz, Pablo Eduardo Schnell, and Linda Tesauro for excellent research assistance. This research was financially supported by the Swiss Federal Office of Energy (SFOE), grant number SI/501305-01.

Abstract
Subsidies for renewable energy are among the most widely used instruments of climate policy. In recent times, they have come under particular scrutiny, especially for their costs. Current assessments, however, implicitly assume that subsidies for renewable energy only have an effect in the jurisdiction in which they are implemented, and that their effects end once the policy is discontinued. With this paper, we challenge both assumptions. First, we show that subsidies for solar energy not only lead to higher adoption in the jurisdiction that implements them, but also to higher adoption in adjacent areas of neighboring jurisdictions, a pattern consistent with social contagion, compared to areas located further away. Second, we show that, compared to control areas, subsidies continue to stimulate adoption even after they are discontinued, another pattern consistent with social contagion. We use a unique dataset of subnational subsidies for solar energy implemented between 2006 to 2017 in Switzerland and data on solar installations, about 60,000 in total, completed over the same period. While our findings do not suggest a change in the ranking of climate policy instruments, they do suggest that current assessments of subsidies for renewable energy may underestimate their cost-effectiveness. Our findings also point to the untapped potential of policies promoting spillovers facilitating the adoption of renewable energy.

Keywords Solar PV; Subsidies for renewable energy; Federalism; Spillovers; Cost-effectiveness

JEL codes D83; Q42; Q48; Q58

1 Introduction

Subsidies for renewable energy have become one of the main policy instruments to ensure a gradual transition towards a low-carbon economy. As of 2017, national or subnational policies in some 113 countries were subsidizing the adoption of renewable energy (REN21, 2018). Subsidies for renewable energy have, however, recently come under intense scrutiny. First, the falling cost of solar photovoltaic (PV) systems (Creutzig et al., 2017) has convinced policymakers in many countries to start phasing these subsidies out. Second, recent studies analyzing the cost-effectiveness of these instruments have pointed to very high implicit costs of carbon, as well as to regressive distributional effects (Borenstein, 2017).

High implicit costs of carbon should not surprise. Economic theory suggests that, by picking winners, subsidies for renewable energies such as solar and wind are less cost-effective than carbon pricing. The estimates of the implicit cost of carbon in the literature are, however, very high, in the order of hundreds of dollars per ton of CO_2 abated. About 20% of greenhouse gas emissions over 57 jurisdictions are currently covered by a carbon price, with most schemes having prices below \$20 per ton of CO_2 and the upper bound being below \$127 per ton of CO_2 (World Bank 2019). Taken together, these facts suggest that subsidies for renewable energy are leading policymakers to start abating greenhouse gas emissions from abatement costs very high in the range, leaving much cheaper opportunities on the table (see McKinsey & Company, 2008).

As for other interventions, a fair assessment should, however, include benefits arising after the intervention is discontinued (Allcott and Rogers, 2014), as well as potential spillover effects to other jurisdictions. Theories of socially-motivated moral behavior suggest that a temporary subsidy can lead to behavioral change lasting, and potentially continuing, beyond the period in which they are in force (Brekke et al., 2003; Nyborg et al., 2006). Adding social network features to such model show that a temporary subsidy, or intervention, can lead to adoption beyond the jurisdiction in which the intervention is implemented (Spencer et al., 2019). The same applies to models of information sharing.

Hence, it is reasonable to assume that the current assessments of subsidies for solar energy may not capture the entire picture, as such exercises have so far focused on the jurisdiction in which the subsidy was implemented, and the period in which it was in force. In the case of solar PV adoption, one particular channel could lead to a cascade of adoption beyond a subsidy's jurisdiction and period of implementation: social contagion. Social contagion has been shown to operate in different contexts such as California, Connecticut, Germany, Switzerland, and the United Kingdom (Bollinger and Gillingham, 2012; Richter, 2013; Graziano and Gillingham, 2015; Rode and Weber, 2016; Baranzini et al., 2017a), and is supposed to be driven by imitation through social norms and information sharing, consistently with the above-mentioned theories.

In this paper, we use the unique context of Switzerland and the patchwork of subnational policies that its fiscal federalism generates, and show that subsidies for solar energy increase adoption also in adjacent areas of neighboring jurisdictions, compared to areas located further away, and that subsidies lead to higher adoption in the jurisdiction in which they are implemented even after they are discontinued, another pattern consistent with social contagion. We use a unique database covering the main instruments implemented by Swiss cantons, the equivalent of American states, between 2016 and 2017, to promote the adoption of renewable energy, focusing in particular on production-based subsidies (feed-in tariffs) and capacity-based subsidies (one-off investment grants). These cantonal policies complement the federal subsidy schemes, which cover all cantons in exactly the same way. Switzerland is a very relevant context also because it represents one of the solar markets in Europe with the highest growth rates and one of the markets with the highest density of solar installations in the world (IEA, 2018).

We proceed as follows. First, following the example of the literature to which we contribute, we assess the effect of a subsidy of either type on adoption in the same canton in which it was implemented. Then, we move to our original research question and analyze spillover effects, in both time and space. Empirically, we analyze spillovers in space by focusing on a subsample of cantons, which never implemented a subsidy of any type. These cantons, however, share a border with other cantons, which may implement a subsidy, potentially at different points in time. This fact provides variation in the exposure of different areas of a canton without subsidy to policies implemented in nearby cantons.

We use data on about 60,000 solar installations, completed between 2006 and 2017, and a unique dataset on cantonal subsidies implemented over the same time range. We find evidence suggesting that these cantonal subsidies are associated with higher adoption of solar energy in the very same jurisdiction in which they are implemented, both in terms of the number of installations and in terms of capacity. Our estimates suggest that the annual number of completed PV systems per 1,000 inhabitants is, on average, 0.35 higher in cantons offering subsidies than in those that do not. This figure represents an increase of about 25% compared to the Swiss average adoption rate over the period 2006-2017.

Most importantly, we find evidence suggesting that cantonal subsidies can bring about adoption of solar energy even in other jurisdictions, which never introduced such measures. In line with our predictions, these effects take place in areas adjacent to the jurisdictions having implemented a subsidy. Our results indicate that municipalities that are adjacent to the cantons implementing subsidies experience a significantly higher adoption rate than more distant municipalities. We find that municipalities located within 10 km from the border of subsidized cantons have 0.6 more PV adoptions per 1,000 inhabitants by year compared with more distant municipalities, with the number of installations decreasing by 0.1 for each additional km from the cantonal border. We also show that such effects persist even after the subsidy has ceased in the nearby cantons, although it decreases over time. These results are consistent with social contagion effects.

This paper contributes to four strands of literature. First, we contribute to a growing literature assessing the (cost-)effectiveness of subsidies for solar energy. With data from the California Solar Initiative, Hughes and Podolefsky (2015) show that an increase of \$0.1 per watt-peak in the rebate provided by the initiative is associated to 10% higher adoption. Their estimate for the implicit cost of carbon ranges from \$130 to \$195 per ton of CO_2. Crago and Chernyakhovskiy (2017) examine the impact of different types of financial and non-financial incentives for residential PV installations implemented by 13 states in the US from 2008 to 2012. Using county-level data, they find that an additional \$1,000 per kW-peak in direct cash rebates led to an increase of nearly 50% in annual installed solar capacity. Their estimate for the implicit cost of carbon of these policies is about \$184 per ton of CO_2.

Second, we contribute to a set of concurrent papers, which also analyze the effect of subsidies for renewable energy, but this time with a long-run perspective and a focus on technological improvements (Gerarden, 2018; Bollinger and Gillingham, 2019). That is, while our original approach assesses spillovers in time through higher adoption on the consumer side, these contributions focus on induced technological change on the supply side.

Third, we contribute to a growing literature analyzing the role of social contagion in the adoption of innovative behaviors, such as agricultural technologies (Munshi, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010), menstrual cups (Oster and Thornton, 2012), or clean cookstoves (Srinivasan and Carattini, 2016). The case of solar PV has also received particular attention, following Bollinger and Gillingham

(2012). In their paper, they find with data for California that an additional installation at the zip-code level is likely to lead to 0.24 additional installations. Graziano and Gillingham (2015) and Rode and Weber (2016) use data for Connecticut and Germany, respectively, to confirm that social contagion is a localized phenomenon, whose effects decay rapidly with distance. Baranzini et al. (2017a) confirm these features of social contagion with data for Switzerland, while showing that the most visible installations drive stronger contagion, and that contagion also affects commercial and not only residential adoption. Also with data for Switzerland, Carattini et al. (2018b) show that language barriers hampering social interactions reduce the adoption of solar PV, with the magnitude of the effect varying as a function of the fraction of people on either side not speaking the language of the other side.

Fourth, we contribute to a historical literature in economics leveraging fiscal federalism to learn from subnational policies (Oates, 1999). Studies about Switzerland have contributed their fair share to this very large literature, examining policies as diverse as employment benefits (Lalive et al., 2005), bequest and income taxes (Brühlart and Parchet, 2014; Eugster and Parchet, 2018; Parchet, 2019), and pricing garbage by the bag (Carattini et al., 2018a).

In terms of policy evaluation, our findings suggest that current assessments may underestimate the cost-effectiveness of policies promoting the adoption of renewable energy. Existing assessments generally assume that a subsidy can only have had an effect on the PV systems that benefited from it. Yet, our results indicate that subsidized PV systems can lead to a substantial number of additional adoptions through social contagion. In order to capture the full extent of the effect of a subsidy, including that resulting from the multiplier effect of social contagion, it seems necessary to conduct several assessments, at different points in time, and also to consider the regions surrounding the region where the subsidy was initially implemented. Importantly, our findings do not change the ranking among climate policy instruments. Absent any evidence in this direction, there is no reason to believe that subsidies for renewable energy would create stronger long-term and cross-boundary effects than carbon pricing. However, they do change our understanding of the cost of climate policy.

Our findings also have several implications in terms of policy design and marketing. Together with other studies revealing the importance of social contagion, our findings point to the largely untapped potential of measures promoting social learning and imitation. Encouraging PV owners to share their experience with their neighbors, e.g. through local public events, and fostering the establishment of social norms that value pro-environmental behavior, e.g. through public education or communication campaigns, could prove effective ways to spur the deployment of solar technology.

In addition, our results suggest that policymakers could reduce the cost of implementing climate policies by designing subsidies in a way that maximizes social spillovers. Rather than providing uniform financial incentives across a whole national (or cantonal) jurisdiction, it may be more effective to rely on geographically targeted subsidies in order to create local "adoption hotspots" with a strong snowball effect (Curtius et al., 2018). Just like the municipalities adjacent to the cantons with subsidies that we analyze in this paper, non-targeted regions close to hotspots should then benefit indirectly from the intervention thanks to cross-border social contagion.

Such targeted approach taking advantage of social contagion could be particularly effective if it achieves a sufficient level of adoption within the hotspot. Indeed, some studies modeling the decision-making process leading to the adoption of green behaviors envisage the existence of threshold levels beyond which the phenomenon of imitation takes off (Nyborg et al., 2006; Carattini et al., 2019). The assumption is that the influence of local social norms unfolds only when a technology or a behavior is widespread enough in the community. At that point, the financial incentive could then be stopped to let the contagion effects take over. Our paper provides empirical evidence that the effect of subsidies can persist, at least for for some time, after discontinuation.

Setting up local and temporary subsidies can easily be done in decentralized political systems such as Switzerland, where municipalities have broad competencies in the field of energy. However, coordination at the national level seems crucial to prevent adjacent jurisdictions from being targeted, and also to target regions with the greatest potential. For example, it would probably be more effective to create a hotspot in the centre of a densely populated area than in an isolated village with no one nearby who could be influenced. Yet, the presence of many potential adopters in proximity does not necessarily guarantee that an area is well suited. Indeed, in some areas where the population is spatially sorted, such as close to cultural or linguistic borders, social interactions may be weaker and thus dampen the impact of social spillovers (Carattini et al., 2018b).

The paper is organized as follows. Section 2 provides the institutional background. Section 3 describes the data and the empirical strategy. Section 4, present our empirical results. Section 5 concludes.

2 Economic background

To promote renewable energy technologies, the Swiss Parliament introduced in March 2008 a feed-in tariff, under the official name of “cost-covering remuneration for feed-in to the electricity grid” (CRF). The CRF is a production-based subsidy that aims to ensure the profitability of electricity production from renewable sources by guaranteeing sufficiently high revenues. Once they join the scheme, owners of solar PV installations benefit from fixed payments for each kWh injected into the grid. The fixed tariff is guaranteed for a period of 20 years (a period of 25 years until 2014) after the completion date of the PV installation. The amount of the fixed tariff is based on the capacity and the type of solar installation (building-attached, building-integrated or ground-mounted).

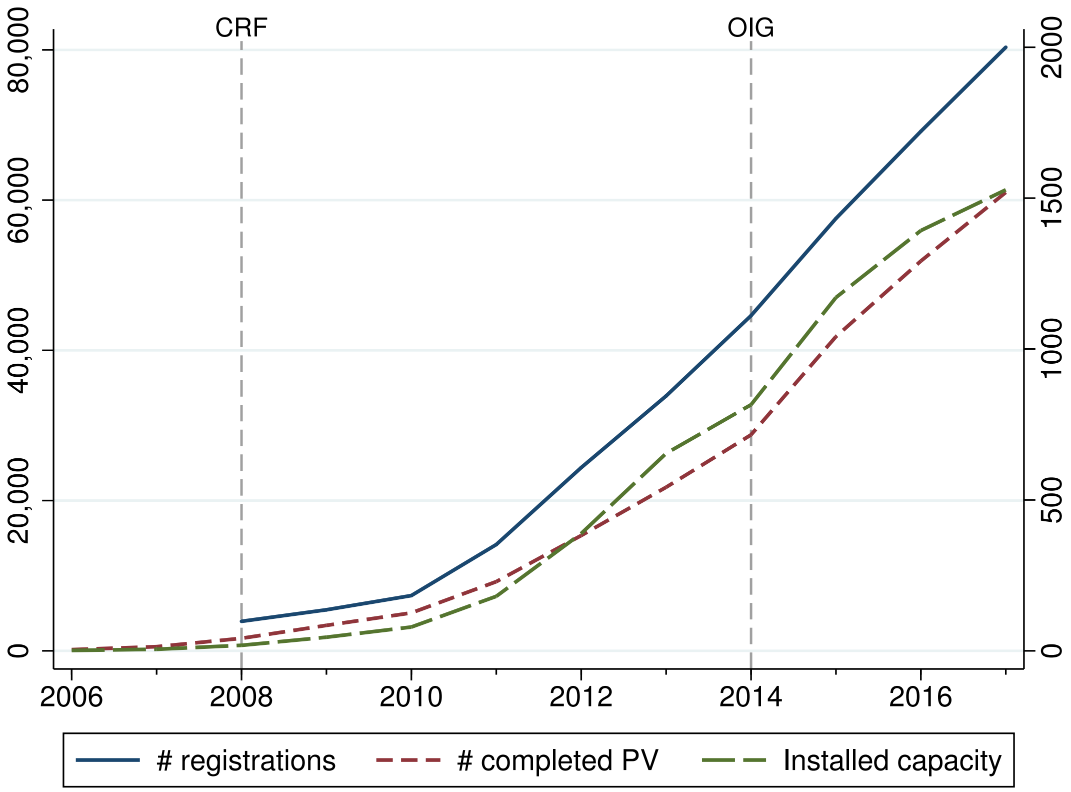
The CRF is exclusively financed by an electricity surcharge paid by Swiss electricity consumers. Demand for solar exceeded policymakers’ expectations, leading promised subsidies to exceed the revenues collected through the electricity surcharge. While policymakers adjusted upward the electricity surcharge several times, such adjustments were not sufficient to close the gap, leading to the establishment of a waiting list.

According to our data, none of the installations that registered after 2012 were able to benefit from the CRF by February 2018. To reduce the waiting time, the Swiss government introduced an alternative instrument, a “one-off investment grant” (OIG), in 2014. Starting from 2014, the OIG became the only option for installations with a peak capacity below 10 kW, whereas installations between 10 and 30 kW could choose whether to apply for the CRF, and be added to the waiting list, or apply for the OIG. Installations above 30 kW could only apply for the CRF, so that no policy change occurred for this subgroup. While the CRF is set to be abolished in 2022, the OIG is currently planned to be in force until 2030. Under the OIG, the contribution amounts to a maximum of 30% of the price of a reference installation and is paid shortly after the completion of a solar installation. The OIG is financed through the same fund as the CRF. Everything else equal, the nominal, undiscounted average subsidy amount under the OIG scheme is lower than the average subsidy amount (cumulated over 20 years) of the CRF.

According to the latest available data (SFOE, 2019a), the total installed PV capacity in Switzerland at the end of 2018 was 2,168 MW, an increase of 14% compared to the previous year, leading solar sources to represent 3.4% of its final electricity consumption.

A very interesting feature of Switzerland, which as mentioned has been exploited in many policy evaluation exercises, relates to its fiscal federalism. The high degree of autonomy of the 26 cantons, which constitute Switzerland's main administrative subdivisions, includes the field of energy. To complement the policies promoting solar energy at the federal level, cantons, and to lesser extent municipalities and electricity utilities, have implemented their own regulations supporting the adoption of solar panels.

Figure 1: Solar PV in Switzerland over the years 2006 to 2017



Note: The scale on the left axis is given in count and applies to registrations and PV installations. The scale on the right axis is given in megawatt-peak (MWp) and applies to the installed capacity. Source: Swiss Federal Office of Energy (SFOE).

3 Empirical approach and data

3.1 Empirical approach

The unique framework of Switzerland allows the implementation of a novel approach to investigate whether social contagion fosters the adoption of solar energy. It also allows us to investigate whether subsidies to renewable energy can have an impact beyond their jurisdiction, and beyond the period in which they are implemented.

Impacts on adoption in other jurisdictions are currently not considered in cost-effectiveness analyses, even though the global provision of a public good usually is. If policies have an impact beyond their jurisdiction, current assessments may underestimate their cost-effectiveness.

Theoretically, it is plausible to assume that social contagion effects, which are usually driven by learning and imitation, do not stop at jurisdictional boundaries. Since social contagion effects imply that there will be more installations in areas where adoption is already relatively high (a snowball effect), if these effects do not stop at jurisdictional boundaries, we should observe a higher level of adoption in regions adjacent to the cantons that subsidize PV.

We answer this research question in two steps. First, we assess whether we observe higher adoption in cantons that implement a subsidy scheme, during its implementation. Next, by focusing exclusively on the cantons that never introduced subsidies, we analyze whether regions that are located close to subsidized territories also have a higher adoption rate than those located further away. In this way, we exploit the implementation of a subsidy in canton i as plausible exogenous source of variation in the neighboring areas of canton j.

A key element in this second approach consists in the ability to attribute to a given municipality in canton j the treatment if they are located sufficiently close to a canton, i, having either a one-off investment subsidy or a production-based subsidy. To attribute the treatment to municipalities in canton j, we proceed in two ways. First, we measure the distance between each municipality and the closest cantonal border. Distance is measured as the crow flies, going from the center of each municipality in canton j, as provided by the GEOSTAT database produced by the Swiss Federal Statistical Office (FSO)[1], to the nearest geographical point on the border of canton i, where canton i is always a canton with either a one-off investment subsidy or a production-based subsidy. That is, our distance variable therefore varies from year to year depending on the introduction or abandon of promotion policies in the nearby cantons. Second, we assume that only municipalities in canton j that are adjacent to the cantonal border between canton j and canton i are treated. The exact location of cantonal borders is provided by the Swiss office of topography (swisstopo).

[1]The FSO determines the center of a municipality on the basis of political and administrative criteria. It corresponds to the central point of the capital of the municipality, which is arguably a good approximation of where the majority of PV installations in a municipality are located. For the boundaries of the cantons and municipalities, we use a geo-referenced dataset produced by the Swiss office of topography (swisstopo).

When we examine the impact of subsidy schemes in canton i on adoption in the same canton i, the following panel fixed-effects model is used:

$$PVinstal_{mit} = \alpha_m + \beta PROD_{it} + \gamma INV_{it} + X'_{mt}\delta + \mu_t + \varepsilon_{mit} \tag{1}$$

The dependent variable, $PVinstal_{mit}$, is a measure of PV technology adoption in municipality m of canton i during year t. The municipal level is the most disaggregated level for which statistics are usually available in Switzerland, and the statistics are generally produced on an annual basis. We use two different measures of adoption: the number of newly installed PV systems and the additional capacity (in kW-peak, or kWp). In most of the specifications, we normalize by the population. For installations that are not completed in the same year in which they are registered, the installation date counts. This is because some of the subsidies that we examine, which are described in the following section, have the objective to accelerate the completion of installations in the waiting list for the federal subsidy. The main explanatory variables of interest are the dummy variables $PROD_{it}$ and INV_{it}, which vary by canton and over time. $PROD_{it}$ indicates the presence of production-based subsidies, including CRF-bridges, and take the value 1 if the municipality i is located in a canton i that offers such policy at time t, and 0 otherwise. Similarly, INV_{it} takes the values 1 if the municipality i is located in a canton c that implements an investment subsidy during time t. X_{mt} represents a vector of control variables that vary over municipalities and years. To account for other, omitted, factors affecting the deployment of solar technology, our model includes municipality fixed effects, denoted α_m, and year fixed effects, denoted μ_t. Municipality-specific fixed effects allow to capture time-invariant unobserved heterogeneity that affect the adoption rate. Time dummies allow to capture the effect of time-varying factors affecting all municipalities, such as changes in federal policies, in the price of PV installations, or in consumer preferences. Finally, ε_{mit} is the i.i.d. error term, clustered at the municipality level.

To investigate the influence of subsidies resulting from social contagion, we focus our analysis on the cantons that do not implement any subsidies between 2006 and 2017. If the financial incentives that we analyze in Equation (1) increase the adoption rate and if we are in presence of social spillovers, we should observe more adoptions in the municipalities that are close to cantons offering financial incentives. However, since social contagion is a localized phenomenon that disappears after a few kilometers (Graziano and Gillingham, 2015; Rode and Weber, 2016; Baranzini et al., 2017a), the more distant municipalities should not be affected. Our approach is therefore to separate the municipalities into two distinct groups. In the first group, which can be interpreted as the "treatment" group, we include all the municipalities whose PV adoption level is likely to be affected by the cross-boundary effects generated by PV installations in the subsidized cantons. The remaining municipalities are included in the second group, which can be interpreted as the "control" group, i.e. those municipalities not affected by cross-boundary effects. The composition of each group is not static. Depending on the introduction or abolition of subsidies in the neighboring cantons, a municipality may change groups from one year to the next.

Among the treated municipalities, we expect the impact to be the strongest in the municipalities that are the closest to the cantons offering a subsidy. For this reason, we use a continuous treatment variable that reflects the distance that separates the center of each municipality and the closest border point of a subsidized canton. Under these assumptions, we estimate the following model :

$$PVadopt_{mt} = \alpha_m + \beta T_{mt} \times D_{mt} + \gamma T_{mt} + \delta D_{mt} + X'_{mt}\eta + \mu_t + \varepsilon_{mt} \qquad (2)$$

where $T_{mt} \times D_{mt}$ is an interaction term between a dummy variable indicating the municipalities in the treatment group and the distance that separates the municipality from the nearest canton implementing a subsidy. The variable T_{mt} takes the value 1 when the municipality m is located within a given cut-off distance from the closest canton i implementing a financial incentive during year t. As we do not know the exact distance up to which cross-border effects operate, we use different cut-off distances in our estimations. Moreover, PV installations may generate social contagion several months after their completion date, which means that cross-border effects could persist after the end of the subsidy in canton i. We thus also use alternative specifications in which we include additional treatment variables that are similar to $T_{mt} \times D_{mt}$ and T_{mt}, but where the variable T_{mt} is set to 1 only for the following periods. D_{it} is a continuous variable measuring the distance from the center of municipality i to the closest border point of the cantons offering subsidies in year t. In this model, the dependent variable $PVadopt_{mt}$ captures the per capita number of solar adoptions in the municipality m during year t. The other components are similar to those in Equation (1).[2]

[2]We tested whether the control variables in X_{mt} are related with the group and distance variables. No trends are identified that could explain a higher level of adoption in the municipalities that are the closest to the cantons with subsidies.

3.2 Data

Solar PV

We use data on solar PV installations provided by the Swiss Federal Office of Energy (SFOE). The data come from the register of the CRF and OIG subsidy schemes. The register contains detailed information on all applications for federal subsidies that have been submitted since 2008.[3] Over the entire period of our analysis, January 1, 2006, to December 31, 2017, the cumulative number of registrations in our data is 80,352, of which 60,985 completed installations.[4] For each installation, we have information on the exact location of the solar installation, the date of registration, the date of installation, and the installed capacity (kWp). We use the exact addresses to assign a given solar installation to a municipality, and a canton, and so to the subnational policies to which it is subject.[5] Additional technical and administrative variables are available in the dataset, including ownership type. Approximately 60% of the installations are owned by households, 26% by private companies, and 3% by utilities or the public sector. The owner of the remaining installations is undefined.

Regarding the time dimension, the date we use depends on the type of analysis. For the analysis of the effect of subsidies, we use the installation date because we aim to analyze whether the cantonal subsidies have achieved their objective, namely to increase the solar PV capacity. To answer this research question, the date of registration to the federal policies is inappropriate because it does not necessarily

[3] While implemented in 2008, the CRF also covered, retroactively, installations completed after January 1, 2006.

[4] The SFOE data should virtually contain the entire universe of solar installations in the country. The overall total capacity obtained with the SFOE data matches relatively closely the estimates for total capacity in Switzerland from Swissolar, the umbrella organization of Swiss solar installers (SFOE, 2018). Some degree of discrepancy may be due to the way Swissolar estimates are produced (i.e. through surveys of installers), to the fact that a small fractions of installations in the country may not be connected to the grid (e.g. huts in remote Alpine locations), and to the fact that for a minority of canton-years, being a beneficiary of cantonal subsidies made it illegal for PV owners to also benefit from financial subsidies. Hence, these latter owners may not appear in the SFOE registry. Such omissions, however, can only lead us, if anything, to underestimate the effect of cantonal policies, thus providing lower-bound estimates.

[5] As a result of mergers among municipalities, the number of municipalities has decreased from about 2,700 in 2006 to just over 2,200 today. In order to have identical boundaries over the entire period of analysis, we spatially referenced the PV installations in the 2,222 municipalities existing as of April 4, 2018. To this end, we first geocoded the street-number level addresses using the HERE API to obtain the geographical coordinates of the PV installations. Through this process, we were able to locate more than 98% of the facilities within the 2018 municipal boundaries. For the remaining 2% of installations, we used the zip code. Zip codes are part of the address, as provided by the SFOE. However, the boundaries of zip codes may not always match those of municipalities. In the end, we were unable to determine the exact location of only 54 installations (less than 0.01%). These are not included in the final sample.

coincide with the date on which the solar panels are installed. According to our data, the installation indeed takes place, on average, nearly 4 months after registration. The registration may thus occur before the introduction of the cantonal subsidy. If so, we would not be able to capture the effect of a cantonal subsidy by using the registration date. Note that, as only completed PV installations are likely to have benefited from cantonal subsidies, we exclude planned installations, i.e. those that are registered but not completed, from our estimates for the impact of subsidies.

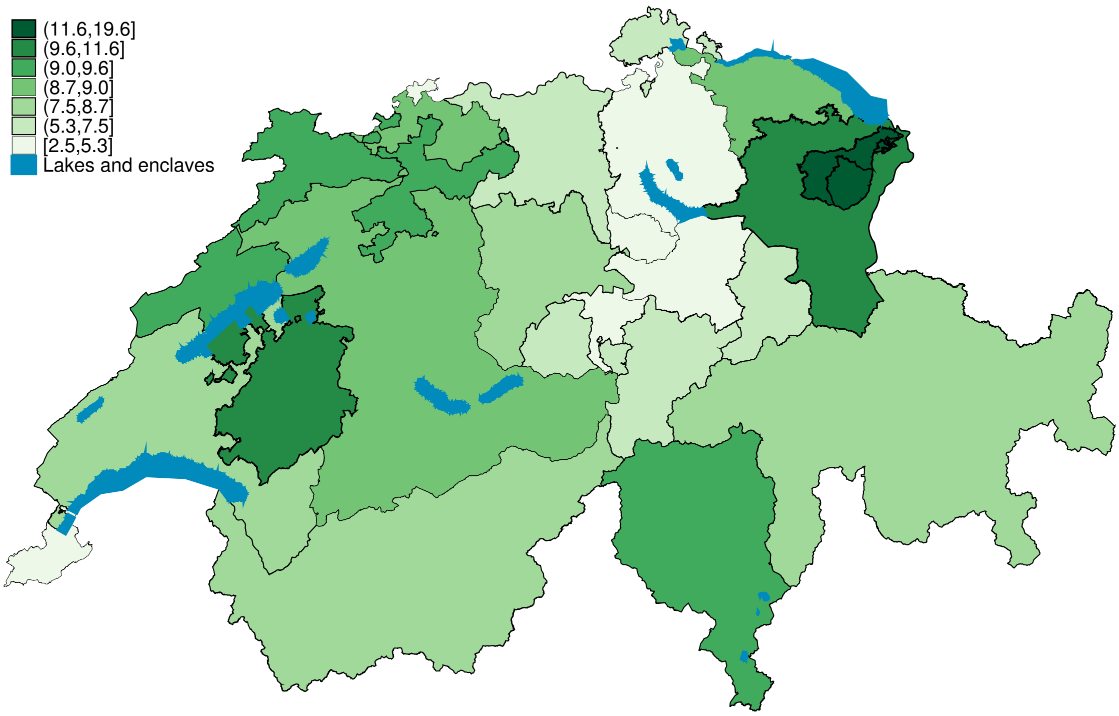
For the analysis of social contagion, however, the registration date is more appropriate than the installation date. Indeed, we are trying to determine whether existing PV installations have triggered new adoptions. In this case, the registration date makes sense since it best approximates the date at which an owner made her decision to adopt.

Individual-level PV data are then aggregated at the municipality-year level to obtain the number of PV adoptions, and the corresponding installed capacity, per municipality and per year. Aggregate adoption at the municipality level is normalized by population, which comes from the Swiss Federal Statistical Office. Table A.1 in the Appendix provides summary statistics for the different measures of solar adoption that we obtain from the SFOE data. In the following sections, we describe how we use these variables as outcomes in our empirical analyses. Additionally, Figure 2 illustrates the geographical variation in the adoption of solar installations that we observe in Switzerland. In particular, Figure 2 shows a map with the total number of completed PV installations per 1,000 inhabitants in all the cantons, as of December 31, 2017. The density of solar adoption varies considerably across cantons. With less than 4 installations per 1,000 inhabitants, the three urban cantons of Geneva, Basel and Zurich and have the lowest density of solar PV. Density is much higher in rural cantons. Comparing two cantons located relatively close to each other, Appenzell Innerrhoden (mostly rural) and Zurich (mostly urban), we observe a sixfold difference in adoption per 1,000 inhabitants.

Cantonal incentives for PV

Our empirical exercise consists in evaluating the effect of cantonal policies on the adoption of solar PV, in neighboring cantons. However, there is no official register, in Switzerland, for all cantonal policies promoting the adoption of solar PV. While some private actors in the Swiss solar market, such as the umbrella organization Swissolar, maintain their own data, these tend to be incomplete and insufficiently detailed for the type of analysis that we undertake in this study. Hence, we collected these data

Figure 2: Number of PV installations per 1,000 inhabitants in the cantons



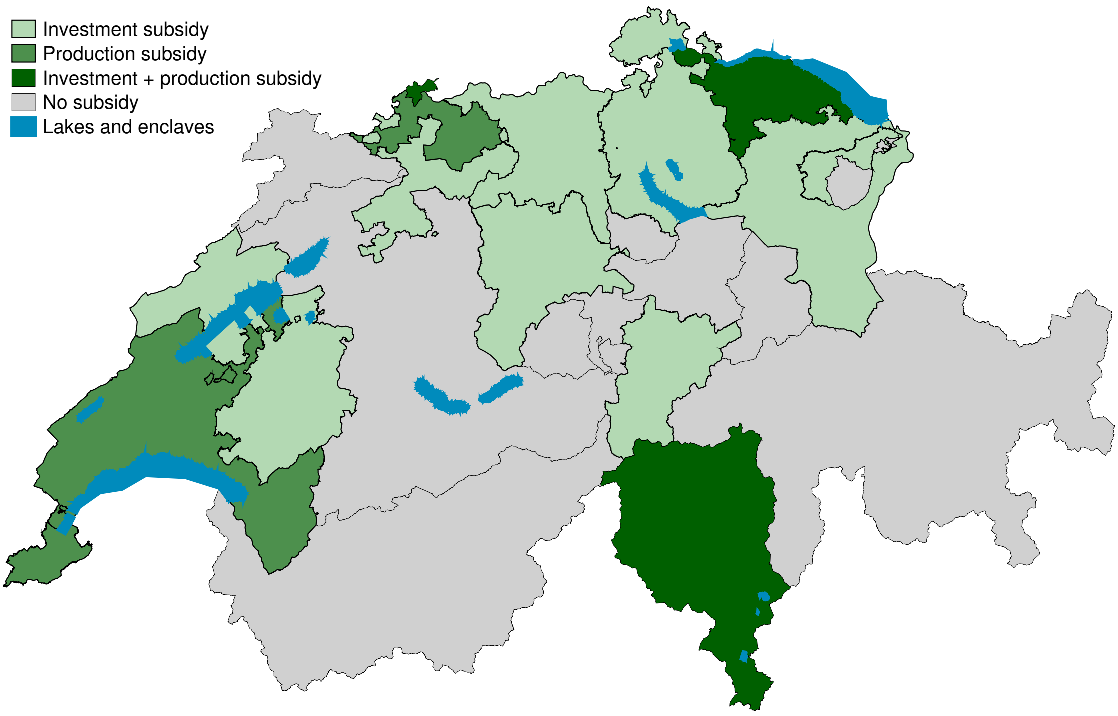
Note: This map shows the total number of completed PV installations per 1,000 inhabitants across cantons, as of December 31, 2017. Sources: Swiss Federal Office of Energy (SFOE), Swiss Federal Statistical Office (FSO) and swissBOUNDARIES3D 2018, Swiss Federal Office of Topography (swisstopo).

ourselves, essentially building a database of policies promoting the adoption of solar PV at the cantonal level for all 26 cantons over the period 2006-2017.

We collected the data as follows. We first contacted the administrative officials in charge of energy policy in all 26 cantons. Officials were asked to fill an online survey, collecting information about subsidies of any type to solar owners as well as tax deductions, among others. In case of a positive response, officials were asked to specify the period over which the policy was in place and eligibility criteria, among other questions. We then matched the information provided in the survey with cantonal laws, ordinances, and regulations and, where needed, asked the administrative officials for additional details. In this way, we were able to build an extensive, if not exhaustive, panel dataset of cantonal policies promoting solar PV. In the panel, a given policy takes value 1 in a given canton if in effect for at least 6 months over that particular year. In the large majority of cases, however, policies are implemented on January 1st and terminated, if ever, on December 31st.

Table 1 provides an overview of the policies used by cantons to support the adoption of solar PV. We also provide a visualization of PV incentives implemented over the entire observation period on a map of Swiss cantons in Figure 3.

Figure 3: Financial incentives for PV in the cantons



Note: This map shows the PV subsidies implemented by the Swiss cantons between 2006 and 2017. Sources: Own data and swissBOUNDARIES3D 2018, Swiss Federal Office of Topography (swisstopo).

Investment subsidies In what follows, we shortly describe the main policies used by cantons. These are one-off investment subsidies and production-based subsidies.[6] We start with one-off investment subsidies, i.e. the subnational equivalent of the OIG. The most common non-fiscal instruments used by the cantons are capacity-based investment subsidies. Capacity is measured in kWp and the payment is realized shortly after the installation is completed. Based on our data, we observe that subsidies vary across cantons across four dimensions. First, when they were implemented and how long they lasted. Second, the magnitude of the subsidy. Third, the subsidy cap, which can be either a relative cap in proportion to the cost of the installation (e.g. 30%) or an absolute cap on the total amount to be transferred, which can also be interpreted as the overall capacity at which the marginal subsidy becomes zero. Fourth, the type of installation, although many cantonal schemes do

[6]Swiss cantons have also offered tax deductions. In the Swiss federal system, the largest portion of income taxes is due to the canton where a person resides. Similar to federal tax credits in the United States, almost all Swiss cantons soon or later decided to make investments in solar energy tax deductible (the two exceptions being the cantons of Grisons and Lucerne). Given the low variation in this policy instrument, we refrain from analyzing it in our context. Cantons also implemented a wide range of communication campaigns, which however fall beyond the scope of this paper.

not distinguish between building-attached, building-integrated, or ground-mounted installations.

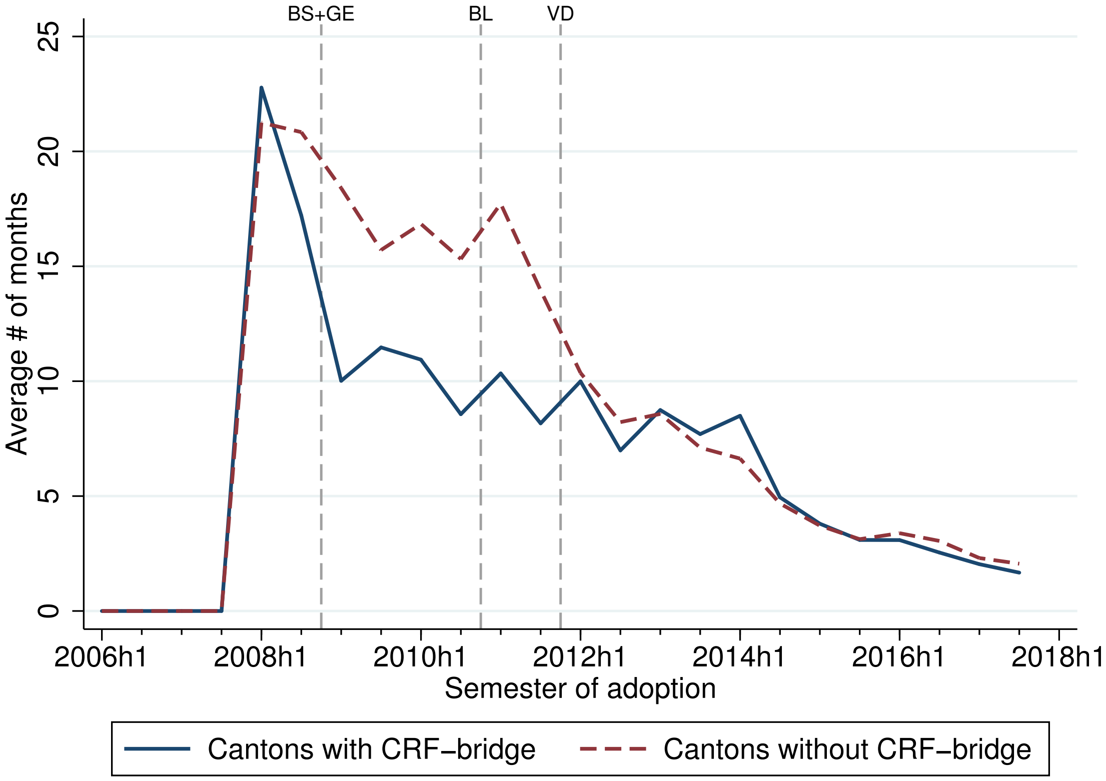
As shown in Table 1 and Figure 3, half of the cantons (13 out of 26) have introduced an investment subsidy at some point since 2006. Before the introduction of the federal FIT in 2008, only two cantons, Fribourg and Ticino, offered a capacity-based investment subsidy. The number of cantons offering investment grants reached its peak in 2009, probably in response to the growing waiting times for the federal CRF, and also as part of small-sized "Green New Deals" aimed at stimulating consumption in reaction to the 2007-2008 financial crisis. We observe in Table 1 that several programs ended in 2013 and 2014, following the introduction of a new federal investment subsidy for solar PV on January 1, 2014.

Production subsidies The second type of subsidies covered in this study are production-based subsidies, i.e. the subnational equivalent of the CRF. Most of these cantonal programs are in the form of a "bridge" for the federal CRF scheme. Under the CRF, the countdown for the 20-year period starts from the date of completion, but the subsidy stream is provided only from the moment that the installation leaves the waiting list. Hence, the longer the period between completion and actual treatment of the subsidy request, the shorter the period through which the subsidy can be enjoyed, and hence the lower the overall subsidy. In presence of a waiting list, the CRF creates an incentive to register the intent to install solar as soon as possible, but also to postpone completion as much as possible. Cantonal schemes providing a bridge for the federal CRF scheme are aimed at correcting the incentive to delay completion. By doing so, cantonal production-based subsidies not only anticipate the completion of installations, but also increase the expected overall subsidy amount, thus stimulating adoption.

As Table 1 indicates, four Swiss cantons have implemented CRF bridges (marked with the letter *c*). The first cantons to introduce such an instrument are the urban cantons of Geneva and Basel-Stadt, in the beginning of 2009. The canton of Basel-Landschaft introduced a similar program in 2011, followed by the canton of Vaud in 2012. In Basel-Landschaft and Basel-Stadt, the fixed injection tariff is exactly the same as the one offered at the Federal level. The tariff in the cantons of Geneva and Vaud is 90% of the CRF tariff, the stated reason being the more favorable sunshine conditions in those cantons compared to the rest of Switzerland.

Figure 4 displays the average duration between the registration of the PV installation to a federal subsidy and its connection to the electricity grid, which reveals the expected impact of the the bridge programs. From 2008 to 2012, installations in the four cantons that implemented a CRF bridge are completed about 5 months earlier than the installations in the cantons without CRF bridge. After 2012, when it became clear that new applicants would never benefit from the CRF, the average duration between the two groups of cantons converges again.

Figure 4: Duration between registration and completion dates, by semester of adoption



Besides the CRF bridges, the cantons of Basel-Landschaft, Ticino, and Thurgau have implemented other forms of production-based incentives for PV. These programs have been introduced either before the implementation of the federal CRF, or once it was no longer possible for new PV installations to benefit from it. Basel-Landschaft passed a law in 2004 requiring utilities to remunerate electricity produced from solar energy at 90 cents per kWh over a period of 20 years. The policy was in force between 2005 and 2010. Ticino introduced its cantonal FIT in 2014, to compensate for the de facto end of the federal CRF. Under the scheme implemented in Ticino, solar owners can apply for both the cantonal FIT and the federal OIG.

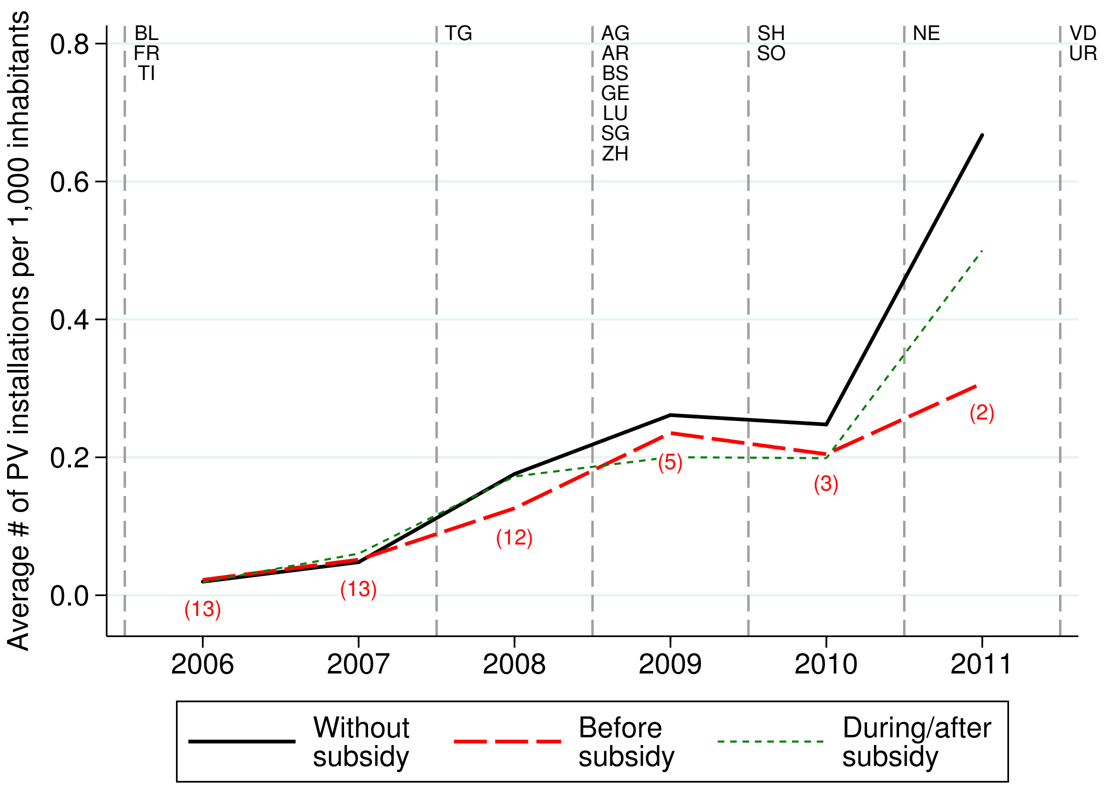
Control variables

Besides financial incentives, many contextual and population characteristics may explain the deployment of solar technology at the local level. To take into account the spatial and temporal heterogeneity of these factors, we use in our empirical analyses a wide range of control variables. We collected the data from different sources to construct a balanced panel dataset containing information for 2,222 municipalities over 12 years. All control variables that we include in the regressions are summarized in Table A.1 in the Appendix, which also lists the data sources. Further details on these variables and explanations of why they are included in our estimates can be found in Baranzini et al. (2017a).

3.3 Identification

The approach we use to determine the direct impact of subsidies, as illustrated in Equation (1), is a differences-in-differences estimation. For the effect we capture through the β and γ coefficients to be attributable to the financial incentives, it is thus necessary that the effects of any unobserved factors at the canton-level remain constant over time and be common across groups of cantons. We test the assumption of parallel trends prior to the introduction of subsidies in Figure 5. The average adoption rate is plotted for the group of cantons without subsidies (black line) and for the group of cantons with subsidies before the implementation of the subsidy (red line), focusing on the period 2006-2011 because all subsidies were introduced before 2012. This graphical inspection confirms that the adoption rate follows a parallel trend. Further, we also observe that the level of adoption is very similar between the two groups, suggesting that political decisions to implement subsidies are not, or only marginally, dependent on the existing penetration rate of solar energy.

Figure 5: Pre-trends: annual PV installation rate in the cantons



Note: The black line represents the 10 cantons that never introduced any subsidy over 2010-2017 (AI, BE, GL, GR, JU, NW, OW, SZ, VS and ZG). The other 16 cantons are represented by the red long dotted line before the introduction of the subsidy and by the green short dotted line during or after the introduction of the subsidy. The numbers in parentheses indicate the number of cantons that have not yet introduced a subsidy, and therefore included in the red line. The vertical bars indicate the cantons that are introducing a subsidy, and therefore the time at which a canton switches from the red line to the green line.

Table 1: Summary of financial incentives for PV, by canton and year.

Incentive	Canton	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Investment subsidy	AG				•								
	AI												
	AR				•	•	•	•	•				
	BE												
	BL												
	BS				•[b]	•[b]	•[b]	•[b]	•[b]	•[b]	•[b]	•[b]	•[b]
	FR	•[a]	•[a]		•								
	GE												
	GL												
	GR												
	JU												
	LU				•								
	NE						•[a]	•[a]	•[a]				
	NW												
	OW												
	SG				•[b]								
	SH					•	•		•	•			
	SO					•[a]	•[a]	•[a]	•				
	SZ												
	TG				•	•	•	•	•	•	•	•	•
	TI	•[a]	•[a]	•[a]	•[a]					•[b]	•[b]	•[b]	•[b]
	UR							•[a]	•[a]	•[a]	•[a]	•[a]	•[a]
	VD												
	VS												
	ZG												
	ZH				•[a]	•[a]	•[a]						
Production subsidy	AG												
	AI												
	AR												
	BE												
	BL	•	•	•	•	•	•[c]	•[c]	•[c]	•[c]	•[c]	•[c]	
	BS				•[c]	•[c]	•[c]	•[c]	•[c]	•[c]	•[c]	•[c]	•[c]
	FR												
	GE				•[c]	•[c]	•[c]	•[c]	•[c]	•[c]	•[c]	•[c]	•[c]
	GL												
	GR												
	JU												
	LU												
	NE												
	NW												
	OW												
	SG												
	SH												
	SO												
	SZ												
	TG			•									
	TI									•	•	•	•
	UR												
	VD							•[c]	•[c]	•[c]	•[c]	•[c]	•[c]
	VS												
	ZG												
	ZH												

Note: [a] indicate cantonal investment subsidies that may be combined with federal schemes (CRF or OIG).
[b] Cantonal investment subsidy must be fully or partially repaid if the PV owner benefits from federal incentives.
[c] Production subsidy is a CRF bridge.

4 Empirical results

4.1 Within jurisdictions

We begin our analysis of the impact of subsidies by exploring their relationship with PV adoption within the territory in which they are implemented. Table 2 shows the results for different specifications of Equation (1). Columns 1 to 3 investigate the impact of the subsidies on the number of PV installations. The dependent variable in column 1, which reports the results of the OLS model, is the number of new PV systems per 1,000 inhabitants by municipality and by year. The coefficients for the two variables indicating the presence of subsidies at the cantonal level are positive and highly significant. We find that the annual installation rate in municipalities located in cantons offering a production subsidy (an investment subsidy) is, on average, 0.589 (0.214) higher than in other municipalities. These estimates can be compared with the average adoption rate over all municipalities and years, which is 1.44 PV installations per 1,000 inhabitants. According to model 1, production subsidies are correlated with higher adoption than investment subsidies.

The positive impact of subsidies appears also when using as outcome variable the total number of installations in a municipality at time t (columns 2 and 3). To account for the count character of the dependent variable, we estimate the models using a Poisson model (in column 2) and a negative binomial model (in column 3). In these specifications, population is used as a control variable.[7]

In columns 4 to 6 of Table 2, we use installed capacity per 1,000 inhabitants as outcome variable. With this outcome variable, we observe that the coefficients are a bit noisier, so that only the coefficient for the investment subsidy is significant at the 10% level in column 4 of Table 2. As described, cantonal subsidies mainly target small size PV installations. Therefore, in columns 5 and 6 we remove from the estimations solar installations exceeding peak capacity of 10 kW. With this adjustment, noise is reduced and both coefficients are more precisely estimated. On average, among installations of less than 10 kW, an extra 3.9 kW (0.8 kW) of peak capacity is installed for every 1,000 inhabitants and per year in municipalities that offer production-based (investment-based) subsidies compared to municipalities that do not. When the adjustment is removed, as shown in column 6 with the total

[7]Poisson and negative binomial fixed effect models cannot be estimated with municipalities for which the dependent variable does not change over time. We therefore exclude 47 municipalities out of 2,222 from regressions 2 and 3 because no solar PV panels were installed in these municipalities by the end of 2015. Our results remain unaffected if these 47 municipalities were also excluded from OLS models in columns 1, 4, 5, and 6.

installed capacity in levels as outcome variable, the effect of the production subsidies is no longer statistically significant.

Table 2: Effects of production and investment subsidies within the jurisdictions

	Number of installations			Installed capacity (kWp)		
					<10 kWp adopt.	
	Rate OLS (1)	Number Poisson (2)	Number NB (3)	Rate OLS (4)	Rate OLS (5)	Number OLS (6)
Production subsidy	0.589^{***}	0.271^{***}	0.197^{***}	9.406	3.885^{***}	2.693^{***}
	(0.071)	(0.043)	(0.034)	(6.651)	(0.363)	(0.857)
Investment subsidy	0.214^{***}	0.205^{***}	0.212^{***}	4.286^{*}	0.776^{***}	1.612^{***}
	(0.036)	(0.045)	(0.027)	(2.419)	(0.166)	(0.329)
Population						0.007^{**}
						(0.003)
ln(Population)		3.291^{***}	0.357^{***}			
		(0.376)	(0.034)			
Density (population/ha)	-0.429^{***}	-0.048	-0.021^{***}	-8.988^{***}	-1.616^{***}	-1.019
	(0.039)	(0.030)	(0.003)	(1.366)	(0.146)	(1.563)
Pop. aged 30-44 (%)	0.018	-0.016	-0.024^{***}	1.109	-0.102	-0.145
	(0.022)	(0.013)	(0.009)	(0.781)	(0.083)	(0.109)
Pop. aged 45-64 (%)	0.017	0.042^{***}	0.007	3.101^{**}	-0.134^{*}	-0.324^{***}
	(0.021)	(0.013)	(0.008)	(1.503)	(0.077)	(0.095)
Pop. aged >65 (%)	-0.009	-0.019	-0.035^{***}	-0.228	-0.074	-0.317^{***}
	(0.025)	(0.014)	(0.007)	(0.881)	(0.095)	(0.117)
Tax payers with income CHF 15-29.9k (%)	0.035	0.016	0.007	-0.593	0.175^{*}	-0.114
	(0.036)	(0.016)	(0.009)	(1.524)	(0.106)	(0.119)
Tax payers with income CHF 30-49.9k (%)	0.016	0.002	-0.002	-0.976	0.139	-0.212^{*}
	(0.030)	(0.015)	(0.007)	(1.534)	(0.102)	(0.116)
Tax payers with income CHF 50-74.9k (%)	0.008	-0.017	-0.018^{**}	-1.368	0.067	-0.297^{**}
	(0.029)	(0.015)	(0.007)	(2.173)	(0.108)	(0.117)
Tax payers with income CHF >75k (%)	0.033	-0.022	-0.010	-0.911	0.147	-0.405^{***}
	(0.027)	(0.016)	(0.007)	(1.607)	(0.101)	(0.122)
Green parties share (%)	0.010	0.002	0.005	1.154^{*}	0.032	0.086^{*}
	(0.007)	(0.005)	(0.003)	(0.591)	(0.029)	(0.049)
Apartment buildings (%)	0.007	-0.009	-0.000	1.141^{**}	-0.003	0.078
	(0.010)	(0.010)	(0.004)	(0.520)	(0.046)	(0.087)
Buildings with apart. and other use (%)	-0.072^{***}	-0.002	0.002	-0.285	-0.106	0.792^{***}
	(0.021)	(0.012)	(0.004)	(1.041)	(0.081)	(0.175)
Commercial/industrial buildings (%)	-0.012	-0.011	-0.017^{**}	-0.250	0.038	0.040
	(0.018)	(0.010)	(0.007)	(0.587)	(0.081)	(0.146)
Average # of rooms per dwelling	0.294	0.720^{***}	0.223	16.256	2.150	-4.661
	(0.354)	(0.253)	(0.143)	(15.839)	(1.698)	(5.123)
Average area per dwelling (sqm)	-0.011	-0.034^{***}	-0.010^{**}	-0.464	-0.048	-0.253^{**}
	(0.011)	(0.007)	(0.004)	(0.762)	(0.050)	(0.126)
Solar irradiance (in W/sqm)	-0.000	-0.002	-0.006^{**}	-0.020	-0.001	-0.104^{**}
	(0.006)	(0.004)	(0.003)	(0.275)	(0.024)	(0.044)
Constant	-0.239		-2.114^{*}	-17.032	-1.414	73.661^{***}
	(3.748)		(1.114)	(152.024)	(13.594)	(23.015)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	26,664	26,100	26,100	26,664	26,664	26,664
R^2	0.2162			0.0272	0.1645	0.2395

Note: Standard errors in parentheses, clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Our results are robust to several changes in the baseline model. Table A.2 in the

Appendix reports the results for a set of alternative specifications, including lagged adoption variables, clustering of standard errors at the cantonal level, and fixed effects covering the territory of the local utilities , interacted with year fixed effects. In column 1, we show with our baseline specification that investment and production subsidies, when combined into a single dummy variable, generate an average of 0.35 additional installations per 1,000 inhabitants and per year. In the specification of column 2, we add a variable for the number of PV installations in the previous year. Such control may help to capture the residual effect of any unobserved factors affecting the adoption rate that is already captured by the space and time fixed effects. In column 3, we group standard errors at the level at which grants are issued to control for any potential serial correlation. Finally, in columns 4 and 5, we capture the space- and time-varying differences among the 543 distribution system operators (DSO) active in Switzerland instead of the spacial differences among municipalities.[8] For all these alternative specifications, the coefficients for the impact of subsidies remain fairly stable and statistically significant at a level of at least 5%.

4.2 Across jurisdictions

In the previous section, we provide evidence that the penetration rate of solar energy is higher where and when cantonal subsidies are available. In this section, we analyze whether the adoption rate is also higher in regions adjacent to the cantons offering subsidies. Our hypothesis is that the higher number of installations in subsidized cantons may generate localized cross-boundary effects, which could lead to a higher level of adoption even beyond the territory in which the subsidy is applied, but only up to a given distance.

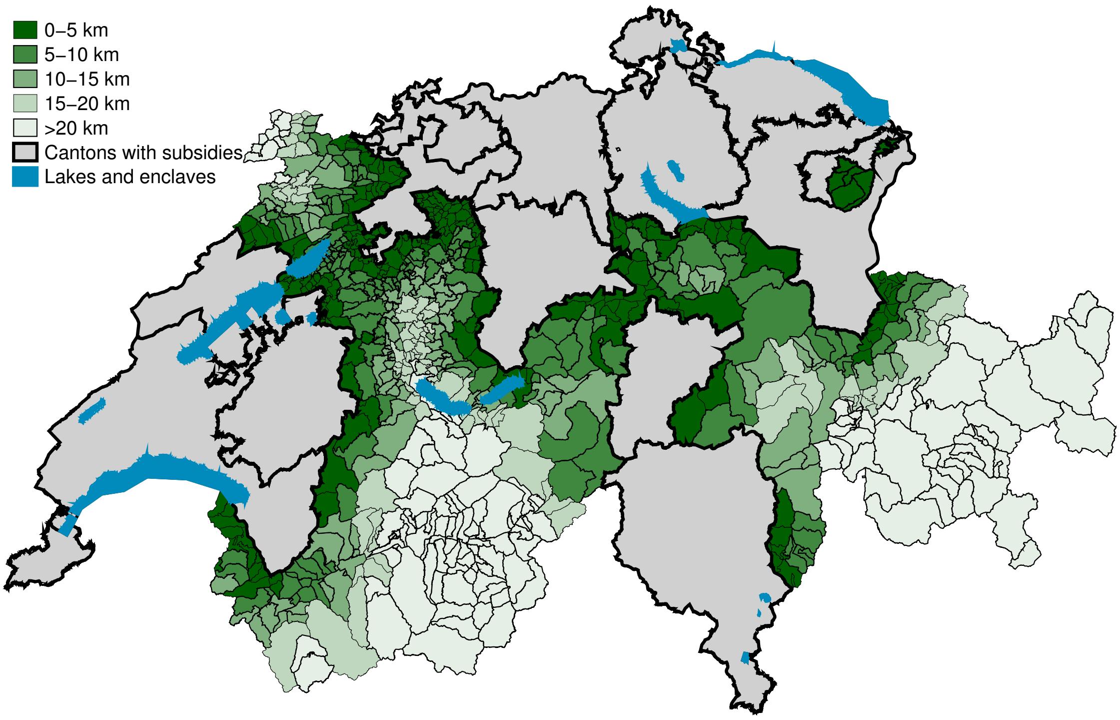
Figure 6 illustrates our distance variable, omitting the time dimension for readability, for all municipalities in the cantons that have never subsidized PV. The cantons that have implemented a financial incentive at some point between 2006 and 2017 are displayed in grey. Municipalities that were at least once adjacent to a canton with a subsidy between 2006 and 2017 are represented in dark green, and the others in light green.

The closer a municipality in a canton without a subsidy is to a canton with a subsidy, the more its level of adoption could be influenced by cross-boundary effects. Figure 7 represents the average number of adoptions per 1,000 inhabitants for municipalities that are located within and beyond 5 km from the closest canton

[8] We use the DSO coverage areas for the year 2017. When more than one DSO operate in a municipality, only the DSO with activities in the largest number of municipalities is selected.

implementing financial incentives for PV, for each year from 2006 to 2017. We observe that the adoption rate is higher in the closest municipalities than in the more distant municipalities for 8 of the 12 years in the period of analysis. Following this initial evidence, we turn to our main model.

Figure 6: Distance to cantons with financial incentives for PV

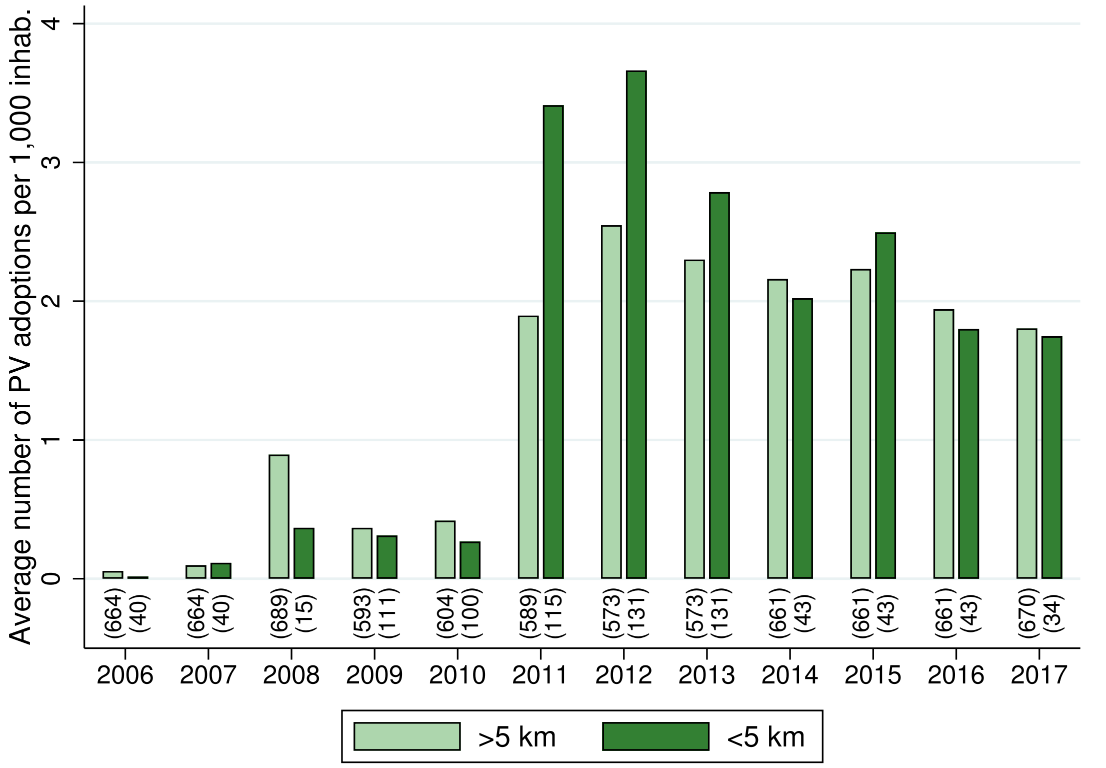


Note: Grey areas correspond to the cantons that have implemented a subsidy for PV between 2006 and 2017. Green shaded areas represent the distance between the municipalities located in cantons that have never implemented financial incentives for PV during this period and the closest canton that has implemented subsidies. Sources: own computations based on GEOSTAT 2018, Swiss Federal Statistical Office (FSO) and swissBOUNDARIES3D 2018, Swiss Federal Office of Topography (swisstopo).

We start the analysis on potential cross-border effects of subsidies by using a simplified version of Equation (2). Instead of using a cutoff distance to define which municipalities are treated and which are not, we simply define the treatment group as all municipalities in cantons without subsidies that are adjacent to cantons with subsidies.[9] Table 3 reports the results. Column 1 shows that municipalities sharing a border with a canton offering a subsidy experience, on average, 0.467 more PV adoptions per 1,000 inhabitants and per year than other, non-adjacent municipalities.

[9]The average (median) distance between the centers of the adjacent municipalities and the nearest canton implementing a subsidy is 2.9 km (2.0 km). The most distant center among the adjacent municipalities is 16.9 km away from the border.

Figure 7: PV adoption rate within 5 km vs. beyond 5km from the closest canton financial incentives for PV, by year



Note: This figure includes 704 municipalities in the cantons that have never subsidized PV. Municipalities are separated between those that are located within or beyond 5 km from the closest canton implementing a financial subsidy for PV. Numbers in parentheses represent the number of municipalities in each group. Source: own calculations based on PV installations data provided by the Swiss Federal Office of Energy (SFOE).

In column 1, we include in the treatment group only the municipalities that are adjacent to a canton with a subsidy. However, spillover effects could still be at work even after the subsidy is discontinued. We test whether this is actually the case in columns 2 to 4 of Table 3. Column 2 shows the results when adding a treatment variable for the first year that follows the end of the subsidy. Column 3 further adds an additional processing variable, specific to the second year after the end of the subsidies, while column 4 considers all subsequent years in a single variable. In column 1, we find a positive and statistically significant cross-border effect during the year that follows the discontinuation of the subsidy. This persistence over time is consistent with the effects of social contagion, as subsidized PV systems in neighboring cantons continue to generate spillovers after their installations. Further, such effects decays with time. While the coefficient for the post-subsidy period is already lower in the first year following the subsidy, column 3 shows that it is further halved in the second year (and is no longer statistically significant). This decrease over time is also consistent with the literature on social contagion in the adoption of solar energy (Graziano and Gillingham, 2015; Baranzini et al., 2017a).

Indeed, the coefficient becomes smaller, and less significant, when we consider municipalities to be treated even if the canton to which they are adjacent has abandoned its subsidy several years earlier.

Table 3: Cross-border effects of financial incentives for PV

	(1)	(2)	(3)	(4)
Adjacent	0.467^{***}	0.522^{***}	0.553^{***}	0.487^{***}
	(0.147)	(0.155)	(0.158)	(0.152)
Adjacent [1st following year]		0.390^{**}	0.420^{**}	
		(0.194)	(0.187)	
Adjacent [2nd following year]			0.235	
			(0.221)	
Adjacent [all following years]				0.044
				(0.149)
Constant	−8.894	−8.708	−8.668	−8.896
	(6.903)	(6.907)	(6.898)	(6.903)
Controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
# Observations	8,448	8,448	8,448	8,448
R^2	0.1638	0.1642	0.1643	0.1638

Note: All models are estimated using OLS regressions. Dependent variables are the number of PV adoptions per 1,000 inhabitants, by municipality and by year. Standard errors in parentheses, clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

We then turn to heterogeneous effects as a function of distance between the municipalities in canton j and the boundary with canton i. In Table 4 we observe that the magnitude of cross-boundary effects decay with distance. This finding is also consistent with social contagion effects.

In Table 4, we estimate heterogeneous effects in two ways. First, we divide the sample in different ways, using cutoff distances of 5, 10, 15, and 20 km when defining treatment and control groups, and the standard specification described by Equation (2).[10] On average, municipalities located within 5 km from subsidized

[10]Outlier municipalities, i.e. those located very far away from all boundaries, are removed

cantons experience 0.9 more PV adoptions per 1,000 inhabitants by year than more distant municipalities. When extending the treatment group to more distant municipalities, as we do in columns 2 to 4, the magnitude of the coefficient shrinks. Second, we augment Equation (2) with an interaction term between the treatment group and the distance. The coefficients for the interaction term reveal that, within the treatment group, it is for the municipalities that are the closest to the border that we observe the largest adoption. The coefficient in column 1 indicates that each additional kilometer away from the subsidized cantons is associated to 0.2 fewer PV adoptions per 1,000 inhabitants per municipality and per year. In columns 2 to 4, this coefficient decreases as the cut-off distance is extended, which also reflects a decreasing effect of the distance.

Heterogeneous effects can also be combined with the discontinuation of subsidies. We do so in Table A.4 in the Appendix. We apply the same procedure as in Table 3, which consists in adding a treatment variable for the year that follows the discontinuation of the financial incentive. Both sets of findings, that effects on adoption can be found even after discontinuation and that cross-boundary effects decrease with distance, are confirmed in A.4, in which they can be seen in conjunction.

from the estimations in Table 4. Including these observations would not affect, qualitatively and quantitatively, our results.

Table 4: Heterogeneous cross-border effects of financial incentives for PV

	(1) <5 km	(2) <10 km	(3) <15 km	(4) <20 km	(5) All
Distance × Treated	-0.213^{**}	-0.095^{***}	-0.036^{**}	-0.029^{***}	-0.007^{***}
	(0.101)	(0.030)	(0.017)	(0.009)	(0.002)
Treated	0.934^{***}	0.645^{***}	0.472^{***}	0.438^{***}	
	(0.334)	(0.204)	(0.173)	(0.160)	
Distance	−0.002	-0.004^{*}	−0.002	−0.002	
	(0.003)	(0.002)	(0.002)	(0.002)	
Constant	−14.964	−1.395	−9.214	−6.016	−8.242
	(16.611)	(10.930)	(11.028)	(8.587)	(6.878)
Controls	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
# Observations	2,616	4,440	5,796	6,876	8,448
R^2	0.2347	0.2120	0.1888	0.1923	0.1641

Note: Standard errors in parentheses, clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

5 Conclusions

Subsidies for renewable energy are among the most widely used instruments of climate policy. In recent times, they have come under particular scrutiny, as political attention around their costs has increased and sufficient data to perform policy evaluation exercises has become available. Such exercises have so far focused on the jurisdiction in which the subsidy was implemented, and the period in which it was in force. Two implicit assumptions underlie this approach. First, that subsidies for renewable energy only have an effect in the jurisdiction in which they are implemented, and that their effects end once the policy is discontinued.

With this paper, we challenge both assumptions. First, we show that subsidies for solar energy are associated to higher adoption also in adjacent areas of neighboring jurisdictions, a pattern consistent with social contagion, compared to areas located further away. Second, we show that, compared to control areas, subsidies are associated to higher adoption even after they are discontinued, another pattern consistent with social contagion.

This paper exploits the unique setting of Switzerland, whose fiscal federalism consistently provides important variation in policymaking across jurisdictions. It uses a unique database covering the main instruments implemented by Swiss cantons between 2016 and 2017 to promote the adoption of renewable energy, focusing in particular on production-based subsidies (feed-in tariffs) and capacity-based subsidies (one-off investment grants). These cantonal policies complement the federal subsidy schemes, which cover all cantons in exactly the same way.

In our empirical analyses, we proceed in two stages. First, we evaluate, similarly to the existing literature, the effect of a subsidy of either type on adoption in the same canton in which it was implemented. Second, we extend the analyses to our original research question, and analyze spillover effects in both space and time. When looking at spillover effects in space, we do not focus on the jurisdictions that implemented a subsidy, but on their neighboring jurisdictions. Within the latter, we compare between areas adjacent to the jurisdictions with the subsidy, and areas located further away. Our data consist of more than 80,000 solar PV adoptions, of which approximately 60,000 were completed between 2006 and 2017. Among the completed installations, about one-third are located in a canton offering a subsidy at the time of completion.

We find evidence that these cantonal subsidies are associated with higher adoption of solar energy in the very same jurisdiction in which they are implemented, both in terms of the number of installations and in terms of capacity. Our estimates indicate that the annual number of completed PV systems per 1,000 inhabitants is, on average, 0.35 higher in cantons offering subsidies than in those that do not. This figure represents an increase of about 25% compared to the Swiss average adoption rate over the period 2006-2017. Although this increase may seem substantial, other studies reveal even higher effects. Based on a counterfactual analysis, Hughes and Podolefsky (2015) found that about 53% fewer residential PV installations would have occurred in California in the absence of a state-wide upfront subsidy program. By analyzing several investment subsidy programs in the Northeast of the United States, Crago and Chernyakhovskiy (2017) estimate that a rebate increase of $1,000 per kWp would increase the number of annual installations by 47%.

Most importantly, we find evidence suggesting that cantonal subsidies may bring about adoption of solar energy even in other jurisdictions, which never introduced such measures. In line with our predictions, these effects take place in areas adjacent to the jurisdictions having implemented a subsidy. Our results indicate that municipalities that are adjacent to the cantons implementing subsidies experience a significantly higher adoption rate than more distant municipalities. We find that municipalities located within 10 km from the border of subsidized cantons have 0.6 more adoptions per 1,000 inhabitants by year compared with more distant municipalities, with the number of installations decreasing by 0.1 for each additional km from the cantonal border. We also show that such effects persist even after the subsidy has ceased in the nearby cantons, although effects decay over time. These results are consistent with social contagion effects.

Our findings suggest that the current assessments may underestimate the cost-effectiveness of policies promoting the adoption of renewable energy. While these assessments generally take into account the value of reducing greenhouse gas emissions, a global public good provision, they do not account for greenhouse gas emissions reduced in adjacent jurisdictions or after discontinuation. Importantly, our findings do not change the ranking among climate policy instruments. Absent any evidence in this direction, there is no reason to believe that subsidies for renewable energy would create stronger cross-boundary effects than carbon pricing. However, they do change our understanding of the cost of climate policy. Further, they point to the largely untapped potential of policies promoting social contagion, within and across jurisdictions, which could further reduce the cost of implementing climate policy. Finally, they point to the need for several assessments, at different points in time, to account for effects arising after the policy is discontinued.

Appendix

Table A.1: Summary statistics

Variables	Mean	Std. Dev.	Min.	Max.	*N*	Source
Dependent variables						
Number of PV installations	2.287	4.56	0.00	85.00	26,664	SFOE
Number of PV installations per 1,000 inhab.	1.075	2.05	0.00	60.61	26,664	SFOE
Installed capacity	57.189	188.87	0.00	8,307.63	26,664	SFOE
Installed capacity per 1,000 inhab.	26.113	152.66	0.00	16,615.26	26,664	SFOE
Installed capacity, <10 kWp	8.154	18.54	0.00	439.23	26,664	SFOE
Installed capacity per 1,000 inhab., <10 kWp	3.777	8.67	0.00	218.10	26,664	SFOE
Number of PV adoptions	2.630	4.75	0.00	58.00	8,448	SFOE
Number of PV adoptions per 1,000 inhab.	1.435	2.65	0.00	47.62	8,448	SFOE
Main independent variables						
Production subsidy	0.141	0.35	0.00	1.00	26,664	
Investment subsidy	0.142	0.35	0.00	1.00	26,664	
Adjacent	0.077	0.27	0.00	1.00	8,448	
Adjacent [+1 year]	0.097	0.30	0.00	1.00	8,448	
Adjacent [lasting]	0.176	0.38	0.00	1.00	8,448	
Treated (<20 km)	0.376	0.48	0.00	1.00	8,448	
Treated (<20 km) [+1 year]	0.451	0.50	0.00	1.00	8,448	
Treated (<20 km) [lasting]	0.647	0.48	0.00	1.00	8,448	
Distance (km)	32.446	26.34	0.11	152.61	8,448	
Controls						
Population	3,602.450	11,738.96	12.00	409,241.00	26,664	FSO
Density (population/ha)	4.018	7.34	0.01	125.97	26,664	swisstopo
Pop. aged 30-44 (%)	20.249	3.12	0.00	44.03	26,664	FSO
Pop. aged 45-64 (%)	29.493	3.46	4.24	56.25	26,664	FSO
Pop. aged >65 (%)	16.990	4.39	0.00	75.00	26,664	FSO
Tax payers with income CHF 15-29.9k (%)	13.207	4.46	0.00	72.62	26,664	FTA
Tax payers with income CHF 30-49.9k (%)	29.102	7.34	0.00	66.67	26,664	FTA
Tax payers with income CHF 50-74.9k (%)	27.111	4.41	0.00	50.00	26,664	FTA
Tax payers with income CHF >75k (%)	28.199	11.50	0.00	72.00	26,664	FTA
Green parties share (%)	10.134	5.57	0.00	72.22	26,664	FSO
Detached houses (%)	59.985	13.83	0.00	99.18	26,664	FSO (BDS)
Apartment buildings (%)	21.317	10.40	0.00	100.00	26,664	FSO (BDS)
Buildings with apart. and other use (%)	13.996	9.60	0.00	85.71	26,664	FSO (BDS)
Commercial/industrial buildings (%)	4.702	3.04	0.00	33.83	26,664	FSO (BDS)
Average # of rooms per dwelling	4.103	0.43	2.15	5.93	26,664	FSO (BDS)
Average area per dwelling (sqm)	111.837	16.15	50.96	185.12	26,664	FSO (BDS)
Solar irradiance (in W/sqm)	145.788	9.64	121.30	190.45	26,664	MeteoSwiss

Note: All variables vary by municipality and by year, except production and investment subsidy that vary by canton and by year.
Summary statistics are computed over all years (2006 to 2017) and all municipalities (2,222), except for variables that are used only in estimations of cross-border effects, which are computed over the 704 municipalities that are located in cantons that have never implemented any subsidy over the years 2006 to 2017.
Given the presence of missing values, data for age have been linearly extrapolated for the years 2006 to 2009, income data for the year 2017, and building and dwelling data for the years 2006 to 2008. Green voting has been linearly interpolated for the years in between two elections, which take place every four years (last in 2015), and lineraly predicted for 2016 and 2017.
When the source of the data is not specified, the variables have been calculated by us. SFOE stands for Swiss Federal Office of Energy. FSO stands for Federal Statistical Office, FSO (BDS) for the Building and Dwelling Statistic of the FSO, FTA for Federal Tax Administration, swisstopo is the Federal Office or Topography and MeteoSwiss is the Federal Office for Meteorology and Climatology.

Table A.2: Effects of production and investment subsidies within the jurisdictions: robustness checks

	(1) Baseline	(2) Add lagged PV	(3) SE clustered by canton	(4) Replace mun. FE by DSO FE	(5) Replace mun. FE by DSO $\times$ year FE
Subsidies	0.350^{***}	0.353^{**}	0.350^{**}	0.345^{***}	0.226^{**}
	(0.036)	(0.128)	(0.129)	(0.125)	(0.106)
Lagged PV count		0.016^{***}			
		(0.005)			
Constant	−0.203	−0.384	−0.203	−2.140	−2.924
	(3.742)	(3.289)	(3.253)	(1.884)	(2.068)
Controls	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	No
DSO FE	No	No	No	Yes	No
DSO by year FE	No	No	No	No	Yes
# Observations	26,664	26,664	26,664	26,664	26,664
R^2	0.2141	0.2147	0.2141	0.2477	0.3147

Note: Robust standard errors in parentheses, clustered at the municipality level in columns 1 and 2, at the canton level in column 3, and at the DSO level in columns 4 and 5. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A.3: Cross-border effects: robustness to excluding most distant municipalities

	(1) All	(2) <20 km	(3) <15 km	(4) <10 km	(5) <5 km
Adjacent	0.467^{***}	0.469^{***}	0.448^{***}	0.498^{***}	0.436^{***}
	(0.147)	(0.147)	(0.148)	(0.152)	(0.161)
Constant	−8.894	−5.744	−8.809	−0.608	−13.673
	(6.903)	(8.526)	(11.004)	(10.848)	(16.756)
Controls	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
# Observations	8,448	6,876	5,796	4,440	2,616
R^2	0.1638	0.1917	0.1882	0.2092	0.2306

Note: Model (1) includes all municipalities in cantons that have never implemented any subsidy for PV between 2006 and 2017. Models (2) to (5) drop municipalities that are, respectively, more than 20, 15, 10 and 5 km from the nearest border of the cantons that have implemented subsidies. All models are estimated using OLS regressions. Dependent variables are the number of PV adoptions per 1,000 inhabitants, by municipality and by year. Standard errors in parentheses, clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A.4: Cross-border effects of financial incentives for PV: effect of distance and time

	(1) <5 km	(2) <10 km	(3) <15 km	(4) <20 km
Distance × Treated	-0.242^{**}	-0.099^{***}	-0.036^{**}	-0.029^{***}
	(0.103)	(0.032)	(0.018)	(0.009)
Distance × Treated [1st following year]	-0.231^{**}	-0.036	-0.007	0.002
	(0.108)	(0.040)	(0.020)	(0.014)
Treated	1.029^{***}	0.699^{***}	0.532^{***}	0.492^{***}
	(0.344)	(0.215)	(0.181)	(0.169)
Treated [1st following year]	0.697^{*}	0.374	0.275	0.173
	(0.354)	(0.243)	(0.199)	(0.184)
Distance	-0.002	-0.004^{*}	-0.002	-0.002
	(0.003)	(0.002)	(0.002)	(0.002)
Constant	-14.755	-0.832	-8.958	-5.954
	(16.814)	(10.979)	(11.034)	(8.598)
Controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
# Observations	2,616	4,440	5,796	6,876
R^2	0.2361	0.2126	0.1893	0.1927

Note: Standard errors in parentheses, clustered at the municipality level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Chapter 4

Demand response management: The power of time-of-use tariffs to accommodate solar energy

This chapter is based on a section of a report written with Sylvain Weber (University of Neuchâtel) for the Swiss Federal Energy Office (Perret et al., 2019). We thank Lionel Bloch, Jordan Holweger, Nicolas Wyrsch for their help in setting up the experiment and cleaning up the data. This research was financially supported by the Swiss Federal Office of Energy (SFOE), grant number SI/501332-01.

This research was presented by Martin Péclat at the ENERDAY 2018 conference, Dresden (Germany), April 2018.

Abstract
The diffusion of solar photovoltaic technology, due to the intermittency of its production, raises important challenges: how to cope with the temporal (and spatial) imbalance between electricity supply and demand? Making production more flexible is the most widely used measure. At the same time, improving the responsiveness of demand could be inexpensive, quick and easy to implement. In this paper, we use a randomized control trial with purely randomly selected households to investigate the impact of time-of-use pricing aimed at shifting demand towards typically sunny hours. We find that our intervention led to behavioral changes enabling an increase in the share of consumption during the sunny hours. Households did not significantly increase their electricity usage during the lower tariff periods that took place in the middle of the day, but they reduced it when solar radiation is limited or absent, especially during the evening-peak. Our results moreover suggest that even a very modest financial incentive, at virtually no cost for the utility, induces a lasting effect among households who perceive the pecuniary benefits of their actions.

Keywords Demand response; Households electricity usage; Solar PV; Randomized control trial

JEL codes C93; D12; L94; Q41

1 Introduction

With the acceleration of the fight against climate change, renewable energy sources (RES) such as solar and wind are expected to meet a growing share of electricity demand. Currently, about a quarter of the world's electricity generation capacity originates from RES, the majority of which is hydropower (IEA, 2019). Yet, according to the International Energy Agency's projection based on today's stated policy objectives, photovoltaic (PV) energy will surpass coal and gas to become the leading source by 2035 (IEA, 2019). In Switzerland, the objective is to increase the average production of RES electricity (excluding hydropower) from 1,260 GWh in 2015 to 4,400 GWh in 2020 and 11,400 GWh in 2035 (SFOE, 2019c).

The transition to low-carbon electricity energy mix involves an increasing share of intermittent RES. For policymakers, regulators and, in the front line, electric utilities, one of the main related challenges is to ensure that electricity supply and demand are at all times in balance. The solutions most often explored, and also the most widely discussed in literature, are of a technical nature (see e.g. Lund et al., 2015 or Kondziella and Bruckner, 2016 for reviews). Focusing mainly on supply, usual solutions consist in increasing backup capacity with dispatchable power plants and in grid extensions. More innovative approaches include, for instance, the use of electric vehicle batteries for storage (Mwasilu et al., 2014; López et al., 2015) or remote activation of electrical equipment, known as "enabling technologies" (Zipperer et al., 2013). These options, however, are expensive (Beaudin et al., 2010), environmentally harmful (Larcher and Tarascon, 2015), entail energy losses (Evans et al., 2012), and may take time to implement.

An alternative approach, belonging to the so-called "demand response" category, aims to adjust the load demand by influencing electricity consumption behavior. Evidence of the effectiveness of these measures, and in particular about the persistence of their effect, is still limited. Also, almost all existing studies investigate incentives targeting electricity conservation or load shifting from peak to off-peak hours. The issue they raise is therefore not directly related to the integration of intermittent electricity generation from RES into the grid.

This paper differs from most of the literature in that it explores an incentive especially designed to take advantage of production overcapacity when solar radiation is abundant. More precisely, we implement a time-of-use (TOU) tariff aimed at redirecting electricity consumption towards the period of the day when, in expectation, solar PV production is at its highest. Although not the primary objective, this measure could have the additional benefit of relieving congestion during peak periods.

In this paper, we attempt to address three main research questions. First, to what extent does a TOU tariff enable demand to act as a buffer during periods of high solar PV production? Second, how persistent is the reaction of households subject to a TOU tariff? Third, does the magnitude of behavior change depend on the gains made?

We explore these questions using a randomized controlled trial involving more than 500 participants, most of whom were purely randomly selected among the eligible population. To the best of our knowledge, this is the first demand response experiment conducted with non-volunteered households. The duration of treatment is also exceptional—up to 18 months—, while other similar trials rarely exceed a few months (Delmas et al., 2013).

Our analysis by difference-in-differences reveals modest TOU pricing-induced load shifting. Overall, we find that the share of daily electricity usage during low tariff hours increases by 0.4 percentage point after introduction of the new pricing scheme. Yet, this rise is mainly related to a greater reduction in consumption during increased tariff hours rather than to a real success of the TOU in attracting consumption to high solar production hours. The reduction reaches a maximum of 6% during peak consumption hours, which is surprisingly close to the results obtained with TOU schemes aimed specifically at peak shaving (Carroll et al., 2014; Di Cosmo et al., 2014; Pon, 2017).

In addition, our results reveal that the treatment effect needs up to three months to unfold. Once this adaptation period is over, the behavior change seem persistent despite average savings of less than CHF 1 per month per household. However, we show that households need to foresee the benefits of their actions in order for them to react. The treatment effect indeed falls to zero for households that have not made any savings on their previous bill.

The remainder of this paper proceeds as follows. Section 2 provides a brief literature review. Section 3 presents the experimental design. Section 4 describes the data, while Section 5 outlines the methodology. Section 6 presents empirical results and Section 7 concludes.

2 Literature review

Albadi and El-Saadany (2008) define demand response (DR) as "the changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time". The time-varying price aimed at inducing the demand response can be designed in various ways. The literature generally distinguishes between the following main options (see e.g. Palensky and Dietrich, 2011): time-of-use pricing (TOU), critical-peak pricing (CPP) and real-time pricing (RTP). While in TOU schemes the price is adjusted by fixed blocks of hours during the day, price variation is more frequent and dynamic in RTP schemes with the purpose of reflecting the marginal cost of production. CPP consist in applying a tariff surcharge for a limited number of days, usually based on a pre-defined consumption threshold.

As reported in several literature reviews (see e.g. Faruqui and Sergici, 2010; Yan et al., 2018), the effectiveness of price-based incentives has been assessed in numerous studies (see for instance Bartusch et al., 2011; Woo et al., 2013b). However, evidence based on randomized control trials and high frequency data, on which we mainly focus hereafter, is much more limited. Moreover, to the best of our knowledge, Weber et al. (2017) is the only contribution that covers an incentive aimed at matching demand with production from intermittent energy sources.

Most recent studies of TOU schemes using randomized controlled trials have found reductions in consumption during peaks ranging from 1.6 to 8.8% (Faruqui et al., 2014; Di Cosmo et al., 2014; Carroll et al., 2014; Pon, 2017; Weber et al., 2017). Using TOU tariffs with different peak to off-peak price ratios, several studies have documented a non-linear relationship between the level of incentive and household response (Reiss and White, 2005; Woo et al., 2013b; Di Cosmo et al., 2014). Energy savings observed in CPP schemes are typically more substantial.[1] For instance, Jessoe and Rapson (2014) and Ito et al. (2018) find reductions ranging up to 18% depending on the particular event and tariff surcharge level. Empirical evidence about the impact of RTP is scarcer. Allcott (2011) finds a general conservation effect but no substantial load shifting, and therefore concludes that RTP should be seen as programs aimed at peak shaving.

Another body of literature has shown that significant modifications in households' consumption can be achieved through non-monetary incentives. The avenues discussed are vast: information provision, social comparison, moral suasion. As documented by several reviews of the literature (Faruqui et al., 2010; Vine et al., 2013; Buchanan et al., 2015) and meta-analyses (Ehrhardt-Martinez et al., 2010; Delmas et al., 2013), this field of research is evolving rapidly. Overall, electric-

[1] In the 15 experiments covered in the review of Faruqui and Sergici (2010), which do not necessarily involve a control group, the decrease in peak demand ranges between 3 and 6% for TOU pricing schemes and 13 to 20% for CPP schemes.

ity conservation behavior can be encouraged by providing consumers with saving advices, individual usage history, peer usage and real time energy usage (Delmas et al., 2013). As Jessoe and Rapson (2014) demonstrate, providing information in conjunction with price-based incentives significantly improves the impact of these incentives. In particular, Pon (2017) shows that households equipped with in-home displays react immediately to the introduction of the TOU, while households without such device have an adaptation period of about 5 months. A recurrent concern about non price-based measures is that their effect may fade out over time. For instance, Allcott and Rogers (2014) identify what they call “action and backsliding”: households tend to react markedly within days of a stimulus and then their efforts gradually diminish.

3 Experimental design

Our field experiment took place between July 2016 and December 2017 among residential customers of *La Goule*, an electricity utility operating in the cantons of Jura, Bern and Neuchâtel (northern Switzerland).[2] We recruited participants in two phases. In a first phase, invitations to complete an online survey were sent by mail to all 1,805 *La Goule* customers with a flat tariff.[3] The letter was attached to the April 2016 electricity bill. To improve response rate, we announced that one randomly selected respondent would be rewarded with a cash prize of CHF 200, and a reminder letter was sent with the July 2016 bill. As of September 30, 2016, 92 households had fully completed the survey and thereby expressed interest in participating in the experiment.

In a second phase, we randomly further selected an additional 505 households from the pool of eligible *La Goule*’s customers who had not yet responded to the survey. This sample consists of all 205 remaining customers under a monthly billing plan and a random draw of 300 customers under a quarterly billing plan. Since the choice of whether or not to participate was not left to households, unlike those who participated in the survey, any self-selection bias can be excluded. In this respect, and also given the large number of participants, we argue that our results have strong external validity, at least for the population of the corresponding geographical area.

[2] No other experiment related to electricity consumption had been conducted with *La Goule*’s customers prior to the one presented in this paper.

[3] A large proportion of *La Goule*’s customers subscribe to a double pricing plan with reduced tariff at night. We have decided not to recruit these households in order to keep the changes induced by our intervention as simple as possible. Households equipped with PV installations, heat pumps or electric heating were also excluded.

The internal validity of the experiment is guaranteed by the random allocation of participants to the treatment and control groups, both of which are approximately the same size.[4] In order to have groups as comparable as possible, we used a stratified randomization procedure taking into account the billing frequency (monthly or quarterly) and annual electricity consumption in 2015.

The experiments were launched in four successive waves. The first two waves, which began on 1 July and 1 October 2016, include households who previously registered through the survey. Randomly selected households participated in the last two waves, depending on their billing frequency. Wave 3 includes monthly-billed households and began in February 2017. Wave 4 includes quarterly-billed households and began in April 2017. After remarkably long treatment periods between 9 and 18 months, all experiments ended on 31 December 2017.

Launching the experiment in successive waves at different times of the year is aimed at enabling the effect of seasonality, if any, to be differentiated from the experiment duration effect. The staggered launch was also driven by external constraints. All households that expressed an interest in participating were to be included in the experiment within a short period of time after responding to the survey, but not all responded at the same time. Some did so immediately after receiving the first invitation letter, and others did so only after the reminder, which we sent out three months later. In addition, we could notify households of the start of the experiment only by means of a letter attached to the electricity bills, which are sent out only four times a year for households with quarterly billing plans.

3.1 Intervention

Our treatment aims at redirecting household consumption towards periods of high solar production using fixed TOU pricing scheme. While households are initially charged a uniform tariff, the price of a kilowatt-hour they consume during the treatment period was reduced by 15 cents between 11am and 3pm and increased by 4 cents outside this time frame.[5] The tariff reduction is substantial, since it corresponds to more than 50% of the pre-treatment price, which was 27.45 cents/kWh

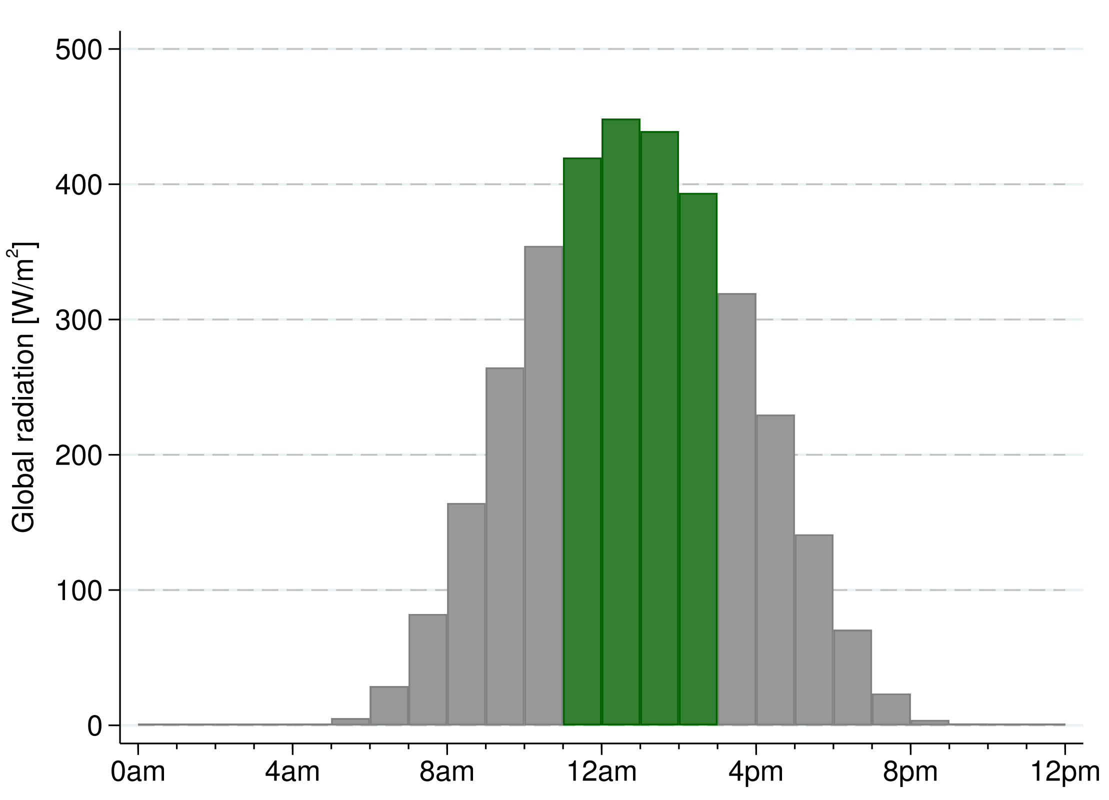
[4]A second treatment with dynamic TOU tariffs varying on a daily basis is omitted from this study due to a too small number of participants (23 households). The implementation of this intervention required participants to provide their mobile phone number, which we could only collect after obtaining the household's consent in the survey.

[5]Monetary amounts are expressed in Swiss Francs (CHF). At the time of the study, CHF 1 was approximately equivalent to USD 1.

in 2017.[6] The increase of 4 cents per kilowatt-hour has been calibrated so that a household with a typical load curve does not obtain any gain, or loss, on its bill compared to a uniform tariff if it does not adapt its load profile. For households in the control groups, the price of a kWh remained the same as in the benchmark period.

Low tariff hours reflect the period of the day when solar energy production is, in expectation, at its highest. Figure 1 shows the average global solar radiation (a measure of the energy supplied by the sun) measured at three stations within or near *La Goule*'s coverage area. We observe that about 50% of the global radiation occurs during the four hours (11am to 3pm) targeted by the intervention.

Figure 1: Average global solar radiation per hour



Note: Average global solar radiation observed in the meteorological stations of La Chaux-de-Fonds, Delémont and Fahy over the years 2013 to 2017. Green bars indicate low tariff hours applied in treatment. Data source: MeteoSwiss.

The low tariff hours are fixed throughout the treatment period. Although such pricing does not reflect the actual day-to-day level of solar production, it has the advantage of being simple for households to understand. Moreover, as opposed to

[6]This price includes not only the energy part, but also transport fees, grid use fees, and various taxes.

dynamic TOU tariffs that would be adjusted in real time (or at least frequently) according to current solar radiation, our intervention should facilitate household's reaction by allowing them to establish new habits and routines.

A few days before the launch of each wave, households in the treatment group received a letter explaining, precisely and in simple terms, the changes in the pricing system. Apart from these factual explanations, we only told them that they could lower their electricity bills by shifting electricity usage to the 11am-3pm period. No instruction or recommendation on the best way to achieve this result was provided. Participants who responded the survey but were then assigned to the control group were informed of their passive role. This contact was necessary to thank them for taking the time to complete the survey. In this letter, we deliberately remained vague about the objectives of the experiment in order not to risk influencing their behavior. Such a risk is totally excluded for randomly selected households in the control group, to whom we never mentioned their participation.

During our intervention, treated households received detailed electricity bills providing daily account of their electricity usage within high and low tariff hours. Most importantly, we showed households how much money they were saving by participating in the experiment. Indeed, in addition to reporting the invoice amount under the TOU tariff, we continued to report the amount under the flat tariff. This double calculation of the amount was necessary because, due to legal constraints and in absence of a formal choice of the TOU tariffs by the households, *La Goule* was unable to impose a binding change in the pricing system on its customers. Participants therefore had to pay only the lowest of the two invoices. As a result, the financial incentive analyzed in this paper consists of a potential reduction in electricity bills, with no risk of losing money.

Our experiment is designed to determine the impact of implementing a TOU tariff, without any other non-financial incentives. However, it is important to note that our experimental settings do not allow to differentiate between the reaction of households linked specifically to the tariff change and the reaction, if any, linked to the simple fact that they are aware of participating in an experiment. Part of the treatment effect that we capture may therefore come from the fact that households feel observed and know that a reaction from them is expected.

4 Data

Consumption data In order to assess whether TOU pricing influences households' electricity consumption, we use high-frequency electricity usage data over the period from 1 January 2016 to 31 December 2017. The utility *La Goule* was one of the first in Switzerland to systematically install advanced consumption measurement devices, often called "smart-meters", among its customers. We were therefore able to obtain the load curves at one-hour or even 15-minute intervals for each of the participating households, over both the treatment and benchmark periods.

Although exceptional in size—over 500 households— and in the time covered—2 years—, the consumption data provided by *La Goule* required extensive verification and filling before we could analyze them. Data-related issues include missing values, over periods ranging from one hour to several weeks, and unrealistic values. In order to have a panel dataset as accurate and balanced as possible, the data were first cleaned, and then completed, using a procedure explained in Appendix 7. Despite this careful procedure, some load curves are partially or completely lost.

Table 1: Number of households and percentage of exploitable data

Wave	Launch date	Control group		Treatment group		Total	
		#	miss.[%]	#	miss.[%]	#	miss.[%]
1	01Jul2016	12 (14)	15.79	12 (15)	3.36	24 (29)	9.57
2	01Oct2016	16 (16)	6.40	15 (16)	9.62	31 (32)	7.96
3	01Feb2017[a]	93 (103)	4.94	97 (102)	6.59	190 (205)	5.79
4	01Apr2017[a]	126 (150)	4.45	130 (150)	3.21	256 (300)	3.82
Total		247 (283)	5.31	254 (283)	4.89	501 (566)	5.10

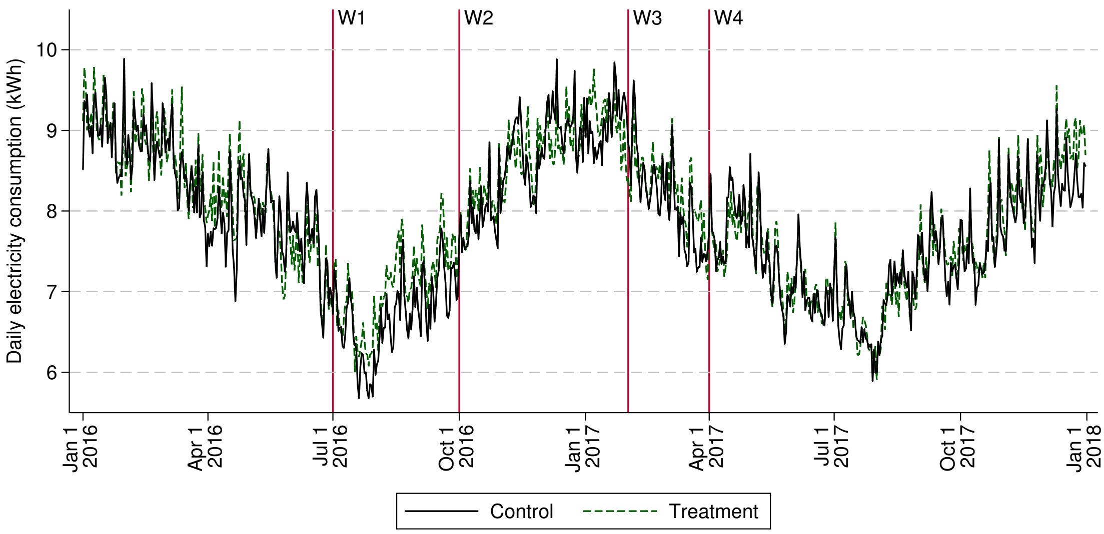
Note: [a] These dates indicate when the treated households were informed of their inclusion in the experiment.However, the TOU tariff came into effect on 1 January 2017 for both waves 3 and 4, when they were not yet aware of their inclusion in the experiment. Numbers in parentheses indicate the number of households initially included in the groups. The percentages indicate the proportion of missing or unusable observations compared to what would be obtained with a fully balanced panel dataset.

Table 1 outlines, for each group and wave, the number of households for which consumption data are available for analysis. It also reports the number of households initially included in the experiment (numbers in parentheses). Of the 566 households recruited, we have a usable sample of 501 households, of which 254 were treated and 247 were in the control group. The load curve of 380 of them is complete and usable over the entire observation period, i.e. from 1 January 2016 to 31 December 2017. For the others, either the beginning or the end (or both) of the load curve is missing due to relocation (62 households), installation of solar panels (6 households), or unreliable smart-meters (99 households). The proportion of unusable or missing data is also reported in the Table 1. Since the reduction in sample size affects both groups in similar proportions, it is unlikely to bias our results.[7]

Our final unbalanced (balanced) panel dataset covers 501 (380) households over an average of 680 (731) days. After aggregating the consumption data of households equipped with smart-meters recording consumption at 15-minute intervals, we obtain a total of 8,578,779 (6,665,960) household-hour observations. In the majority of the analyzes, however, we use a daily panel with 347,558 (277,780) household-day observations. In this case, rather than energy consumption, we compute the proportion of daily electricity consumed between 11am and 3pm.

Figure 2 illustrates the data by showing the average daily electricity consumption for the households in each group. No systematic differences between the two groups appear. We notice a significant seasonal pattern, with daily consumption 30 to 40% higher during winter peaks than during summer troughs. Annual consumption averages around 2,900 kWh.

Figure 2: Average daily electricity consumption for treatment and control group



Note: Red vertical lines indicate the launch date of each wave.

A potential concern is that missing consumption data may result in differences between control and treatment groups, which would impede the internal validity

[7]Obviously, we are unable to test this statement for households whose load curve has been completely lost. However, we show in Table D.1 that focusing on households for which we have complete data (380 households) or on the unbalanced panel (501 households) does not affect our results. Excluding imputed data also has no impact.

of our experiment. Table 2 reports the results of the t-tests on the differences in the mean characteristics of the two groups, both for the whole dataset (unbalanced panel) and for households with complete load curves only (balanced panel). An alternative way to test the success of the random allocation is to use a probit model where the dependent variable takes the value 1 for the treatment group and the value 0 for the control group. This group indicator is then regressed on the characteristics of the participants. We report the results of such a model in Table B.2 in the Appendix. For each of these tests, the hypothesis that there are no differences cannot be rejected. We conclude that the internal validity of the results presented in this paper is guaranteed.

Table 2: Summary statistics of treatment and control groups: metering data

Group:	Treatment		Control		Difference (T-C)
Period:	Benchmark	Treatment	Benchmark	Treatment	Benchmark
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean [SE]
Unbalanced panel					
Electricity consumption (kWh/day)	8.094	7.544	8.060	7.466	0.034
	(4.940)	(4.864)	(4.998)	(4.397)	[0.444]
Electricity consumption 11am-3pm (kWh/day)	1.680	1.591	1.658	1.554	0.022
	(1.092)	(1.084)	(1.016)	(1.016)	[0.094]
Proportion 11am-3pm	0.198	0.200	0.199	0.199	−0.001
	(0.042)	(0.045)	(0.046)	(0.046)	[0.004]
# Households	254	254	247	247	501
Balanced panel					
Electricity consumption (kWh/day)	8.146	7.604	8.185	7.635	−0.040
	(4.706)	(4.456)	(5.170)	(4.492)	[0.507]
Electricity consumption 11am-3pm (kWh/day)	1.686	1.618	1.707	1.602	−0.021
	(0.986)	(0.965)	(1.037)	(1.005)	[0.104]
Proportion 11am-3pm	0.200	0.204	0.202	0.201	−0.002
	(0.041)	(0.043)	(0.044)	(0.044)	[0.004]
# Households	201	201	179	179	380

Note: Standard deviations in parentheses. Last column reports the difference in the means (of benchmark period) between the two groups. Standard errors of t-tests on the equality of means are also reported in brackets. $^{*}p < 0.10$, $^{**}p < 0.5$, $^{***}p < 0.01$. Appendix 7 provides additional summary statistics and tests of significant differences in the means between the two groups.

Weather data Our dataset is completed with meteorological data obtained from *MeteoSwiss*, the Swiss Federal Office of Meteorology and Climatology. Temperature, rainfalls and sunshine duration data are collected in three stations located within or near *La Goule*'s coverage area. We use the average of the three stations because we do not know the exact location of the participants. The correlation coefficients between weather stations are very high anyway, since the geographical spread is limited (about 50 km at most between two stations). In order to have the same resolution as for the consumption data, we use hourly data for all three variables.

Survey data In addition to data on electricity consumption and weather conditions, we have information on various characteristics of the households who participated in the pre-experiment survey. Survey data include socio-economic characteristics such as household size, income, occupation rate and age of the respondent. In addition, we also collected information about residence characteristics and environmental preferences and awareness. Unfortunately (and as already mentioned), only a small number of participants completed the survey. Survey data are thus only used to verify that the allocation of the households in the treatment and control groups did not result in significant differences between the two groups but not for the analysis of the treatment effects.

5 Methodology

Our field experiment is characterized by a pre-treatment period during which all participants face the same electricity price, followed by a treatment period during which a new pricing scheme is introduced for participants who have been randomly assigned in the treatment group. In such a randomized control trial, it is possible to causally estimate the effect of treatment using a difference-in-differences (DiD) approach.

The main aim of this paper is to estimate the proportion of electricity that households are willing to move to the hours of the day when solar production is on average highest. As our intervention consists of the introduction of a TOU tariff at fixed hours, the overall household response can be assessed by analyzing the change in the daily proportion of electricity that is used during low tariff hours. We therefore estimate the following model using aggregate data at the daily level for each household:

$$Pr_{it} = \beta T_{it} + \alpha_i + \delta_t + \gamma X_t^{'} + \varepsilon_{it} \tag{1}$$

where Pr_{it} is the daily proportion of electricity consumed by household i between 11am and 3pm on day t. Variable T_{it} is a DiD treatment dummy that takes a value of 1 for households in the treatment group when exposed to the TOU tariff. It takes a value of 0 for households in the control group and all observations during the benchmark period. The average treatment effect is given by coefficient β, which measures the variation, in percentage points, in the daily proportion of electricity used between 11am and 3pm.

We account for persistent differences across participants by including household fixed effects, denoted α_i. To capture the difference in the dependent variable between the benchmark and the treatment period, the model incorporates time-specific fixed effects, denoted by δ_t. As the experiments were launched in four successive waves, all of which started on the 1st of the month, we use month by year fixed effects. By doing so, seasonal variation common to all households is also accounted for. Finally, to obtain more precise estimates of households reaction to TOU pricing, our models control for weather conditions. Vector of variables X_t includes the average temperature, rainfalls and sunshine duration between 11am and 3pm in day t. ε_{it} is an error term.

To disentangle the differences in reactions between households, and their evolution over time, we also run alternative specifications in which we add interactions between the variable T_{it} and different characteristics and time indicators.

To further our understanding of households' intra-day response, we evaluate the impact of our intervention on the hourly electricity usage using the following model:

$$\ln(kwh_{iht}) = \sum_{h=0}^{23} \beta_n (T_{it} \times H_h^n) + \alpha_i + \delta_t + \lambda_h + \gamma X_{ht}^{'} + \varepsilon_{iht} \tag{2}$$

where $\ln(kwh_{iht})$ is the natural log of electricity consumption (in kWh) for household i in hour h of day t. In this model, the DiD variable T_{it} is interacted with a vector of 24 hourly dummies, denoted by H_h^n, that indicate each of the hours of the day. In addition to household and month fixed effects, this model controls for within-day consumption patterns by including hour of the day fixed effects, referred to as λ_h. The coefficients of interest are included in the β_n vector. Since the dependent variable is in logarithmic form, the value of the regression coefficients indicates the percentage change in energy use for a given hour.[8]

The panels datasets we use to estimate Equations (1) and (2) are characterized by large time series (730 days or 17,542 hours) on a comparatively small number of cross-sectional units (501 households at most). The dominant time series dimension may introduce auto-correlation in the error terms, while cross-sectional dimension may imply heteroskedasticity (Wooldridge, 2010). To avoid a bias in standard errors of the coefficients, econometricians usually prescribe the use of feasible generalized least square (FGLS) and panel corrected standard errors (PCSE) estimation tech-

[8] To be completely accurate, the exact percentage can be obtained with $\exp(\beta) - 1$.

niques. As extensively discussed in the literature, each of these techniques has its own relative merits (see e.g. Beck and Katz, 1995; Reed and Webb, 2010; Cameron and Miller, 2015). In this paper, we therefore systematically report the results of the two estimation techniques, using a first-order autoregressive coefficient (AR1).

To establish a causal relationship from a DiD estimation, we must ensure that the treatment and control groups share parallel trends before the treatment is introduced. Figures 3 and 4, which we discuss in Section 6, provide a first visual indication that the two groups are not already diverging during the benchmark period. A more explicit test of the common trend assumption is reported in Appendix 7. Using a "placebo" difference-in-differences estimation, we show that the treatment effect is non-existent for the months preceding the actual start of the experiments. We therefore conclude that, without our intervention, the consumption behavior of the treated households would have remained similar to that of the control group.

6 Results

6.1 Impact of TOU tariff on proportion 11am–3pm

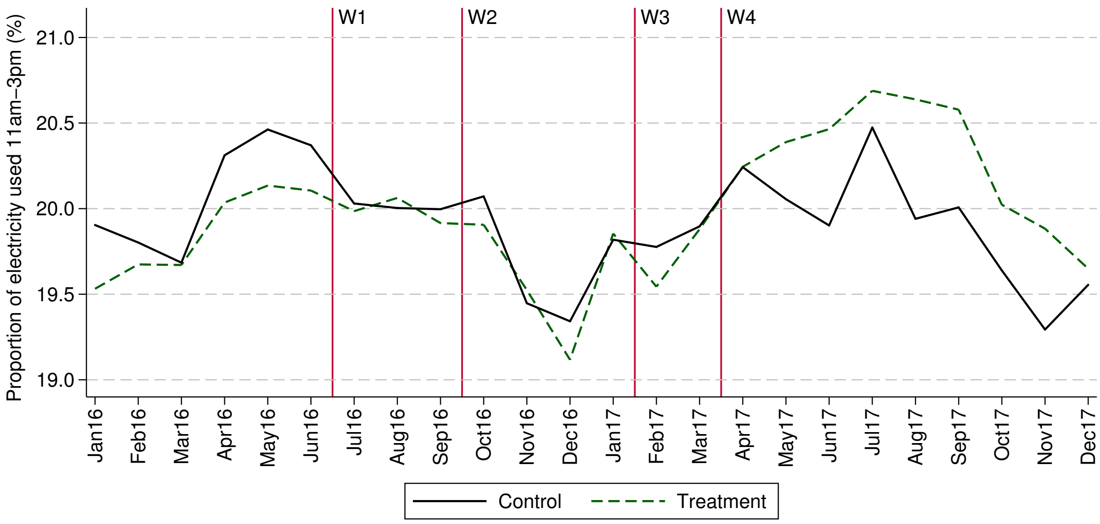
We begin our investigation of the treatment effect with a descriptive analysis. Figure 3 shows the evolution, month after month, of the proportion of electricity consumed between 11am and 3pm in the control and treatment groups. Before the experiments were launched, i.e. when all households (including those in the treatment group) were under the flat tariff, the proportions appear relatively similar or even slightly higher for the control group.[9] However, from April 2017 onwards, i.e. when all households in the treatment group are confronted with the TOU tariff, the proportion becomes permanently larger for the treated group. Yet, these differences are small. On average, the proportion of the treatment group was 0.01 percentage point lower than that of the control group during the pre-treatment period, and 0.2 percentage points higher during the treatment period. These observations, although purely descriptive, are in line with the expected effect of our treatment.

We start the DiD analysis of households' response by estimating Equation (1) with participants from the four waves.[10] Table 3 reports the estimation results for

[9]Note that between the launch of wave 1 and that of wave 4, some households in the treatment group are still in their pre-treatment/benchmark period. However, given the much larger size of waves 3 and 4 compared to that of waves 1 and 2, one should not expect to detect any impact during this "mixed" period in the illustrative Figure 3.

[10]Since PCSE and FGLS estimation techniques require a fully balanced panel dataset, only the participants for which we have complete data (after imputation) are included in the estimations. However, as shown in Table D.1, which loosens some assumptions about the structure of the error

Figure 3: Average proportion of electricity consumed between 11am and 3pm for treatment and control group, by month



Note: Red vertical lines indicate the starting date of each wave.

our preferred specification using PCSE, FGLS, and OLS regression techniques. The coefficients for treatment effect are consistent, positive and statistically significant in all three models. Specifically, we find that households on TOU tariffs increase the share of electricity they consume between 11am and 3pm by about 0.4 percentage point. By comparing these figures with the average daily proportion of consumption between 11am and 3pm, which is 20.1% in the benchmark period, we deduce that about 2% of electricity usage might be shifted using such a pricing system.

Our results are robust to changes in the specification. Table D.2 in the Appendix presents the results of alternative models including day-of-week fixed effects, leaving out weather controls, with period indicator instead of month fixed effects, and with a group indicator rather than household fixed effects.

The effect of the treatment may seem modest. However, it should be linked to the potential gains for participating households, which were also very low. On average, households saved only CHF 0.85 per month thanks to their participation in the experiment. For more than 50% of households, the cumulative savings over the entire duration of the experiment amount to less than CHF 5. By way of comparison, the average monthly electricity bill in our sample is CHF 65. It should also be remembered that households did not incur any financial risk by participating.

term to allow the use of an unbalanced panel, the results are similar if we add the households for which the consumption could not be imputed over the entire period. Excluding all imputed observations does not affect our results either.

Table 3: Treatment effect: proportion of electricity used between 11am and 3pm

	(1) PCSE AR1	(2) FGLS AR1	(3) OLS
Treatment effect	0.0045^{***}	0.0041^{***}	0.0045^{***}
	(0.0007)	(0.0004)	(0.0017)
Rainfalls (mm)	0.0007^{**}	0.0005^{***}	0.0006^{***}
	(0.0003)	(0.0001)	(0.0001)
Sunshine duration (minutes)	-0.0000^{***}	-0.0000^{***}	-0.0000^{***}
	(0.0000)	(0.0000)	(0.0000)
Temperature (°C)	-0.0001	-0.0001^{*}	-0.0001
	(0.0001)	(0.0000)	(0.0001)
Constant	0.1903^{***}	0.1902^{***}	0.2009^{***}
	(0.0035)	(0.0031)	(0.0013)
Month FE	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
# Observations	277,780	277,780	277,780
# Households	380	380	380
R^2	0.1589		0.0027

Note: Robust SE in parentheses, clustered at the household level. *p<0.1, **p<0.05, ***p<0.01.

The household always had to pay the cheapest bill between the one obtained with the TOU tariff and the one obtained with the simple tariff. The amount invoiced was therefore bounded by the amount of the official bill. One could therefore imagine that the change in behavior would have been more important had the TOU tariff been strictly applied, not only in case of a gain but also in the event of a loss.

6.2 Impact of TOU tariff on electricity consumption

In the previous section, we have demonstrated that the TOU tariff was successful in inducing changes in consumption. However, how households have attempted to reduce their bills has not yet been identified. The increase in the proportion may come from a real shift in consumption towards 11am and 3pm, but it could also result from a comparatively higher reduction in consumption outside this time slot.

In this section, we analyze the impact of TOU pricing on hourly electricity consumption using Equation (2). Figure 4 provides a preliminary visual inspection. It compares the average daily load curve of the treatment and control groups for the reference period and the treatment period.[11] As expected given the random allocation, the consumption profiles are almost identical between the two groups prior to treatment (sub-figure (a)). Given the modest reactions identified in the previous section, it is also not surprising that no major changes appear for the treatment period (sub-figure (b)). Taking into account both the differences between groups and periods, one may notice a slight reduction at night and evenings.

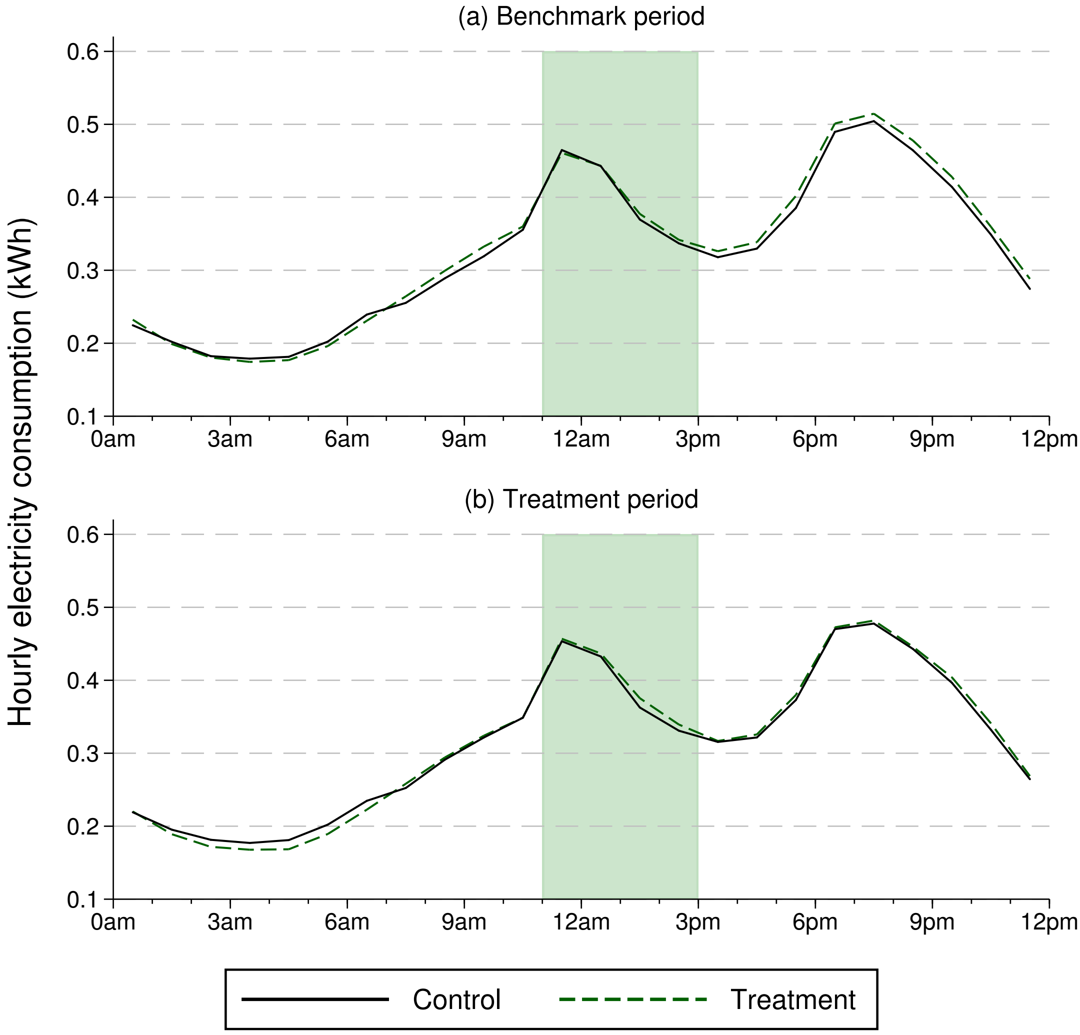
Table 4 reports the estimation results for a simplified version of Equation (2) measuring the average treatment effect within all low and all high tariff hours. Using the PCSE and FGLS AR1 estimation techniques, the results indicate a statistically significant average reduction of 1.3 to 2.1% in consumption during high tariff hours. However, despite a reduction of more than 50% in the price of electricity, households do not seem to have increased their consumption between 11am and 3pm. Over this four-hour period, the decrease reaches 1.3 to 1.7%. Note that, due to extremely high computational power requirement, these estimates include a group indicator instead of household fixed effects. Time-invariant differences between households are therefore not considered. That said, household fixed effects are very rarely used in the literature. Notwithstanding the risk of bias due to serial correlation, we also present the results of OLS regressions, with and without household fixed effects, in columns 3 and 4 for indication. Unlike models without household fixed effects, column 4 indicates a small (not statistically significant) increase in consumption between 11am and 3pm.

The reduction on both high and low tariff hours indicates an overall conservation effect. Such an overall reduction in demand, by a few percentage points, has been found in a number of other trials involving TOU pricing schemes (for instance in Carroll et al., 2014; Di Cosmo et al., 2014; Weber et al., 2017; Pon, 2017) and even critical peak pricing schemes (Ito et al., 2018). The explanation generally given is that participants are paying more attention to their electricity consumption, as a consequence of their participation in an experiment. The lack of increase in consumption during low tariff hours may also be explained by consumers' greater sensitivity to price increases than to price decreases (see e.g. Kalyanaram and Winer, 1995).

Figure 5 displays the coefficients for the hourly treatment effect computed using Equation (2) with PCSE estimation technique and without household fixed effects.

[11] As the experiments started in successive waves, using the entire benchmark and treatment periods would imply seasonal bias. The figures therefore focus on comparable sub-periods.

Figure 4: Daily load profiles, by group and period



Note: Green shaded areas indicate the low tariff hours. To avoid a seasonal bias and thereby allow valid comparisons, only the following sub-periods are used in sub-figure (a) (in sub-figure (b)):

- 01Jan2016 (01Jan2017) to 30Jun2016 (30Jun2017) for wave 1
- 01Jan2016 (01Jan2017) to 30Sep2016 (30Sep2017) for wave 2
- 01Feb2016 (01Feb2017) to 31Dec2016 (31Dec2017) for wave 3
- 01Apr2016 (01Apr2017) to 31Dec2017 (31Dec2017) for wave 4

The evening is the period of the day when the reduction in consumption is the most important. The maximal reduction (-5.7%) is reached between 7pm and 8pm, which coincides with the consumption peak (see Figure 4). While not reflected in the coefficients for hour groups in Table 4, we observe a slight increase in consumption around the end of the low tariff period (1pm-3pm).

Although this was not the primary objective of our intervention, our results sug-

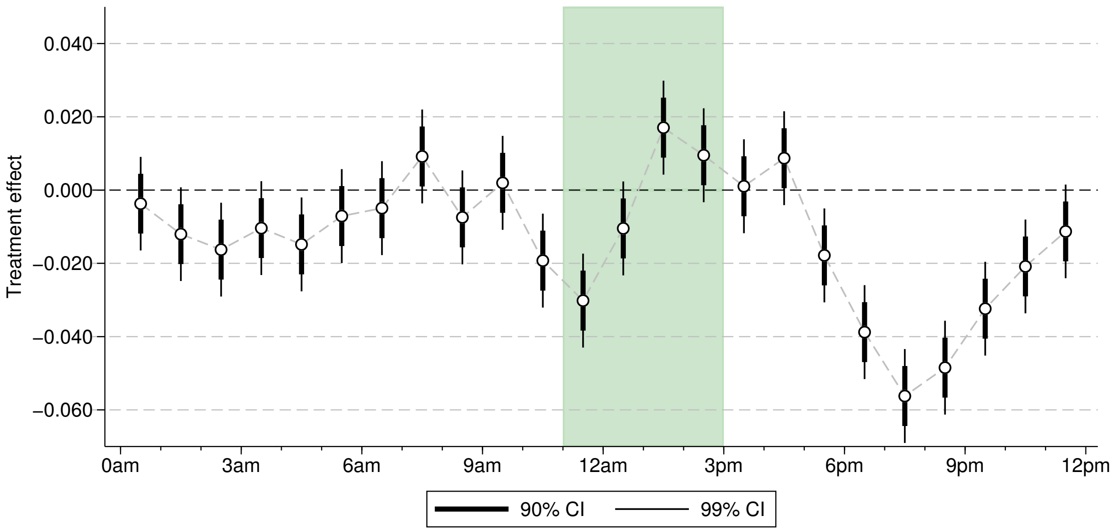
Table 4: Treatment effect: hourly electricity consumption

	(1) PCSE AR1	(2) FGLS AR1	(3) OLS	(4) OLS
Treatment effect				
11am-3pm (low tariff)	-0.0125^{***}	-0.0168^{***}	-0.0035	0.0041
	(0.0035)	(0.0027)	(0.0378)	(0.0248)
3pm-11am (high tariff)	-0.0132^{***}	-0.0205^{***}	-0.0152	-0.0075
	(0.0028)	(0.0023)	(0.0325)	(0.0197)
Treatment group	0.0292^{***}	0.0325^{***}	0.0292	
	(0.0019)	(0.0016)	(0.0638)	
Precipitations (in mm)	0.0047^{***}	0.0036^{***}	0.0122^{***}	0.0122^{***}
	(0.0013)	(0.0010)	(0.0010)	(0.0010)
Sunshine duration (in minutes)	-0.0012^{***}	-0.0010^{***}	-0.0016^{***}	-0.0016^{***}
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Average temperature (in ° C)	-0.0087^{***}	-0.0084^{***}	-0.0067^{***}	-0.0067^{***}
	(0.0004)	(0.0003)	(0.0004)	(0.0004)
Constant	-1.7520^{***}	-1.7513^{***}	-1.7568^{***}	-1.7414^{***}
	(0.0073)	(0.0059)	(0.0510)	(0.0193)
Month FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Household FE	No	No	No	Yes
# Observations	6,665,960	6,665,960	6,665,960	6,665,960
# Households	380	380	380	380
R^2	0.0524		0.1026	0.1679

Note: Robust SE in parentheses, clustered at the household level. *p<0.1, **p<0.05, ***p<0.01.

gest that TOU tariffs targeting solar hours could have beneficial effects in alleviating grid congestion during peak hours. Remarkably, the magnitude of the decline we find in the evening is close to those measured in other TOU pricing trials involving much larger price increases. For instance, Carroll et al. (2014) find that monthly-billed households, on average, reduced their consumption by 8.7% during two-hour peaks with tariffs that are 42-270% higher than the pre-experiment flat tariff. In our experiment, the price per kWh was increased by only 15%.

Figure 5: Treatment effect, by hour



Note: This Figure plots the hourly treatment effect coefficients estimated with Equation (2) using PCSE AR1 (without households fixed effects). Corresponding results are reported in Table D.4.

6.3 Heterogeneity in demand response

In this section, we examine the magnitude of the treatment effect, and its evolution over time, depending on how participants are recruited, how often they are billed, and how much they have saved. For simplicity, all analyses are performed using the same approach as in Section 6.1, i.e. through the daily proportion of electricity usage between 11am and 3pm.

Randomly-selected vs. self-selected Unlike most randomized control trials in the literature, the vast majority of the households in our experiment are randomly selected from the population. Only 10% of the participants, those in the first two waves, filled an online survey. Since this latter group of households has expressed an interest in participating, its behavior change may be more substantial than that of other households. We test whether volunteers were more enthusiastic in Table 5. Columns (1) and (4) show the estimation results for a specification similar to that of Equation (1), to which we add a treatment variable specific to waves 1 and 2. This additional variable can be seen as a triple difference, i.e. as the difference in reaction of self-selected households compared to the average reaction of all treated households.

The results confirm a significantly greater effect for self-selected households (waves 1 and 2) than for other households. On average, the share of electricity they consume between 11am and 3pm is about 0.23 percentage point higher than that of all households in the treatment group during treatment.

Table 5: Treatment effect: self-selected vs. randomly selected households

	PCSE AR1			FGLS AR1		
	(1) All waves	(2) Waves 1+2	(3) Waves 3+4	(4) All waves	(5) Waves 1+2	(6) Waves 3+4
Treatment effet	0.0043***	0.0094***	0.0042***	0.0038***	0.0048**	0.0039***
	(0.0007)	(0.0024)	(0.0008)	(0.0004)	(0.0019)	(0.0004)
Treatment effet × Waves 1+2	0.0023			0.0025**		
	(0.0019)			(0.0010)		
Rainfalls	0.0007**	−0.0001	0.0008***	0.0005***	0.0001	0.0005***
	(0.0003)	(0.0005)	(0.0003)	(0.0001)	(0.0004)	(0.0001)
Sunshine duration	−0.0000***	−0.0000***	−0.0000***	−0.0000***	−0.0000***	−0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Temperature	−0.0001	−0.0000	−0.0001	−0.0001*	0.0001	−0.0001
	(0.0001)	(0.0002)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Constant	0.1891***	0.1884***	0.2022***	0.1888***	0.1862***	0.2021***
	(0.0037)	(0.0043)	(0.0051)	(0.0032)	(0.0039)	(0.0048)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	277,780	29,971	247,809	277,780	29,971	247,809
# Households	380	41	339	380	41	339
R^2	0.1589	0.1469	0.1604			

Note: Robust SE in parentheses, clustered at the household level. *p<0.1, **p<0.05, ***p<0.01.
Observation period: 01Jan2016 to 31Dec2017
Using balanced panel only.

In the other columns of Table 5, we analyze separately the treatment effect for self-selected households (columns 2 and 5) and randomly selected households (columns 3 and 6). In line with results in columns 1 and 4, the coefficients are larger for volunteer participants. The estimations focusing on waves 1 and 2 can be directly compared to those of Weber et al. (2017). The trial they assess, conducted exclusively on self-announced households, share similarities with ours, including the implementation of a financial incentive aimed at redirecting consumption towards midday hours. While the average gain of participants in their experiment is more than 20 times higher than in ours,[12] they find a 0.09-1.4 percentage point increase in the share of electricity used between 11am and 3pm, which is only about twice

[12] Weber et al. (2017) organized a competition with rewards paid in cash for the best-performing households. Each month, an amount of CHF 10, 30 or 50 was distributed to 15 households among 22 in their financial incentive treatment group. This represents an average monthly reward of about CHF 20 for all participating households.

as much our estimates (0.5-0.9 percentage points). This comparison suggests a non-linear relationship between households' response and incentive level. Such a decreasing marginal reaction has been assessed in several studies Reiss and White, 2005; Woo et al., 2013a; Di Cosmo et al., 2014.

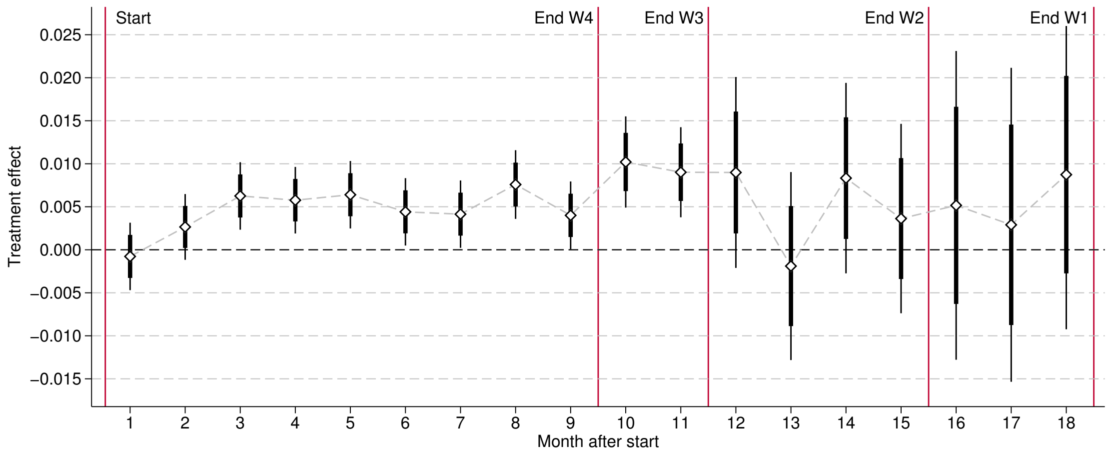
Evolution over time With modest potential monetary savings, households' efforts to adapt their consumption behavior may fade over time. We analyze the persistence of the treatment effect by interacting the treatment variable in Equation (1) with dummy variables that indicate the number of months since the beginning of the experiment.

Figure 6 displays the coefficients for the monthly interaction terms and Table D.3 in the Appendix reports the corresponding estimates. We observe that households' reaction was not immediate and developed gradually. The treatment effect is almost non-existent in the first month following the introduction of the TOU tariff, and only becomes statistically significant from the second month onwards. The coefficient increases again in the third month before stabilizing. This evolution pattern within the first months suggests that, with the arrival of new bills, households are learning the benefits they can derive from developing new consumption habits. This hypothesis is confirmed by Pon (2017), who compares the response of households with in-home displays (IHD), allowing them to see in real time the effect of their actions, and those who are not equipped with IHD. She finds that households without IHD respond more slowly than those with IHD, but the reactions of the two groups gradually converge.

From the third month onwards, the increase in the share of daily consumption between 11am and 3pm fluctuates around 0.5 percentage point. At this point, we have no indication of a gradual motivation loss of households over time. It should be noted, though, that the treatment effect is estimated with only households in waves 1 and 2 for experiment durations longer than nine months (hence the widening of the confidence intervals).

Households in the different waves are not strictly comparable. In particular, wave 3 include monthly-billed households whereas wave 4 include quarterly-billed households, and the literature has shown that a higher billing frequency, by repeatedly reminding the household of its objectives, helps to maintain—or revive—the effect (see Allcott and Rogers, 2014). Figure 7 compares the evolution of the treatment effect between waves 3 and 4. This breakdown of the sample reveals a decrease in response from the fifth month of treatment among households under quarterly billing. On the contrary, households under monthly billing seem to increase their

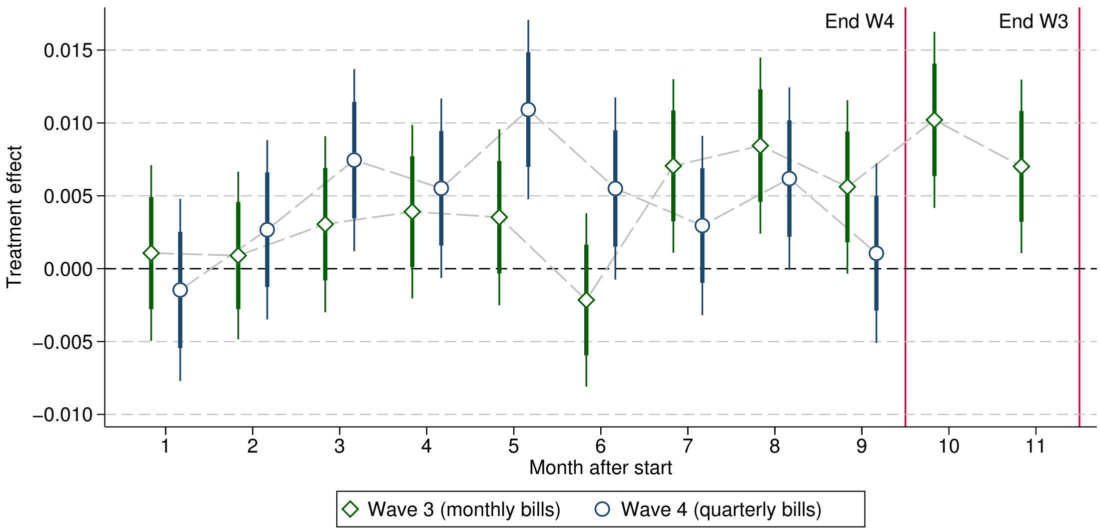
Figure 6: Evolution of the treatment effect by month



Note: Red vertical lines indicate the start and end date of each wave. The coefficients are estimated with PCSE AR1 from the specification of Equation (1) in which the treatment variable is interacted with dummies that indicate the number of months since the start of the experiment. The complete estimation results are provided in Table D.3. Thick (thin) whiskers represent 90% (99%) confidence intervals.

responsiveness to the TOU tariff. Figure D.1 in the Appendix repeats the analysis for waves 1 and 2, in which all households are self-selected and receive monthly invoices. We find a much more parallel evolution and the effect remains stable.

Figure 7: Treatment effect for waves 3 and 4, by wave and month



Note: Red vertical lines indicate the start and end date of each wave. The coefficients are estimated with PCSE AR1 from the specification of Equation (1) in which the treatment variable is interacted with dummies that indicate the number of months since the start of the experiment. The complete estimation results are provided in Table D.5. Thick (thin) whiskers represent 90% (99%) confidence intervals.

Financial savings Depending on their natural intra-day consumption pattern, some participants are favored while others are penalized by the TOU pricing scheme. For households that, for example, are rarely present at home in the middle of the day, making significant efforts may not be sufficient to achieve a reduction in the electricity bill. These inequalities may have led some participants to completely give up trying to adapt to the TOU tariffs.[13]

In Table 6, we explore whether the households that benefit most from their participation are also the most responsive. Following the same procedure as in Table 5, we interact the DiD variable from Equation (1) with three alternative earnings indicators.

The first indicator identifies households who would have saved money over the entire treatment period had the TOU been binding. The calculation is done for the entire processing period. Of the 380 households, 182 would have benefited. Columns 1 and 4 of Table 6 show the results. We find that the "winners", with an impact of 0.7 percentage point higher than that of the "losers" (0.1 percentage point), drive almost all the effect of the treatment. These results therefore suggest that, in the absence of monetary savings, households are getting discouraged.

The second indicator is similar the the first one, except that winners and losers are identified for each month, based on the previous bill. Results are reported in columns 2 and 5 of Table 6. We find an even greater response from households benefiting from savings on the last bill. Moreover, households that "lost" the previous month now appear to have not reacted at all. Figure 8 deepens the analysis by examining the evolution month after month.[14] The losers seem not to have tried to change their consumption habits, even in the first months. One explanation for this lack of any attempt is that, when households received their notification of participation, the previous month's invoice was already applying the TOU tariff. They were thus already able to appreciate how far they were from achieving savings.

The third indicator used to assess the differentiated response is a continuous variable. It measures the difference, in CHF and for the previous invoice, depending on whether the TOU or flat tariff is used. Results are shown in columns 3 and 6 of Table 6. We find that for every additional CHF saved on the previous bill, households shifted an additional 0.3 percentage point of their daily consumption to the 11am-3pm period. This result confirms that significant amounts are not required to modify

[13]As a reminder, the TOU is not binding. If the invoice issued under the TOU tariff is higher than that issued under the flat tariff, the participant pays only the latter.

[14]For readability reasons, we do not display the coefficients for months 12 to 18 (waves 1 and 2 only) on the figure, but the complete results of the estimates are available in Table D.7 in the Appendix.

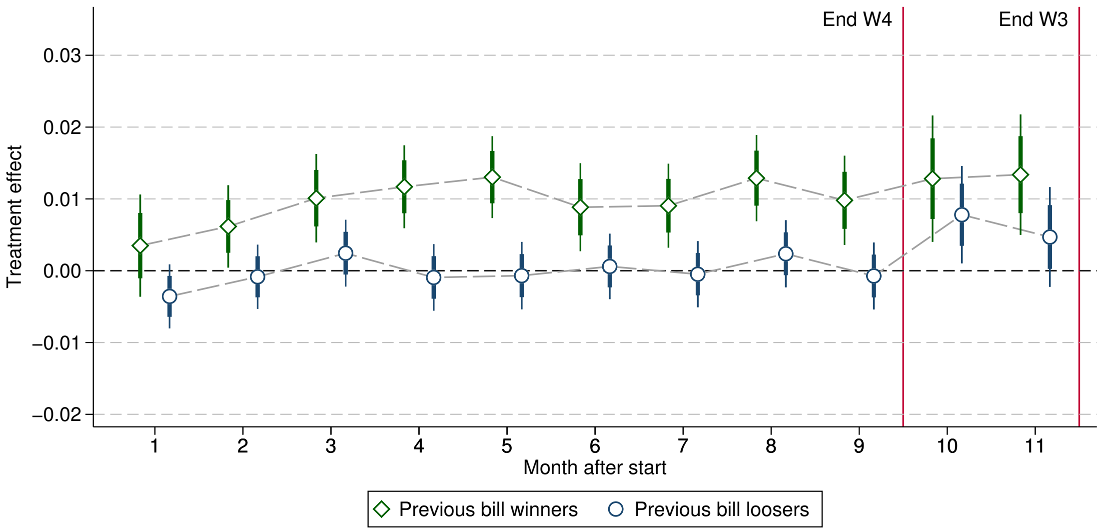
Table 6: Treatment effect: financial savings

	PCSE AR1			FGLS AR1		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect	0.0011	−0.0000	0.0044***	0.0011***	0.0003	0.0041***
	(0.0008)	(0.0008)	(0.0007)	(0.0004)	(0.0004)	(0.0004)
Treatment effect × Winner (overall)	0.0069***			0.0064***		
	(0.0014)			(0.0005)		
Treatment effect × Winner (previous bill)		0.0096***			0.0081***	
		(0.0011)			(0.0005)	
Treatment effect × Savings (previous bill)			0.0030***			0.0026***
			(0.0002)			(0.0001)
Constant	0.1925***	0.1920***	0.1917***	0.1921***	0.1916***	0.1914***
	(0.0036)	(0.0036)	(0.0035)	(0.0031)	(0.0031)	(0.0031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	277,780	277,780	277,780	277,780	277,780	277,780
# Households	380	380	380	380	380	380
R^2	0.1591	0.1594	0.1599			

Note: Robust SE in parentheses, clustered at the household level. *p<0.1, **p<0.05, ***p<0.01.
Observation period: 01Jan2016 to 31Dec2017
Using balanced panel only.

household's intra-day electricity demand. It also corroborates previous evidence showing a relationship between incentive level and household response (Reiss and White, 2005; Woo et al., 2013a; Di Cosmo et al., 2014).

Figure 8: Treatment effect according to financial saving, by month



Note: Red vertical lines indicate the start and end date of each wave. The coefficients are estimated with PCSE AR1 from the specification of Equation (1) in which the treatment variable is interacted with dummies that indicate the number of months since the start of the experiment and a dummy variable that indicates whether the households saved or lost money in the previous month. Only the coefficients for the first 11 months are reported. The complete estimation results are provided in Table D.7. Thick (thin) whiskers represent 90% (99%) confidence intervals.

7 Conclusions and implications

The central purpose of this study is to assess whether TOU pricing is an adequate instrument to cope with increasing penetration levels of intermittent solar energy. Past studies on demand response are numerous, but almost all focus on the reduction of electricity usage, either globally or during peak periods. In contrast, the experiment presented in this paper implements pricing scheme designed to attract consumption towards periods of the day when solar radiation is, in expectation, the highest. Our study therefore sheds new light on a problematic that is likely to intensify as a result of the acceleration of the diffusion of PV.

To address our research questions, we set up a field experiment involving households that were randomly selected in the population and randomly assigned to a treatment and control group. Since we have high frequency consumption data both before and during the experiment, we are able to estimate the causal effect of the implementation of the TOU tariff. Our intervention lasted up to 18 months for some participants, allowing us to evaluate the persistence of the households' response.

Our results contribute to the ongoing discussion on the impact of time-based pricing. They also provide some practical insights about the potential of demand-side management to meet the needs for flexibility.

First, despite a reduction in electricity prices of more than 50% between 11am and 3pm, households do not seem ready to significantly increase their consumption in this time slot. Such price incentives therefore do not seem appropriate to induce households to reallocate their consumption towards hours of high solar electricity production. However, such an intervention may prove successful in increasing the proportion of solar electricity in the consumption mix. Indeed, an unexpected side-benefit of our intervention is a significant reduction in consumption when solar production is low or nonexistent, in particular during evening peaks.

Second, even very small levels of financial incentives are sufficient to achieve a sustained change in households demand. In our experiment, the average savings made by households were less than CHF 1 per month, while other studies obtain a very similar demand response with much larger amounts. In addition, the effect we are measuring is probably a lower bound because the participants in our experiment were not exposed to any financial risk. It should also be noted that a properly calibrated TOU tariff can be implemented without any loss of revenue for the utility. If the tariff in our experiment had been binding, the revenues realized with households whose bills increased would have been sufficient to offset the gains realized by households whose bills decreased.

A third lesson stems from our experience with smart-meter data. With flat tariff, the utility only needs a single meter reading when issuing the invoice. However, time-based tariffs require high granularity records of electricity usage in order to apply the correct rate to the customers' hourly consumption. Although the installation of smart-meters removes this technical barrier, the numerous missing or erroneous values we have discovered in our database reveal that utilities will need to carefully examine the reliability of their systems before proposing new pricing schemes to their customers.

Appendix A: Data cleaning and imputation

This section explains how the raw data we received from the electricity provider *La Goule* were processed before being used in this paper. The procedures were developed and executed by Lionel Bloch and Jordan Holweger (EPFL). More detailed information (in French) can be found in Perret et al. (2019).

The purpose of the cleaning and imputation work is twofold. First, it aims at eliminating implausible consumption values, which result from transmission problems between smart-meters and computer servers where data are stored. Second, it aims at filling the missing values (i.e. those resulting from cleaning, but also those that were already missing in the raw data) in order to have complete load curves.

Identification of non-plausible data For a consumption measurement to be considered valid, the use of electricity (over 15 minutes or one hour) must be strictly greater than 0. Technical problem was considered to have occurred when the observation indicates a consumption equal to zero. It is indeed highly unlikely that a participant would disconnect all of its electrical equipment from the grid, especially since only *La Goule*'s customers living in their main residence were eligible.

An additional condition for a measurement to be considered valid relates to the maximum power over a given interval. The power limit has been set at 10 kW for households with a load curve available in 15-minute intervals and at 8 kW for households with a load curve available in 1-hour intervals.[15] The maximum values differ because, while it is possible that high power peaks may occur over relatively short intervals (15 minutes), it appears much less likely that such high power levels would be sustained over longer intervals (1 hour). Since the households studied were not supposed to be equipped with large electrical appliances (electric heating, heat pumps, heavy machinery), a longer interval results in a reduction in the average power over the interval.

Imputation of missing values The imputation of missing values, including the non-plausible observations identified in the previous step, is done by considering each load curve separately. Load curves showing a percentage of valid data below 50% are excluded from this procedure because imputing reliable values from such a small amount of data is not possible.

[15]The maximum values of 10 and 8 kW are based on statistical analyses of the observed load curves.

The technique used for imputation is to fill in the missing values with the average consumption before or after the missing data point. Specifically, for each missing observation, three non-missing observations are selected within an interval of -10 weeks to +10 weeks, giving priority to the nearest observations. Of course, only observations whose time (hour or quarter of an hour) and day of the week match are selected. The average of these selected observations is then used to fill in the missing value.

Appendix B: Random assignments

Table B.1: Summary statistics of treatment and control groups: waves 1 and 2

	Treatment			Control			Difference (T-C)	
	Mean	(SD)	#HH	Mean	(SD)	#HH	Mean	[SE]
Metering data								
Electricity consumption (kWh/day)	7.57	(3.75)	27	8.29	(5.78)	28	0.72	[1.32]
Electricity consumption 11am-3pm (kWh/day)	1.61	(0.90)	27	1.80	(1.27)	28	0.20	[0.30]
Proportion 11am-3pm	0.20	(0.04)	27	0.21	(0.05)	28	0.01	[0.01]
Survey data								
Household size	2.26	(0.98)	27	2.18	(0.98)	28	−0.08	[0.27]
Activity rate (household index)	0.49	(0.36)	27	0.48	(0.37)	28	−0.01	[0.10]
Income in CHF 1,000 (midpoints)	6.91	(3.69)	23	5.92	(2.78)	26	−0.99	[0.93]
Age in 10 years (midpoints)	5.46	(1.68)	27	5.39	(1.64)	28	−0.07	[0.45]
High education	0.26	(0.45)	27	0.18	(0.39)	28	−0.08	[0.11]
Detached house	0.48	(0.51)	27	0.54	(0.51)	28	0.05	[0.14]
Owner	0.52	(0.51)	27	0.57	(0.50)	28	0.05	[0.14]
Number of rooms	7.19	(1.90)	27	7.29	(1.94)	28	0.10	[0.52]
Accommodation size (in square meters)	160.92	(159.19)	25	169.72	(139.37)	25	8.80	[42.32]
Number of appliances	21.58	(5.04)	26	20.89	(4.76)	28	−0.68	[1.33]
Ecological bulbs (%)	38.89	(29.69)	27	34.26	(27.86)	27	−4.63	[7.84]

Note: Summary statistics for metering data are computed over the benchmark period, i.e. from 1 January 2016 to 30 June 2016 for wave 1 and from 1 January 2016 to 30 September 2016 for wave 2. Standard deviations in parentheses. Last two columns report the difference in the means between the two groups and standard errors of t-tests on the equality of means. $^{*}p < 0.10$, $^{**}p < 0.5$, $^{***}p < 0.01$.

Table B.2: Probit results

	All waves				Waves 1+2			
	(1)		(2)		(3)		(4)	
Av. daily consumption	−0.042	(0.041)	−0.008	(0.053)	−0.100	(0.229)	0.207	(0.314)
Av. consumption 11am-3pm	0.227	(0.214)	0.039	(0.276)	0.427	(1.130)	−0.938	(1.490)
Av. proportion 11am-3pm	−2.212	(2.245)	−1.052	(2.685)	−5.746	(8.623)	0.804	(11.360)
Household size							−0.105	(0.257)
Activity rate							−0.688	(0.820)
Income							0.124	(0.097)
Age							0.137	(0.180)
High education							−0.003	(0.551)
Detached house							−0.125	(0.909)
Owner							−0.498	(0.789)
Number of rooms							−0.303*	(0.180)
Accommodation size							0.001	(0.002)
Number of appliances							0.045	(0.054)
Ecological bulbs (%)							1.026	(0.915)
Constant	0.414	(0.426)	0.285	(0.516)	1.206	(1.639)	−0.152	(2.560)
# Observations	501		380		55		44	

Note: The dependent variable takes the value 1 for the control group, an 0 otherwise. Column (1) includes all households for which data are available. Columns (2) focuses on the households with no missing consumption data over the entire observation period. Columns (3) and (4) repeat the same procedure for households in the first two waves only.

Appendix C: Parallel trend assumption

In order to test the assumption of parallel trends between the treatment and control groups, we take advantage of the relatively long period of time for which we have data before the start of the experiments. By adding "lead" treatments preceding the actual treatment in a DiD estimation, we can investigate whether both groups behave in a similar way during the benchmark period. See Angrist and Pischke (2008) for a detailed presentation of the method, and Weber et al. (2017) for an implementation to field experiments with TOU tariffs. More precisely, we estimate the following "placebo" model :

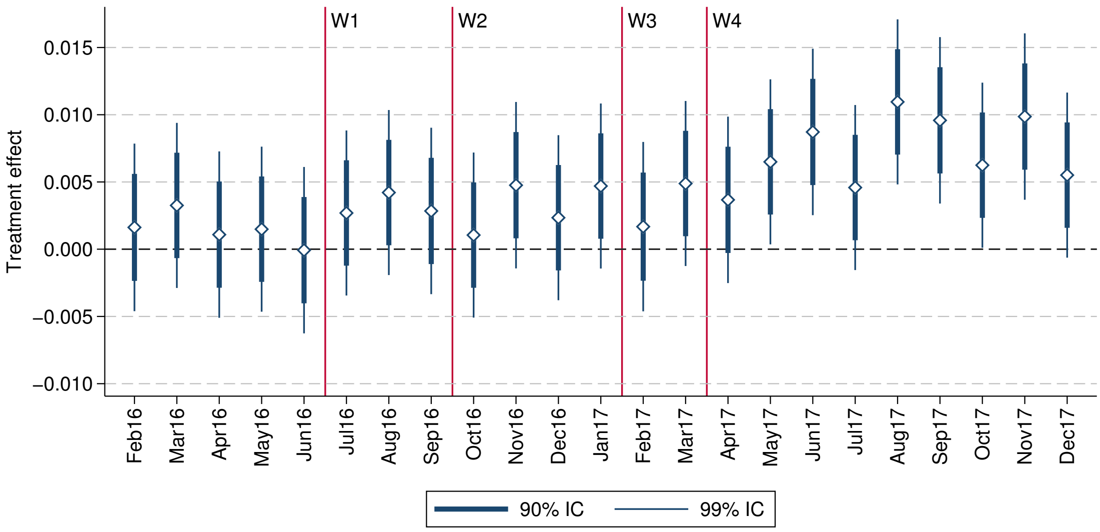
$$Pr_{it} = \sum_{m=Feb16}^{Dec17} \beta_m (G_{it} \times M_t) + \alpha_i + \delta_t + \gamma X_t^{'} + \varepsilon_{it} \tag{3}$$

where G_{it} is a dummy variable that takes the value 1 for the households in the treatment group, and 0 otherwise. It is interacted with a vector of dummy variables for each month of the observation period, denoted M_t. As in our baseline model (see Section 5), we include weather control variables ($X_t^{'}$), household fixed effects (α_i) and month fixed effects (δ_t) in the estimation.

The benchmark period in this DiD estimation is restricted to the month of January 2016. We therefore estimate all monthly effects in relation to this reference month. Since our intervention started in July 2016 for the first wave, we expect no significant effects before that date.

Figure C.1 shows that the monthly fictitious treatments for the months of February to June 2016 are indeed not statistically different from 0 at the 90% level. This result confirms the parallel trends between the two groups. As expected, some coefficients become significant after the launch of the first wave, reflecting our intervention. From April 2017 onward, when all households in the treatment group face the TOU tariff, all monthly coefficients are positive and statistically significant.

Figure C.1: Treatment effect: parallel trend assumption



Note: This figure reports the β_m coefficients obtained from the estimation of Equation (3) with panel corrected standard errors and auto-regressive coefficient of degree 1. Since PCSE AR1 technique requires balanced panel data, only the 380 participants for whom we have the load curve from 1 January 2016 to 31 December 2017 are included. Results (not reported) are however similar if we include all households and estimate the model with OLS regression.

Appendix D: Additional results and robustness checks

Table D.1: Treatment effect: including all households and excluding imputed data

	Including households with missing data			Excluding filled observations		
	(1)	(2)	(3)	(4)	(5)	(6)
	PCSE AR1	FGLS AR1	OLS	PCSE AR1	FGLS AR1	OLS
Treatment effet	0.0038***	0.0038***	0.0038**	0.0046***	0.0046***	0.0047***
	(0.0006)	(0.0006)	(0.0015)	(0.0008)	(0.0008)	(0.0017)
Rainfalls	0.0006**	0.0006***	0.0006***	0.0009***	0.0008***	0.0008***
	(0.0003)	(0.0001)	(0.0001)	(0.0003)	(0.0002)	(0.0002)
Sunshine duration	−0.0000***	−0.0000***	−0.0000***	−0.0000***	−0.0000***	−0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Temperature	−0.0001	−0.0001*	−0.0001	−0.0001	−0.0001	−0.0000
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Constant	0.1565***	0.1565***	0.1991***	0.1899***	0.1898***	0.2030***
	(0.0070)	(0.0053)	(0.0012)	(0.0038)	(0.0040)	(0.0014)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	347,558	347,558	347,558	229,547	229,547	229,547
# Households	501	501	501	380	380	380
R^2	0.1647		0.0024	0.1552		0.0031

Note: Robust SE in parentheses, clustered at the household level. *p<0.1, **p<0.05, ***p<0.01.
The models in this table are estimated with unbalanced panel datasets (missing observations). The standard errors in PCSE models are therefore adjusted based only on available observations that are common to two households (pairwise selection). The standard errors in FGLS models are assumed to be iid as heteroskedastic error structure with autocorrelation cannot be used.

Table D.2: Treatment effect: alternative specifications

	PCSE AR1				FGLS AR1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment effet	0.0045^{***}	0.0045^{***}	0.0048^{***}	0.0030^{***}	0.0041^{***}	0.0041^{***}	0.0045^{***}	0.0029^{***}
	(0.0007)	(0.0007)	(0.0007)	(0.0009)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Treatment period			-0.0018^{*}				-0.0017^{***}	
			(0.0009)				(0.0003)	
Treatment group				-0.0012^{**}				-0.0012^{***}
				(0.0006)				(0.0003)
Rainfalls	0.0005^{**}		0.0007^{**}	0.0007^{***}	0.0004^{***}		0.0005^{***}	0.0005^{***}
	(0.0002)		(0.0003)	(0.0003)	(0.0001)		(0.0001)	(0.0001)
Sunshine duration	-0.0000^{***}		-0.0000^{***}	-0.0000^{***}	-0.0000^{***}		-0.0000^{***}	-0.0000^{***}
	(0.0000)		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)
Temperature	-0.0001^{*}		0.0003^{***}	-0.0001	-0.0001^{**}		0.0003^{***}	-0.0001^{**}
	(0.0001)		(0.0001)	(0.0001)	(0.0000)		(0.0000)	(0.0000)
Constant	0.1844^{***}	0.1890^{***}	0.1904^{***}	0.2020^{***}	0.1970^{***}	0.1890^{***}	0.1905^{***}	0.2013^{***}
	(0.0033)	(0.0036)	(0.0031)	(0.0022)	(0.0031)	(0.0031)	(0.0031)	(0.0008)
Month FE	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Day of week FE	Yes	No	No	No	Yes	No	No	No
Household FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
# Observations	277,780	277,780	277,780	277,780	277,780	277,780	277,780	277,780
# Households	380	380	380	380	380	380	380	380
R^2	0.1642	0.1581	0.1581	0.0018				

Note: Robust SE in parentheses, clustered at the household level. *p<0.1, **p<0.05, ***p<0.01.

Table D.3: Treatment effect by month: all waves

	(1) PCSE AR1		(2) FGLS AR1		(3) OLS	
Treatment effect, winners						
Month 1	0.0037	(0.0031)	0.0035	(0.0028)	0.0022*	(0.0013)
Month 2	0.0061**	(0.0028)	0.0062***	(0.0022)	0.0049***	(0.0012)
Month 3	0.0102***	(0.0032)	0.0101***	(0.0024)	0.0101***	(0.0012)
Month 4	0.0116***	(0.0035)	0.0117***	(0.0022)	0.0112***	(0.0011)
Month 5	0.0131***	(0.0035)	0.0130***	(0.0022)	0.0106***	(0.0011)
Month 6	0.0090***	(0.0034)	0.0088***	(0.0024)	0.0077***	(0.0012)
Month 7	0.0090***	(0.0031)	0.0091***	(0.0023)	0.0092***	(0.0012)
Month 8	0.0130***	(0.0036)	0.0129***	(0.0023)	0.0119***	(0.0012)
Month 9	0.0098***	(0.0036)	0.0098***	(0.0024)	0.0089***	(0.0013)
Month 10	0.0127**	(0.0051)	0.0128***	(0.0034)	0.0117***	(0.0019)
Month 11	0.0136***	(0.0049)	0.0134***	(0.0033)	0.0121***	(0.0018)
Month 12	0.0189	(0.0118)	0.0188***	(0.0059)	0.0170***	(0.0032)
Month 13	0.0043	(0.0066)	0.0045	(0.0067)	0.0054	(0.0038)
Month 14	0.0129	(0.0109)	0.0128*	(0.0067)	0.0103***	(0.0038)
Month 15	0.0035	(0.0076)	0.0035	(0.0068)	0.0034	(0.0039)
Month 16	0.0095	(0.0121)	0.0098	(0.0098)	0.0031	(0.0060)
Month 17	0.0033	(0.0054)	0.0032	(0.0111)	−0.0023	(0.0068)
Month 18	0.0027	(0.0061)	0.0025	(0.0103)	−0.0014	(0.0062)
Treatment effect, loosers						
Month 1	−0.0036	(0.0023)	−0.0036**	(0.0017)	−0.0021***	(0.0008)
Month 2	−0.0008	(0.0025)	−0.0008	(0.0017)	−0.0011	(0.0008)
Month 3	0.0024	(0.0025)	0.0024	(0.0018)	0.0027***	(0.0008)
Month 4	−0.0010	(0.0024)	−0.0009	(0.0018)	−0.0014*	(0.0008)
Month 5	−0.0007	(0.0026)	−0.0007	(0.0018)	0.0006	(0.0008)
Month 6	0.0005	(0.0027)	0.0006	(0.0018)	−0.0002	(0.0008)
Month 7	−0.0005	(0.0026)	−0.0005	(0.0018)	−0.0003	(0.0008)
Month 8	0.0024	(0.0029)	0.0024	(0.0018)	0.0025***	(0.0009)
Month 9	−0.0008	(0.0028)	−0.0007	(0.0018)	0.0007	(0.0008)
Month 10	0.0077*	(0.0042)	0.0078***	(0.0026)	0.0089***	(0.0012)
Month 11	0.0047*	(0.0028)	0.0047*	(0.0027)	0.0058***	(0.0012)
Month 12	−0.0070	(0.0068)	−0.0069	(0.0062)	−0.0036	(0.0036)
Month 13	−0.0062	(0.0061)	−0.0063	(0.0056)	−0.0053*	(0.0030)
Month 14	0.0037	(0.0065)	0.0039	(0.0055)	0.0080***	(0.0031)
Month 15	0.0038	(0.0080)	0.0038	(0.0054)	0.0035	(0.0030)
Month 16	0.0006	(0.0179)	0.0006	(0.0090)	0.0032	(0.0051)
Month 17	0.0043	(0.0138)	0.0043	(0.0079)	0.0020	(0.0048)
Month 18	0.0198	(0.0322)	0.0201**	(0.0092)	0.0215***	(0.0050)
Rainfalls	0.0006***	(0.0001)	0.0007**	(0.0003)	0.0005***	(0.0001)
Sunshine duration	−0.0000***	(0.0000)	−0.0000***	(0.0000)	−0.0000***	(0.0000)
Temperature	−0.0001	(0.0001)	−0.0001	(0.0001)	−0.0001*	(0.0000)
Constant	0.1923***	(0.0016)	0.1924***	(0.0036)	0.1916***	(0.0031)
Month FE	Yes		Yes		Yes	
Household FE	Yes		Yes		Yes	
# Observations	277,780		277,780		277,780	
# Households	380		380		380	
R^2	0.1831		0.1596			

Note: Robust SE in parentheses, clustered at the household level. *p<0.1, **p<0.05, ***p<0.01.

Table D.4: Treatment effect: hourly electricity usage

	(1) PCSE AR1		(2) FGLS AR1		(3) OLS	
Treatment effect						
0am-1am	-0.0037	(0.0050)	-0.0161^{***}	(0.0037)	-0.0044	(0.0374)
1am-2am	-0.0120^{**}	(0.0050)	-0.0169^{***}	(0.0037)	-0.0125	(0.0361)
2am-3am	-0.0163^{***}	(0.0050)	-0.0215^{***}	(0.0037)	-0.0165	(0.0362)
3am-4am	-0.0104^{**}	(0.0050)	-0.0157^{***}	(0.0037)	-0.0104	(0.0361)
4am-5am	-0.0148^{***}	(0.0050)	-0.0207^{***}	(0.0037)	-0.0149	(0.0365)
5am-6am	-0.0071	(0.0050)	-0.0175^{***}	(0.0037)	-0.0071	(0.0367)
6am-7am	-0.0049	(0.0050)	-0.0168^{***}	(0.0037)	-0.0047	(0.0358)
7am-8am	0.0092^{*}	(0.0050)	-0.0050	(0.0037)	0.0097	(0.0378)
8am-9am	-0.0075	(0.0050)	-0.0192^{***}	(0.0037)	-0.0071	(0.0379)
9am-10am	0.0020	(0.0050)	-0.0133^{***}	(0.0037)	0.0022	(0.0372)
10am-11am	-0.0193^{***}	(0.0050)	-0.0247^{***}	(0.0037)	-0.0191	(0.0385)
11am-12am	-0.0302^{***}	(0.0050)	-0.0303^{***}	(0.0037)	-0.0301	(0.0438)
12am-1pm	-0.0105^{**}	(0.0050)	-0.0144^{***}	(0.0037)	-0.0105	(0.0398)
1pm-2pm	0.0170^{***}	(0.0050)	-0.0042	(0.0037)	0.0169	(0.0370)
2pm-3pm	0.0095^{*}	(0.0050)	-0.0053	(0.0037)	0.0095	(0.0366)
3pm-4pm	0.0010	(0.0050)	-0.0112^{***}	(0.0037)	0.0009	(0.0365)
4pm-5pm	0.0087^{*}	(0.0050)	-0.0065^{*}	(0.0037)	0.0084	(0.0347)
5pm-6pm	-0.0178^{***}	(0.0050)	-0.0221^{***}	(0.0037)	-0.0176	(0.0357)
6pm-7pm	-0.0388^{***}	(0.0050)	-0.0353^{***}	(0.0037)	-0.0388	(0.0375)
7pm-8pm	-0.0562^{***}	(0.0050)	-0.0465^{***}	(0.0037)	-0.0563	(0.0361)
8pm-9pm	-0.0485^{***}	(0.0050)	-0.0461^{***}	(0.0037)	-0.0489	(0.0359)
9pm-10pm	-0.0324^{***}	(0.0050)	-0.0368^{***}	(0.0037)	-0.0331	(0.0362)
10pm-11pm	-0.0208^{***}	(0.0050)	-0.0278^{***}	(0.0037)	-0.0214	(0.0370)
11pm-0am	-0.0113^{**}	(0.0050)	-0.0187^{***}	(0.0037)	-0.0117	(0.0377)
Treatment group	0.0292^{***}	(0.0019)	0.0329^{***}	(0.0016)	0.0292	(0.0638)
Rainfalls	0.0047^{***}	(0.0013)	0.0037^{***}	(0.0010)	0.0123^{***}	(0.0010)
Sunshine duration	-0.0012^{***}	(0.0000)	-0.0010^{***}	(0.0000)	-0.0016^{***}	(0.0001)
Temperature	-0.0087^{***}	(0.0003)	-0.0083^{***}	(0.0003)	-0.0067^{***}	(0.0004)
Constant	-1.7542^{***}	(0.0073)	-1.7536^{***}	(0.0059)	-1.7593^{***}	(0.0509)
Month FE	Yes		Yes		Yes	
Household FE	No		No		No	
# Observations	6,665,960		6,665,960		6,665,960	
# Households	380		380		380	
R^2	0.0525				0.1027	

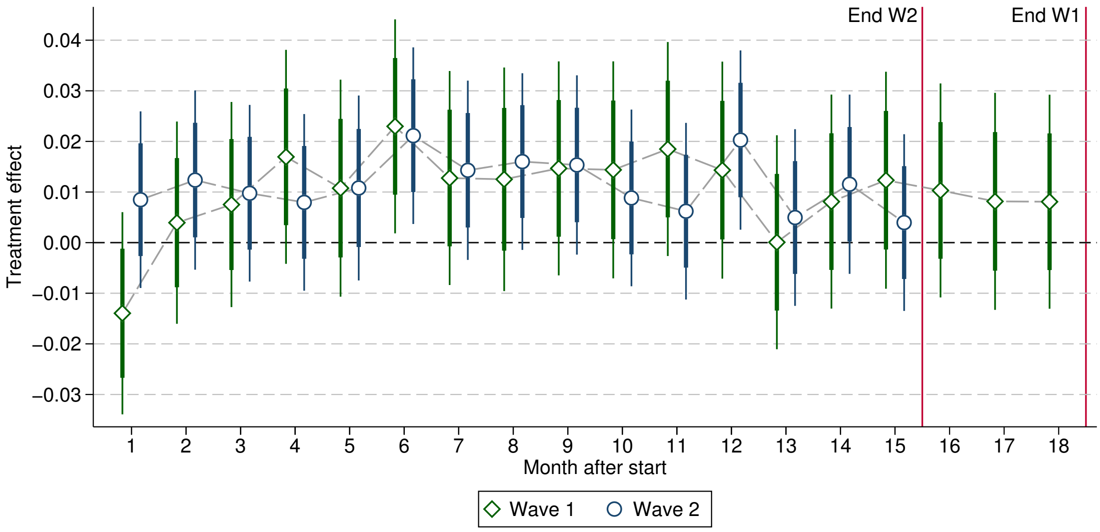
Note: Robust SE in parentheses, clustered at the household level. *p<0.1, **p<0.05, ***p<0.01.

Table D.5: Treatment effect for waves 3 and 4, by wave and month

	(1) PCSE AR1		(2) FGLS AR1		(3) OLS	
Treatment effect, wave 3						
February 17	0.0011	(0.0023)	0.0017	(0.0012)	0.0011	(0.0031)
March 17	0.0009	(0.0022)	−0.0006	(0.0012)	0.0009	(0.0034)
April 17	0.0031	(0.0023)	0.0040***	(0.0013)	0.0031	(0.0037)
May 17	0.0039*	(0.0023)	0.0028**	(0.0013)	0.0040	(0.0036)
June 17	0.0035	(0.0023)	0.0040***	(0.0013)	0.0034	(0.0043)
July 17	−0.0021	(0.0023)	−0.0030**	(0.0013)	−0.0020	(0.0036)
August 17	0.0071***	(0.0023)	0.0071***	(0.0013)	0.0070*	(0.0036)
September 17	0.0084***	(0.0023)	0.0086***	(0.0013)	0.0085**	(0.0042)
October 17	0.0056**	(0.0023)	0.0071***	(0.0013)	0.0056	(0.0042)
November 17	0.0102***	(0.0023)	0.0112***	(0.0013)	0.0102**	(0.0045)
December 17	0.0070***	(0.0023)	0.0071***	(0.0013)	0.0071*	(0.0038)
Treatment effect, wave 4						
April 17	−0.0015	(0.0024)	−0.0004	(0.0011)	−0.0013	(0.0030)
May 17	0.0027	(0.0024)	0.0027**	(0.0011)	0.0026	(0.0033)
June 17	0.0075***	(0.0024)	0.0079***	(0.0011)	0.0075**	(0.0036)
July 17	0.0055**	(0.0024)	0.0050***	(0.0011)	0.0054	(0.0037)
August 17	0.0109***	(0.0024)	0.0104***	(0.0011)	0.0110***	(0.0035)
September 17	0.0055**	(0.0024)	0.0056***	(0.0011)	0.0055	(0.0034)
October 17	0.0030	(0.0024)	0.0026**	(0.0011)	0.0030	(0.0034)
November 17	0.0062**	(0.0024)	0.0062***	(0.0011)	0.0062*	(0.0036)
December 17	0.0011	(0.0024)	0.0015	(0.0011)	0.0010	(0.0035)
Rainfalls	0.0008***	(0.0003)	0.0005***	(0.0001)	0.0007***	(0.0001)
Sunshine duration	−0.0000***	(0.0000)	−0.0000***	(0.0000)	−0.0000***	(0.0000)
Temperature	−0.0001	(0.0001)	−0.0001	(0.0000)	−0.0001*	(0.0001)
Constant	0.2021***	(0.0051)	0.2019***	(0.0048)	0.2005***	(0.0014)
Month FE	Yes		Yes		Yes	
Household FE	Yes		Yes		Yes	
# Observations	247,809		247,809		247,809	
# Households	339		339		339	
R^2	0.1606				0.0030	

Note: Robust SE in parentheses, clustered at the household level. *p<0.1, **p<0.05, ***p<0.01.

Figure D.1: Treatment effect for waves 1 and 2, by wave and month



Note: Red vertical lines indicate the start and end date of each wave. The coefficients are estimated with PCSE AR1 from the specification of Equation (1) in which the treatment variable is interacted with dummies that indicate the number of month since the start of the experiment. The complete estimation result is provided in Table D.6. Thick (thin) whiskers represent 90% (99%) confidence intervals.

Table D.6: Treatment effect for waves 1 and 2, by wave and month

	(1) PCSE AR1		(2) FGLS AR1		(3) OLS	
Treatment effect, wave 1						
July 16	-0.0140^{*}	(0.0078)	-0.0007	(0.0064)	-0.0141	(0.0135)
August 16	0.0039	(0.0078)	0.0096	(0.0064)	0.0041	(0.0081)
September 16	0.0075	(0.0079)	0.0106	(0.0065)	0.0077	(0.0087)
October 16	0.0170^{**}	(0.0082)	0.0139^{**}	(0.0066)	0.0165	(0.0110)
November 16	0.0108	(0.0083)	0.0060	(0.0067)	0.0111	(0.0110)
December 16	0.0230^{***}	(0.0082)	0.0128^{*}	(0.0066)	0.0232^{*}	(0.0115)
January 17	0.0128	(0.0082)	-0.0004	(0.0066)	0.0124	(0.0122)
February 17	0.0125	(0.0086)	0.0010	(0.0069)	0.0126	(0.0149)
March 17	0.0147^{*}	(0.0082)	0.0088	(0.0066)	0.0150	(0.0126)
April 17	0.0144^{*}	(0.0083)	0.0132^{**}	(0.0067)	0.0141	(0.0117)
May 17	0.0185^{**}	(0.0082)	0.0086	(0.0066)	0.0185	(0.0123)
June 17	0.0143^{*}	(0.0083)	0.0123^{*}	(0.0067)	0.0144	(0.0183)
July 17	0.0001	(0.0082)	0.0020	(0.0066)	0.0002	(0.0106)
August 17	0.0081	(0.0082)	0.0059	(0.0066)	0.0078	(0.0147)
September 17	0.0123	(0.0083)	0.0062	(0.0067)	0.0125	(0.0124)
October 17	0.0103	(0.0082)	0.0033	(0.0066)	0.0101	(0.0148)
November 17	0.0082	(0.0083)	0.0019	(0.0067)	0.0083	(0.0110)
December 17	0.0081	(0.0082)	0.0125^{*}	(0.0066)	0.0081	(0.0172)
Treatment effect, wave 2						
October 16	0.0085	(0.0068)	0.0045	(0.0055)	0.0084	(0.0096)
November 16	0.0124^{*}	(0.0069)	0.0077	(0.0056)	0.0122	(0.0088)
December 16	0.0098	(0.0068)	-0.0009	(0.0055)	0.0099	(0.0124)
January 17	0.0080	(0.0068)	-0.0051	(0.0055)	0.0077	(0.0153)
February 17	0.0108	(0.0071)	0.0015	(0.0058)	0.0109	(0.0144)
March 17	0.0211^{***}	(0.0068)	0.0086	(0.0055)	0.0210	(0.0161)
April 17	0.0143^{**}	(0.0069)	0.0068	(0.0056)	0.0143	(0.0100)
May 17	0.0160^{**}	(0.0068)	0.0045	(0.0055)	0.0161	(0.0139)
June 17	0.0153^{**}	(0.0069)	0.0111^{**}	(0.0056)	0.0155	(0.0120)
July 17	0.0088	(0.0068)	0.0081	(0.0055)	0.0088	(0.0083)
August 17	0.0062	(0.0068)	0.0038	(0.0055)	0.0061	(0.0089)
September 17	0.0203^{***}	(0.0069)	0.0133^{**}	(0.0056)	0.0204^{*}	(0.0104)
October 17	0.0050	(0.0068)	0.0010	(0.0055)	0.0047	(0.0114)
November 17	0.0115^{*}	(0.0069)	0.0105^{*}	(0.0056)	0.0117	(0.0094)
December 17	0.0040	(0.0068)	-0.0019	(0.0055)	0.0038	(0.0122)
Rainfalls	-0.0001	(0.0005)	0.0001	(0.0004)	-0.0001	(0.0004)
Sunshine duration	-0.0000^{***}	(0.0000)	-0.0000^{***}	(0.0000)	-0.0000^{***}	(0.0000)
Temperature	-0.0000	(0.0002)	0.0001	(0.0001)	0.0000	(0.0002)
Constant	0.1876^{***}	(0.0044)	0.1865^{***}	(0.0039)	0.2048^{***}	(0.0043)
Month FE	Yes		Yes		Yes	
Household FE	Yes		Yes		Yes	
# Observations	29,971		29,971		29,971	
# Households	44		44		44	
R^2	0.1478				0.0049	

Note: Robust SE in parentheses, clustered at the household level. *p<0.1, **p<0.05, ***p<0.01.

Table D.7: Treatment effect by month of year: previous bill winners

	(1) PCSE AR1		(2) FGLS AR1		(3) OLS	
Treatment effect, winners						
Month 1	0.0037	(0.0031)	0.0035	(0.0028)	0.0022^{*}	(0.0013)
Month 2	0.0061^{**}	(0.0028)	0.0062^{***}	(0.0022)	0.0049^{***}	(0.0012)
Month 3	0.0102^{***}	(0.0032)	0.0101^{***}	(0.0024)	0.0101^{***}	(0.0012)
Month 4	0.0116^{***}	(0.0035)	0.0117^{***}	(0.0022)	0.0112^{***}	(0.0011)
Month 5	0.0131^{***}	(0.0035)	0.0130^{***}	(0.0022)	0.0106^{***}	(0.0011)
Month 6	0.0090^{***}	(0.0034)	0.0088^{***}	(0.0024)	0.0077^{***}	(0.0012)
Month 7	0.0090^{***}	(0.0031)	0.0091^{***}	(0.0023)	0.0092^{***}	(0.0012)
Month 8	0.0130^{***}	(0.0036)	0.0129^{***}	(0.0023)	0.0119^{***}	(0.0012)
Month 9	0.0098^{***}	(0.0036)	0.0098^{***}	(0.0024)	0.0089^{***}	(0.0013)
Month 10	0.0127^{**}	(0.0051)	0.0128^{***}	(0.0034)	0.0117^{***}	(0.0019)
Month 11	0.0136^{***}	(0.0049)	0.0134^{***}	(0.0033)	0.0121^{***}	(0.0018)
Month 12	0.0189	(0.0118)	0.0188^{***}	(0.0059)	0.0170^{***}	(0.0032)
Month 13	0.0043	(0.0066)	0.0045	(0.0067)	0.0054	(0.0038)
Month 14	0.0129	(0.0109)	0.0128^{*}	(0.0067)	0.0103^{***}	(0.0038)
Month 15	0.0035	(0.0076)	0.0035	(0.0068)	0.0034	(0.0039)
Month 16	0.0095	(0.0121)	0.0098	(0.0098)	0.0031	(0.0060)
Month 17	0.0033	(0.0054)	0.0032	(0.0111)	-0.0023	(0.0068)
Month 18	0.0027	(0.0061)	0.0025	(0.0103)	-0.0014	(0.0062)
Treatment effect, loosers						
Month 1	-0.0036	(0.0023)	-0.0036^{**}	(0.0017)	-0.0021^{***}	(0.0008)
Month 2	-0.0008	(0.0025)	-0.0008	(0.0017)	-0.0011	(0.0008)
Month 3	0.0024	(0.0025)	0.0024	(0.0018)	0.0027^{***}	(0.0008)
Month 4	-0.0010	(0.0024)	-0.0009	(0.0018)	-0.0014^{*}	(0.0008)
Month 5	-0.0007	(0.0026)	-0.0007	(0.0018)	0.0006	(0.0008)
Month 6	0.0005	(0.0027)	0.0006	(0.0018)	-0.0002	(0.0008)
Month 7	-0.0005	(0.0026)	-0.0005	(0.0018)	-0.0003	(0.0008)
Month 8	0.0024	(0.0029)	0.0024	(0.0018)	0.0025^{***}	(0.0009)
Month 9	-0.0008	(0.0028)	-0.0007	(0.0018)	0.0007	(0.0008)
Month 10	0.0077^{*}	(0.0042)	0.0078^{***}	(0.0026)	0.0089^{***}	(0.0012)
Month 11	0.0047^{*}	(0.0028)	0.0047^{*}	(0.0027)	0.0058^{***}	(0.0012)
Month 12	-0.0070	(0.0068)	-0.0069	(0.0062)	-0.0036	(0.0036)
Month 13	-0.0062	(0.0061)	-0.0063	(0.0056)	-0.0053^{*}	(0.0030)
Month 14	0.0037	(0.0065)	0.0039	(0.0055)	0.0080^{***}	(0.0031)
Month 15	0.0038	(0.0080)	0.0038	(0.0054)	0.0035	(0.0030)
Month 16	0.0006	(0.0179)	0.0006	(0.0090)	0.0032	(0.0051)
Month 17	0.0043	(0.0138)	0.0043	(0.0079)	0.0020	(0.0048)
Month 18	0.0198	(0.0322)	0.0201^{**}	(0.0092)	0.0215^{***}	(0.0050)
Rainfalls	0.0006^{***}	(0.0001)	0.0007^{**}	(0.0003)	0.0005^{***}	(0.0001)
Sunshine duration	-0.0000^{***}	(0.0000)	-0.0000^{***}	(0.0000)	-0.0000^{***}	(0.0000)
Temperature	-0.0001	(0.0001)	-0.0001	(0.0001)	-0.0001^{*}	(0.0000)
Constant	0.1923^{***}	(0.0016)	0.1924^{***}	(0.0036)	0.1916^{***}	(0.0031)
Month FE	Yes		Yes		Yes	
Household FE	Yes		Yes		Yes	
# Observations	277,780		277,780		277,780	
# Households	380		380		380	
R^2	0.1831		0.1596			

Note: Robust SE in parentheses, clustered at the household level. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

General Conclusion

1 Main findings and policy implications

This thesis empirically investigates the role of social contagion in the diffusion of solar PV and the possibility of modifying electricity demand to accommodate the variable production from solar energy. Three aspects related to the phenomenon of social contagion in the adoption of solar PV are addressed: the underlying drivers of peer effects, the obstacles to their deployment, and their implications in conjunction with subsidies.

Chapter 1 uses geolocalized data of virtually all PV systems in Switzerland to provide new evidence about the existence of peer effects, or social contagion, in the adoption of solar technology. In line with previous studies (e.g. Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Rode and Weber, 2016), we find that households' decisions to install solar PV panels are dependent on the number of past adoptions in the surrounding area. In particular, we show that distance and vintage are important determinants of social contagion: the closer and more recent a PV system is, the greater its impact on the adoption of new PV systems. We contribute to the literature by showing that these peer effects also exist among firms and farms, although in a lesser extent than among households.

Addressing our main research questions, we investigate the variation of social spillovers with various technical characteristics of the solar panels and of the buildings on which they are installed. More visible installations are found to impact adoptions more heavily. By combining the visibility indicators and the ownership, we are able to document the relative role of learning and visibility effects.

The results obtained in chapter 1 provide insights for practitioners and policy-makers alike. Leveraging social contagion could indeed represent a promising option for governments and stakeholders in the PV sector, especially in the post-subsidy era that many countries are entering and in a context where "first choice" policies such as carbon taxes still face strong opposition. In the United States in particular, solar panel installers, electricity utilities and local authorities, sometimes through public-private partnerships, have started undertaking specific initiatives to take advantage of social contagion. These include the installation of curbside signs communicating the presence of a solar panel in the house next door, the implementation of marketing strategies based on group pricing for neighbors, or the use of volunteer solar advocates in the local community (Bollinger and Gillingham, 2012; Kraft-Todd et al., 2018; Bollinger et al., 2019). However, an effective implementation of such strategies requires information on which agents are affected by social contagion and on how installation characteristics affect them.

By investigating the variation of peer effects at a higher level of detail, our study provides guidance and support for the use of targeted initiatives leveraging peer effects for both residential and commercial adoption. These initiatives should not only focus on households' incentives for conspicuous conservation (Sexton and Sexton, 2014), but also on accelerating learning across businesses, for instance through clusters and industry-specific umbrella organizations. Our results also demonstrate that visibility-driven mechanisms are an important component of peer effects. Apart from encouraging PV owners to discuss their experience with their neighbors, measures could seek to make existing PV systems more visible, either physically or online, in order to increase awareness of the technology and social pressure. Our results also warn of the potentially harmful effects of the industry's current trend towards making residential solar panels as invisible as possible.

Chapter 2 further investigates the role of social contagion, and of learning effects in particular. This chapter develops an novel approach to reveal the importance of social spillovers by showing that solar PV adoption is lower in regions where the spillovers are hampered. More specifically, we show that municipalities that are close the language border between French and German parts of Switzerland experience a substantially slower PV uptake. We attribute this effect the language difference, which makes social interactions between PV owners and potential adopters more difficult. In line with the functioning of localized social spillovers, the negative impact of the border decreases with distance and is less pronounced in municipalities with a high proportion of the population speaking the other language.

The role of barriers to social contagion and their consequences for the diffusion of new technologies has received little attention in the literature. By showing how powerful a language border can be in hampering the adoption of solar PV—about 20% fewer adoptions—, our study reveals the importance of active interpersonal discussions for the diffusion of new technologies. Our results in chapter 2 provide additional support for policies leveraging social contagion effects, in particular those aimed at facilitating information and knowledge exchange among peers. This could be achieved, for instance, by offering potential adopters networking opportunities with owners of solar panels nearby, which may help overcome information asymmetries and reduce the uncertainty associated with investments in solar energy. Policymakers and practitioners could implement these measures as a priority in regions characterized by low social spillovers. Many regions could be concerned. Indeed, the strength and frequency of social interactions are likely to be affected not only by language borders, but also by cultural, ethnic, political or religious borders.

Chapter 3 presents evidence suggesting that the impact of subsidies for solar PV is not limited to the period and region in which they are implemented. Our findings show that subsidies may lead, through social contagion, to higher adoption rates even after the subsidy ends and also in adjacent unsubsidized areas. To arrive at these conclusions, we first evaluate the linkages between the canton-level financial incentives in Switzerland and solar PV adoption in the very same canton where they are implemented. As expected, we observe that Swiss cantons offering production and capacity-based subsidies experience higher adoption rates than cantons without such subsidies. We then use this result to explore our main research question, which relates to the cross-boundary effects of cantonal subsidies. Our hypothesis is that the higher number of PV systems in subsidized cantons generates more social contagion than elsewhere, which could lead to a higher level of adoption even beyond the territory in which the subsidy is applied, as spatial peer effects should not stop at jurisdictional borders. Consistently with this hypothesis, we find that municipalities in cantons that never implemented any financial incentive for PV, but located near the border of a canton that did, benefited from higher adoption with respect to municipalities located further away from the border. In line with the theoretical intuition, we also find that cross-border social contagion effects persist, albeit less and less strongly, after the discontinuation of the subsidy.

A central implication of these findings is that current assessments may underestimate the cost-effectiveness of policies promoting the adoption of renewable energies. For a comprehensive assessment, and thereby enabling decision-makers to better design their interventions, it seems necessary to consider long-term effects and effects beyond jurisdictional boundaries. Our results also highlight the potential usefulness of implementing temporary interventions in limited and carefully selected geographical areas . Rather than providing uniform financial incentives across a whole national (or cantonal) jurisdiction, policymakers could create adoption hotspots through targeted and temporary subsidies (Curtius et al., 2018). If they succeed in significantly increasing the level of adoption locally, these targeted measures could trigger a snowball effect in adoption that lasts over time and also benefits neighboring regions.

Finally, **chapter 4** demonstrates that the introduction of time-of-use tariffs could be part of the solution to cope with an increasing share of generation from intermittent renewable energy sources. Using a randomized control trial, we show that households' consumption behavior can be altered by lowering the price of electricity when solar power is abundant and increasing it the rest of the time. Our results indicate that a persistent increase in the share of daily electricity consumption during reduced tariff hours can be achieved even with very small financial incentives. However, the main effect of our intervention was to induce households to significantly reduce their consumption during evening peak hours, despite a very small increase in the price per kilowatt-hour. By analyzing the heterogeneity of the treatment effect among participants, we find that only those households who saved money on the previous bill took action to change their consumption habits.

The results of this field experiment provide some practical insights for distribution system operators seeking to develop alternative tariff systems to meet the challenge of intermittent production from renewable energies. First, it seems futile to expect an increase, in absolute terms, in household electricity consumption during periods of high solar production by relying solely on a reduction in the price per kilowatt-hour during these periods. The main benefit to be expected from a time-of-use tariff such as the one implemented in our experiment is probably a reduction of consumption when the price per kilowatt-hour is raised. Our results show that this reduction can be substantial—up to 6%—, which may help to relieve grid congestion and reduce the need for costly back-up generation capacity. Second, even if modest financial incentives may be sufficient to induce a sustained change in consumption behaviors, it seem necessary that households can actually save money and be aware of it. Indeed, our results show that households that did not save any money compared to a single tariff had little or no response to our intervention. This result suggests that replacing a flat tariff with a time-of-use tariff that would systematically disadvantage the consumers is unlikely to be effective in changing the intra-day consumption patterns. Finally, our experience with high-frequency data collected by smartmeters has revealed that some of these devices may not be reliable. Electric utilities should therefore carefully assess the risk of technical problems before offering time-varying tariffs to their customers.

2 Limitations

The four analyses presented in this thesis have several drawbacks. In particular, all three chapters exploring the role of social contagion are performed at the municipality level, whereas in essence, contagion is a phenomenon between individuals. As mentioned in the description of our empirical approaches, aggregation at the municipality level has many advantages, but it also causes information and accuracy losses. Another potential source of imprecision comes from the fact that we use crow-fly distances. Using road distances, for instance, could allow to better account for physical barriers. Calculating such distances between thousands of pairs of PV systems is, however, an enormous task.

Our assessment of the direct impact of cantonal subsidies on PV adoption rate, i.e. where and when they are applied, should be considered with caution since we do not differentiate between generous subsidy programs and those offering very small incentives, nor between those with very broad eligibility conditions and those restricted, for instance, to residential installations. It should be noted, however, that this limitation does not affect our results on the existence of cross-border effects. In addition, despite all our efforts and precautions when collecting data on cantonal subsidies, we cannot rule out the possibility that mistakes have been made.

3 Potential for future research

This thesis obviously leaves many questions unanswered. The first three chapters analyze the issue of social contagion extensively and with various approaches, but the central dimension chosen to measure it is that of geographical proximity. However, social contagion certainly also operates over much greater distances, since people move around and their social relationships are not limited to their direct neighbors. To capture the full extent of social spillovers, future research could therefore seek to modelize the movements and social networks of individuals.

Another avenue for future research follow from our finding that subsidies lead to additional adoption through social contagion. It would be of considerable interest to (re)calculate the cost-effectiveness of a given program, taking into account not only the adoptions where and when it is implemented, but also adoptions triggered across jurisdictional boundaries and after termination.

Chapter 4 investigates the potential of time-of-use tariffs to integrate an increasing share of solar energy into the grid. This issue is still largely unexplored in the literature, while many electric utilities seem interested in offering such pricing schemes to their customers. In order to gain a deeper understanding of household response, it seems crucial to set up randomized controlled trials in which participants would run the risk of losing money, and not just savings.

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