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# Social Contagion in the Adoption of Renewables (SCAR)

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# Zusammenfassung

Die Subventionierung erneuerbarer Energien kann durch die Mechanismen der sozialen Ansteckung einen positiven Adoptionskreislauf schaffen, der die Annahme wahrscheinlicher macht, wenn Nachbarn sich für die Installation einer bestimmten Technologie für erneuerbare Energien entschieden haben. Dieses Projekts hat das Ausmass und die Dynamik dieser Peer-Effekte bei der Nutzung der Photovoltaik durch Haushalte und Unternehmen in der Schweiz kausal bewertet. Wir nutzen den einzigartigen Kontext der Schweiz, insbesondere das Vorhandensein scharfer Sprachbarrieren und verschiedenen kantonalen Subventionen, um die Rolle und die Vielfalt der sozialen Ansteckung bei der Nutzung erneuerbarer Energien zu untersuchen. Wir wenden auch Wahlversuchstechniken an, um die bevorzugten Attribute zu identifizieren, die möglicherweise zur Einführung der Photovoltaik in Haushalten führen, einschließlich der Rolle von politischen Risiken und anderen Maßnahmen.

# Résumé

Les subventions aux énergies renouvelables peuvent créer un cercle vertueux d'adoption par le biais de la contagion sociale, ce qui pourrait rendre l'adoption plus probable lorsque les voisins ont déjà choisi d'installer une technologie donnée. Ce projet a évalué de manière causale l'ampleur et la dynamique de ces effets de pairs dans l'adoption de l'énergie solaire photovoltaïque par les ménages et les entreprises en Suisse. Nous exploitons le contexte unique de la Suisse, en particulier la présence de barrières linguistiques et de diverses subventions cantonales, pour examiner le rôle de la contagion sociale dans l’adoption des énergies renouvelables et comment cet élément peut changer notre compréhension des politiques de soutien au renouvelable. Nous appliquons également des techniques de choix discret pour identifier les attributs susceptibles de conduire à l'adoption du solaire photovoltaïque, y compris le rôle des risques politiques et autres interventions.

# Summary

Subsidising renewables may create a virtuous circle of adoption through the mechanisms of social contagion, which makes adoption more likely where neighbours have chosen to install a given renewable energy technology. This project assessed causally the magnitude and dynamics of these peer effects in the adoption of solar photovoltaic energy by households and firms in Switzerland. We exploit the unique context of Switzerland, in particular the presence of sharp language barriers and various cantonal subsidies, to examine the role and drivers of social contagion in the adoption of renewable energy and to shed light on how social contagion may change our understanding of how policies promoting the adoption of renewable energy work. We also apply choice experiment techniques to identify the preferred attributes potentially leading to adoption of solar photovoltaic panels by households and firms, including the role of policy risk and other interventions.

# Main findings

- Our project shows that social contagion contributes to solar PV diffusion in Switzerland. 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. Not only households, but also firms and farms react to neighbouring PV panels. Companies are however more influenced by panels installed by other companies, compared to panels installed by households. We show that more visible building-integrated systems drive stronger contagion than building-attached systems and that large PV systems weight more heavily on decisions than smaller ones. We provide evidence that both visibility and word-of-mouth are important drivers of social contagion, and confirm that social contagion is a very localized and short-term phenomenon, whose strength declines with distance and time.
- We confirm that social contagion is an important vector of solar PV diffusion by implementing an original approach and showing that a 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 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% fewer PV adoptions.
- We show that cantonal subsidies are associated to higher adoption in the cantons where they are implemented. We find that the annual adoption rate in municipalities located in cantons offering a production subsidy (an investment subsidy) is, on average, 0.542 (0.249) higher than in other municipalities. These figures can be compared with the average adoption rate over all municipalities and years, which is 1.44 PV installations per 1,000 inhabitants. Furthermore, we exploit the unique context of Switzerland and leverage its fiscal federalism to analyse how policies implemented in a given canton may also affect adoption in the adjacent areas of neighbouring cantons, most likely through the channel of social contagion.
- Policy risk negatively affects households' willingness to invest in solar, therefore policymakers should provide stable and predictable framework conditions for residential PV investors.

# Contents

# Abbreviations

| | |
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| DCE | Discrete choice experiment |
| FIT | Feed-in tariff |
| SFOE | Swiss Federal Office of Energy |
| Solar PV | Solar photovoltaics |

# 1 Introduction

The main goal of the Swiss Energy Law is to guarantee a sufficient, diversified, safe, cost-effective and ecological energy supply. To this end, the 2050 Energy Strategy aims to improve energy efficiency, increase the use of domestic renewable energies and gradually phase out nuclear power. At the same time, by signing the Paris Agreement, Switzerland aims to reduce greenhouse gas emissions by 70–85 % by 2050 and to halve them by 2030, compared with 1990 levels. To comply with the Agreement, the Federal Council decided to set an even more ambitious target, i.e. reducing the net carbon emissions to zero by 2050. The transition towards a greener economy requires to switch from fossil to renewable sources of energy. Around the world, this transition has proven to be difficult due to lock-in effects. Increasing the share of renewable energy in Switzerland has important benefits to climate change mitigation to the extent that European countries are connected as far as electricity markets are concerned. Reducing the fraction of Swiss imports, especially after nuclear energy will be phased out, could potentially imply lower demand on backstop technologies relying on coal or gas.

Given the important resistance to the adoption of first-best instruments such as carbon taxes to foster the adoption of renewable energies (cf. Thalmann 2004; Saelen and Kallbekken 2011; Baranzini & Carattini 2014; Carattini et al. 2017; Baranzini & Carattini 2017), some European countries, including Switzerland, subsidize the adoption of renewable energy. This type of policy comes with important costs, which can represent hundreds of euros per ton of $CO_2$ abated (cf. Marcantonini & Ellerman 2014; Marcantonini & Valero 2015; Crago & Chernyakhovskiy 2017). Over the long run, however, such subsidies may create a virtuous circle of adoption through the mechanisms of social contagion, which makes adoption more likely where the installed base is larger. The academic literature shows indeed that thanks to social contagion, the likelihood of adoption of solar photovoltaic (PV) panels is higher in neighbourhoods where the installed PV base is larger (e.g. Bollinger and Gillingham 2012; Graziano and Gillingham 2015). In principle, temporary subsidies in a given region may thus lead to a higher pace of adoption even when the financial incentive is discontinued.

This project focuses on the adoption of solar PV panels by households and firms in Switzerland. It uses spatial econometrics techniques to identify the magnitude and drivers of peer effects in the adoption of solar PV and to assess how such effects may vary in presence of national and subnational policy interventions and of cultural barriers to social spillovers. In addition, we analyse how people may respond to policy measures and other types of interventions, by relying on survey data and choice-experiment techniques. More precisely, we aim at:

1. Assessing the strength and drivers of peer effects in the adoption of solar PV in Switzerland.
2. Leveraging the exogenous presence of cultural borders in Switzerland and the countrywide implementation of a feed-in tariff to measure the effect of social spillovers (or lack thereof).
3. Exploiting the subnational variation in financial supporting schemes to evaluate their direct and indirect effect on PV deployment.
4. Applying choice-experiment techniques to identify the preferred attributes potentially leading to adoption of solar PV by households and firms.

In the following Sections, we summarize the main achievements of the project. Annexes 1-5 include the full documents with additional information and details on the above-mentioned topics composing the project.

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# 2 Assessing peer effects in the adoption of solar PV in Switzerland

## 2.1 Motivation and goals

To achieve the objective of 2°C maximum increase in global temperatures included in the Paris Agreement of the United Nations Framework Convention on Climate Change, greenhouse gas emissions have to be drastically reduced. Consequently, governments are currently facing the challenge of turning their pledges into effective policies. Economists have long advocated the use of carbon pricing as central instrument of a climate policy package (Baranzini et al., 2017), but given the unfavourable political economy of carbon pricing, some jurisdictions have turned to subsidies for renewable energy as an alternative to first-best policies. Recent work suggests the existence of an alternative policy approach: the use of social norms. People seem indeed to follow local social norms even in global dilemmas ((Carattini, Levin, and Tavoni 2019) and the culture of cooperation that helps solving many social dilemmas seems to be also helpful in driving climate-friendly behaviour (Carattini et al., 2015). In the United States, solar panel installers have started undertaking specific initiatives to leverage social contagion, such as kerbside signs communicating the presence of a solar panel in the nearby home or demonstration sites and group pricing for neighbours (Bollinger and Gillingham, 2012).

In our paper, we analyse the adoption of PV panels in Switzerland. Hence, we contribute to this nascent literature studying the role of social contagion in the adoption of clean technologies. We address the following main questions: How do peer effects work in practice? Do they apply in the same way to all types of solar panels, and does it depend on their visibility? Do they emerge only for residential adopters, does contagion also work for firms, and between households and firms?

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 the impact of PV characteristics, such as size and type, on the magnitude of social spillovers. 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 number of 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 reflection (Manski, 1993). We address the issues of 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 time-varying socio-economic controls and detailed location characteristics to account for spatial and temporal heterogeneity.

## 2.2 Results

Based on geolocalized data, this paper provides new evidence of the existence of peer effects in the adoption of the PV 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 adopt the solar technology are dependent on pre-existing adoption. In particular, we show that distance is an important determinant of social contagion: PV systems installed further away generate persistently lower impact on the adoption of new PV systems than the nearest ones. Beside this proximity effect, our results also indicate that the oldest nearby installations have a lower impact in the adoption choice than the most recently built PV systems. We contribute to the literature by showing that these effects are not limited to residential adoptions. Our analysis reveals that firms and farms also react to neighbouring PV panels, although in 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. Addressing our main research questions, we investigate the variation of social spillovers with ownership, size and type 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 building-integrated than building-attached PV systems.

By combining the analysis of ownership, size and type, our study contributes to the understanding of the drivers behind social contagion. In particular, by looking simultaneously at size and more visible types, we are able to document the relative role of learning and visibility effects. We find that both operate in the diffusion of solar panels. Our evidence complements that of Narayanan and Nair (2013) on hybrid cars, who find with data for California that peer effects work only for Toyota Priuses, and not for the other hybrid model in their data, the Honda Civic Hybrid, suggesting an important role for visibility effects with respect to learning effects (see also Sexton and Sexton 2014).

Our results provide useful insights for practitioners and policymakers alike. Leveraging social contagion could indeed represent a valuable option for many governments, potentially including those that are currently planning to phase out subsidies to solar energy. This could be done, for example, through the installation of demonstration PV systems in carefully selected locations, information campaigns, initiatives engaging local communities, group pricing, and interventions to provide networking opportunities with solar owners or installers of solar panels (Jacobsen, Kotchen, and Clendenning 2013; Bollinger, Gillingham, and Tsvetanov 2016; Bollinger and Gillingham 2017; Kraft-Todd et al. 2018). However, an effective implementation of such strategies requires information on which agents are affected by social contagion and on how adoption decisions are influenced by the choice of others.

See Annex 1 for additional details: What drives social contagion in the adoption of solar photovoltaic technology?

# 3 The impact of cultural borders in the diffusion of solar PV

## 3.1 Motivation and goals

The literature shows that social spillovers are an important driver of technology adoption in general (e.g. Arndt, 1967; Bass, 1969), and of solar PV in particular (e.g. Graziano and Gillingham, 2015;

Rode and Weber, 2016). 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 analyse the effect of cultural borders on the adoption of solar PV. Language groups live in geographically distinct regions separated by sharp language borders that are exogenous to the implementation of federal policies promoting the adoption of solar PV. In 2008, Switzerland introduced a countrywide feed-in tariff (FIT) for the electricity generated from solar PV systems. By strongly 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.

We base our analysis on the dataset provided by SFOE, which we completed with socio-economic characteristics related to the adoption of solar installations, such as age, income, level of unemployment, and green preferences, and a second set of variables measuring contextual factors that may be linked to the feasibility and profitability of PV installations, such as the type of building and solar radiation. We identify the boundary between French- and German-speaking parts as 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. Natural barriers are also absent from most of the boundary. 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.

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. To define the language border, we thus combine two datasets. The first dataset, provided by the Swiss federal statistical office, contains 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 is different from each other (one French- and one German-speaking), we obtain the language border as the line generated by the shared borders of these municipalities. 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 closest 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. Starting from 2,289 municipalities, we select 733 municipalities whose PV installations are located on average less than 25 km away from the language border. This leaves us with 18,960 PV installations.

## 3.2 Results

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 the 2008 FIT. Our hypotheses are as follows. First, we expect the FIT to lead to more PV 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 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. We find that since the implementation of the FIT, municipalities closer to the border experience substantially lower adoption. The number of “missing” PV systems is non-negligible, i.e. between 5 and 6 per municipality, depending on the specification. That is, the presence 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 (about 26), this represents a loss of approximately 20%.

We further investigate the mechanisms behind the effect of the language border, by considering the language skills of the municipalities' population. Indeed, people in some municipalities may be fluent in the language of the other side of the border. 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. We indeed find that the impact of the border is 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.

See Annex 2 for additional details: Social interactions and the adoption of solar PV: evidence from cultural borders

# 4 Preferences for solar PV

## 4.1 Preferences for solar PV by firms

Since 2007, the Swiss authorities have set an objective to increase the share of renewables (excluding hydro) in the electricity production mix by 10% by 2030. Consequently, several instruments were introduced to foster the production capacity from renewables, in particular a feed-in tariff (FIT) scheme aimed at covering electricity production costs in 2008 and a direct investment subsidy in 2014. In addition, following the Fukushima accident, Switzerland adopted a new Energy Strategy, including a ban on new nuclear plants and the gradual phase out of the existing ones, which increases the need for developing renewable electricity production. In this context, it is particularly relevant to understand the factors that explain the adoption of renewable technologies. Although there are several studies analyzing the factors explaining the adoption of renewable technologies by households (e.g. Ameli and Brandt, 2014; Bollinger and Gillingham 2012; Rode and Weber 2016), the literature for firms is scarcer (see Mattes et al. 2014).

In this part of the project, we thus analyzed the determinants of the adoption of solar photovoltaic (PV) technology by firms, which account for around 30% of total electricity consumption in Switzerland. To investigate the determinants of firm preferences for solar PV, we designed a survey which includes a discrete choice experiment (DCE). In the DCE, we asked each firm to choose 12 times among 3 options: two alternative PV installations or no (new) PV installation (status quo). PV installations differed from one another along technical and financial aspects. We selected the following four attributes: type of mounting system; existence of a digital display screen; annual cash flow; and net price. The inclusion of attributes such as the type of mounting system and digital display screens are consistent with the focus of the project on the adoption of PV panels in Switzerland and its possible social contagion, which may be influenced by aesthetics and reputational effects. We set the levels of the attributes "cash flow" and "net price" to replicate the financial effects of leasing, capital subsidies, and FIT. Besides the DCE, we also included in the survey a series of questions aimed at confirming the influence of peers (other spatially close firms, direct competitors, etc.) in the adoption decision. In particular, a randomized intervention was embedded in the survey design, providing to a randomly-selected set of respondents municipality-specific information about the descriptive norm, i.e. the number and cumulative capacity of existing installations around the firm's headquarters.

We organized the collection of firms' stated preferences for solar PV in two steps. First, we prepared a pretest to ensure that the questions and the DCE were well understood by the respondents, and that the attributes included in the DCE and their levels were correctly selected. Between July and September 2017 we sent 2,700 invitations by email to Geneva-based firms. 119 firms filled the survey (at least partially), and 85 firms did so completely. Second, we prepared a final survey in collaboration with Satiscan, a Geneva-based polling organization. In February 2018, Satiscan started to invite Swiss firms to participate in the survey, by email, paper letters and telephone, in French and German. The invited firms were selected from a representative pool of 9,341 firms, provided by the Swiss Federal Statistical Office, and stratified according to four firm sizes, three economic sectors, and two language regions (French- and German-speaking regions of Switzerland). A total of 6,686 firms were contacted. Disappointingly, only 82 firms filled (at least partially) the survey between April 9 and July 10 2018, when we decided to terminate the survey. The final sample is composed by 72 firms who filled the survey completely, corresponding to a dismal response rate of around 1%.

Although the results are not representative of all companies in Switzerland because sample size is much smaller than expected, it is still possible to provide estimations of relevant parameters. These, however, need to be interpreted with particular caution. Results are obtained not only for the final sample, but also for the pretest sample and a combination of the two. It should be noted that no changes were implemented in the DCE itself (attributes and levels) between the pretest and the final survey, so that an analysis using both samples together is legitimate. However, some control questions were applied to the final survey, making it impossible to replicate all models on both samples. We conduct the analysis on the responses of the firms that answered all 12 choice tasks in the DCE, thus resulting in (157 firms × 12 choice tasks) = 1,884 observations.

The survey encompassed a section dedicated to collect information related to the current situation and behavior of firms regarding electricity consumption. A sizeable proportion of firms (14% and 19%, in the Geneva and Swiss sample, respectively) have solar PV systems already installed in their buildings. Moreover, around half (42% and 54%) state that they could install new or additional PV capacities. Among firms with PV systems already installed, almost ¾ state they would be ready to install additional panels. Among firms currently without PV systems, between 36% and 50% indicate they would be ready to install panels. Overall, it thus appears that around half the firms are not interested at all by PV systems: they currently do not have one and state they would not install one.

From descriptive results of the DCE responses, we observe that respondents selected the status quo (SQ) situation in more than 38% of all choice tasks, i.e. the firm prefers the current situation rather than any of the two alternative systems proposed in the DCE. We highlight that the share of firms with only SQ choices differs substantially according to our intervention, in which a map showing information about installed PV around the firm's headquarters was randomly displayed or hidden. Among "control" firms, i.e. firms that were not displayed the information, almost 28% systematically opted for the status quo. This proportion is halved to 14% among "treated" firms, i.e. firms that were displayed the information concerning installed PV in the surroundings of their headquarters. This provides a first indication that the implemented treatment had a positive impact on firms' (stated) willingness to adopt a PV system. On the other side, one third of the firms always selected one of the two offered installations in each of their 12 choice tasks (i.e. they never selected the status quo choice). The difference between PV owners and non-owners is large, with respectively 15.4% and 37.4% of the firms always selecting an installation. Applied panels turn out to be more popular than integrated panels. Firms selected more frequently the installations with screens. Unsurprisingly, installations that provide a larger annual cash flow and the less expensive are preferred. Given their aesthetic advantages, we expected that integrated solar panels would be selected more often than applied ones. A possible explanation would be that companies are aware of the heavier construction work involved or the lower yields in terms of electricity production.

To investigate firm preferences regarding solar PV systems, the econometric strategy builds on McFadden's (1974) random utility (profit) theory. On average, results confirm that firms display the expected preferences regarding higher annual cash flows and lower installation price. The average willingness to pay (WTP) for an additional CHF in annual cash flow amounts to CHF 12.5. The results suggest that distributing a given amount through an investment subsidy (to decrease installation upfront costs) or through a production subsidy (with regular payments year after year) would have a similar impact on PV adoption by firms. For instance, firms seem to be indifferent between an installation with a net price of CHF 20,000 and a cash flow of CHF 0, and an installation with a net price of CHF 30,000 bringing in grants of CHF 500 per year over 20 years (i.e. a subsidy of 500 × 20 = CHF 10,000 in total). Stated preferences are less well-established regarding mounting types and display screens. Overall, it appears that firms tend to prefer applied panels (over integrated panels) and installations with a display screen. Finally, the results show that the treatment incentivizes respondents to select one of the two offered PV installations rather the status quo. This finding tends to confirm the existence of peer effects in adoption decisions by firms, and not only by households (see Baranzini et al., 2017).

See Annex 3 for additional details: Preferences for solar PV by firms: Results from a discrete choice experiment.

## 4.2 Preferences for solar PV by households

Households are an important source of investment in solar photovoltaics. Therefore, policymakers in Switzerland – similar to their peers in other countries – have tried to create a supportive policy environment for residential PV investors, including introduction of feed-in tariffs and one-off investment grants. While such policies can improve the economics of residential PV investments, they also entail an element of risk, such as unexpected or even retroactive policy changes, or uncertainties related to long waiting times for receiving policy incentives. Policy risk can have potentially detrimental effects on the decision to invest in PV. The objective of this module of the research project was to assess whether in a risky environment, households will continue to invest in solar PV systems, and hence provide a key contribution to decarbonizing the energy system. We investigated this question by analyzing stated preferences for the intention to invest in residential solar PV systems under different levels of policy and market risk. Stated preferences were obtained through a discrete choice experiment, which we coupled with a randomized informational treatment to examine the role of information asymmetries on the assessment of policy risk. In our choice experiment, participants had to trade-off between hypothetical solar PV systems for their house, each of which was characterized by different levels of policy- and market-driven investment risk. In the treatment condition, additional information from publicly available sources was provided to participants to make them aware of the possibility of policy changes that can potentially affect financial support for the PV system. Hence, we were able to test directly whether policy risk is entirely factored in to households' expectations or if, instead, households proceed to a revision of their beliefs when new information makes policy risk salient. The study was realized online by a sample of 750 Swiss households, selected to represent a realistic segment of potential PV investors.

We find that households tend to underappreciate policy risk. However, if policy risk becomes salient to them and it is factored in in their investment decisions, it significantly reduces their intention to invest in solar PV. The negative impact of policy risk is larger for risk averse individuals. With a salient policy risk, some individuals shy away from an investment in solar altogether, rather than reduce the amount of money they invest in the technology. Therefore we conclude that upfront financial support is more conducive to residential solar investments than support spread over time, not just because households are impatient or liquidity constrained, but because households discount future subsidy payments to take into account the risk that the government may fail to stick to its promise. Moreover, we find that, compared to other categories of renewable investors, households are less sensitive to market risk.

Our results have important policy implications: Mitigating policy risk for residential solar investors could be a more effective approach to fostering investment decisions than increasing the level of financial incentives. In particular, paying out the full financial support to a residential solar producer within one year, instead of after an undetermined period of time – hence minimizing the materiality of policy risk – would have the same positive impact on residential solar adoption as increasing the amount of financial support from 30 % to 40 % of the initial investment, or could compensate for a reduction in financial support from 30 % to 20 %.

See Annex 4 for additional details: The price of risk in residential solar investments.

# 5 The impact of cantonal subsidies on the diffusion of solar energy in Switzerland

## 5.1 Motivation and goals

In 2008, Switzerland introduced the *cost-covering remuneration for feed-in to the electricity grid* (CRF), a production-based subsidy that aims to ensure the profitability of electricity production from renewable sources. In international comparison, this instrument was considered at its launch to be one of the most attractive, due to the long payment period and high level of tariffs (REN21, 2008). However, since the financial resources allocated to this instrument turned out to be insufficient to cover the growing demand for solar energy, a waiting list was introduced already a few months after its introduction. For new applicants, the waiting time quickly reached several years. According to our data, none of the installations that registered after 2012 were able to benefit from the CRF. To reduce the waiting list, the Swiss authorities introduced the *One-off investment grant* (OIG) in 2014, a one-time investment-based subsidy paid after completion of the PV installation.

The implementation of promotion policies at the federal level has played a major role in the deployment of solar technology in Switzerland. In 2017, more than 60,000 registered installations were connected to the electricity grid, compared to only a few hundred in 2006. At the same time, many cantons implemented their own subsidies to accelerate the adoption of renewable energy in their regions. Hence, the unique context of Switzerland provides again interesting variation that can be exploited for empirical purposes. In this part of the project, we aim at using policy changes in a given canton as a shock to the adjacent areas of neighbouring cantons. As illustrated in (Spencer, Carattini, and Howarth 2019), a social intervention, or policy, affecting a seed population can lead to a cascade of adoption well beyond the seed population itself, through social networks and contagion. In the same way, interventions can have long-lasting effects even after being discontinued, again through social contagion. If not fully captured, such positive externalities may lead to an underestimation of the cost-effectiveness of a given policy or intervention. Hence, in this specific part of the project, we leverage the fact that some cantons have introduced subsidies and other did not, and that the programmes have been introduced and discontinued at different times.

In our analyses, we proceed as follows. First, we evaluate whether there is any association between the implementation of a cantonal subsidy in a given canton and adoption in that very same canton, in subsequent years. Second, we analyse the novel question of whether a policy change in a given canton generates spill-over effects that go beyond its jurisdiction and affect, in particular, the adjacent areas of a neighbouring canton.

To this end, we need to access an extensive collection of cantonal policies promoting solar energy. However, in Switzerland, there is no such register listing extensively cantonal policies for the promotion of solar PV panels. 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 built these data ourselves, by collecting all the policies promoting the adoption of solar PV at the cantonal level for all 26 cantons over the period 2006-2018. We proceeded 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.

Apart from tax credit, which are used widely by cantons thus providing insufficient variation for our study, the most common instrument used by the Swiss cantons for promoting solar PV is a capacity-based investment subsidy. Half of the cantons (13 out of 26) have introduced an investment subsidy at some point since 2006. Before the introduction of the federal CRF in 2008, only two cantons, Fribourg and Ticino, offered a capacity-based subsidy. Several programs ended in 2013 and 2014, following the introduction of the OIG at the federal level in 2014.

The second type of financial incentive that we analyse is a production-based subsidy, introduced by four Swiss cantons. Most of these cantonal programs are in the form of a “bridge” for the federal CRF scheme, i.e. a transitional funding for the time spent on the federal waiting list that is discontinued once the CRF kicks in. Descriptive evidence from 2008 to 2012 suggest that the installations in the four cantons with CRF bridges have been completed about 5 months earlier than those in the cantons without a CRF bridge.

## 5.2 Results

To evaluate the linkages between the different types of canton-level financial incentives and solar PV adoption in the very same canton where they are implemented, we run different panel fixed-effects models that include a standard set of control variables used to account for potential observed and unobserved heterogeneity. We find higher adoption in the cantons that implemented a cantonal subsidy, after its implementation. For instance, we find that the annual number of adoptions per 1,000 inhabitants in municipalities located in cantons offering a production subsidy (an investment subsidy) is, on average, 0.542 (0.249) higher than in other municipalities. As an indication, a broad comparison of these figures with the average annual adoption rate, which is 1.44 PV installations per 1,000 inhabitants, suggests that cantonal subsidies are associated with an increase of about 17 to 37 % in PV installations. We also find that on average, and among installations of less than 10 kWp, an extra 3 kWp (1 kWp) of additional capacity for every 1,000 inhabitants and per year in in cantons that offer production-based (investment-based) subsidies compared to cantons that do not.

We then use these findings as a starting point to analyse our main research question, which relate to the the (causal) cross boundary effects of cantonal subsidies. Our hypothesis is that the higher number of installations 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 social contagion and social networks should may 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. That is, our results indicate that the adoptions rate in municipalities that are close to the cantons implementing subsidies experience a significantly higher adoption rate than more distant municipalities. Specifically, we find that municipalities located within 10 km from the border of subsidized cantons have about 0.7 more PV adoptions per 1,000 inhabitants by year compared with more distant municipalities, with the number of adoptions decreasing by 0.1 for each additional km away from the cantons with subsidies. We also analyse whether the cross-border social contagion effects persist over time. In line with the theoretical intuition, we find higher adoption in neighbouring municipalities even several years after the canton to which they are adjacent discontinued its subsidy programs, although such effects decay with time.

See Annex 5 for additional details: Local subsidies for solar energy, cross-boundary effects, and effects beyond discontinuation.

# 6 Social contagion and the long-lasting effect of temporary policies and interventions

## 6.1 Motivation and goals

Strong empirical evidence suggests that people infer prevailing pro-environmental norms based on the behaviour of people they encounter and engage with. These norms seem to be adopted in response to both internal motivation and social pressure. Despite the *global* public good property of climate change mitigation, individuals tend to follow *local* social norms also when engaging in climate-friendly behaviour (Carattini, Levin, and Tavoni 2019). Understanding how climate-friendly behaviours become normative, and how normative behaviours spread, is crucial to accelerate the transition towards a low-carbon economy.

To formalize such behaviour, the economic literature has introduced theoretical models that include moral and social drivers (Brekke, Kverndokk, and Nyborg 2003; Nyborg, Howarth, and Brekke 2006). We complement this theoretical literature by analysing the adoption of climate-friendly behaviour in presence of social networks. Leveraging insights from the network-science literature, we add, to a model of socially contingent moral motivation, characteristics of human social behaviour, which have been shown, as mentioned, to matter for climate-friendly behaviour, but which have been neglected by most theoretical models. The goal is to convert the society to a stable "green equilibrium" characterized by high levels of climate-friendly behaviour. To choose a good set of individuals to temporarily subsidize, we characterize the long-term effect of a subsidy. This effect depends on a spatially-heterogeneous pattern of adoption that evolves according to a local update rules, in which, in every period, individuals revise their beliefs on whether to adopt a climate-friendly behaviour, based on the adoption of their neighbours.

## 6.2 Results

Our network moral-motivation model leads naturally to spatial-heterogeneity in climate-friendly norms, consistent with the empirical evidence in the literature and produced in the other parts of this project. In line with non-network models, we show that temporary subsidies can lead to stable equilibria with positive adoption, even when the subsidy is discontinued. In our model, however, regulators can achieve significant savings by targeting subsidies, or social interventions, to specific groups. With our computational exercises, using small semi-realistic networks, we quantify the gains of targeting subsidies, or social interventions, towards optimal seed groups. These gains may be large compared to widespread subsidies, or random selection of seed groups, and depend on the society's structural characteristics. Hence, considering social networks may change radically the performance of initiatives aimed at promoting the adoption of green behaviour.

From a policy perspective, this paper supports the emergence of a "third way" in helping the transition to a greener economy. While carbon pricing is expanding its global coverage (World Bank 2019), policy failures are turned into lessons to improve the chances of implementing carbon pricing schemes (Carattini, Carvalho, and Fankhauser 2018), and calls for a global carbon price are intensifying (Weitzman 2014; Nordhaus 2015; Stiglitz et al. 2017; Carattini, Kallbekken, and Orlov 2019), most of the efforts to reduce greenhouse gas emissions still rely on subsidies for renewable energy (REN21 2008). Governments around the world, however, are phasing these subsidies down. As governments slowly but steadily expand the use of carbon pricing, and reduce the reliance on subsidies for renewable energy, a third way can contribute to reduce greenhouse gas emissions.

Measuring social contagion effects is only a first step in this third way. The following step consists in leveraging these effects to spur adoption of climate-friendly behaviours and technologies. Two important challenges limit the widespread adoption and generalization of these interventions. The first challenge is represented by the persistence of the behavioural changes generated by these interventions. The second, related, challenge concerns the cost-effectiveness of these interventions. The question for practitioners and policymakers is how to best target interventions to improve their cost-effectiveness, and how to generate stable climate-friendly norms. In this respect, the use of social networks is crucial. In this context, policymakers, and practitioners, can create temporary targeted subsidies, or targeted public education campaigns, that normalize pro-environmental behaviour.

This part of the project provides the necessary insights to define which individuals should be approached by policymakers, and practitioners, with the option of subsidized adoption. While differentiated subsidies may not always be feasible in practice, information about temporary subsidies can be targeted at some groups, especially with the help of practitioners. Many policies and social interventions can be designed in a way that leverages social contagion in the adoption of a given climate-friendly behaviour. Solar ambassadors, individuals with some influence at the very local level and with, usually, direct experience with solar installations, have for instance played an important role in how solar energy has spread across neighbourhoods in the Northeast of the United States (Kraft-Todd et al. 2018). Practitioners can also decide to adapt their pricing models, based on the insights of this model. For instance, with Solarize campaigns in the United States, discounts are often available for potential adopters of solar energy for the duration of the initiative, which in each state takes place in a selected number of towns.

See Annex 6 for additional details: Short-Term Interventions for Long-Term Change: Spreading Stable Green Norms in Networks.

# 7 Outlook and next steps

The next steps of the project consist mainly in the valorisation of the results that we have obtained. In particular, we plan to refine and deepen some of the analyses presented in this document in order to (re)submit them for consideration for publication in academic journals. We also plan to release a working paper version for the deliverable described in section 5, with which we will make available the data collected with the project's funding on subsidies and other promotion measures at the cantonal level (e.g. via Harvard's Dataverse repository).

Many avenues for future research follow from this project. First, the project sets the stage for designing promising randomized controlled trials, leveraging social contagion, increasing the visibility of people's behaviour (e.g. Carattini, Gosnell, and Tavoni 2019), or addressing learning across firms. Second, it points to several options for local officials to engage in the promotion of solar energy at the local level, which could also be done in combination with randomized controlled trials (for instance with an over-subscription design, see (Duflo, Glennerster, and Kremer 2006). Third, our research on the preferences for solar PV of households shows that positive solar investment decisions are strongly driven by self-consumption opportunities. Preliminary analysis suggests that the attractiveness of self-consumption does not seem to be exclusively related to electricity bill savings, a fact that is still scarcely investigated in the literature. Further research could explore further motivations to become prosumers, including non-financial ones, such as a desire for independence, and test whether they hold true also for group self-consumption opportunities, including those recently made possible by the Eigenverbrauchgemeinschaften, EVG (or Zusammenschluss zum Eigenverbrauch, ZEV) regulation in Switzerland, or by the regulation on "jointly acting renewables self-consumers" in the European Union.

# 8 National and international cooperation

## 8.1 National

To perform Section 5, our project required data about subnational subsidies for solar PV. These subsidies are provided at different administrative levels, i.e. at the municipal, cantonal, and, of course, federal level. Given this important heterogeneity, we contacted several companies to obtain information on solar subsidies, i.e. Swissolar, Energiefranken (Faktor Verlag AG), and Subventionsbatiment (Docu Media Suisse Sarl). We completed existing information by contacting all the 26 Swiss Cantonal Energy Offices to answer our web-based survey on cantonal and municipal solar PV subsidies programmes.

At our request, we also obtained specific databases from the Swiss Federal Office of Energy (SFOE), from the Swiss federal statistical office (FSO), from the Federal office for meteorology and climatology (MeteoSwiss), from the Federal Tax Administration (FTA), from the State Secretariat for Economic

Affairs (SECO) and from www.toitsolaire.ch, a joint project between MeteoSwiss, the Swiss federal office of topography (swisstopo) and the Swiss federal office of energy (SFOE).

From an academic perspective, we note that Martin Péclat is enrolled in the PhD programme in Economics of the University of Neuchâtel. His PhD Thesis on solar PV adoption in Switzerland is supervised by prof. Milad Zarin-Nejadan, University of Neuchâtel, and prof. Andrea Baranzini, HEG Genève.

Beatrice Petrovich, lead author of deliverable 4.2, is enrolled in the PhD programme of the Institute for Economy and the Environment at the University of St. Gallen, under the supervision of prof. Rolf Wuestenhagen. Deliverable 4.2 follows from the ongoing collaboration between Stefano Carattini and the University of St. Gallen. Beatrice Petrovich's contribution to deliverable 4.2 was crucial, from conception to execution. In turn, SCAR funded part of her doctorate.

## 8.2 International

Stefano Carattini realized this project while being based, initially, at HEG Geneva and the London School of Economics and Political Science, before moving to Yale University (as a Postdoctoral Fellow, later Associate Research Scientist, and Lecturer) and then to Georgia State University (as Assistant Professor in the Department of Economics). His research under this grant benefitted from his collaborations, among others, with Kenneth Gillingham (Yale University) and Richard Howarth (Dartmouth College), as well as Simon Levin (Princeton University) and Alessandro Tavoni (London School of Economics and University of Bologna). Stefano Carattini was invited to present his research, among many others, by the Department of Energy in Washington, D.C.

# 9 Publications

Baranzini Andrea, Stefano Carattini & Martin Péclat (2017): "What drives social contagion in the adoption of solar photovoltaic technology?" London, Grantham Research Institute on Climate Change and the Environment Working Paper 270, link: click here.

Carattini Stefano, Martin Péclat & Andrea Baranzini (2018): "Social interactions and the adoption of solar PV: evidence from cultural borders." London, Grantham Research Institute on Climate Change and the Environment Working Paper 305, link: click here.

Spencer Gwen, Stefano Carattini & Richard B. Howarth (2019), "Short-term Interventions for Long-term Change: Spreading Stable Green Norms in Networks", *Review of Behavioral Economics*, forthcoming.

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# Appendix 1

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

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

Andrea Baranzini[†], Stefano Carattini[‡§], Martin Péclat[†¶]

**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 panels, which may contribute to accelerate the transition to a low-carbon economy. While the existing literature has focused on residential adoption only, we extend the analysis to private firms and farms, and include solar panels with different characteristics. We exploit a unique large dataset providing detailed information on about 60,000 solar installations in Switzerland, including their specific location at the street level and details on the timing of the technological adoption, and couple it with rich socioeconomic data at the municipality level. Our detailed data allow us to adopt an empirical strategy addressing the main threats to identification associated with social contagion, including homophily and reflection. 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 in a lesser extent than households. Furthermore, companies are more influenced by panels installed by other companies, compared to panels installed by households. By distinguishing between building-integrated and building-attached PV systems and including capacity categories, we provide evidence that both learning and imitation are important components of social contagion. As a result, our findings provide new insights on the mechanisms of social contagion and how they could be leveraged with targeted interventions.

**Keywords** Social contagion; Peer effects; Solar panels; Renewable energy; Technology adoption
**JEL codes** D83; O33; Q42; R11; R12

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# 1 Introduction

Reducing greenhouse gas emissions and preventing dangerous interferences with the climate system is among the top challenges of this century. Governments recently 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., 2017), yet the number of countries pricing carbon remains limited (World Bank, Ecofys and Vivid Economics 2016). Carbon pricing faces important obstacles in terms of popularity, which have led to the failure of several policy proposals (Thalmann, 2004; Dresner et al., 2006; Carattini et al., 2017a). When implemented, its effectiveness has been hampered by exemptions and exceptions (Baranzini and Carattini, 2014; Farid et al., 2016). Given the unfavorable political economy of carbon pricing, some jurisdictions have turned to subsidies for renewable energy as an alternative to "first-best" policies. While these subsidies have considerably contributed to the expansion of renewable energies in countries such as Germany or Italy, they have recently come under critique for their very high cost (Marcantonini and Ellerman, 2014; Marcantonini and Valero, 2015; Crago and Chernyakhovskiy, 2017).

Recent work suggests the existence of an alternative policy approach: the use of social norms. People seem indeed to follow local social norms even in global dilemmas (Carattini et al., 2017b) 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) and of hybrid cars (Narayanan and Nair, 2013), in particular through social contagion. In the United States, solar panel installers 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 and group pricing for neighbors (Bollinger and Gillingham, 2012).

In this paper, we analyze the adoption of PV panels in Switzerland. We hence contribute to this nascent literature studying the role of social contagion in the adoption of clean technologies. 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.

Social contagion is expected to work through both word-of-mouth (learning) and visibility (imitation). The former is supposed to act upon the learning costs and the uncertainty that households face when considering the option of an investment in solar PV. The latter effect stems from the motivation of individuals to stay in tune with the norm and thus adopt pro-environmental behaviour when this is sufficiently spread and visible (cf. Carattini et al., 2017b).

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 the impact of PV characteristics such as size and type on the magnitude of social spillovers. Our analysis is based on a rich dataset containing very detailed geographic and technical information on 59,819 PV systems in Switzerland, covering all applications made over the years 2008-2015. The data include residential installations, but also adoptions by firms and farms. We also possess details on the specific installed capacity (in kW peak) and type of installation, i.e. building-attached, building-integrated and ground-mounted PV systems. Our rich dataset allows us to be the first coupling 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 are able to address the main threats to identification, i.e. self-selection of households into specific neighborhoods (homophily), correlated unobservables and simultaneity, and deliver causal estimates of peer effects.

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.

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. 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 in 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. Addressing our main research questions, we investigate the variation of social spillovers with ownership, size and type 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 building-integrated than building-attached PV systems. By combining the analysis of ownership, size and type, our study contributes to the understanding of the drivers behind social contagion. In particular, by looking simultaneously at size and more visible types, we are able to document the relative role of learning and visibility effects. We find that both operate in the diffusion of solar PV technology in Switzerland, but with different strengths. Our results shed new light on the specific mechanisms behind social contagion in the case of the adoption of solar panels. Our evidence complements that of Narayanan and Nair (2013) on hybrid cars, who find with data for California that peer effects work only for Toyota Priuses, and not for the other hybrid model in their data, the Honda Civic Hybrid, suggesting an important role for visibility effects with respect to learning effects (see also Sexton and Sexton 2014).

Our results provide useful 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. 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 with an unprecedented level of detail, our study provides useful 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, but also on accelerating learning across businesses, for instance through clusters and industry-specific umbrella organizations. Of course, learning-driven social contagion among firms is likely to depend on the generosity of the current subsidy system, whereas social contagion in the adoption of residential installations is likely to survive, to the extent that it is driven by pro-social and pro-environmental motives, to changing financial incentives.

## 2 Context

As a Member State to the Convention on Climate Change having ratified the Kyoto Protocol (COP3), the Doha amendment (COP18), and having ratified 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 Agreements, Switzerland pledged for 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 provides the main measures related to the energy sector and thus directly determine 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 for the time being 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]

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 kWp. Hence, the scheme does not only support the adoption by residential owners, but also by the private sector.

[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 increased three times in the following years and since 2016 is at CHF 84 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.

The CRF strongly contributed to the deployment of PV technology in Switzerland (see Figure 1). From a few thousands of installations in 2008, the number of PV systems has increased to reach approximately 60,000 in December 2015. Overall, the total capacity remains however modest. In 2015, the electricity production by solar panels in Switzerland corresponded to 1.92 % (1.12 TWh) of final electricity consumption, a low figure compared to 7.4 % in 2016 in Germany, the European leader in terms of PV capacity (Wirth and Schneider, 2017). 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 connections, 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 1962).

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 *causally* identify social spillovers can however be a challenging task. There are three threats that could confound a causal estimation of past adopters' effect on current adoption behavior.[3] The first issue is spatial sorting related to the self-selection of households into specific neighborhoods (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 neighborhood 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 federal subsidies or technology maturity. Finally, potential differentiated time evolution

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

across regions should be accounted for by incorporating interaction effects between regions and time. 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 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 within a given radius around the installation of interest. More precisely, for each new adopter, we count the number of PV installations that (i) are located within a maximal Euclidean distance of 9 km 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).[4]

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. Second, social spillovers 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*.

To investigate how distance may affect the strength of social contagion, we generate installed bases for the following sections: 0-0.333 km, 0.333-1 km, 1-3 km, and 3-9 km.[5] 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

[4]In our data, the median time lag between the PV purchasing decision and the installation is 126 days, 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 $adoption\_date_k$ by subtracting the median time lag that we observe in our data to the completion date. In any case, including or not these observations do not affect our estimates neither qualitatively nor quantitatively. All additional estimations are available by the authors upon request.

[5]These sections are chosen so that the area of a band is always a constant multiple of the previous band.

consider three groups of characteristics: the type of owner (household, firm or farm), capacity ($<$10, 10-29.9, 30-99.9 or $>$100 kWp), and the mounting system (building-integrated or building-attached). 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. 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 $i$ during a quarter $t$ ($Average\ PV_{i,t}$) as follows:

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

where $\triangle PV_{i,t}$ is the number of new PV systems installed in the municipality $i$ during the quarter $t$ and $Installedbase_k$ 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 neighboring installations. From the individual installed based we create a municipality-specific vector containing all the spatiotemporal variables ($Average\ PV_{i,t}$), which may be defined according to the installation characteristics available in our dataset. All observations are used, and the panel is always balanced.

## 3.2 Econometric model

In our empirical estimation, we explain the number of new adoptions of solar PV ($\Delta PV_{i,t}$) in a municipality $i$ 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:

$$\Delta PV_{i,t} = \alpha + \beta Average\, PV_{i,t} + \gamma C_{i,t} + \phi_i + \mu_t + \lambda_{c,t} + \varepsilon_{i,t} \tag{2}$$

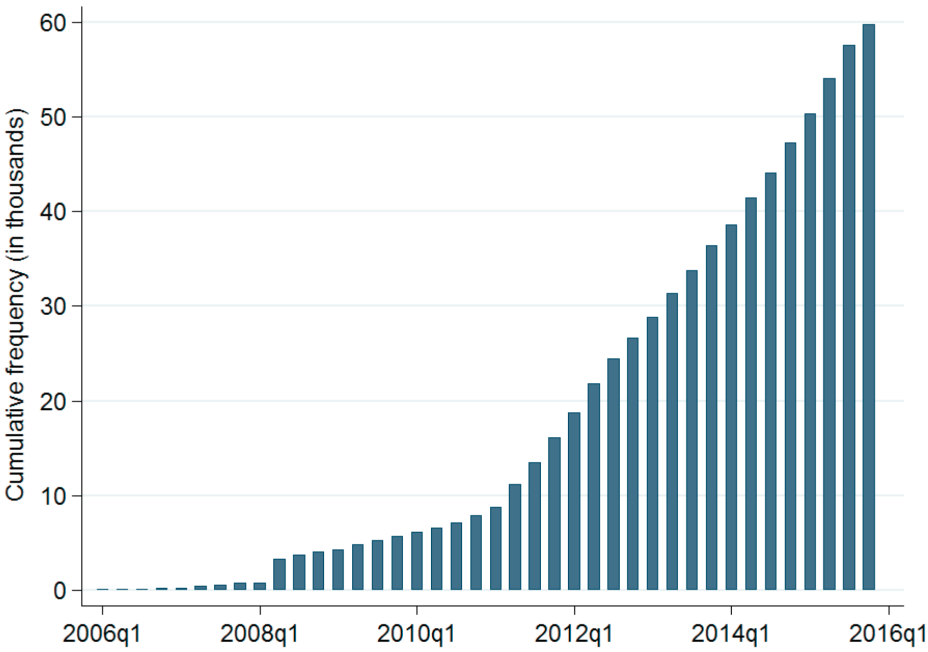
where $Average\, PV_{i,t}$ is a vector of selected spatiotemporal variables. This vector contains the main explanatory variables of interests and allows, depending on the specification, to consider separately the neighboring PV installations according to their distance, time since completion or characteristics. $C_{i,t}$ is a vector of control variables capturing the potential effect of time-varying heterogeneity, $\phi_i$ represents municipality-specific fixed effects controlling for time-invariant unobserved heterogeneity, $\mu_t$ stands for quarter-specific time dummies controlling for countrywide (and beyond), time-varying factors potentially affecting the adoption rate, 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). $\varepsilon_{i,t}$ is the i.i.d. error term, clustered at the municipality level. 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 a on fully balanced panel dataset.

As a result, $\Delta PV_{i,t}$ and $Average\, PV_{i,t}$ take the value 0 when there is no adoption in a municipality during a particular quarter.

### 3.2.1 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) and containing information on 59,819 solar PV systems adopted in Switzerland in the decade between January 2006 and December 2015. 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.[6] 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).[7]

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.

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 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

[6]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.

[7] 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 in 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.

relevant for the definition of the subsidy rate. Table 1 shows that around three quarter of the installations are building-attached (BAPV), i.e. applied on the roof or facades. 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 (less than 700 installations in total) prevents us to analyze them specifically.[8]

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%).

### 3.2.2 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 is the municipality, and data

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

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 photo-voltaics, 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 a installations with missing values for the ownership category.

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.[9]

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, although the data are often unavailable. In our context, these data are obtained from a large register containing individual information on all buildings and dwellings in the country, 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 be relevant as they can affect the energy consumption of residential and

[9]Every year a number of municipalities is involved in mergers. We select the list of all municipalities (2'242) having at least one installation as of December 31, 2015, and build a balanced panel dataset that is easily matched with PV installation data.

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 <14.9 kCHF | 2.45 | 5.81 | 0.00 | 61.98 | FTA |
| % tax payers with income 15-29.9 kCHF | 13.25 | 4.39 | 0.00 | 65.05 | FTA |
| % tax payers with income 30-49.9 kCHF | 29.65 | 7.35 | 0.00 | 61.82 | FTA |
| % tax payers with income 50-74.9 kCHF | 27.14 | 4.39 | 0.00 | 49.02 | FTA |
| % tax payers with income >75 kCHF | 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: 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.

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.

# 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 $\beta$. We estimate the baseline model including all solar panels in our dataset and provide fresh evidence from Switzerland on the existence of peer effects in the adoption of the PV technology. We also investigate with a high level of precision how distance and time between PV installations impact the magnitude of social contagion.

Table 3 provides our baseline results. All columns include the complete range of fixed effects presented in section 3.2. 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 0.08 installations per quarter.

A closer look at the bands 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 installa-

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, 0.333 km | 0.0842*** | | | |
| | (0.0160) | | | |
| Average PV, last *period* only, 0.333 km | | 0.204*** | 0.146*** | 0.106*** |
| | | (0.0326) | (0.0241) | (0.0192) |
| Average PV, except last *period*, 0.333 km | | 0.0366* | 0.0264 | 0.0384 |
| | | (0.0174) | (0.0194) | (0.0232) |
| Average PV, 0.333-1 km | 0.0161* | | | |
| | (0.0072) | | | |
| Average PV, last *period* only, 0.333-1 km | | 0.128*** | 0.0646*** | 0.0300** |
| | | (0.0266) | (0.0175) | (0.0111) |
| Average PV, except last *period*, 0.333-1 km | -0.00174 | 0.00184 | 0.00878 | |
| | | (0.0074) | (0.0087) | (0.0113) |
| Average PV, 1-3 km | 0.00873*** | | | |
| | (0.0018) | | | |
| Average PV, last *period* only, 1-3 km | | 0.0379*** | 0.0262*** | 0.0170*** |
| | | (0.0068) | (0.0044) | (0.0028) |
| Average PV, except last *period*, 1-3 km | | 0.00282 | 0.000881 | -0.00142 |
| | | (0.0026) | (0.0030) | (0.0040) |
| Average PV, 3-9 km | 0.00384*** | | | |
| | (0.0002) | | | |
| Average PV, last *period* only, 3-9 km | | 0.0163*** | 0.0116*** | 0.00754*** |
| | | (0.0013) | (0.0009) | (0.0005) |
| Average PV, except last *period*, 3-9 km | | 0.00164*** | 0.000733 | -0.0000871 |
| | | (0.0004) | (0.0005) | (0.0006) |
| Constant | 3.057* | 2.341 | 2.418 | 2.831* |
| | (1.3097) | (1.2757) | (1.2797) | (1.2877) |
| Pop. characteristics | Yes | Yes | Yes | Yes |
| Contextual factors | Yes | Yes | Yes | Yes |
| Observations | 89680 | 89680 | 89680 | 89680 |
| $R^2$ | 0.348 | 0.362 | 0.362 | 0.357 |

Standard errors in parentheses, clustered at the municipality level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: The dependent variable is the number of new PV system adoptions in a municipality-year quarter. 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.

tions 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 area, and decrease as distance increases. For comparison, Graziano and Gillingham (2015) find weaker peer 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 3-9 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 0.2, while it falls at 0.04 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 0.2 new adoptions per quarter and its effect is on average nearly six times larger than for all remaining older installations. The coefficient falls to 0.15 (0.11) 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. These results are consistent with Graziano and Gillingham (2015), the only other study analyzing how the strength of peer effects may change with the age of an installation. As far as imitation is concerned, the intuition is that new installations are more likely to catch people 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.

Table A.1 in the Appendix shows that when we take all radii together, and the full period in our sample, the coefficient for social contagion is 0.07. As in Graziano and Gillingham (2015), we interpret this coefficient as the average of the effects captured by the different spatiotemporal variables. Figure A.1 shows how peer effects evolve over time. 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 A.1 displays the estimated coefficients (and confidence intervals) using for the spatiotemporal variables all surrounding installations, regardless of the date of connection to the grid (cf. column (1) in Table 3), all surrounding installations that have been connected to the grid for less than 6 months, and all surrounding installations that have been connected to the grid for more than 6 months (cf. column (2) in Table 3). Figure A.1 shows that over time, as the market becomes more mature, and solar panels become more mainstream, the importance of social contagion for new adoptions decreases. 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 fits however 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. We are not aware of any such initiative having taken place in Switzerland. To the extent that our results can be compared with theirs for California, our data suggest that the strength of social contagion might have well decreased in California, had no initiatives to leverage social contagion taken place.

Besides providing evidence for the presence of peer effects, our results reveal some interesting correlations between the adoption of solar panels and some population characteristics and contextual variables. We report in Table A.2 in the Appendix the coefficients for our 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. Given the visibility of solar panels, this correlation is consistent with Sexton and Sexton (2014), who 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 strong upper-middle class (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 A.2) nor with a lag (cf. Lamp, 2016).

### 4.2 Effect of size, type and ownership

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 peer effects? We focus on the variation across our measures of social spillovers for the following three characteristics of the installations in our dataset: ownership, type and size. To the best of our knowledge, we are the first to investigate peer effects for firms and farms and to analyze the influence of the type of PV systems (building-attached or building-integrated) on the magnitude of social contagion. We also deepen the examination of the effects on social contagion of panels of varying size, already undertaken by Bollinger and Gillingham (2012), by relying on power

Table 4: Main specifications focusing on size

| | (1)<br>All<br>adopt. | (2)<br><10 kWp<br>adopt. | (3)<br>10-29.9 kWp<br>adopt. | (4)<br>30-99.9 kWp<br>adopt. | (5)<br>>100 kWp<br>adopt. |
|---|---|---|---|---|---|
| Average PV, <10 kWp | 0.127*** | 0.106*** | 0.0845*** | 0.0908*** | 0.0779*** |
| | (0.0090) | (0.0058) | (0.0062) | (0.0082) | (0.0090) |
| Average PV, 10-29.9 kWp | 0.0702*** | 0.0312* | 0.0729*** | 0.0747*** | 0.0655*** |
| | (0.0181) | (0.0130) | (0.0134) | (0.0164) | (0.0139) |
| Average PV, 30-99.9 kWp | 0.271*** | 0.208*** | 0.202*** | 0.219*** | 0.212*** |
| | (0.0402) | (0.0269) | (0.0214) | (0.0306) | (0.0267) |
| Average PV, >100 kWp | 0.234*** | 0.171*** | 0.200*** | 0.150** | 0.141*** |
| | (0.0453) | (0.0392) | (0.0368) | (0.0497) | (0.0311) |
| Constant | 2.941* | 1.943** | 0.206 | -0.175 | 0.107 |
| | (1.2802) | (0.7484) | (0.3854) | (0.2285) | (0.1784) |
| Pop. characteristics | Yes | Yes | Yes | Yes | Yes |
| Contextual factors | Yes | Yes | Yes | Yes | Yes |
| Observations | 89680 | 89680 | 89680 | 89680 | 89680 |
| $R^2$ | 0.328 | 0.331 | 0.356 | 0.288 | 0.292 |

Standard errors in parentheses, clustered at the municipality level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: 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. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius. Installed bases are generated based on installation size.

categories. 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.

**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. To examine how the size of the installation affects learning and imitation, we look at social contagion between installations with the same capacity, knowing that learning is likely to be stronger for comparable installations.

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 peer effects than smaller ones. This finding is in line with the hypothesis stated in Bollinger and Gillingham (2012), but which was not confirmed empirically. The remaining columns look at whether contagion is stronger for panels of the same size. Interestingly, we find that peer effects are not stronger for installations of the same size, suggesting that learning is probably not dominating the effect of imitation.

**Type** The analysis of installation size provides a first evidence suggesting an important role of visibility in adoption. To investigate further the drivers of social contagion, we exploit the fact that our unique 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 facades or steep roofs, they are likely to be more visible, since they are more exposed to the view of passersby

Table 5: Main specifications focusing on type

| | (1) All adopt. | (2) BIPV adopt. | (3) BAPV adopt. |
|---|---|---|---|
| Average PV, BIPV | 0.194*** (0.0176) | 0.187*** (0.0133) | 0.174*** (0.0185) |
| Average PV, BAPV | 0.113*** (0.0067) | 0.0549*** (0.0046) | 0.110*** (0.0069) |
| Constant | 2.907* (1.2821) | -0.120 (0.4051) | 2.319* (1.0558) |
| Pop. characteristics | Yes | Yes | Yes |
| Contextual factors | Yes | Yes | Yes |
| Observations | 89680 | 89680 | 89680 |
| $R^2$ | 0.327 | 0.293 | 0.326 |

Standard errors in parentheses, clustered at the municipality level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: 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. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius.

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. We further analyze this question in the following sections.

Table 6: Main specifications focusing on ownership

| | (1) HH adopt. | (2) Firms adopt. | (3) Farms adopt. | (4) HH adopt. | (5) Firms adopt. | (6) Farms adopt. |
|---|---|---|---|---|---|---|
| Average PV | 0.112*** | 0.0933*** | 0.0908*** | | | |
| | (0.0039) | (0.0049) | (0.0090) | | | |
| Average PV, same *owner* | | | | 0.0853*** | 0.205*** | 0.329*** |
| | | | | (0.0103) | (0.0126) | (0.0925) |
| Average PV, other *owners* | | | | 0.131*** | 0.0258** | 0.0871*** |
| | | | | (0.0063) | (0.0081) | (0.0091) |
| Constant | 3.168*** | -0.524 | 0.0800 | 3.187*** | -0.456 | 0.0657 |
| | (0.9492) | (0.3388) | (0.1184) | (0.9573) | (0.3336) | (0.1180) |
| Pop. characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Contextual factors | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 89680 | 89680 | 89680 | 89680 | 89680 | 89680 |
| $R^2$ | 0.440 | 0.249 | 0.280 | 0.441 | 0.267 | 0.284 |

Standard errors in parentheses, clustered at the municipality level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: The dependent variable is the number of PV system adoptions by a particular type of owner, in a municipality-quarter. 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.

**Ownership** Previous studies on social spillovers in the diffusion of PV technology have limited their analysis to households-owned installations (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Rode and Weber, 2016) and even more specifically to residential roof-mounted solar panels (Rode and Weber, 2016). Our PV database includes all installations, regardless of their owner's status. Most importantly, the individual level categorical variable "owner" allows us to assess whether social contagion is a driver of adoptions only among households or may also be at play 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 type of 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 6 present the coefficients of 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 in 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.

Peer 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 learning: learning is likely to work better when one learns from a similar situation. Firms are more likely to learn from neighboring firms, and farmers are more likely to learn from other farmers. Imitation is also more likely to work among close peers.

We test this hypothesis by computing a new set of installed bases: one spatiotemporal variable accounts for same-owner installations, and another account for all remaining installations. As shown in columns (5) and (6) of Table 6, 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.

**Size and ownership** Are households more influenced by non-household neighbors than by their peers simply because non-household PV installations are larger? Table A.3 in the Appendix focuses on the contagion from existing installations of different sizes to new adoptions by households only.

As in Table 6, 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 counterintuitive 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 A.4 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 A.5 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 peer 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 A.6 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 A.6 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.

# 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.

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 location 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. We consider pre-existing installations for all the different characteristics available in our dataset. We focus on ownership and differentiate between residential adoptions, and adoptions by firms and farms. We focus on type, and differentiate between building-integrated and building-attached systems. We focus on size, and assess how social contagion may be dependent on the size of the installation.

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. firms (farms) are mainly influenced by the nearby firm-owned (farm-owned) installations. Furthermore, we observe that more visible building-integrated systems drive stronger contagion than building-attached systems and that large PV systems weight more heavily on decisions than smaller ones. 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 policy-makers 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.

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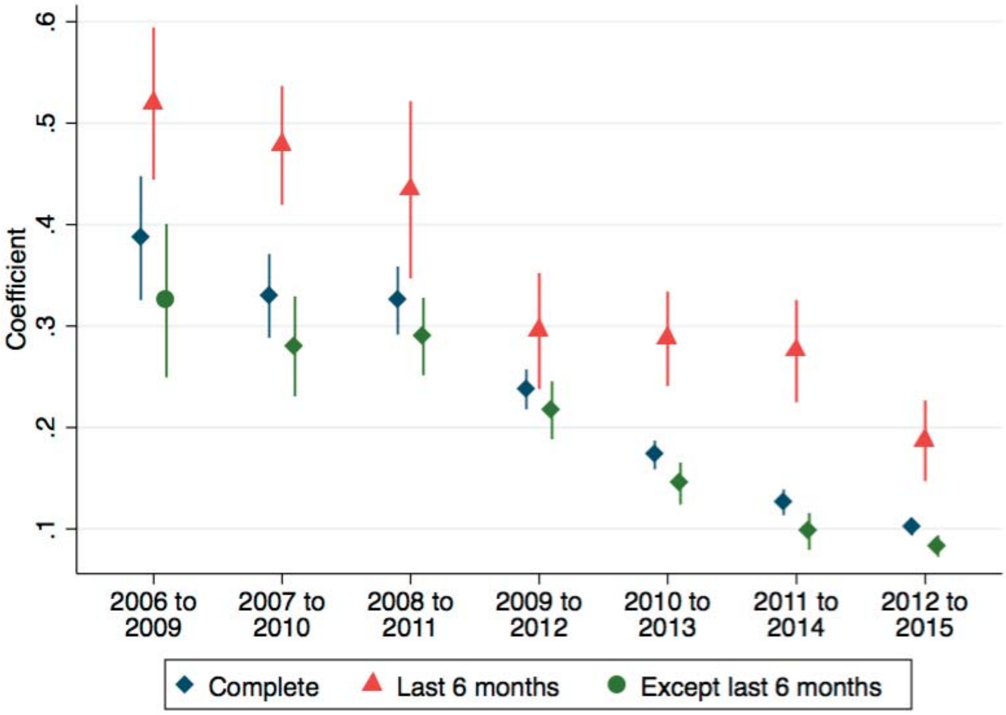
# Appendix

Figure A.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. Consistently with Table 3, the most recent installations drive stronger social contagion for all periods. 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 A.1: Baseline specifications including all PV adoptions for the years 2006-2015, all radii

| | (1) Complete | (2) 6 months | (3) 12 months | (4) 24 months |
|---|---|---|---|---|
| Average PV, all radii | 0.00512*** | | | |
| | (0.0001) | | | |
| Average PV, last *period* only, all radii | | 0.0229*** | 0.0155*** | 0.00982*** |
| | | (0.0011) | (0.0006) | (0.0003) |
| Average PV, except last *period*, all radii | | 0.00175*** | 0.000748** | -0.0000376 |
| | | (0.0002) | (0.0003) | (0.0003) |
| Constant | 3.183* | 2.433 | 2.433 | 2.888* |
| | (1.3405) | (1.3151) | (1.3173) | (1.3226) |
| Pop. characteristics | Yes | Yes | Yes | Yes |
| Contextual factors | Yes | Yes | Yes | Yes |
| Observations | 89680 | 89680 | 89680 | 89680 |
| $R^2$ | 0.345 | 0.358 | 0.359 | 0.354 |

Standard errors in parentheses, clustered at the municipality level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: The dependent variable is the number of new PV system adoptions in a municipality-year quarter.

Table A.2: Baseline specifications including all PV adoptions during the years 2006 to 2015.

| | (1) Complete | (2) 6 months | (3) 12 months | (4) 24 months |
|---|---|---|---|---|
| Average PV, 0.333 km | 0.0842*** (0.0160) | | | |
| Average PV, last *period* only, 0.333 km | | 0.204*** (0.0326) | 0.146*** (0.0241) | 0.106*** (0.0192) |
| Average PV, except last *period*, 0.333 km | | 0.0366* (0.0174) | 0.0264 (0.0194) | 0.0384 (0.0232) |
| Average PV, 0.333-1 km | 0.0161* (0.0072) | | | |
| Average PV, last *period* only, 0.333-1 km | | 0.128*** (0.0266) | 0.0646*** (0.0175) | 0.0300** (0.0111) |
| Average PV, except last *period*, 0.333-1 km | | -0.00174 (0.0074) | 0.00184 (0.0087) | 0.00878 (0.0113) |
| Average PV, 1-3 km | 0.00873*** (0.0018) | | | |
| Average PV, last *period* only, 1-3 km | | 0.0379*** (0.0068) | 0.0262*** (0.0044) | 0.0170*** (0.0028) |
| Average PV, except last *period*, 1-3 km | | 0.00282 (0.0026) | 0.000881 (0.0030) | -0.00142 (0.0040) |
| Average PV, 3-9 km | 0.00384*** (0.0002) | | | |
| Average PV, last *period* only, 3-9 km | | 0.0163*** (0.0013) | 0.0116*** (0.0009) | 0.00754*** (0.0005) |
| Average PV, except last *period*, 3-9 km | | 0.00164*** (0.0004) | 0.000733 (0.0005) | -0.0000871 (0.0006) |
| % population aged 30-44 | 0.0105* (0.0051) | 0.0110* (0.0049) | 0.0108* (0.0049) | 0.0105* (0.0050) |
| % population aged 45-64 | -0.0103* (0.0050) | -0.0113* (0.0048) | -0.0113* (0.0048) | -0.0111* (0.0049) |
| % population aged 65-100 | -0.0356*** (0.0076) | -0.0345*** (0.0074) | -0.0343*** (0.0074) | -0.0345*** (0.0075) |
| % tax payers with income 15-29.9 kCHF | 0.0103 (0.0067) | 0.00935 (0.0063) | 0.00916 (0.0063) | 0.00980 (0.0065) |
| % tax payers with income 30-49.9 kCHF | 0.0121 (0.0065) | 0.0112 (0.0061) | 0.0110 (0.0062) | 0.0118 (0.0063) |
| % tax payers with income 50-74.9 kCHF | 0.0155* (0.0066) | 0.0141* (0.0062) | 0.0141* (0.0062) | 0.0150* (0.0064) |
| % tax payers with income >75 kCHF | 0.00610 (0.0066) | 0.00506 (0.0062) | 0.00497 (0.0063) | 0.00553 (0.0064) |
| # of unemployed individuals | 0.00117 (0.0008) | 0.00113 (0.0008) | 0.00113 (0.0008) | 0.00115 (0.0008) |
| Green voting (in %) | 0.0163*** (0.0048) | 0.0145** (0.0045) | 0.0145** (0.0045) | 0.0160*** (0.0046) |
| % apartment buildings | -0.00693 (0.0062) | -0.00787 (0.0061) | -0.00791 (0.0061) | -0.00758 (0.0061) |
| % buildings with residential/commercial use | 0.0507*** (0.0096) | 0.0498*** (0.0095) | 0.0499*** (0.0095) | 0.0502*** (0.0096) |
| % commercial/industrial buildings | 0.0106 (0.0092) | 0.00847 (0.0091) | 0.00771 (0.0091) | 0.00785 (0.0091) |
| Average # of rooms per dwelling | -0.665* (0.2847) | -0.642* (0.2784) | -0.647* (0.2791) | -0.651* (0.2827) |
| Average area per dwelling | -0.00958 (0.0063) | -0.00902 (0.0061) | -0.00870 (0.0061) | -0.00871 (0.0062) |
| Solar radiation (in W/sqm) | -0.00134 (0.0035) | 0.00303 (0.0035) | 0.00268 (0.0035) | -0.000728 (0.0035) |
| Constant | 3.057* (1.3097) | 2.341 (1.2757) | 2.418 (1.2797) | 2.831* (1.2877) |
| Observations | 89680 | 89680 | 89680 | 89680 |
| $R^2$ | 0.348 | 0.362 | 0.362 | 0.357 |

Standard errors in parentheses, clustered at the municipality level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: The dependent variable is the number of new PV system adoptions in a municipality-quarter. 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 A.3: Main specification focusing on size and ownership

| | (1) HH adopt. |
|---|---|
| Average PV, <10 kWp, HH | 0.0788*** (0.0129) |
| Average PV, <10 kWp, other owners | 0.132*** (0.0098) |
| Average PV, 10-29.9 kWp, HH | 0.0873** (0.0334) |
| Average PV, 10-29.9 kWp, other owners | 0.0848*** (0.0175) |
| Average PV, 30-99.9 kWp, HH | 0.362*** (0.0865) |
| Average PV, 30-99.9 kWp, other owners | 0.191*** (0.0352) |
| Average PV, >100 kWp, HH | 0.323* (0.1458) |
| Average PV, >100 kWp, other owners | 0.189*** (0.0393) |
| Constant | 3.160*** (0.9546) |
| Pop. characteristics | Yes |
| Contextual factors | Yes |
| Observations | 89680 |
| $R^2$ | 0.443 |

Standard errors in parentheses, clustered at the municipality level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: 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. 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 A.4: Main specifications focusing on type and ownership

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | HH adopt. | Firm adopt. | Farm adopt. | HH adopt. | Firm adopt. | Farm adopt. |
| Average PV, BIPV | 0.175*** | 0.178*** | 0.234*** | | | |
| | (0.0158) | (0.0244) | (0.0260) | | | |
| Average PV, BAPV | 0.0988*** | 0.0767*** | 0.0583*** | | | |
| | (0.0058) | (0.0071) | (0.0105) | | | |
| Average PV, BIPV, same *owner* | | | | 0.105*** | 0.270*** | 0.510*** |
| | | | | (0.0273) | (0.0366) | (0.1374) |
| Average PV, BAPV, same *owner* | | | | 0.0855*** | 0.187*** | 0.274** |
| | | | | (0.0126) | (0.0147) | (0.0999) |
| Average PV, BIPV, other *owners* | | | | 0.207*** | 0.0711** | 0.228*** |
| | | | | (0.0216) | (0.0271) | (0.0262) |
| Average PV, BAPV, other *owners* | | | | 0.110*** | 0.0200* | 0.0554*** |
| | | | | (0.0079) | (0.0091) | (0.0105) |
| Constant | 3.009** | -0.564 | 0.0216 | 3.066** | -0.482 | 0.0103 |
| | (0.9416) | (0.3338) | (0.1155) | (0.9474) | (0.3315) | (0.1154) |
| Pop. characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Contextual factors | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 89680 | 89680 | 89680 | 89680 | 89680 | 89680 |
| $R^2$ | 0.442 | 0.252 | 0.305 | 0.443 | 0.268 | 0.308 |

Standard errors in parentheses, clustered at the municipality level. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

Note: Dependent variable is the number of PV system adoptions by a particular type of owner in a municipality quarter. 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 column (4) to (6), installed bases are generated based on installation type and ownership.

Table A.5: Main specifications focusing on size and type

| | (1) All adopt. | (2) HH adopt. | (3) Firms adopt. | (4) Farms adopt. |
|---|---|---|---|---|
| Average PV, BIPV, <10 kWp | 0.193*** | 0.167*** | 0.162*** | 0.168*** |
| | (0.0209) | (0.0189) | (0.0263) | (0.0298) |
| Average PV, BAPV, <10 kWp | 0.113*** | 0.0972*** | 0.0691*** | 0.0193 |
| | (0.0113) | (0.00972) | (0.00910) | (0.0132) |
| Average PV, BIPV, 10-29.9 kWp | 0.183*** | 0.181*** | 0.155** | 0.275*** |
| | (0.0360) | (0.0308) | (0.0589) | (0.0518) |
| Average PV, BAPV, 10-29.9 kWp | 0.0445* | 0.0564** | 0.0315 | 0.0957*** |
| | (0.0208) | (0.0176) | (0.0197) | (0.0215) |
| Average PV, BIPV, 30-99.9 kWp | 0.214*** | 0.185*** | 0.363** | 0.433*** |
| | (0.0648) | (0.0518) | (0.121) | (0.0649) |
| Average PV, BAPV, 30-99.9 kWp | 0.289*** | 0.230*** | 0.204*** | 0.197*** |
| | (0.0454) | (0.0407) | (0.0364) | (0.0399) |
| Average PV, BIPV, >100 kWp | 0.250* | 0.322*** | 0.284* | 0.482*** |
| | (0.112) | (0.0917) | (0.123) | (0.0978) |
| Average PV, BAPV, >100 kWp | 0.240*** | 0.158*** | 0.199*** | 0.246*** |
| | (0.0491) | (0.0399) | (0.0536) | (0.0655) |
| Constant | 2.753* | 2.922** | -0.659* | -0.00464 |
| | (1.272) | (0.938) | (0.329) | (0.113) |
| Pop. characteristics | Yes | Yes | Yes | Yes |
| Contextual factors | Yes | Yes | Yes | Yes |
| Observations | 89680 | 89680 | 89680 | 89680 |
| $R^2$ | 0.329 | 0.444 | 0.256 | 0.324 |

Standard errors in parentheses, clustered at the municipality level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: The dependent variable is the number of PV system adoptions by all types of owners (column (1)) or by a particular type of owner (column (2) to (4)), in a municipality-year quarter. 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 A.6: Main specifications focusing on size, type and ownership

| | (1) HH adoptions. | (2) Firms adoptions. | (3) Farms adoptions. |
|---|---|---|---|
| Average PV, BIPV, same *owner*, <10 kWp | 0.101** (0.0332) | 0.248*** (0.0306) | 0.600 (0.5302) |
| Average PV, BAPV, same *owner*, <10 kWp | 0.0809*** (0.0153) | 0.195*** (0.0170) | -0.246 (0.3988) |
| Average PV, BIPV, other *owners*, <10 kWp | 0.200*** (0.0279) | 0.0175 (0.0313) | 0.166*** (0.0299) |
| Average PV, BAPV, other *owners*, <10 kWp | 0.111*** (0.0115) | -0.0172 (0.0109) | 0.0205 (0.0132) |
| Average PV, BIPV, same *owner*, 10-29.9 kWp | 0.0936 (0.0496) | 0.246* (0.0961) | 0.0979 (0.2693) |
| Average PV, BAPV, same *owner*, 10-29.9 kWp | 0.0843* (0.0408) | 0.112* (0.0450) | 0.138 (0.1902) |
| Average PV, BIPV, other *owners*, 10-29.9 kWp | 0.240*** (0.0342) | 0.113 (0.0803) | 0.282*** (0.0529) |
| Average PV, BAPV, other *owners*, 10-29.9 kWp | 0.0491** (0.0185) | 0.0530 (0.0305) | 0.0940*** (0.0219) |
| Average PV, BIPV, same *owner*, 30-99.9 kWp | 0.243* (0.1063) | 0.601** (0.2214) | 0.404* (0.1754) |
| Average PV, BAPV, same *owner*, 30-99.9 kWp | 0.422*** (0.1175) | 0.217*** (0.0619) | 0.417** (0.1597) |
| Average PV, BIPV, other *owners*, 30-99.9 kWp | 0.161** (0.0561) | 0.215* (0.0936) | 0.432*** (0.0684) |
| Average PV, BAPV, other *owners*, 30-99.9 kWp | 0.203*** (0.0389) | 0.177*** (0.0457) | 0.180*** (0.0407) |
| Average PV, BIPV, same *owner*, >100 kWp | 0.838*** (0.2010) | 0.345* (0.1650) | 0.614* (0.2837) |
| Average PV, BAPV, same *owner*, >100 kWp | 0.198 (0.1742) | 0.168* (0.0663) | 0.110 (0.4785) |
| Average PV, BIPV, other *owners*, >100 kWp | 0.314*** (0.0904) | 0.218 (0.1827) | 0.466*** (0.0842) |
| Average PV, BAPV, other *owners*, >100 kWp | 0.171*** (0.0412) | 0.327*** (0.0817) | 0.238*** (0.0646) |
| Constant | 3.020** (0.9418) | -0.599 (0.3250) | -0.0104 (0.1134) |
| Pop. characteristics | Yes | Yes | Yes |
| Contextual factors | Yes | Yes | Yes |
| Observations | 89680 | 89680 | 89680 |
| $R^2$ | 0.446 | 0.275 | 0.326 |

Standard errors in parentheses, clustered at the municipality level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: The dependent variable is the number of PV system adoptions by a particular type of owner, in a municipality-quarter. Spatiotemporal variables are computed based on individual installed bases within a 1 km radius.

# Appendix 2

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

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

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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

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# 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 with 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., 2017). 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., 2017). 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 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., 2017). Social spillovers are expected to work through both social learning (word-of-mouth) and social norms (imitation). The former relates 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., 2017).

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. (2017), 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., 2017). Baranzini et al. (2017) 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., 2017). Fourth, installations that are more visible are more likely to lead to further adoptions than less visible ones. Baranzini et al. (2017) 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. (2017) 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 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. 2017 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

[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.

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.

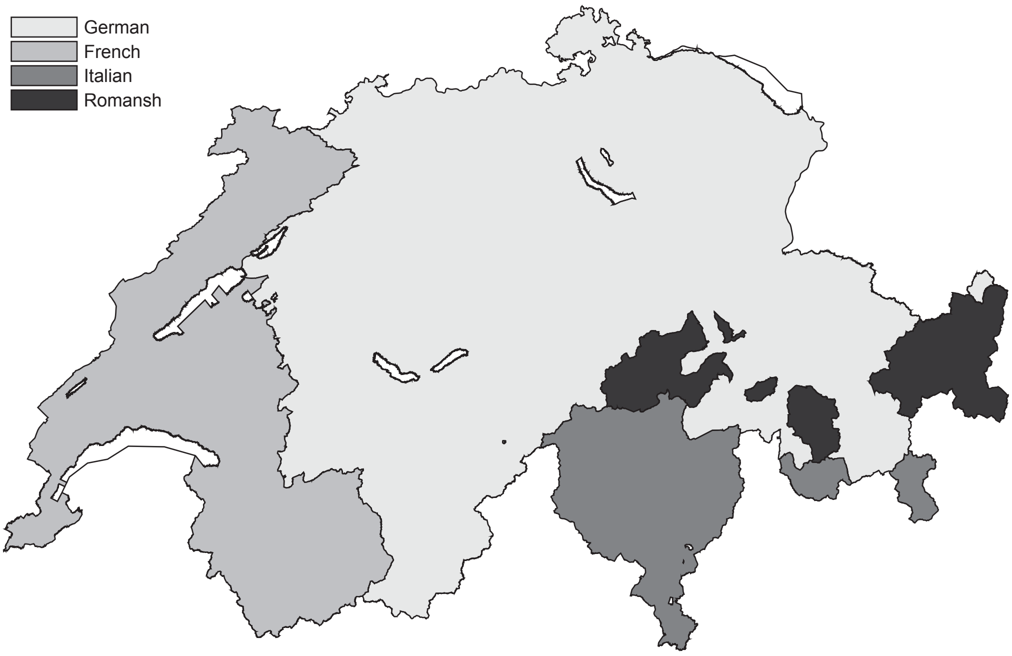
The second set of variables measures contextual factors that may be linked to the feasibility and profitability of PV installations. We use variables characterizing the type of building and solar irradiance. Building characteristics are of particular relevance, although in existing studies those data 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 1 in the Appendix.

## 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, 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

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. White 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).

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.

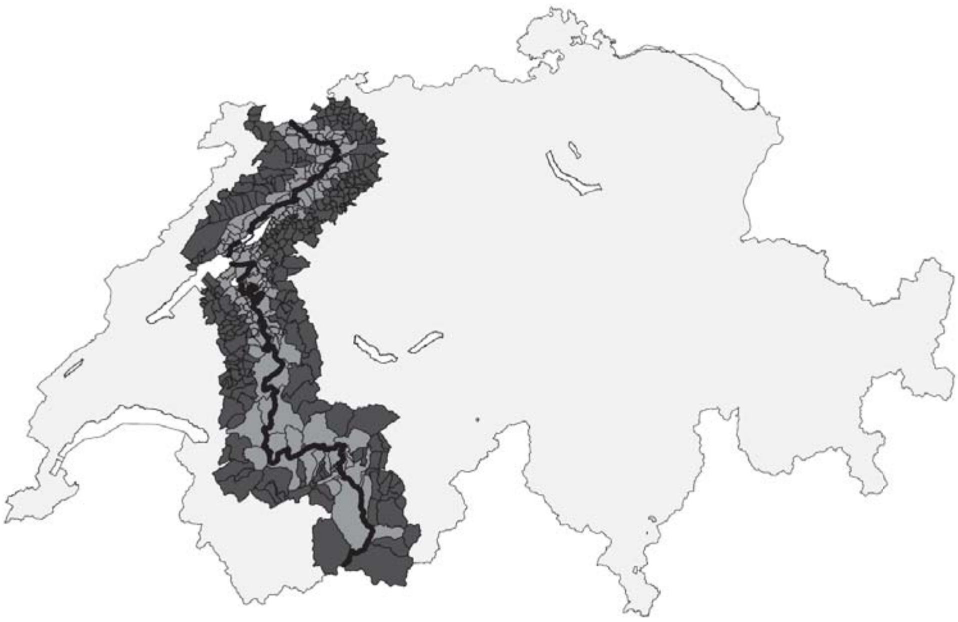
To perform our analysis of the impact of the border on PV adoption, we first need to precisely identify the location of the language border. Then, we compute the distances of each PV installation to the border. For reasons of political sensitivity, no official source provides precise geographical data 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 Swiss federal statistical office (FSO), contains 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 closest 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

[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.

[3]Our results remain unaffected if we use, for each municipality, a single measure of distance to

Figure 2: French-German language border and surrounding municipalities



Note: The black line shows the language border between the French- (West) and the German-speaking (East) parts of Switzerland. Light grey areas represent the municipalities whose PV installations are located on average less than 5 km away from the border. Dark grey areas show the municipalities whose PV installations are located on average between 5 and 15 km away from the border. White areas are either lakes or foreign enclaves. The rest of the map (in very light 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)

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.

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 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 $\beta$ 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 0.15 CHF to 0.49-0.90 CHF,[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 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 $\Delta PV_{it}$ is the number of new adoptions in a municipality $i$ during the year $t$ and $\epsilon_{it}$ 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

[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.

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, $\alpha_i$, to capture potential time-invariant unobserved heterogeneity, and year-specific time dummies, $\mu_t$, 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 $\chi^2$ (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 with distance to the language border. No specific pattern is identified. The same applies to the distribution of installers, measured in 2018 (see Figure 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 $\beta$ 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

[7]Approximately half the lenght 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.

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 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 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 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

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.

would expect about 11% less PV installations for each extra kilometer.

## 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 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

[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.

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.

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.

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 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 at 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

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.

border: the estimated losses within 5 and 15 km from the border represent approximately 20% of the total number of PV adoptions that there would have been 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.

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

[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

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.

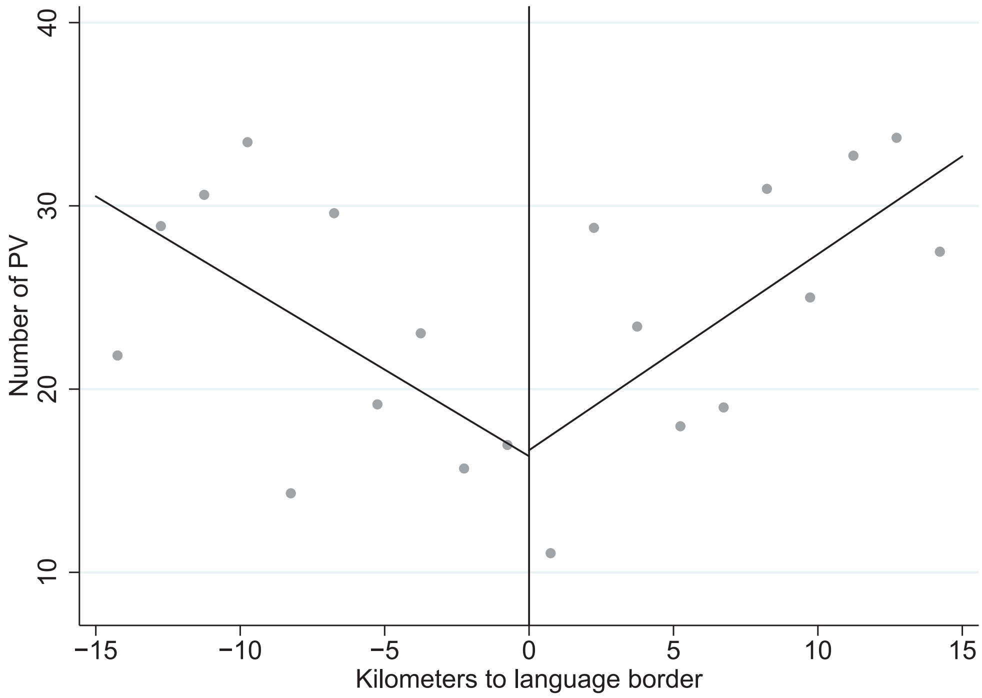
Table 4 quantifies the effects illustrated by Figure 3. Column (1) of Table 4 shows that the discontinuity in culture is associated with no significant change in the rate of adoption of solar PV. Columns (2) and (3) measure the slope of adoption, as a function of distance from the border, for the Western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

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 2 and Table 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 thorough 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 2 and Table 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 2 show fitted values from linear regressions. Fitted values from second-degree polynomial regressions would provide similar results.

[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).

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.

missing adoptions per municipality per kilometer (see model (2), fifth column, in Table 3).

### 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

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

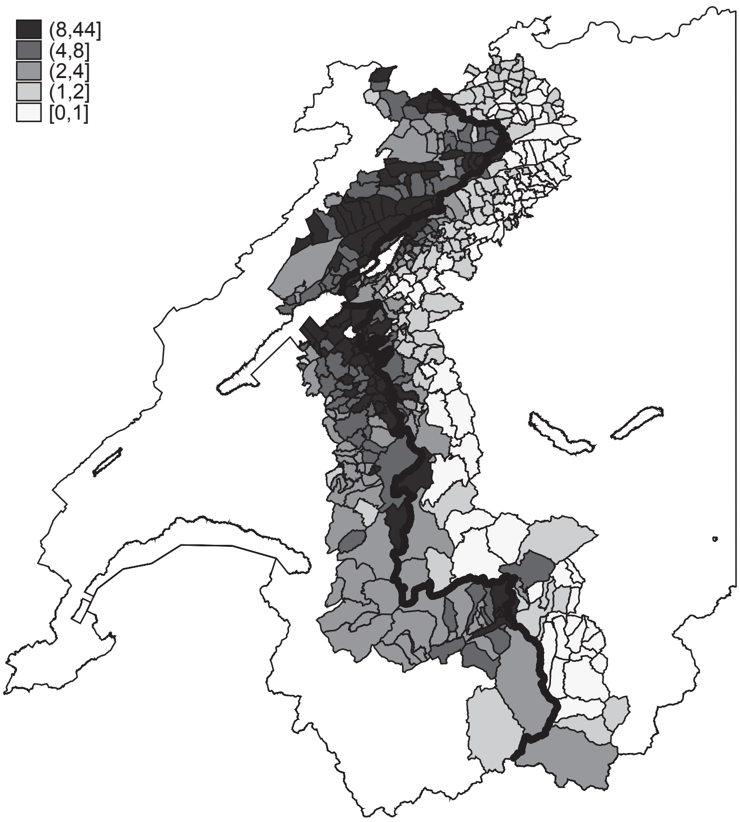
| | RD | West | East |
|---|---|---|---|
| | (1) | (2) | (3) |
| RD estimate | 0.329 | | |
| | (3.959) | | |
| Distance | | -0.945** | 1.069*** |
| | | (0.406) | (0.361) |
| Constant | | 16.338*** | 16.667*** |
| | | (2.873) | (2.725) |
| *N* | 436 | 188 | 248 |
| $R^2$ | | 0.0198 | 0.0362 |

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 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. 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

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




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

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

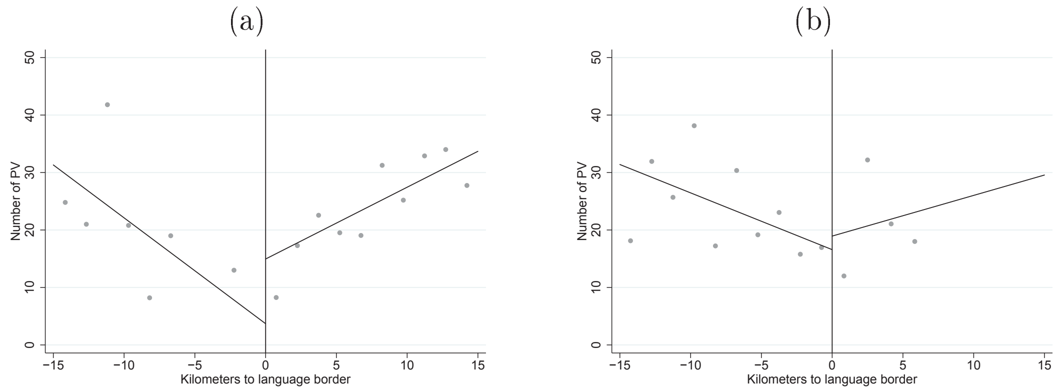
[11]The smaller number of observations on each side of the border, after the separation of the municipalities in two groups based on the median fluency, makes the results rarely statistically significant with bandwidths smaller than 15 km. However, regardless of the level of fluency, we always observe 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.

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.

steeper in plot (a), with a below median-share of population speaking the language 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).

# 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.

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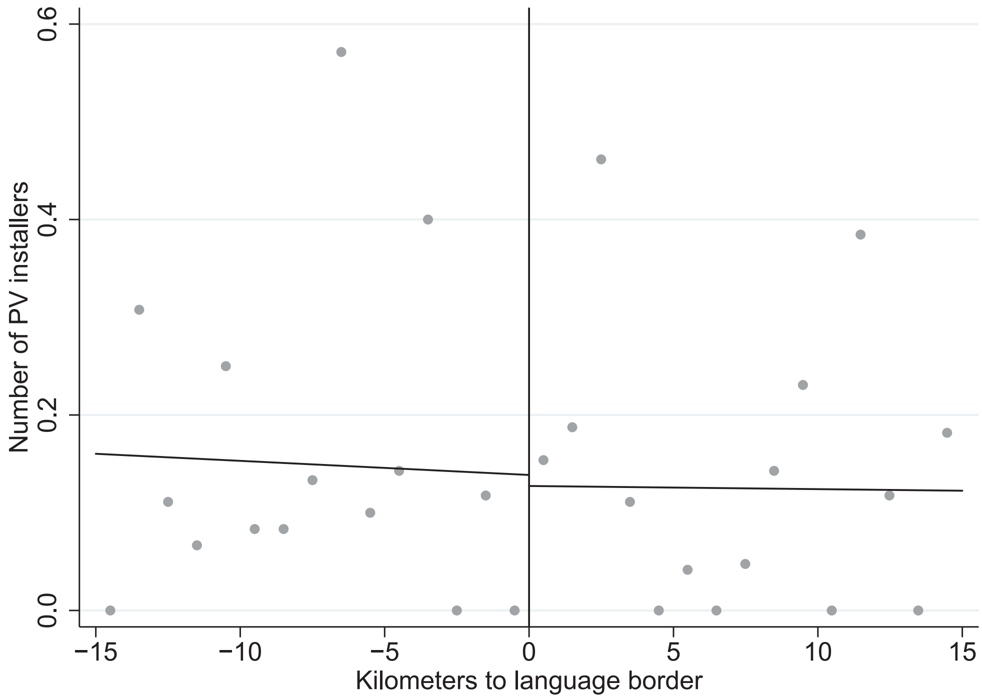
# Appendix

Table 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 <14.9 kCHF | 2.55 | 6.43 | 0.00 | 54.73 | FTA |
| % tax payers with income 15-29.9 kCHF | 13.71 | 4.22 | 0.00 | 65.05 | FTA |
| % tax payers with income 30-49.9 kCHF | 31.10 | 6.74 | 0.00 | 61.54 | FTA |
| % tax payers with income 50-74.9 kCHF | 27.94 | 4.24 | 0.00 | 49.02 | FTA |
| % tax payers with income >75 kCHF | 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 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 2: Effect of distance to the language border on PV adoptions (semi-elasticity)

| | 5 km | 10 km | 15 km | 20 km | 25 km |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (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 3: Effect of distance to the language border on PV adoptions: with coefficients for control variables

| | 5 km | | 10 km | | 15 km | | 20 km | | 25 km | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | | (4) | | (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 15-29.9 kCHF | 0.657 | (0.481) | 0.089 | (0.302) | -0.145 | (0.294) | -0.045 | (0.281) | -0.097 | (0.268) |
| % tax payers with income 30-49.9 kCHF | 0.799** | (0.336) | 0.388 | (0.256) | 0.422** | (0.203) | 0.622*** | (0.204) | 0.807*** | (0.206) |
| % tax payers with income 50-74.9 kCHF | 0.353 | (0.314) | 0.048 | (0.267) | -0.153 | (0.216) | 0.063 | (0.213) | 0.058 | (0.189) |
| % tax payers with income >75 kCHF | 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 | |

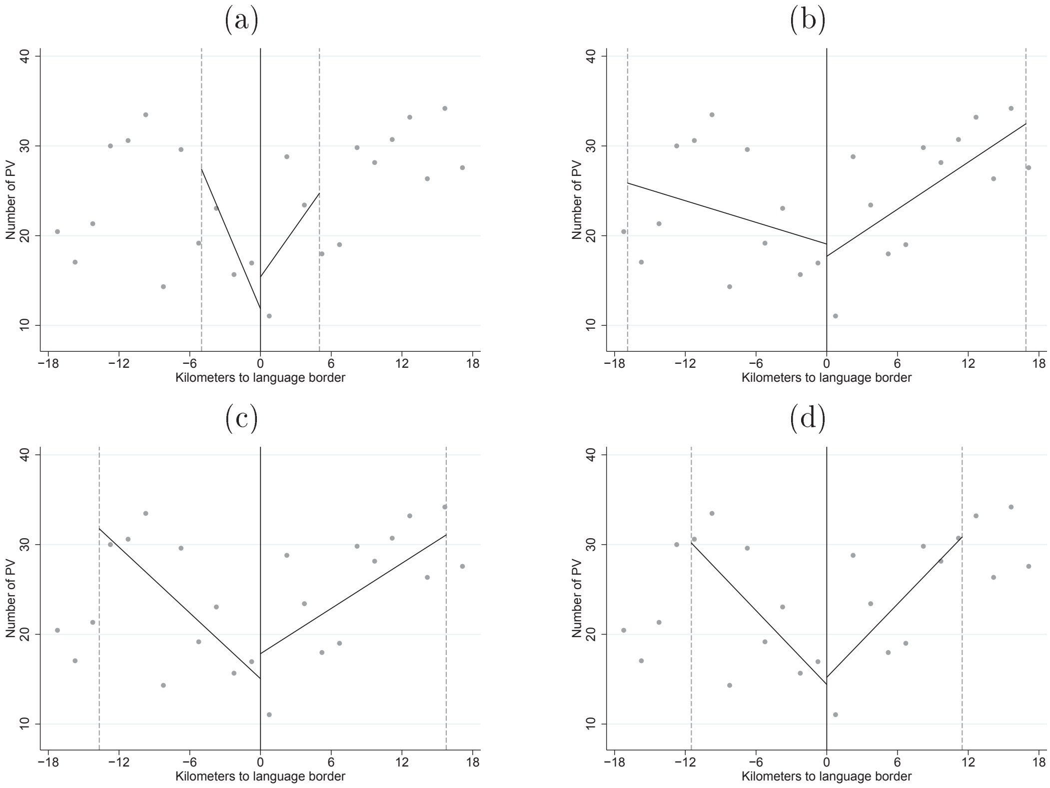
Note: Heteroskedasticity-consistent standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. The dependent variable is the total number of PV system adoptions in a municipality by the end of 2015.

Table 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 | | 15 km | | 5 km | | 15 km | | 5 km | | 15 km | |
| | (1) | | (2) | | (3) | | (4) | | (5) | | (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 15-29.9 kCHF | 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 30-49.9 kCHF | 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 50-74.9 kCHF | 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 >75 kCHF | 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 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 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<br>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.

# Appendix 3

# Preferences for solar PV by firms: Results from a discrete choice experiment

# Preferences for solar PV by firms:

# Results from a discrete choice experiment[1]

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## 1 Introduction

As stated by Stern (2008), greenhouse gas emissions (GHGs) are the biggest market failure the world has seen. All economic agents produce emissions when consuming or producing goods. Emissions accumulate in the atmosphere for centuries, causing irreversible and possibly catastrophic climate changes. Although the precise consequences are still uncertain, their effect on the environment is becoming more and more obvious (see e.g. IPCC, 2018). In response to this challenge, 185 countries have ratified the Paris Agreement and have submitted nationally determined contributions aimed at keeping the global temperature increase below 2 degrees Celsius above pre-industrial levels (cf. https://unfccc.int/). By ratifying the Paris Agreement, Switzerland committed to reduce its GHGs emissions by half by 2030 compared to their 1990 level, in particular by increasing the use of renewable energy, reducing waste and improving efficiency.

A specificity of Switzerland is its electricity production sector, which is practically carbon-free, with fossil fuels representing less than 3% of total production, while hydro and nuclear represent about 60% and 30%, respectively. Since 2007, the Swiss authorities have set an objective to increase the share of renewables (excluding hydro) in the production mix by 10% by 2030. Consequently, several instruments were introduced to foster the production capacity from renewables, in particular a cost-covering remuneration for feed-in to the electricity grid in 2008 (FIT) and a direct investment subsidy in 2014. In addition, following the Fukushima accident, Switzerland adopted a new Energy Strategy, including a ban on new nuclear plants and the gradual phase out of the existing ones, which increases the dependence in the development of renewables for electricity production. It is therefore essential to understand the factors that explain the adoption of renewable technologies. Although there are several studies analyzing the factors explaining the adoption of renewables by households (e.g. Ameli and Brandt, 2014; Bollinger and Gillingham 2012; Rode and Weber 2016), the literature for firms is scarcer (see Mattes et al. 2014).

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[1] This study uses data from a discrete choice experiment that was conceived and designed by Andrea Baranzini, Stefano Carattini and Martin Péclat. It also uses data from a randomized intervention, which was conceived and designed by Stefano Carattini and implemented by Martin Péclat. All authors acknowledge financial support from the Swiss Federal Office of Energy, grant number SI/501305-01. All contents and conclusions are the sole responsibility of the authors.

In this paper, we analyze the determinants of the adoption of solar photovoltaic (PV) technology by firms in Switzerland, which account for around 30% of total electricity consumption. To investigate the determinants of firm preferences for solar PV, we designed a discrete choice experiment (DCE). DCE is a well-established technique to elicit stated preferences. In a DCE, respondents choose one of several alternatives in a series of hypothetical situations, with some characteristics of the alternatives being changed in every situation. On this basis, it is possible to determine the preferences for each of the attributes. The DCE is therefore a sophisticated method, but in which respondents are confronted with relatively simple choices.

A DCE is particularly appropriate when the product can be designed in different ways, which is the case for solar PV. It has been increasingly used over the last years in environment-related fields (see Barreiro-Hurle et al., 2018). In Switzerland, DCEs have for instance been applied to investigate subsidies for investments in the energy efficiency of buildings (Alberini et al., 2013), carbon taxes (see Carattini et al., 2017), or electricity-saving tariffs (Hille et al., 2019).

We organized the collection of firms' stated preferences for solar PV in two steps. First, we prepared a pretest to ensure that the questions and the DCE are well understood by the respondents, and that the attributes included in the DCE and their levels are correctly selected. Second, we developed and conducted the final survey in collaboration with a polling organization.

For the pretest phase, the survey was fully handled by the project team and implemented in the software *Sawtooth*. In July 2017, we sent 2,700 invitations by email to Geneva-based firms. Between July 28 and September 13 2017, 119 firms filled the survey (at least partially), and 85 firms did so completely.[2] The response rate is therefore just over 3%, which is relatively low in comparison to the standard response rate in online surveys. Nevertheless, it should be noted that this measure constitutes a lower bound. Indeed, a substantial fraction of the 2,700 firms probably never received the invitation, because of invalid emails or firewalls. The actual response rate is therefore certainly well above 3%.

The final survey was developed in collaboration with *Satiscan*, a Geneva-based polling organization. In February 2018, *Satiscan* started to invite Swiss firms to participate in the survey, by email, paper letters and telephone. The survey was available both in French and German. The invited firms were selected from a representative pool of 9,341 firms, which had been provided by the Swiss Federal Statistical Office (FSO), and stratified according to four firm sizes, three economic sectors, and two language regions (French- and German-speaking regions of Switzerland).[3] A total of 6,686 firms were contacted. Disappointingly, only 82 firms filled (at least partially) the survey between April 9 and July 10 2017, when we decided to stop the survey. The final sample is composed by only 72 firms who filled the survey completely, corresponding to a dismal response rate of around 1%.

[2] An answer is considered as complete whenever the DCE is fully answered, i.e., when 12 non-missing choices were provided by a firm in the DCE, even when some answers to the pre- or post-DCE questions are missing.

[3] Sole proprietorship firms were excluded because they are constituted by a single physical person, which makes them very similar to households.

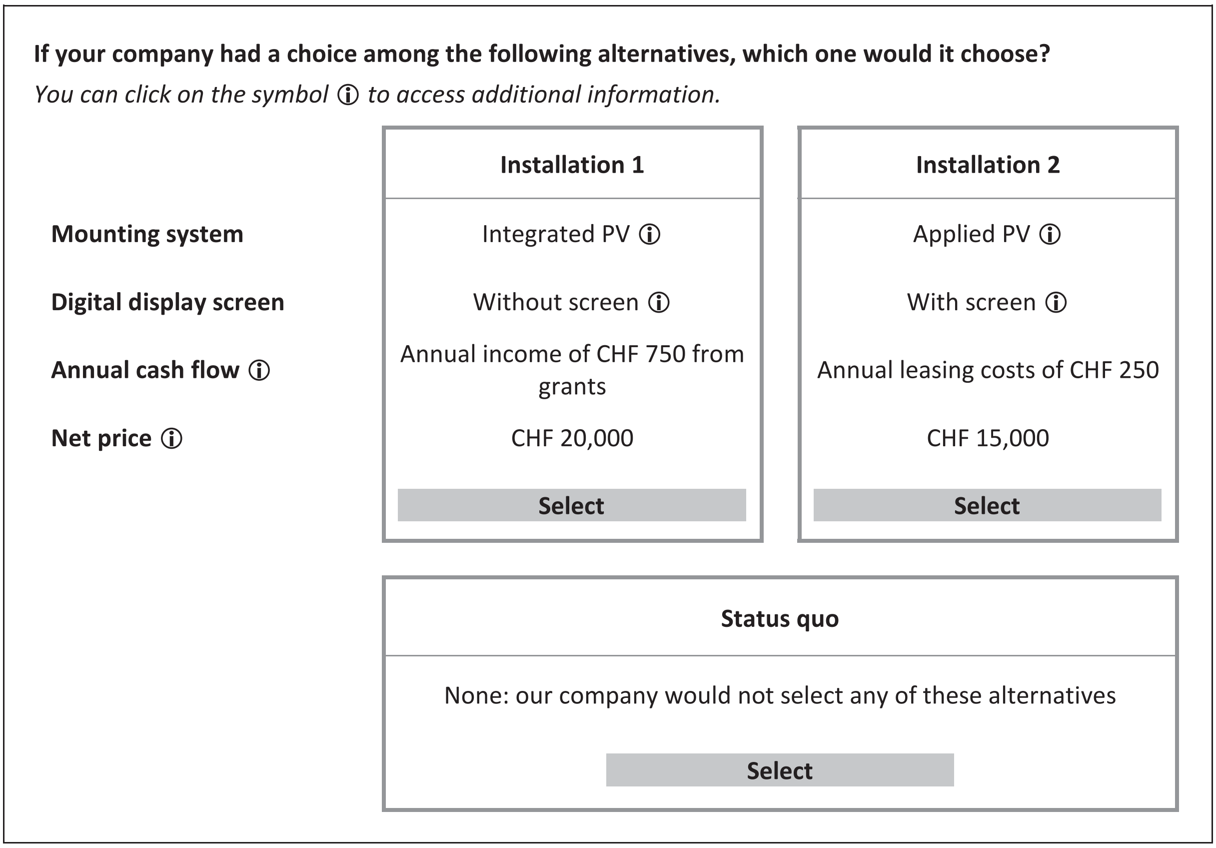
This document provides an analysis of the data collected in the survey. Even though sample size is much lower than expected, it is possible to provide estimations of the expected parameters. Results are obtained not only for the final sample, but also for the pretest sample and a combination of the two. It should be noted that no changes were implemented in the DCE itself (attributes and levels) between the pretest and the final survey, so that we can analyze the DCE using both samples together. However, some control questions were applied to the final survey, making it impossible to replicate all models on both samples.

Section 2 presents the DCE included in the survey and the choices to which the firms were confronted. In Section 3 we discuss the statistics of our samples and give first descriptive results of the DCE. Section 4 presents our empirical strategy and the results, while Section 5 concludes.

## 2 The discrete choice experiment

In the DCE included in the survey, we asked each firm to choose 12 times among 3 options: two alternative PV installations or no (new) PV installation (status quo). Figure 1 shows a sample choice task submitted to respondents. PV installations differ from one another by their technical and financial characteristics.

**Figure 1: A sample choice task**




During the design of the DCE, we conducted face-to-face interviews with several PV installers and experts to determine the relevant attributes and calibrate their levels. We selected the following four attributes: type of mounting system; existence of a digital display screen; annual cash flow; and net price. Table 1 summarizes the attributes and their levels. In order to maintain an acceptable level of complexity, we decided not to include an attribute for the size of solar panels. The experimental design was created with the software *Sawtooth* using the the 'balanced overlap' design option. This design generation method ensures that all levels of the attributes appear approximately an equal number of times in the design, while ensuring that some levels are occasionally repeating within a given choice task.[4]

On the page introducing the DCE, we explained that all offered installations have a capacity of 10 kWp, which corresponds to the median capacity of the PV systems installed in Swiss firms. The inclusion of attributes such as the type of mounting system and digital display screens are consistent with the focus of the project on the adoption of PV panels in Switzerland and its possible social contagion, which may be influenced by aesthetics and reputational effects. We set the levels of the attributes "cash flow" and "net price" to replicate the financial effects of leasing, capital subsidies, and FIT. More precisely, the net price represents the initial costs to the adopter, i.e. the purchase price of the installation less any investment subsidy. As the price of a 10 kWp installation in 2017 was around CHF 30,000,[5] the different levels of the "net price" attribute are intended to represent investment subsidies varying between 0 and 50% of the purchase price. The cash flow, on the other hand, represents the annual income or expenditures related to the PV installation during the 20 years following the installation. We chose a 20-year period because it falls in the range of the duration generally covered by FIT policies,[6] and corresponds to the typical duration of leasing contracts.[7] Positive cash flows reflect a situation where the installation benefits from fixed revenues thanks to a production subsidy (i.e. a feed-in tariff), whereas negative cash flows reflect a the situation where the installation is rented (and where the upfront costs would therefore be lower). It should be noted that the annual cash flow does not include revenues from the sale of the electricity production surplus nor possible savings on the electricity bill. We made clear to the respondent that these benefits were not included in the cash flows displayed during the DCE.

Besides the DCE, we also included a series of questions aimed at confirming the influence of peers (other spatially close firms, direct competitors, etc.) in the adoption choices. In particular, a randomized intervention was embedded in the survey design, providing to a randomly-selected set of respondents municipality-specific information about the descriptive norm, i.e. the number and cumulative capacity of existing installations around the firm's headquarter. The Appendix includes the final version of the survey (in French, and with only one of the 12 questions in the DCE part).

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[4] For additional details, see *Sawtooth* documentation (https://www.sawtoothsoftware.com/help/lighthouse-studio/manual/hid_web_cbc_designs_1.html).

[5] According to the "Solar calculator" of SuisseEnergie (https://www.suisseenergie.ch/).

[6] The FIT payment period was 20 years until 2017. This period has been decreased to 15 years since 2018 (see for instance OECD, 2017).

[7] So-called solar power purchase agreements (PPA) are typically offered for a range from 10 to 25 years (see for instance https://bluecells.dk/en/financing/).

**Table 1: Attributes and levels**

| Attributes | Levels |
|---|---|
| Type of mounting system | • Applied PV<br>• Integrated PV |
| Existence of a digital display screen | • With screen<br>• Without screen |
| Annual cash flow | • Annual income of CHF 750 from grants<br>• Annual income of CHF 500 from grants<br>• Annual income of CHF 250 from grants<br>• CHF 0<br>• Annual leasing costs of CHF 250<br>• Annual leasing costs of CHF 500<br>• Annual leasing costs of CHF 750 |
| Net price | • CHF 15'000<br>• CHF 20'000<br>• CHF 25'000<br>• CHF 30'000 |

To ensure respondents' understanding, a short document providing details on the attributes and their levels was accessible during the questionnaire. In addition, the type of mounting was presented using pictures, as displayed in Figure 2.

**Figure 2: Types of mounting**

A. Applied

B. Integrated

# 3 Descriptive statistics

## 3.1 Firm characteristics

Table 2 provides descriptive statistics for the two samples of firms interviewed during the pre-test and the final survey. By design, the major difference between the two samples is related to the location of the firms: the pre-test sample was drawn from a sample of firms located in Geneva while the final sample was drawn from a nationally representative sample (excluding Ticino). Firms interviewed during the pre-test are thus (almost) exclusively located in Geneva,[8] while firms interviewed during

[8] A few firms in the pre-test nevertheless indicated that their main buildings are located outside the canton of Geneva. This situation is not implausible: some firms might be active in Geneva (so that they were included in the sample) but their main buildings may be in another canton.

the final survey are globally representative of the spatial distribution of firms in Switzerland. The cantons of Zürich, Geneva, Vaud, and to a lesser extent Valais and Bern, are the most represented.

The differences between the pre-test and final samples nevertheless extend beyond location. For instance, the distribution of firm size differs in the two samples. Compared to the pretest, smallest and largest firms were over-represented in the final survey. Compared to the overall distribution of firm sizes in Switzerland, it appears that micro- and small firms are under-represented in the survey, while medium and large firms are over-represented, a divergence that is largely explained by the exclusion of sole proprietorship firms from the pool of eligible respondents.[9]

The legal form of the firms is more or less equivalent in the two samples, but the distribution is also slightly different from what is observed in general in Switzerland. Associations and foundations are over-represented (about 14% in the samples, compared to around 2% in Switzerland). In the samples, about 60% of the firms are limited companies (SA) while this type of firms represents around 46% of the Swiss firms. These differences in legal forms are consistent with the differences in firm sizes observed above, and are again largely due to the exclusion of sole proprietorship firms.

Unsurprisingly, the distribution of firms across sectors also differs between the two samples. A disproportionate share of firms interviewed in the pretest (Geneva) are active in services (NOGA sectors Q and S) or in construction (F), while substantial proportions of those in the final survey (Switzerland) are in professional, scientific and technical activities (M), wholesale and retail trade (G), or manufacturing (C).

The survey encompassed a section dedicated to collect information related to the current situation and behavior of firms regarding electricity consumption. It is interesting to observe that a sizeable proportion of firms (14% and 19%, in the Geneva and Swiss sample, respectively) have solar PV systems already installed in their buildings. Moreover, around half (42% and 54%) state that they could install new or additional PV capacities. In particular, among firms with PV systems already installed, almost ¾ state they would be ready to install additional panels. Among firms currently without PV systems, around 36% and 50% indicate they would be ready to install panels. Overall, it thus appears that around half the firms are not interested at all by PV systems: they currently do not have one and state they would not install one. Moreover, we emphasize that a considerable share (36% and 22%) of the firms in the samples indicate that they currently consume green electricity that is more expensive than the standard electricity mix offered by their provider.

[9] Statistics on the Swiss firms are available from the Federal Statistical Office webpage: https://www.bfs.admin.ch/bfs/fr/home/statistiques/industrie-services/entreprises-emplois.html.

**Table 2: Descriptive statistics**

| | Pre-test % | Final survey % |
|---|---|---|
| **Firm size** | | |
| Micro-enterprises (1-9 FTE) | 20.0 | 51.4 |
| Small enterprises (10-49 FTE) | 52.9 | 25.0 |
| Medium-sized enterprises (50-249 FTE) | 22.4 | 11.1 |
| Large enterprises (250+ FTE) | 4.7 | 12.5 |
| **Legal form** | | |
| Sole proprietorship | 11.8 | 1.4 |
| Limited company (SA) | 61.2 | 56.9 |
| Limited liability company (SàRL) | 5.9 | 19.4 |
| Associations, foundations | 12.9 | 15.3 |
| Cooperative company | 1.2 | 2.8 |
| Public enterprise | 3.5 | 0.0 |
| Other | 3.5 | 4.2 |
| **Sector (NOGA classification)** | | |
| A. Agriculture, forestry and fishing | 4.7 | 0.0 |
| C. Manufacturing | 5.9 | 11.1 |
| D. Electricity, gas, steam and air conditioning supply | 0.0 | 0.0 |
| E. Water supply, sewerage, waste management and remediation activities | 1.2 | 0.0 |
| F. Construction | 11.8 | 8.3 |
| G. Wholesale and retail trade; repair of motor vehicles and motorcycles | 2.4 | 16.7 |
| H. Transportation and storage | 7.1 | 1.4 |
| I. Accommodation and food service activities | 4.7 | 2.8 |
| J. Information and communication | 1.2 | 5.6 |
| K. Financial and insurance activities | 7.1 | 6.9 |
| L. Real estate activities | 1.2 | 8.3 |
| M. Professional, scientific and technical activities | 4.7 | 18.1 |
| N. Administrative and support service activities | 2.4 | 0.0 |
| O. Public administration and defence; compulsory social security | 1.2 | 0.0 |
| P. Education | 5.9 | 1.4 |
| Q. Human health and social work activities | 14.1 | 8.3 |
| R. Arts, entertainment and recreation | 2.4 | 2.8 |
| S. Other service activities | 21.2 | 8.3 |
| U. Activities of extraterritorial organisations and bodies | 1.2 | 0.0 |
| **Canton** | | |
| Zürich | 1.2 | 18.1 |
| Bern | 0.0 | 8.3 |
| Luzern | 0.0 | 2.8 |
| Schwyz | 0.0 | 1.4 |
| Zug | 0.0 | 4.2 |
| Fribourg | 1.2 | 2.8 |
| Solothurn | 0.0 | 2.8 |
| Basel-Landschaft | 0.0 | 2.8 |
| St. Gallen | 0.0 | 4.2 |
| Graubünden | 0.0 | 2.8 |
| Aargau | 0.0 | 1.4 |
| Thurgau | 0.0 | 1.4 |
| Vaud | 2.4 | 13.9 |
| Valais | 1.2 | 11.1 |
| Neuchâtel | 0.0 | 5.6 |
| Genève | 94.1 | 13.9 |
| unknown | 0.0 | 2.8 |
| **Environmental behavior** | | |
| Firm owns or rents solar PV | 14.1 | 19.4 |
| Firm could install new or additional PV | 41.2 | 54.2 |
| Firm benefits from an energy or environmental certification* | 10.7 | 9.7 |
| Firm has a document formalizing its social responsibility* | 29.8 | 25.0 |
| Firm buys green electricity more expensive than standard* | 35.7 | 22.2 |
| Firm is considered a large consumer according to MoPEC* | 17.9 | 9.7 |
| # obs. | 85 | 72 |

*Results based on 84 firms in the pre-test, because one firm did not answer these questions. Answers 'I do not know' were considered as 'No'. MoPEC stands for “Modèle de prescriptions énergétiques des cantons”. It is a set of requirements on the use of energy in the building sector jointly developed by the Swiss cantons.

## 3.2 DCE responses

Before investigating firms' preferences based on regression analyzes, we provide a descriptive analysis of the responses to the DCE. We recall that during the survey (both in the pre-test and in the final survey), each firm is faced with 12 choice tasks, in which there are three possible choices: two alternative PV systems and one status quo. This latter choice implies that the firm prefers the current situation, rather than any of the two alternative systems. In the following analysis, we only consider the responses if the firm answered all 12 choice tasks, i.e. the 157 firms that were already used for the descriptive statistics in previous section. The following statistics are thus based on a total number 157 × 12 = 1,884 observations.

Figures 3 to 6 show the attributes of the PV systems selected by respondents during the DCE. We first highlight the similarity of answers in the pre-test and the final survey. Despite the above-mentioned differences in the two samples, the similarity in the DCE answers shows that it will be possible to make estimations based on the joint sample to increase robustness of the results when investigating firms' stated preferences.

Then, we observe a high proportion of status quo (SQ) choices. In more than 38% of all choice tasks, respondents indeed selected the status quo. The proportion of status quo choices is somewhat larger in the subsample of firms with PV systems (48%) than in the subsample of firms without PV systems (36%). This finding was expected, considering that it is inherently more complicated to install additional panels when existing ones are already in operation. In other terms, the "status quo" situation is simply different for the two subsamples of firms with or without existing panels, and this modifies the incentives for installing (additional) capacities.

It is also interesting to note that 32 out of the 157 firms of the combined sample (20%) systematically selected the status quo. This proportion is not different among PV owners (19.2%) and non-owners (20.6%). However, we note that, among the firms that stated that they would not install PV in general, about 60% selected at least once a PV installation during the choice experiment. These firms probably face constraints in their building, but would be ready to install PV according to their stated preferences. We highlight that the share of firms with only status quo choices differs substantially depending on whether or not the firm was submitted to our intervention, in which a map showing information about installed PV around the firm's headquarters was randomly displayed or hidden. Among "control" firms, i.e. firms that did not receive the information, almost 28% systematically opted for the status quo. This proportion is halved to 14% among "treated" firms, i.e. firms that received the information concerning installed PV in the surroundings. This provides a first indication that the implemented treatment had a positive impact on firms' (stated) willingness to adopt a PV system.

On the other side, one third of the firms always selected one of the two offered installations in each of their 12 choice tasks (i.e. they never selected the status quo choice). The difference between PV owners and non-owners is large in this case, with respectively 15.4% and 37.4% of the firms always selecting an installation.

For those firms who selected one of the two proposed installations, Figures 3 to 6 show descriptive statistics on the firms' preferences for the different attribute levels. Applied panels turn out to be more popular than integrated panels (Figure 3). Firms selected more frequently the installations with screens (Figure 4). Unsurprisingly, installations that provide a larger annual cash flow (Figure 5) and the less expensive (Figure 6) appear to be preferred. Given their aesthetic advantages, we expected that integrated solar panels would be chosen more often than applied ones. A possible explanation would be that companies are aware of the heavier construction work involved or the lower yields in terms of electricity production.

**Figure 3: Type of mounting in selected installations**

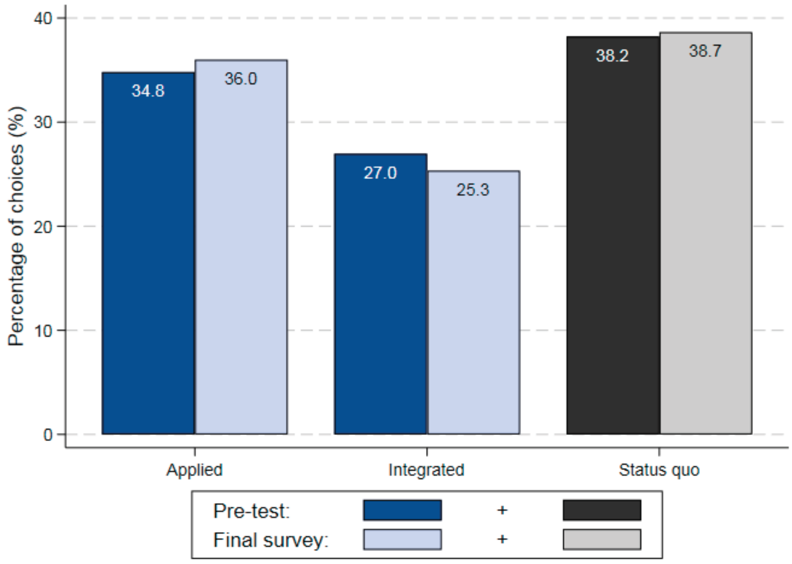



**Figure 4: Presence or absence of screens in selected installations**

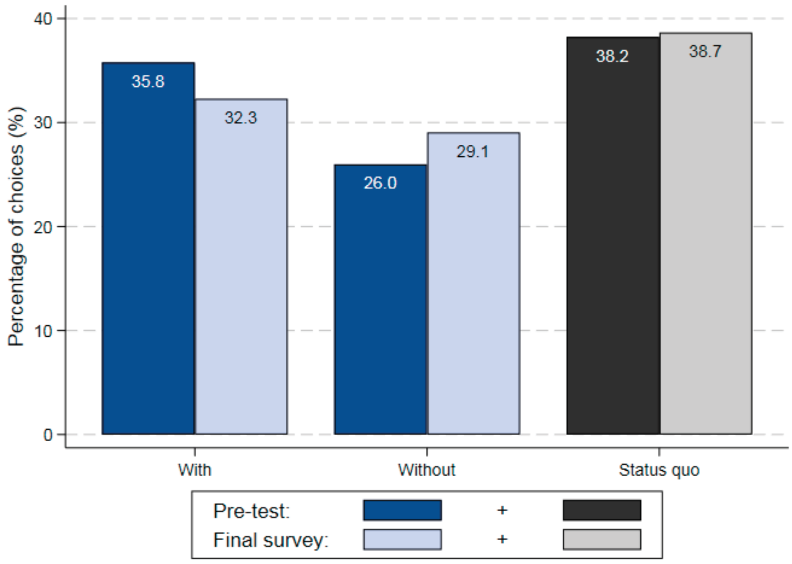


**Figure 5: Annual cash flows of selected installations (in CHF)**

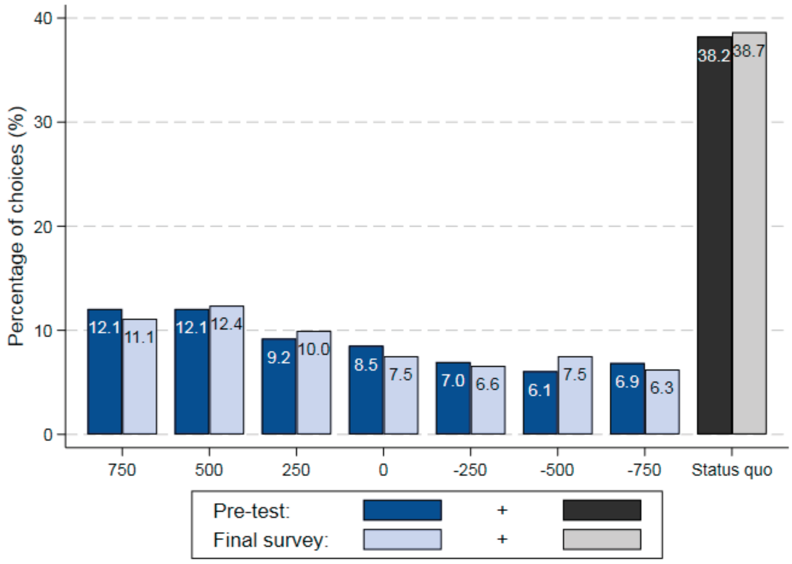
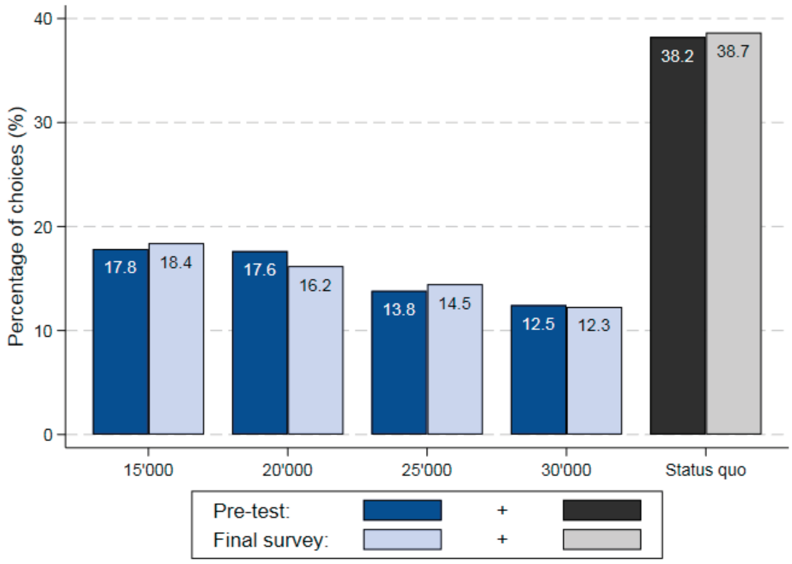



**Figure 6: Price of selected installations (in CHF)**




# 4 Preferences of firms regarding solar PV systems

## 4.1 Econometric strategy

To investigate firm preferences regarding solar PV systems, the econometric strategy builds on McFadden's (1974) random utility (profit) theory. The sample is composed of $N$ firms (i.e. 157 firms, among which 85 in the pre-test and 72 in the final sample) who make a choice between $J = 3$ alternatives on $T = 12$ choice occasions. Firm $n$ derives a profit $\pi_{njt}$ from choosing alternative $j$ in choice occasion $t$ given by:

$$\pi_{njt} = \beta_n' x_{njt} + ASC_j + \varepsilon_{njt} \quad (1)$$

$$\text{with} \quad n = 1, \dots, N, \;\; j = 1, 2, 3, \quad t = 1, \dots, 12,$$
$$ASC_j = 0 \text{ for } j = 1{,}2, \quad ASC_j = ASC_{SQ} \text{ for } j = 3$$

Vector $x_{njt}$ is a set of attributes relating to alternative $j$ and possibly characteristics of firm $n$ (interacted with the attributes, because they are constant within firms). An alternative-specific constant $ASC_{SQ}$ is included to distinguish the status quo from the other two alternatives (see below). $\varepsilon_{njt}$ is a random term that is assumed to be an independently and identically distributed extreme value.

Equation (1) can be estimated either by a conditional logit model, in which case the parameters of interest are constant ($\beta_n = \beta, \forall\, n$), or by a mixed logit model, in which the parameters vary randomly over individuals ($\beta_n$). An appealing feature of mixed logit models is that thanks to the random parameters they allow relaxing the independence of irrelevant alternatives (IIA) assumption, which might be of concern in the setting of a DCE. We therefore report the results from both conditional logit models and mixed logit models in the following subsections.

We follow Scarpa et al. (2005, 2007) and include for the status quo alternative ($j = 3$) an alternative-specific constant $ASC_{SQ}$. In their approach, they recommend to offer a status quo option during the choice tasks, and then to include an alternative specific constant in the estimation to avoid the so-called status quo bias (or status quo effect) (see Oehlmann et al. (2017) for a recent and comprehensive study on the status quo effect). Hence, the model that we finally estimate writes:

$$\pi_{njt} = \begin{cases} \beta_n' x_{njt} + \eta_i + \varepsilon_{njt} & \text{for } j = 1, 2 \text{ (installations)} \\ \beta_n' x_{njt} + ASC_{SQ} + \varepsilon_{njt} & \text{for } j = 3 \text{ (status quo)} \end{cases} \tag{2}$$

where $\eta_i \sim \mathcal{N}(0, \sigma^2)$ is an additional error component allowing for correlation of profits across alternatives 1 and 2. This model is therefore analog to a nested logit, whereby a first nest is associated to the status quo alternative and the second nest is associated with changes from the status quo and contains both of the offered installations. The additional strength of the above model over a nested logit is the absence of an IIA restriction thanks to random parameters, and the $ASC_{SQ}$ that captures any remaining systematic effect on the status quo alternative. Such models can be estimated in Stata using the mixlogit command (Hole, 2007).

Based on the estimated coefficients in (2), we are able to assess the willingness-to-pay (WTP) for the attributes of the alternatives. Indeed, given that the coefficients of the model indicate the marginal profit of the attributes, the WTP for attribute $k$ can be computed as the ratio of the coefficient of this attribute to the coefficient of price (which is the cost attribute in our context):

$$WTP_k = -\frac{\beta_k}{\beta_{price}} \tag{3}$$

These ratios are also known as implicit prices and indicate how much money a firm is ready to pay in addition for a one-unit increase in attribute $k$ (or, in the case variable $k$ is binary, for a PV installation with rather than without attribute $k$).

The estimated means and standard deviations of the random coefficients from the mixed logit models provide information on the share of firms that place a positive value on the attributes and the share of firms that place a negative value. Given that the coefficients are normally distributed, these shares can be computed as follows:

$$\text{Share that values attribute k positively} = 100 \cdot \Phi\left(\frac{\beta_k}{SD_k}\right)$$
$$\text{Share that values attribute k negatively} = 100 \cdot \Phi\left(-\frac{\beta_k}{SD_k}\right)$$

where $\Phi$ is the cumulative standard normal distribution, and $\beta_k$ and $SD_k$ are the mean and the standard deviation of the $k^{\text{th}}$ coefficient, respectively.

## 4.2 Results

Table 3 presents the results of the conditional and mixed logit models explaining the preferences of firms for solar PV. Columns (1) to (4) present the results with estimations based on the pre-test sample, while columns (5) to (8) are based on the final survey sample. All models contain an alternative specific constant ($ASC_{SQ}$) for the status quo alternative. We do not account for a possible correlation between error terms of alternatives 1 and 2 (i.e. the non-status quo alternatives) in odd-numbered columns, while we do so in the even-numbered columns. The first panel of Table 3 reports the mean coefficients, while the second panel reports the standard deviations (only for the mixed logit models).

All estimations provide a globally coherent picture. Indeed, the coefficients always have the same sign (except one[10]) and remain comparable across all estimations. The conditional logit models are extremely close for both samples. In the mixed logit models, which account for individual heterogeneity, some coefficients are different, but this was expected considering the size of the samples and the differences in the characteristics of the firms. Overall, the estimations therefore appear quite robust. From the log-likelihood and BIC statistics, it turns out that mixed models with correlated errors (columns (4) and (8)) should be favored. The following comments mostly focus on these estimations.

On average, firms display the expected preferences regarding higher annual cash flows and lower installation price. These two parameters related to the financial attributes are significant and stable across all estimations. The heterogeneity measured in the mixed logit models appears relatively small. Applying equation (3), the WTP for an additional CHF in annual cash flow amounts to CHF 14 (column (4)) and CHF 22 (column (8)). During the DCE, respondents were informed that annual cash flows from the installations would be received (or paid) over the next 20 years. The measured WTPs are therefore consistent with annual discount rates ranging from 0 (or even slightly negative) to 3.7%, which seem to make sense in the current context of very low (or even slightly negative) interest rates.[11] These

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[10] The only parameter for which there is a sign reversal is the display screen, which shows a negative (but not statistically significant) coefficient in the mixed logit models estimated on the final survey sample.

[11] The implicit annual discount rate can be computed as the internal rate of return (IRR) of an investment that would imply an upfront cost equivalent to the estimated WTP and then provide a cash flow equivalent to 1 per year during the following 20 years. The IRR is therefore given by the rate that makes the net present value (NPV) of the following investment equal to 0:

$$NPV = -WTP + \sum_{t=1}^{20} \frac{1}{(1+IRR)^t} = \beta_{cash\ flow} + \sum_{t=1}^{20} \frac{\beta_{price}}{(1+IRR)^t} = 0$$

results suggest that distributing a given amount through an investment subsidy (to decrease installation upfront costs) or through a production subsidy (with regular payments year after year) would have a similar impact on PV adoption by firms. For instance, firms seem to be indifferent between a CHF 20,000 installation with a cash flow of CHF 0 and a CHF 30,000 installation bringing in CHF 500 per year over 20 years (i.e. a subsidy of 500 × 20 = CHF 10,000 in total). The two are indeed equivalent in case the discount rate applied by firms is close to zero as calculated above.

Stated preferences are less well-established regarding mounting types and display screens. Overall, it appears that firms tend to prefer applied panels (over integrated panels) and installations with a display screen. However, there is a relatively strong heterogeneity across firms along these dimensions. Indeed, the results suggest that integrated panels are preferred by 39-44% of the firms, while applied panels are preferred by 56-61%. There is thus no clear result regarding preferences for a certain mounting type. We expected the presence of a screen to exert a positive impact on firms' preferences. However, findings are ambiguous too. In the pre-test sample, 69% of the firms show results in line with expectations, but only 31% of the firms in the final survey do so. For this attribute as well, it is thus complicated to draw a clear conclusion.

Because of the small size of the samples and considering the relative consistency of the results, we pool both samples for the remainder of the analysis. The next steps indeed involve separating the firms by control/treatment groups and along various characteristics. Doing so on small samples would not be extremely meaningful and it therefore seems preferable to combine the 157 firms. Table 4 provides similar estimations as in Table 3, except that they are based on the pooled sample. The results are largely consistent, but with the advantage of being more stable across specifications. Based on the estimation in column (4), the average WTP for an additional CHF in annual cash flow amounts to CHF 12.5, but with substantial heterogeneity across firms.

**Table 3: Conditional and mixed logit models explaining firm preferences for solar PV, pre-test and final survey samples separated**

| | Pre-test | | | | Final survey | | | |
|---|---|---|---|---|---|---|---|---|
| | Conditional logit models | | Mixed logit models | | Conditional logit models | | Mixed logit models | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Mean** | | | | | | | | |
| Integrated panels | -0.356 | -0.478$^{*}$ | -1.345$^{**}$ | -1.480 | -0.368$^{*}$ | -0.454$^{*}$ | -0.185 | -0.527 |
| | (0.219) | (0.273) | (0.668) | (1.051) | (0.216) | (0.262) | (0.610) | (0.609) |
| With screen | 0.491$^{***}$ | 0.576$^{***}$ | 0.995$^{***}$ | 1.254 | 0.194 | 0.233 | -0.143 | -0.559 |
| | (0.142) | (0.184) | (0.351) | (1.454) | (0.132) | (0.166) | (0.364) | (0.461) |
| Annual cash flow (CHF 1,000) | 0.920$^{***}$ | 1.141$^{***}$ | 1.860$^{***}$ | 2.847$^{***}$ | 0.903$^{***}$ | 1.066$^{***}$ | 1.878$^{***}$ | 2.721$^{***}$ |
| | (0.165) | (0.218) | (0.539) | (0.657) | (0.210) | (0.273) | (0.456) | (0.612) |
| Net price (CHF 1,000) | -0.059$^{***}$ | -0.079$^{***}$ | -0.151$^{***}$ | -0.206$^{*}$ | -0.059$^{***}$ | -0.072$^{***}$ | -0.083$^{**}$ | -0.126$^{**}$ |
| | (0.018) | (0.023) | (0.052) | (0.108) | (0.019) | (0.023) | (0.033) | (0.063) |
| $ASC_{SQ}$ | 0.272 | 0.376$^{*}$ | 0.499$^{**}$ | 1.159$^{***}$ | 0.284$^{***}$ | 0.392$^{*}$ | 0.463$^{**}$ | 1.003$^{***}$ |
| | (0.192) | (0.211) | (0.226) | (0.289) | (0.205) | (0.231) | (0.233) | (0.280) |
| **S.D.** | | | | | | | | |
| Integrated panels | - | - | 3.605$^{***}$ | 5.179$^{***}$ | - | - | 2.659$^{***}$ | 3.708$^{***}$ |
| | | | (0.958) | (1.216) | | | (0.615) | (0.697) |
| With screen | - | - | 2.644$^{**}$ | 2.601$^{**}$ | - | - | 1.334$^{*}$ | 1.057$^{*}$ |
| | | | (1.221) | (1.154) | | | (0.788) | (0.540) |
| Annual cash flow (CHF 1,000) | - | - | 2.148$^{***}$ | 1.675$^{**}$ | - | - | 2.436$^{***}$ | 4.160$^{***}$ |
| | | | (0.760) | (0.653) | | | (0.494) | (0.821) |
| Net price (CHF 1,000) | - | - | 0.250$^{***}$ | 0.251$^{**}$ | - | - | 0.269$^{***}$ | 0.329$^{***}$ |
| | | | (0.066) | (0.108) | | | (0.068) | (0.075) |
| Correlated errors | No | Yes | No | Yes | No | Yes | No | Yes |
| # Obs. | 3,060 | 3,060 | 3,060 | 3,060 | 2,592 | 2,592 | 2,592 | 2,592 |
| # Firms | 85 | 85 | 85 | 85 | 72 | 72 | 72 | 72 |
| Log-Likelihood | -1,057.37 | -965.22 | -940.55 | -794.42 | -899.75 | -849.97 | -820.41 | -726.70 |
| BIC | 2,154.86 | 1,978.59 | 1,953.34 | 1,669.10 | 1,838.81 | 1,747.10 | 1,711.55 | 1,532.01 |

**Table 4: Conditional and mixed logit models explaining firm preferences for solar PV, pre-test and final survey samples pooled**

| | Pre-test and final survey pooled | | | |
|---|---|---|---|---|
| | Conditional logit models | | Mixed logit models | |
| | (1) | (2) | (3) | (4) |
| **Mean** | | | | |
| Integrated panels | -0.361** | -0.467** | -0.867** | -0.302 |
| | (0.153) | (0.189) | (0.387) | (0.866) |
| With screen | 0.354*** | 0.415*** | 0.484* | 0.504 |
| | (0.098) | (0.125) | (0.275) | (0.460) |
| Annual cash flow (CHF 1,000) | 0.916*** | 1.109*** | 1.608*** | 2.601*** |
| | (0.131) | (0.172) | (0.281) | (0.505) |
| Net price (CHF 1,000) | -0.059*** | -0.076*** | -0.113*** | -0.209*** |
| | (0.013) | (0.016) | (0.032) | (0.067) |
| $ASC_{SQ}$ | 0.277** | 0.383** | 0.471*** | 1.029*** |
| | (0.140) | (0.155) | (0.160) | (0.199) |
| **S.D.** | | | | |
| Integrated panels | - | - | 3.096*** | 4.808*** |
| | | | (0.433) | (0.984) |
| With screen | - | - | 1.638*** | 2.504*** |
| | | | (0.557) | (0.729) |
| Annual cash flow (CHF 1,000) | - | - | 1.922*** | 2.304*** |
| | | | (0.418) | (0.514) |
| Net price (CHF 1,000) | - | - | 0.229*** | 0.267*** |
| | | | (0.044) | (0.054) |
| Correlated errors | No | Yes | No | Yes |
| # Obs. | 5,652 | 5,652 | 5,652 | 5,652 |
| # Firms | 157 | 157 | 157 | 157 |
| Log-Likelihood | -1,958.96 | -1,817.70 | -1,768.37 | -1,544.30 |
| BIC | 3,961.11 | 3,687.24 | 3,614.50 | 3,175.01 |

## 4.3 Treatment effects

During the survey, respondents were randomly allocated between a control and a treatment group. Just before the DCE, we provided respondents in the treatment group with information regarding how many firms and households had already installed a solar PV in their municipality. Furthermore, they were displayed a map such as the one in Figure 7 showing the location of the nearby solar PV installations.[12] The map was automatically centered on the location of the respondent. The objective of the treatment is to investigate whether firms' preferences are impacted by the decisions of their peers. Indeed, the empirical literature has shown that social contagion effects influence adoption choice for the solar PV technology (see e.g. Bollinger and Gillingham, 2012; Baranzini et al., 2017), but evidence of imitation effects for firms remain scarce. We thus expect the treatment to impact positively the choice of an installation (and therefore that the occurrence of status quo choices decrease among treated firms).

To investigate the effects of the treatment, we rerun the estimations by separating the control and treatment groups. Table 5 reports the results. Most coefficients are not different between the control group (columns (1) to (4)) and the treatment group (columns (5) to (8)). All attributes appear to have an equivalent marginal utility in both groups. The major differences that we find between the two groups is in the alternative specific constant (ASC) associated with the status quo alternative. Indeed,

[12] The map can be accessed at the following url: https://www.repowermap.org/?ln=en.

this coefficient decreases by a factor 2 to 8 (depending on the specification). This shows that the utility of the status quo alternative is negatively and substantially influenced by the treatment. In other terms, the treatment incentivizes respondents to select one of the two offered PV installations rather the status quo. This finding tends to confirm the existence of peer effects in adoption decisions by firms, and not only by households (see Baranzini et al., 2017).

**Figure 7: Map showing solar PV installations around Ittigen (BE)**

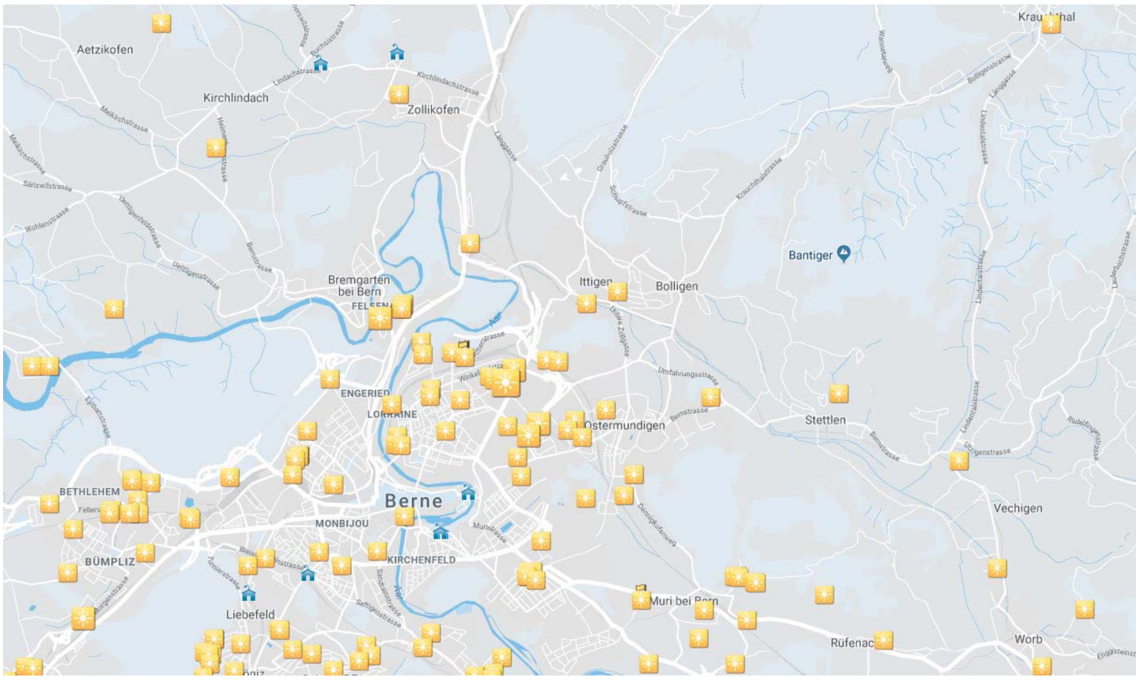

**Table 5: Conditional and mixed logit models explaining firm preferences for solar PV, control and treatment groups**

| | Control group | | | | Treatment group | | | |
|---|---|---|---|---|---|---|---|---|
| | Conditional logit models | | Mixed logit models | | Conditional logit models | | Mixed logit models | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Mean** | | | | | | | | |
| Integrated panels | -0.443 | -0.551 | -1.736** | -1.706*** | -0.308* | -0.426* | -0.575 | -1.429 |
| | (0.270) | (0.340) | (0.760) | (0.635) | (0.182) | (0.220) | (0.860) | (0.902) |
| With screen | 0.412** | 0.499** | 0.443 | 1.461*** | 0.328*** | 0.379** | 0.476* | 0.316 |
| | (0.161) | (0.212) | (0.751) | (0.549) | (0.124) | (0.151) | (0.283) | (0.500) |
| Annual cash flow (CHF 1,000) | 1.282*** | 1.608*** | 2.490*** | 3.491*** | 0.671*** | 0.780*** | 1.445*** | 2.100*** |
| | (0.249) | (0.348) | (0.489) | (0.919) | (0.140) | (0.177) | (0.369) | (0.508) |
| Net price (CHF 1,000) | -0.051** | -0.061** | -0.118** | -0.230*** | -0.064*** | -0.084*** | -0.064 | -0.125** |
| | (0.020) | (0.024) | (0.046) | (0.059) | (0.018) | (0.022) | (0.045) | (0.064) |
| $ASC_{SQ}$ | 0.515** | 0.646*** | 0.789*** | 1.599*** | 0.061*** | 0.164*** | 0.204*** | 0.814*** |
| | (0.208) | (0.238) | (0.237) | (0.291) | (0.191) | (0.208) | (0.219) | (0.278) |
| **S.D.** | | | | | | | | |
| Integrated panels | - | - | 3.493*** | 6.477*** | - | - | 2.230*** | 3.913** |
| | | | (0.704) | (1.301) | | | (0.397) | (1.523) |
| With screen | - | - | 1.518** | 2.500*** | - | - | 1.370*** | 1.906*** |
| | | | (0.620) | (0.651) | | | (0.425) | (0.481) |
| Annual cash flow (CHF 1,000) | - | - | 3.185*** | 4.725*** | - | - | 1.208** | 1.094*** |
| | | | (0.650) | (1.004) | | | (0.480) | (0.352) |
| Net price (CHF 1,000) | - | - | 0.347*** | 0.511*** | - | - | 0.206*** | 0.263*** |
| | | | (0.077) | (0.089) | | | (0.053) | (0.037) |
| Correlated errors | No | Yes | No | Yes | No | Yes | No | Yes |
| # Obs. | 2,736 | 2,736 | 2,736 | 2,736 | 2,916 | 2,916 | 2,916 | 2,916 |
| # Firms | 76 | 76 | 76 | 76 | 81 | 81 | 81 | 81 |
| Log-Likelihood | -919.64 | -846.94 | -806.72 | -663.80 | -1,023.53 | -955.31 | -940.02 | -823.34 |
| BIC | 1,878.85 | 1,741.36 | 1,684.67 | 1,406.75 | 2,086.96 | 1,958.48 | 1,951.84 | 1,726.46 |

## 4.4 Heterogeneous effects

An additional investigation concerns differences in behaviors of firms with different characteristics. Because characteristics are constant in the dataset, these must be interacted with the attributes of the alternatives, to be included in the estimations.

An interesting hypothesis is whether firms that install solar PV do so because they can afterwards show it to their customers. Installing solar PV could then be more appealing to firms that host their customers frequently. To test for this hypothesis, we interact the screen attribute with a dummy variable indicating whether customers visit the firm on a regular basis and that solar PV are (or could be) seen by them.

Table 6 reports the estimations encompassing this additional variable. It turns out that the new coefficients, albeit all positive, are not significant in any of the specifications. We cannot therefore assess with certainty whether there is a significant difference along this dimension. The sample size may well be a reason for such a non-result.

**Table 6: Conditional and mixed logit models explaining firm preferences for solar PV, firms separated by visible PV or not**

| | Conditional logit models | | Mixed logit models | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Mean** | | | | |
| Integrated panels | $-0.361^{**}$ | $-0.468^{**}$ | $-0.711^{**}$ | $-1.083^{*}$ |
| | (0.153) | (0.189) | (0.308) | (0.650) |
| With screen | $0.313^{***}$ | $0.357^{***}$ | $0.456^{*}$ | 0.889 |
| | (0.106) | (0.137) | (0.248) | (0.989) |
| With screen x Visible PV | 0.206 | 0.273 | 0.351 | 0.221 |
| | (0.263) | (0.316) | (0.667) | (1.062) |
| Annual cash flow (CHF 1,000) | $0.920^{***}$ | $1.115^{***}$ | $1.643^{***}$ | $2.273^{***}$ |
| | (0.133) | (0.175) | (0.296) | (0.484) |
| Net price (CHF 1,000) | $-0.059^{***}$ | $-0.075^{***}$ | $-0.088^{***}$ | $-0.114^{**}$ |
| | (0.013) | (0.016) | (0.027) | (0.058) |
| $ASC_{SQ}$ | $0.278^{**}$ | $0.385^{**}$ | $0.483^{***}$ | $1.047^{***}$ |
| | (0.140) | (0.156) | (0.163) | (0.212) |
| **S.D.** | | | | |
| Integrated panels | - | - | $2.647^{***}$ | $3.737^{***}$ |
| | | | (0.337) | (0.785) |
| With screen | - | - | $1.783^{***}$ | $2.130^{***}$ |
| | | | (0.411) | (0.581) |
| With screen x Visible PV | | | 0.215 | $2.128^{**}$ |
| | | | (1.144) | (0.834) |
| Annual cash flow (CHF 1,000) | - | - | $1.947^{***}$ | $1.929^{***}$ |
| | | | (0.440) | (0.703) |
| Net price (CHF 1,000) | - | - | $0.227^{***}$ | $0.336^{***}$ |
| | | | (0.031) | (0.064) |
| Correlated errors | No | Yes | No | Yes |
| # Obs. | 5,652 | 5,652 | 5,652 | 5,652 |
| # Firms | 157 | 157 | 157 | 157 |
| Log-Likelihood | -1,958.39 | -1,816.86 | -1,766.56 | -1,534.81 |
| BIC | 3,968.63 | 3,694.20 | 3,628.15 | 3,173.29 |

# 5 Conclusion

Despite the difficulties encountered during the survey and the failure to collect a sample of the envisaged size, the analysis of the stated preferences of firms provides interesting results. Given the low number of observations and response rate, the (external) validity of the results is of course questionable, but the discrete choice experiment design and the econometric analyses were conducted using state-of-the-art techniques.

Overall, findings show that firms tend to prefer applied panels (rather than integrated panels), installations with a display screen, and of course installations that provide a higher annual cash flow and that cost less. Regarding the first two attributes, mixed logit models reveal important heterogeneity across firms. Preferences for applied or integrated panels and for the presence or absence of a display screen therefore vary from firm to firm.

The treatment that was introduced in the survey, whereby half of the respondents were given additional information regarding the existing PV installation around their location, appears to have positively impacted their likelihood to select an installation in the DCE. Albeit not absolutely conclusive because of the organizational challenges faced, the results are nevertheless encouraging and speak in favor of a well-crafted experiment. Repeating a similar survey in the future could lead to interesting and important insights.

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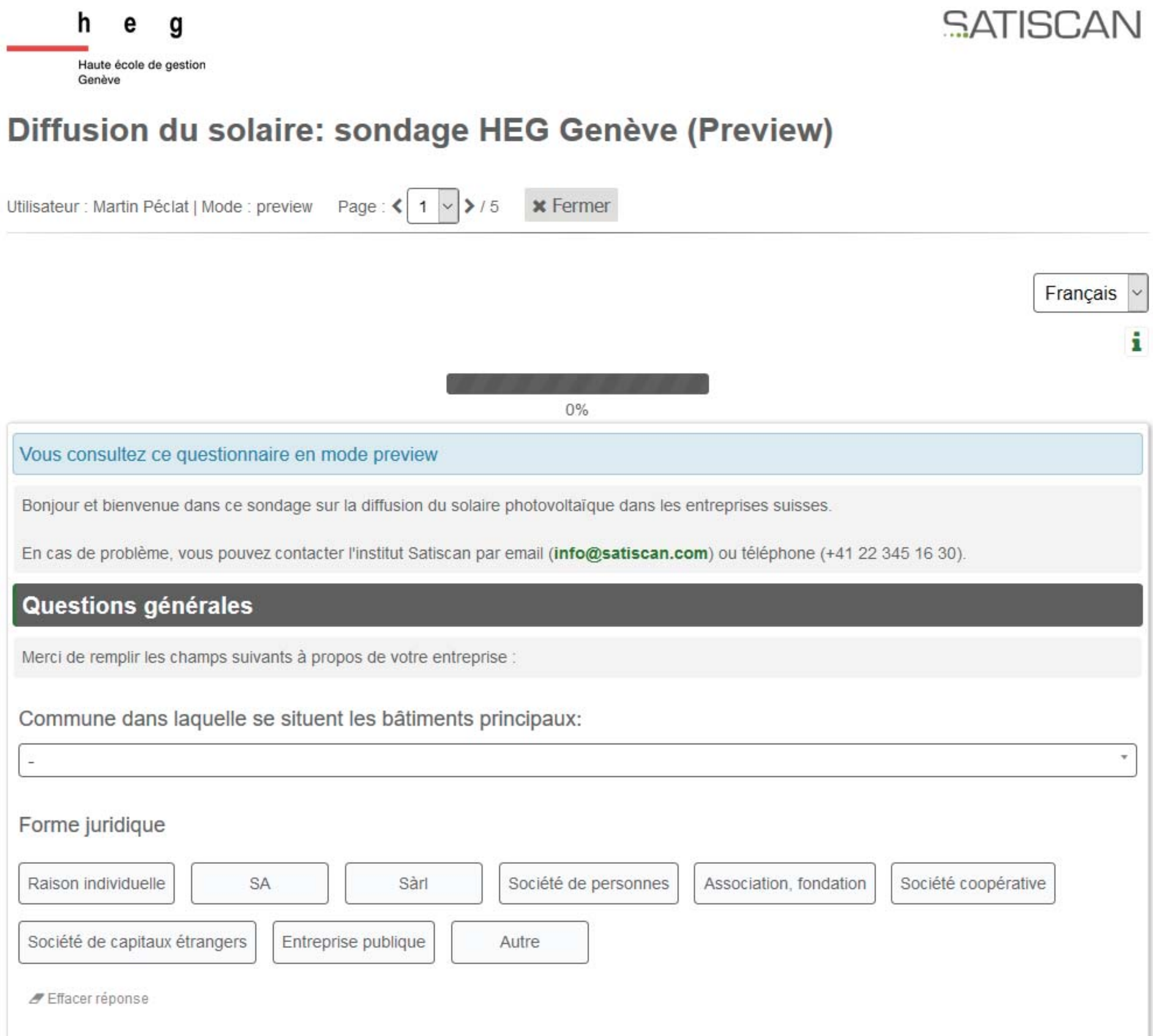
## Appendix: Survey



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Diffusion du solaire: sondage HEG Genève (Preview)

Utilisateur : Martin Péclat | Mode : preview    Page : 1 / 5    Fermer

Français

0%

Vous consultez ce questionnaire en mode preview

Bonjour et bienvenue dans ce sondage sur la diffusion du solaire photovoltaïque dans les entreprises suisses.

En cas de problème, vous pouvez contacter l'institut Satiscan par email (info@satiscan.com) ou téléphone (+41 22 345 16 30).

Questions générales

Merci de remplir les champs suivants à propos de votre entreprise :

Commune dans laquelle se situent les bâtiments principaux:

-

Forme juridique

Raison individuelle | SA | Sàrl | Société de personnes | Association, fondation | Société coopérative | Société de capitaux étrangers | Entreprise publique | Autre

Effacer réponse

Nombre d'équivalents plein temps (EPT)

Fonction de la personne répondant au questionnaire :

Directeur, gérant, propriétaire

Responsable énergie

Autre

Effacer réponse

Page suivante

Vous consultez ce questionnaire en mode preview

## Le photovoltaïque dans votre entreprise

Votre entreprise possède-elle ou loue-t-elle une ou plusieurs installations solaires photovoltaïques?

Oui

Non

Effacer réponse

Votre entreprise aurait-elle la possibilité de construire une installation photovoltaïque supplémentaire (toit ou terrain à disposition)?

Oui

Non

Effacer réponse

Page précédente

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Vous consultez ce questionnaire en mode preview

## Le photovoltaïque dans votre entreprise

Votre entreprise possède-elle ou loue-t-elle une ou plusieurs installations solaires photovoltaïques? ✔

Oui

Non

Effacer réponse

Votre entreprise aurait-elle la possibilité de construire une installation photovoltaïque (toit ou terrain à disposition)?

Oui

Non

Effacer réponse

← Page précédente

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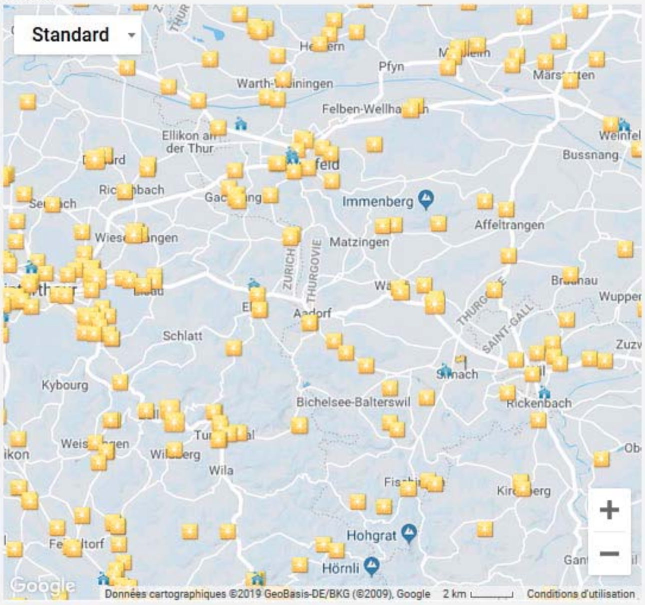
20%

## Le photovoltaïque près de chez vous

Dans votre commune (Aadorf), au moins 13 entreprises et 30 ménages ont choisi d'installer des panneaux solaires photovoltaïques. Au total (tous types de propriétaires confondus), votre commune compte plus de 56 installations solaires photovoltaïques pour une puissance cumulée de 2'385 kWp. Ces installations permettent de produire environ 2'253 MWh par année, soit l'équivalent de la consommation annuelle moyenne de 644 ménages.

Avant de passer à la suite, vous avez également la possibilité de prendre connaissance des installations photovoltaïques existantes dans votre région à l'aide de la carte ci-dessous. Chaque petit logo jaune représente une installation photovoltaïque et permet d'obtenir plus d'informations en cliquant dessus:

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20%

Vous consultez ce questionnaire en mode preview

## Votre entreprise et le solaire photovoltaïque

Pour la suite du questionnaire, nous ferons l'hypothèse que votre entreprise dispose d'un toit ou terrain et des autorisations nécessaires à l'installation de panneaux solaires photovoltaïques.

ATTENTION: les 12 questions qui suivent constituent la partie la plus importante du sondage. Dans chacune des questions, vous devrez choisir l'installation photovoltaïque qui correspond le mieux aux besoins et attentes de votre entreprise ou ne pas installer cette technologie, si le choix proposé ne vous convenait pas.
Les propositions d'installations sont faites par paires. Toutes les installations ont une puissance de 10kWc, mais elles diffèrent de par leur système de montage des panneaux solaires et de par la présence ou non d'un écran d'affichage. Leurs prix nets au moment de l'achat ainsi que leurs flux annuels liés aux subventions ou au leasing varient également. Ces données résultent des politiques énergétiques actuelles ou de politiques que l'on pourrait mettre en place dans le futur.
Si aucune des deux installations proposées ne convient à votre entreprise, vous pouvez toujours choisir d'en rester à la situation actuelle. En sélectionnant l'option « Status quo », vous indiquez que le choix d'installations proposées ne vous convient pas et que donc vous préféreriez plutôt ne pas installer cette technologie. Merci de bien évaluer les propositions alternatives et de choisir comme si votre entreprise se trouvait vraiment devant ces choix. Il n'y pas de bonne ou de mauvaise réponse.

Si vous ne l'avez pas encore fait, nous vous invitons à lire le document explicatif fourni en annexe de l'invitation à ce sondage avant de continuer. Vous pouvez aussi retrouver ce document ici **bref document explicatif (PDF).**

← Page précédente | → Page suivante

20%

Si votre entreprise avait le choix parmi les alternatives suivantes, laquelle choisirait-elle ? **1 / 12**

| | Installation 1 | Installation 2 | Statu quo |
|---|---|---|---|
| **Type de montage** | Panneaux ajoutés | Panneaux integrés | Aucune: Notre entreprise ne choisirait aucune de ces alternatives. |
| **Écran d'affichage** | Avec écran | Avec écran | |
| **Flux annuel** | Recettes annuelles de CHF 750 liées aux subventions | 0 CHF | |
| **Prix net** | CHF 25'000 | CHF 15'000 | |

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80%

Vous consultez ce questionnaire en mode preview

## Questions additionnelles à propos de votre entreprise

Est-ce que votre entreprise possède une certification énergétique ou environnementale, par exemple ISO 5001 (Énergie) ou ISO 14'000 (Système management environnemental) ?

- Oui
- Non
- Ne sais pas

Effacer réponse

Disposez-vous d'un document formalisant les valeurs du développement durable et/ou de la RSE (responsabilité sociétale) dans votre entreprise?

- Oui
- Non
- Ne sais pas

Effacer réponse

Votre entreprise achète-t-elle son électricité à un prix supérieur que le tarif le plus bas afin de bénéficier de produits d'électricité « verts », par exemple avec garanties d'origines (GO) ou certification « Naturemade » ?

- Oui
- Non
- Ne sais pas

Effacer réponse

Votre entreprise est-elle considérée comme un «gros consommateur» au sens du MoPEC (consommation annuelle d'électricité supérieure à 0,5 GWh) et est-elle donc tenue de réaliser des actions de performance énergétique (Loi sur l'énergie)?

- Oui
- Non
- Ne sais pas

Effacer réponse

Page précédente

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90%

## Questions sur vos choix dans le photovoltaïque

Pour quelle(s) raison(s) votre entreprise a-t-elle investi dans l'achat d'une installation photovoltaïque? *Plusieurs choix possibles*

- ☐ Rentabilité satisfaisante
- ☐ Gain d'image
- ☐ Pour réduire notre empreinte environnementale
- ☐ Pour atteindre nos objectifs de RSE (responsabilité sociétale de l'entreprise)
- ☐ Nous avons reçu des témoignages positifs de la part de personnes ou d'entreprises qui ont acheté une installation photovoltaïque
- ☐ Nous avons constaté que plusieurs entreprises de la région possèdent une installation photovoltaïque
- ☐ Autre

Vos clients se rendent-ils fréquemment sur le(s) site(s) de votre entreprise et ont-ils la possibilité de constater visuellement la présence de votre installation photovoltaïque ?

- Oui
- Non

Effacer réponse

Votre entreprise a-t-elle entrepris de communiquer activement le fait qu'elle a investi dans le photovoltaïque, par exemple au travers d'une campagne de communication, d'un écran affichant la production dans le hall d'entrée, ou de messages d'information sur ses produits?

- Oui
- Non
- Ne sais pas

Effacer réponse

Veuillez indiquer l'importance des éléments suivants dans votre décision d'installer des panneaux solaires dans votre entreprise:

| | Forte importance: élément déterminant dans la décision | Importance modérée : élément non déterminant dans la décision | Pas d'importance dans la décision |
|---|---|---|---|
| Présence de panneaux solaires chez les ménages et entreprises de la région | ○ | ○ | ○ |
| Présence de panneaux solaires chez les entreprises leader du secteur | ○ | ○ | ○ |
| Présence de panneaux solaires chez vos concurrents | ○ | ○ | ○ |
| Conseils et témoignages de la part d'autres entreprises ou de ménages ayant acheté une installation | ○ | ○ | ○ |
| Conseils de spécialistes du solaire (installateur, experts, etc.) | ○ | ○ | ○ |

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# Diffusion du solaire : sondage HEG Genève

100%

Votre questionnaire a bien été enregistré, merci !
Si vous le souhaitez, vous pouvez modifier vos réponses en suivant ce lien: Editer les réponses

Questions: info@satiscan.com ou +41 22 345 16 30

# Appendix 4

# The price of risk in residential solar investments

# The price of risk in residential solar investments

January 11, 2020

Beatrice Petrovich
Chair for Management of Renewable Energies – University of St. Gallen

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Department of Economics, Andrew Young School of Policy Studies, Georgia State University, CESifo, and Grantham Research Institute on climate change and the environment, London School of Economics and Political Science

Rolf Wüstenhagen
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## Abstract

Households are key actors in the energy transition, especially when it comes to investments in a decentralized energy system. The phasing-out of feed-in tariffs, and unexpected policy changes in the wake of an increasingly polarized climate debate, require investors in residential solar PV systems to bear new risks. Using a discrete choice experiment coupled with a randomized informational treatment, we test whether policy and market risks deter households from investing in solar, and how this relates to individual risk preferences and information asymmetries. We find that policy risk reduces households' intention to invest in solar, especially for risk-averse individuals and high salience of policy risks. Conversely, households seem less sensitive to market risk: residential solar investors accept volatile revenues, as long as a price floor for excess electricity sold to the grid is guaranteed. Our study suggests that keeping policy uncertainty low is more important for residential solar investors than fully hedging against fluctuating electricity prices.

## Highlights

- Policy risk negatively affects households' willingness to invest in solar
- Households may underappreciate policy risk due to information asymmetries
- If new information makes policy risk salient, some are likely to leave the market
- Households are rather insensitive to market risk, if a positive price floor exists
- Residential solar investors care more about stable policies than secure revenues

## Keywords

residential solar investors; risk preferences; policy risk; market risk; discrete choice experiment; information asymmetries

## 1 Introduction

Transitioning from fossil to renewable electricity generation is necessary to successfully address climate change. Among all renewable energy solutions, solar photovoltaics (PV) are expected to expand globally the most over the next 5 years, with small-scale solar PV systems playing a key role (IEA 2018b). Over the last ten years, households, in particular, have contributed substantially to the financing of small-scale solar capacity (Bergek, Mignon, and Sundberg 2013; Karneyeva and Wüstenhagen 2017; Clean Energy Wire 2018), by investing in solar PV systems installed on residential buildings. Households tend to represent the lion's share in terms of the number of installed systems and often also play an important role in terms of installed capacity.

Households are hence important actors in the energy transition – not just as consumers, but also as investors. Policymakers in many countries are currently reconsidering the design of promotion policies for renewable energy technologies such as residential solar PV, for a variety of reasons including the dramatic decrease in PV technology cost, considerations regarding the high implicit cost of carbon of these programmes, and distributional effects (e.g. Borenstein 2017; Creutzig et al. 2017; Crago and Chernyakhovskiy 2017). Some governments are switching from production-based feed-in tariffs to one-off investment grants. These revisions are in line with recent research, suggesting that households have relatively high discount rates, which imply higher solar adoption with immediate one-off payments rather than equivalent production subsidies over several years, or, equivalently, lower costs for taxpayers to achieve a given renewable energy target (Bollinger et al. 2018; De Groote and Verboven 2019). Such high discount rates may, however, not only relate to pure time preferences (see Andreoni and Sprenger 2012). They may also relate to risk. A predictable and stable framework is deemed critical for attracting investment (World Bank 2019), and the energy sector is no exception. Past literature (Mitchell, Bauknecht, and Connor 2006; Butler and Neuhoff 2008; Barradale 2010; Lüthi and Wüstenhagen 2012; Salm 2018) has shown that reducing policy and market risk is an important feature of effective and efficient policy design. In this literature, and by extension in this paper, "policy risk" is defined as the risk of regulatory changes, for instance following budget cuts, that worsen the investment case, while "market risk" refers to the risk emerging from the fact that future monetary benefits from renewable generation depend on the uncertain evolution of electricity market variables, such as the price of electricity.

However, despite the importance of residential investors in financing the energy transition, past empirical studies assessing the role of risk in investment decisions have traditionally focused mostly on corporate and institutional investors. Understanding the mechanisms behind households' decisions to adopt solar PV is crucial to lead to more cost-effective policy designs while managing voters' expectations, which is important at a time where polarization in the climate policy debate increases the risk of policy reversals. With this paper, we aim to contribute to closing this research gap by investigating to what extent households' willingness to invest in solar PV systems depends on policy and market risk.

This question is especially relevant in a situation where recent policy developments have made the investment environment risky for owners of residential solar PV systems. For instance, recently, a number of European countries (IEA 2018a) unexpectedly, and in some cases retrospectively, reduced subsidies to solar producers. Policy uncertainty has also concerned federal renewable support schemes in the United States (Barradale 2010). Hence, in these situations policy risk has materialized, leading to losses for solar investors compared to initial expectations. Moreover, the change in the policy design from promotion instruments that provide residential solar investors with long term state-guaranteed revenues (e.g. feed-in tariffs) to investment grants, feed-in premia, and incentives for self-consumption (REN21 2017), implies a higher degree of uncertainty in future electricity cost savings from self-consumption, and in revenues from sales of excess electricity production. That is, solar investors are also becoming increasingly subject to market risk.

In this risky environment, would households continue to invest in solar PV systems, and hence provide a key contribution to decarbonizing the energy system? We investigate this question by analyzing stated preferences for intention to invest in residential solar PV systems under different levels of policy and market risk. Stated preferences are obtained through a discrete choice experiment, which we couple with a randomized informational treatment to examine the role of information asymmetries on the assessment of policy risk. In our choice experiment, participants have to trade off between hypothetical solar PV systems for their house, each of which is characterized by different levels of policy- and market-driven investment risk. In the treatment condition, additional information from publicly available sources is provided to participants to make them aware of the possibility of policy changes that can potentially affect financial support for the PV system. Hence, we can test directly whether policy risk is entirely factored in to households' expectations or if, instead, households proceed to a revision of their beliefs when new information makes policy risk salient. The study was realized online by a sample of 750 Swiss households, selected to represent a realistic segment of potential PV investors. Switzerland, with more than 60,000 installations, is one of Europe's fastest growing residential solar markets and one of the countries in the world with the highest density of solar PV (IEA 2018a). Switzerland is also one of the countries transitioning from feed-in tariff to investment grants and one of the countries in which policy changes were implemented. In particular, it has been characterized by policy risk ever since the introduction of feed-in tariffs in 2009, since both the timing and the amount of the subsidy were characterized by uncertainty (Karneyeva and Wüstenhagen 2017). Furthermore, in the Swiss federal system, local utilities have significant leeway in determining retail prices, exposing solar investors across the country to varying levels of market risk. Finally, Switzerland is a very interesting context to analyze households' (voters') expectations, due to the high permeability of its democratic system.

We find that households tend to underappreciate policy risk. However, if policy risk becomes salient to them and it is factored in in their investment decisions, it significantly reduces their intention to invest in solar PV. The negative impact of policy risk is larger for individuals with stronger risk aversion. With a salient policy risk, some individuals shy away from an investment in solar altogether, rather than reduce the amount of money they invest in the technology. Therefore we conclude that upfront financial support is more conducive to residential solar investments than support spread over time, not just because households are impatient or liquidity constrained, but because households discount future subsidy payments to take into account the risk that the government may fail to pay the promised amounts. Moreover, we find that, compared to other categories of renewable investors, households are less sensitive to market risk.

The remainder of this paper is structured as follows: Section 2 presents the related literature and provides an overview of the relevance of policy and market risk for solar investments; Section 3 presents methodology and data; results are presented and discussed in Section 4; finally, Section 5 concludes by providing policy recommendations.

## 2 Policy background and literature review

As mentioned, a number of countries recently implemented policy changes impacting the profitability of solar investments. Italy and Spain reduced the level of financial support promised to already existing PV systems in 2016; Bulgaria, the Czech Republic, and Romania have discussed or applied such measures in the last three years (IEA 2018a); Switzerland's new Energy Law, passed in 2017, reduced the amount of financial support for already existing PV systems that were in the waiting list for feed-in tariffs (Swiss Federal Office of Energy 2018; *Beobachter* 2018). In the United States, renewal uncertainty concerning the federal production tax credit has deterred long-term investment in wind energy (Barradale 2010). Despite growing awareness of the urgency of addressing climate change and increasing cost-competitiveness of renewable energy sources, the increasing polarization of the climate change debate (Fisher, Waggle, and Leifeld 2013; Pidgeon 2012) could make U-turns in energy and climate policy more likely, thus increasing risk for investors. This makes our examination of policy risk all the more relevant.

In light of a dramatic decrease in PV technology cost (Creutzig et al. 2017), several governments are reconsidering their policies supporting renewables. In particular, all over Europe we observe the phase-out of policies that provide solar investors with a secure revenue stream such as feed-in tariffs, or FITs (IEA 2018a). Currently discussed or recently implemented alternative support schemes include investment grants, feed-in premia, auctions, and incentives for self-consumption of solar energy (REN21 2017).

This change has implications in terms of risk borne by solar producers: compared to FITs, the risk related to fluctuating electricity prices (market risk) is shifted from electricity consumers onto residential adopters. The new instruments imply that solar producers have to recover their upfront investment cost through future revenue streams that are uncertain: energy cost savings from self-consumption and revenues from sales of excess electricity production. The amount and stability of electricity sales depend on the characteristics of the agreement that solar investors have with the counterparty purchasing excess solar power (local electric utility, grid operator, or other private entity). The realized amount of energy cost savings from self-consumption is also uncertain at the time of the investment decision, as it depends on the evolution of retail electricity prices and rules on grid charges.

This paper contributes to two strands of literature. First, we contribute to an emerging literature on the role of risk in renewable energy investment decisions, which has focused so far mainly on professional investors. Second, we contribute to a broader literature on the adoption of renewable energy and the diffusion of new technologies more in general. Specifically, this paper complements recent evidence showing that households tend to highly discount subsidies for new technologies if these are not paid immediately to them, implying higher adoption with immediate grants rather than continuous feed-it tariffs, ceteris paribus.

We start with the first strand of literature, which examines the role of risk in the renewable energy investment decisions of corporate and institutional investors. This literature identifies two main sources of risk that significantly deter investment decisions of professional investors: policy and market changes. As for market risk, the success of FITs in creating viable markets for emerging renewable energy technologies has been explained by their ability, with respect to business as usual, to reduce market risk borne by producers (Mitchell et al. 2006, Butler & Neuhoff 2008), to which both corporate and institutional investors are sensitive (Salm and Wüstenhagen 2018; Salm 2018). As for policy risk, it has been demonstrated that European and US-based professional investors tend to be very sensitive to policy uncertainty (Barradale 2010; Lüthi and Wüstenhagen 2012).

The impact of risk on households' solar investment decisions is less investigated. Suggestive evidence on a potential role of risk in household investment decisions can be, however, found in recent studies on households adopting solar energy (Bollinger et al. 2018; De Groote and Verboven 2019) as well as from a growing literature on the diffusion of energy efficient technologies in the residential sector. Hence, we turn to the second strand of literature. Recent empirical studies on solar adoption in the residential sector found that households significantly discount future monetary benefits that they could obtain from solar PV systems. De Groote and Verboven (2019), find, for instance, that Belgian households apply an implicit discount rate of 15 % when comparing immediate and future subsidies, which is much higher than the real market interest rate of about 3 %. This finding could be attributed to present bias or intrinsic consumer myopia (i.e. systematic myopic overvaluation of the present compared to the future, leading to hyperbolic discounting of future payoffs, see Thaler 1981). The very high observed implicit discount rates found in the literature may, however, not only be driven by time preferences (Andreoni and Sprenger 2012). Risk preferences may also play a role. Households may assign a probability to the government's commitment to pay out future incentives. That is, risk-averse households may anticipate that a longer time span over which subsidies are received may imply a higher risk of policy change. Hence, if households consider the possibility that a policy may be retrospectively changed, they would rationally display, all else equal, a stronger preference for immediate payments.

For instance, the literature on the diffusion of energy efficient technologies in the residential sector shows that households pay attention to risk in their investment decisions concerning energy efficient technologies. In particular, a number of studies have shown that risk averse individuals tend to be less likely to invest in energy efficiency than risk neutral individuals (Sutherland 1991; Hassett and Metcalf 1993; Farsi 2010; Qiu, Colson, and Grebitus 2014; Schleich et al. 2019). These findings are consistent with learning by doing and learning from others in the adoption of new technologies (Bass 1969; Mansfield 1961), which play an important role in the market for residential solar PV (e.g. Bollinger and Gillingham 2012; Graziano and Gillingham 2015). Information asymmetries may lead individuals to overestimate risk, leading to lower adoption of a new technology (Conley and Udry 2010). However, information asymmetries may also lead individuals to underestimate risk and over-adopt compared to a perfect-information counterfactual. When new information is released, and processed by the individual, beliefs are revised and individuals may regret their decision to switch to the new technology.

Summarizing, previous studies suggest that households, similarly to professional investors, form perceptions on policy and market risk, which enter their calculations when investing in solar PV. However, perceived risk may differ from actual risk for households who underestimate or fail to take into account some risk elements when evaluating investment opportunities. Underappreciation of risk may be especially likely when such risk is not particularly salient (Simon 1955, 1959), and when the likelihood of a given realization is small, as it may be the case with policy reversals.

Based on the literature, we expect that, everything else equal, households' likelihood to invest in solar PV systems decreases when policy or market risk increases. Moreover, we conjecture that, everything else equal, households' willingness to invest in solar decreases when policy risk becomes more salient. To what extent variation in risk affects people's behavior should depend on their risk preferences, in line with economic theory; therefore we expect that, everything else equal, households who have stronger risk aversion are less likely to invest in solar PV systems and are more sensitive to changes in policy and market risk, or in its salience.

# 3 Methodology and Data

To investigate the impact of risk on households' solar investment decisions, we use a discrete choice experiment (DCE) coupled with a random informational treatment. DCEs are an indirect method of eliciting individual stated preferences for different product features. It is rooted in the marketing and transport literatures (Green and Srinivasan 1990; Train 2009) and enjoys growing popularity in energy and environmental economics (Johnston et al. 2017), political science (Bechtel and Scheve 2013; Hainmueller, Hopkins, and Yamamoto 2014), and investor research (Masini and Menichetti 2012; Salm 2018). Participants in DCEs have to choose repeatedly between two, or more, hypothetical product alternatives which vary on a number of dimensions, known as "product attributes", such as price, brand etc. (Green and Srinivasan, 1990). The analysis of participants' choices over several rounds ("choice tasks"), where the levels of the attributes are randomly combined across the presented alternatives, allows to estimate the impact of each attribute on the likelihood to purchase the product, as well as the influence on changes in attribute levels on respondents' utility, and hence ultimately willingness to pay (Green and Srinivasan 1990).

In what follows we describe the data and sampling procedure, the randomized informational treatment, the DCE design, and the empirical approach for the data analysis. Annex II shows the full survey questionnaire, translated to English.[1]

## Data and Sampling procedure

In December 2018, a sample of 750 Swiss households participated in our survey. We carefully identified a sample of potential residential solar PV investors in Switzerland. This is important because the validity of stated preference studies crucially depends on a realistic choice setting (Boyle, Welsh, and Bishop 1993; Czajkowski, Hanley, and LaRiviere 2015) .

We selected our sample of Swiss potential residential solar PV investors by stratifying survey invitations and implementing precise screening rules for participation in the survey. Our sample was recruited by a professional Swiss market research firm, that operates a panel of 100,000 people living in Switzerland. Invitations were initially sent to 1,335 Swiss households and stratified according to language region, age, gender, political orientation, and education, in order to match the distribution of these variables in the Swiss population. In order to be

[1] The original questionnaire was available in French, German, and Italian.

selected for the survey, respondents had to own a house, not installed solar photovoltaics yet, and be interested in purchasing a PV system in the next 5 years[2]. Strong actual readiness to invest in solar energy by our survey respondents is confirmed by the fact that many respondents were willing to take tangible action towards the purchase of a solar PV system after completing the survey. In particular, 26 % of the survey respondents chose to be redirected to an online platform, run by the federal government, that provides non-binding quotes for the actual purchase of a solar PV system. The market research firm remunerated the respondents who successfully completed the survey by means of 'credit points' that they can spend in designated online shops. A quality control question was added to exclude inattentive respondents.[3]

Relevant covariates for our sample were measured in the final section of the survey, including the elicitation of risk preferences (i.e. whether respondents tend to be risk seeker or risk averse, in a context unrelated to solar investments), time preferences (i.e. how much respondents discount future certain gains and so how patient they are), and environmental preferences. Other socio-demographic and psychographic features were gathered through the market research agency. Table S1 in Supplementary Materials presents the corresponding descriptive statistics for our sample and compares them with the distribution in the entire Swiss population.

## Treatment

In the first section of the survey, all respondents in our sample read a short introductory text, explaining the features of solar PV systems and informing about existing federal incentives for residential solar PV investors in Switzerland. In particular, they were told about the existence of a one-off investment grant that covers a share of the system cost and is paid after the system is commissioned. All respondents were told that the waiting time for the payment of the grant may exceed two years[4]. Then, respondents were randomly assigned to one of two groups (treatment and control group), with only one group (treatment group) been provided additional information about policy risk connected to solar investments in Switzerland. The randomized provision of information aimed at testing the role of policy risk's salience. Treated respondents were told about policy changes to solar subsidies that actually took place in Switzerland and were informed about factors that could reduce the promised amount of financial support for

[2] The corresponding screening question was: "Would you consider installing a solar PV system in the next 5 years? Please consider that the cost range for a typical solar PV system for a residential house in Switzerland is CHF 15,000-30,000, depending on capacity, preferred features, installer etc". Respondents who answered negatively were excluded from the survey.
[3] Our "trap question" consisted of a simple attention check asking: "Please select the word 'energy' from the following list." Respondents were given a list of four items to choose from, including 'energy', 'politics', 'environment' , 'buildings' and 'I do not know'. Observations of 42 respondents who selected the wrong answer to this question were not included in the sample.
[4] Note that in 2018 the Swiss federal government committed to significantly shorten the waiting time for solar incentives, reducing the waiting time for small solar PV systems to 1.5 years. All respondents were informed about this after completing the questionnaire (see copy of the questionnaire translated to English in Annex II).

solar PV systems. People in this group saw a snapshot of an article in one of the most frequently read Swiss online news portals reporting about long delays in the payment of solar subsidies.[5] The information that we provided was publicly available, so in principle, in the absence of information asymmetries, all respondents could have been aware of it. Table S2 in the Supplementary materials section compares the information set between the treatment and control group.

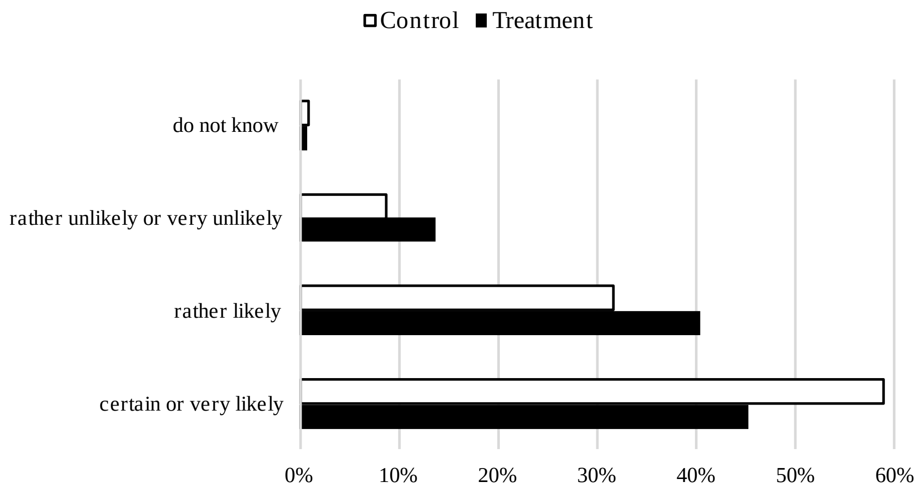
Table S3 in Supplementary Materials shows that the two groups are very well, albeit not perfectly, balanced in terms of covariates. As per standard procedure, we include covariates as control variables in our empirical estimations.

Responses to a question on perceived policy risk connected to solar investments, placed after the choice experiment section, suggest that our treatment led to an update of people's beliefs on policy risk, consistent with the presence of information asymmetries. In particular, we asked each respondent: "If you buy a solar system today and the federal government promises you to pay an investment grant after a certain waiting time, how likely do you think it is that you are indeed going to be reimbursed?". The share of people who responded "sure" or "very likely" drops from 59 % to 45 % for the treatment compared to the control group, while the share of people who responded "rather unlikely" or "very unlikely" increases from 9 % in the control group to 14 % in the treatment group (Figure 1). All these differences are statistically significant at the 95% confidence level (Table S4 in Supplementary Materials).

[FIGURE 1 ABOUT HERE]

[5] The article was a real article published on the swissinfo.ch portal in December 2017 and available in German, French and Italian (https://www.swissinfo.ch/fre/solaire--des-ann%C3%A9es-d-attente-pour-des-subventions-f%C3%A9d%C3%A9rales/43725970; https://www.swissinfo.ch/ger/alle-news-in-kuerze/jahrelange-wartezeit-fuer-subventionen-des-bundes-fuer-solaranlagen/43725688; https://www.swissinfo.ch/ita/sussidi-per-impianti-solari--tempi-di-attesa-si-allungano/43726218).

**Figure 1. Perceived policy risk connected to solar investments, by experimental group (% of respondents)**




Y-axis labels represent possible answers to the survey question: "If you buy a solar system today and the federal government promises you to pay an investment grant after a certain waiting time, how likely you do you think it is that you are indeed going to be reimbursed?"

## Discrete choice experiment

In the second section of the survey, respondents faced 8 consecutive choice tasks. In each choice task, the respondents had to choose one out of three hypothetical solar PV systems for her own house or select the opt-out option ("I would not choose any of these options"). By giving to respondents the possibility to reject all displayed options, we are able to measure not only the relative preference for a given attribute, but also the overall likelihood that a solar PV system would be accepted. Right before making their choices, respondents were asked to assume that all the proposed solar PV systems could be installed on their house as it was and were asked to answer in the way they would if they were actually taking a real investment decision, as well as reminded about their budget constraint, in line with standard recommendations in the literature (Arrow et al., 1993) on how to reduce hypothetical bias.

Displayed solar PV systems were described by a set of 5 attributes, each featuring 4 levels (Table 1). Attribute levels were randomly combined between and across the triplets.[6]
Two attributes were chosen to simulate different degrees of policy and market risk. The levels of the attribute "waiting time for grant" simulated increasing policy risk (from "immediate reimbursement" to "undetermined" waiting time), while the levels of the attribute "payment

[6] All combinations between attribute levels were allowed, with the only exception of the combination between the lowest system cost level (CHF 15,000) and the highest self-consumption level (100 %). The constraint was introduced to rule out a combination that might have otherwise seemed unrealistic, even with a 5-year horizon, according to expert interviews. An efficient DCE design was generated with Sawtooth software. 900 versions of the choice experiment were created and randomly assigned to the 750 respondents.

for surplus electricity" simulated increasing market risk (from a fixed compensation to the variable payment with the widest range). The selection of attributes and corresponding levels is further discussed in Annex I. Figure S1 in the Supplementary Materials provides an example of a choice task screen.

[TABLE 1 ABOUT HERE]

**Table 1. Attributes and attribute levels for the choice experiment**

| **Attribute** | **Levels** | **Explanatory text shown to respondents** |
|---|---|---|
| Investment cost | CHF 15k<br>CHF 20k<br>CHF 25k<br>CHF 30k | This is the total cost of the solar PV system including installation and grid connection. You have to pay this upfront. It excludes government support (see below under "investment grant"). |
| Self-consumption | 25 %<br>50 %<br>75 %<br>100 % | Thanks to your solar PV system, a share of your yearly electricity consumption will be covered by your own production; you will buy less electricity from the grid and have lower electricity bills over the life time of the solar system (20 years). |
| Investment grant | 10 %<br>20 %<br>30 %<br>40 % | The federal government reimburses you this share of the total cost you spend for the solar PV system. This sum is paid after the system is commissioned (see below under "waiting time for investment grant"). |
| Waiting time for investment grant | No waiting time (immediate reimbursement)<br>Shorter than 1 year<br>1-2 years<br>Undetermined | The federal government reimburses you part of the total upfront cost, this is the time that you have to wait to receive the money from the government. |
| Payment for surplus electricity | Fixed: 8 cent/kWh<br>Variable: ranging from 6 to 10 cent/kWh<br>Variable: ranging from 4 to 12 cent/kWh<br>Variable: ranging from 0 to 16 cent/kWh | When you produce more electricity than you use, surplus electricity goes directly into the grid and you will receive a payment for the electricity you send to the grid. The payment can be fixed or variable. A fixed payment remains the same over the lifetime of the solar system. A variable payment depends on the market price of electricity. |

## Empirical approach

We estimate a conditional logit model (McFadden 1973; Hoffman and Duncan 1988) for the likelihood to invest in a solar PV system, based on 5,784 choices made by 750 respondents. In the model, the likelihood to invest is a function of the solar PV system characteristics (i.e. the attribute levels in the choice experiment), the characteristics of the individual making the choice (i.e. the covariates measured in the survey), and the experimentally controlled situational factor (i.e. receiving additional information that could make the policy risk more salient to the respondent).

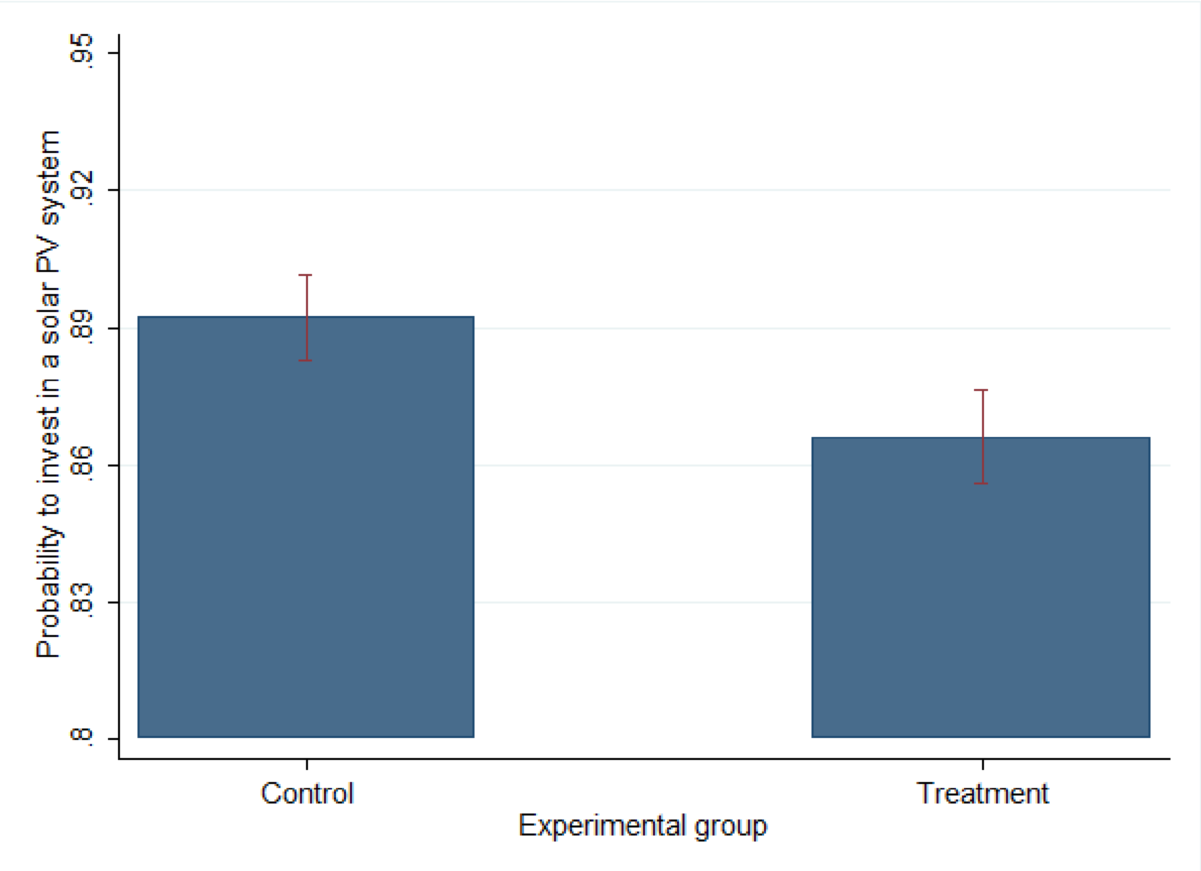
The model estimation rests on three assumptions, in line with the theory of consumer behavior developed by Lancaster (1966). First, individuals, when facing different product alternatives, choose the one that maximizes the latent utility they obtain from the product; second, each attribute level can have a distinctive impact on the overall product utility, which is, therefore, the sum of utilities from each product attribute; third, there is some degree of randomness in choices, captured by the error term.

## 4 Results and discussion

Households tend to underestimate policy risk when making solar investment decisions. In fact, if Swiss households factored in the risk of unexpected solar subsidy cuts in their decisions, we should not observe any difference in likelihood to invest between the treatment and the control group. Instead, our data show that, when policy risk becomes more salient, regardless of the actual level of policy risk, the probability to invest in a solar PV system declines (Figure 2). More specifically, households who receive information making the policy risk more salient (in the treatment group), even if they initially declared to be interested in investing in solar PV, are significantly more likely to reject all of the available investment options, compared to those who did not receive such information (control group). Underestimation of policy risk may not be good for long-run solar adoption. In fact, households who are initially not aware of this kind of risk and (over)invest in solar may then regret their decisions, in case the policy risk materializes. This, in turn, might erode general trust in solar promotion policies, and climate policy in general.

[FIGURE 2 ABOUT HERE]

**Figure 2. Probability to invest in a solar PV system, by experimental group**




Probability to invest in a solar PV system is the frequency of not choosing the opt-out option ("NONE: I would not choose any of these options") in the choice task. Whiskers represent 90 percent confidence intervals. Estimates in the figure are comparable to intention-to-treat estimates.

When policy risk becomes salient to households, intention to invest drops, regardless of the actual level of policy risk. Receiving just one piece of information on policy risk at the time of investment decision, as in our experimental treatment condition, leads to a statistically significant 3 % reduction in the probability that a Swiss homeowner a priori interested in solar intends to invest in a PV system for her house, after seeing realistic options for it (which goes from 89.2 % to 86.6 %). The effect is only slightly smaller (2.5 %) when we control for our set of covariates[7] and the characteristics of the solar system in the DCE (column 2 of Table 2). Treated respondents become more sensitive to policy risk compared to those in the control group (Figure A10 in the Appendix).

[TABLE 2 ABOUT HERE]

**Table 2. Choice experiment: estimated marginal effects from conditional logit model**

| | | Without controls (1) | Without controls, IV approach (2) | With controls (3) | With controls, IV approach (4) | With controls, time preferences (5) | With controls, time preferences, IV approach (6) | With controls, time preferences, and treatment/ risk preference interaction (7) | With controls, time preferences, and treatment/ risk preference interaction, IV approach (8) |
|---|---|---|---|---|---|---|---|---|---|
| Waiting time | Immediate[a] | | | | | | | | |
| | <1 year | -0.04 | -0.03 | -0.02 | -0.02 | -0.03 | -0.02 | -0.02 | -0.02 |
| | | (0.009)** | (0.009)** | (0.010)* | (0.010)* | (0.010)* | (0.010)* | (0.010)* | (0.01) |
| | 1-2 year | -0.09 | -0.07 | -0.07 | -0.07 | -0.08 | -0.07 | -0.07 | -0.07 |
| | | (0.009)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** |
| | Undetermined | -0.17 | -0.15 | -0.15 | -0.15 | -0.15 | -0.15 | -0.15 | -0.15 |
| | | (0.010)** | (0.009)** | (0.009)** | (0.009)** | (0.009)** | (0.010)** | (0.010)** | (0.010)** |
| Payment for surplus electricity | Fixed: 8 cent/kWh[a] | | | | | | | | |
| | Variable: 6 - 10 cent/kWh | -0.03 | -0.01 | -0.01 | -0.01 | -0.02 | -0.01 | -0.02 | -0.01 |
| | | (0.009)** | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| | Variable: 4 - 12 cent/kWh | -0.03 | -0.01 | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 |
| | | (0.009)** | (0.01) | (0.01) | (0.01) | (0.010)* | (0.01) | (0.010)* | (0.01) |
| | Variable: 0 - 16 cent/kWh | -0.07 | -0.05 | -0.05 | -0.05 | -0.05 | -0.05 | -0.05 | -0.05 |
| | | (0.009)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** |
| Investment cost | CHF 15,000[a] | | | | | | | | |
| | CHF 20,000 | -0.05 | -0.02 | -0.03 | -0.02 | -0.03 | -0.02 | -0.03 | -0.02 |

[7] Socioeconomic characteristics (age, gender, education, income, financial assets, region of residence), environmental preferences, technical affinity, self-reported political orientation, and whether the household knows or is aware of anybody among acquaintances and neighbors who has a solar PV system (see Table S1 for details).

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | (0.010)** | (0.010)* | (0.011)* | (0.011)* | (0.011)** | (0.011)* | (0.011)** | (0.011)* |
| | CHF 25,000 | -0.11 | -0.09 | -0.10 | -0.09 | -0.10 | -0.09 | -0.10 | -0.09 |
| | | (0.011)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** |
| | CHF 30,000 | -0.17 | -0.15 | -0.15 | -0.15 | -0.16 | -0.15 | -0.16 | -0.15 |
| | | (0.012)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** |
| Investment grant | 10 %[a] | | | | | | | | |
| | 20 % | 0.09 | 0.12 | 0.12 | 0.13 | 0.12 | 0.13 | 0.12 | 0.13 |
| | | (0.011)** | (0.012)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** |
| | 30 % | 0.18 | 0.21 | 0.20 | 0.21 | 0.20 | 0.21 | 0.20 | 0.21 |
| | | (0.013)** | (0.012)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** |
| | 40 % | 0.26 | 0.29 | 0.29 | 0.30 | 0.29 | 0.30 | 0.29 | 0.30 |
| | | (0.014)** | (0.013)** | (0.014)** | (0.014)** | (0.013)** | (0.014)** | (0.014)** | (0.014)** |
| Self-consumption | 25 %[a] | | | | | | | | |
| | 50 % | 0.21 | 0.28 | 0.26 | 0.27 | 0.26 | 0.27 | 0.26 | 0.27 |
| | | (0.017)** | (0.017)** | (0.017)** | (0.018)** | (0.017)** | (0.018)** | (0.017)** | (0.018)** |
| | 75 % | 0.44 | 0.50 | 0.49 | 0.50 | 0.48 | 0.50 | 0.48 | 0.50 |
| | | (0.017)** | (0.015)** | (0.015)** | (0.016)** | (0.015)** | (0.016)** | (0.015)** | (0.016)** |
| | 100 % | 0.61 | 0.65 | 0.64 | 0.65 | 0.64 | 0.65 | 0.64 | 0.65 |
| | | (0.016)** | (0.012)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** |
| Treatment | | -0.07 | | -0.025 | | -0.027 | | 0.01 | |
| | | (0.018)** | | (0.012)* | | (0.012)* | | (0.02) | |
| Interaction between policy risk and treatment | | | -0.06 | | -0.07 | | -0.14 | | -0.11 |
| | | | (0.007)** | | (0.016)** | | (0.019)** | | (0.020)** |
| Time preferences | | | | | | 0.03 | 0.04 | 0.02 | 0.03 |
| | | | | | | (0.004)** | (0.004)** | (0.004)** | (0.004)** |
| Treatment and high risk aversion | | | | | | | | -0.05 | |
| | | | | | | | | (0.021)* | |
| Interaction between policy risk, treatment and high risk aversion | | | | | | | | | -0.02 |
| | | | | | | | | | (0.006)** |
| Choice tasks | | 6000 | 6000 | 5272 | 5272 | 5272 | 5272 | 5272 | 5272 |
| Respondents | | 750 | 750 | 659 | 659 | 659 | 659 | 659 | 659 |
| Controls | | NO | NO | YES | YES | YES | YES | YES | YES |

Standard errors in parentheses, clustered by respondent in specification (1), heteroskedasticity-consistent standard errors in the others. All models without case-specific constant term. Estimates report marginal effects (at means) from alternative-specific conditional logit model. Dependent variable is the probability to invest in solar PV system. The reduction in number of observations in specifications (3)-(8), compared to specifications (1)-(2), follows from missing data for some of the covariates included in the model.
*** p<0.01, ** p<0.05, * p<0.1.

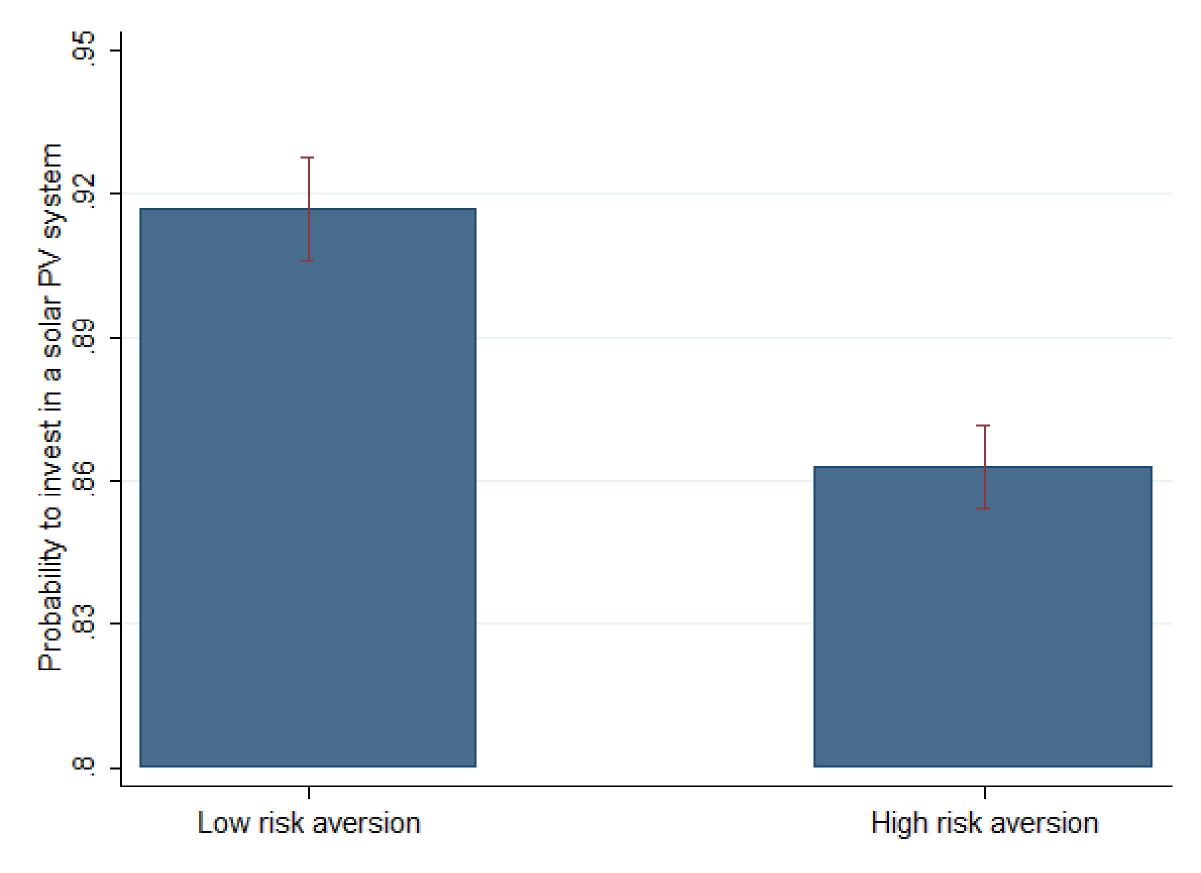
Note that our treatment consists in exposing individuals to additional information. With this type of approach, known as intent to treat, we cannot ensure perfect compliance with the treatment. That is, individuals are free to ignore our information, which is equivalent to refusing the treatment (non-compliance) in the standard causal jargon. As per standard procedure (Angrist, Imbens, and Rubin 1996), we recover treatment effects from intent to treat with an instrumental variable (IV) approach, relying on the variables measuring perceived policy risk. When we correct our estimates for the fact that not everyone was treated as intended, the impact of the revised beliefs on the materiality of policy risk following exposure to our treatment increases to 7 % (column 4 of Table 2).

Hence, revision of beliefs related with policy risk is causally associated to a relatively important decline in the intention to invest in solar. Figure 2 focuses on the extensive margin, i.e. whether policy risk influences the intention to invest in solar energy. We now turn to the intensive margin, i.e. whether households are more likely to select cheaper installations as policy risk becomes more salient. On the intensive margin, we find that, while salience of policy risk reduces the probability to invest, the amount that a household is willing to invest per solar PV system is not significantly lower for households in the treatment group (Figure A7, Figure A8, Figure A9 and Table A2 in Appendix). That is, households exposed to the treatment are less likely to adopt solar panels, no matter how expensive. This finding suggests that policy risk may push some individuals to drop their intention to invest in solar altogether, rather than reduce the size of their investment.

We then investigate how the treatment changes intentions to invest in solar energy depending on the respondent's risk preferences. Straightforwardly, if some individuals in our sample were indifferent to risk, changing the salience of policy risk should have no effect whatsoever on their behavior. First, however, we need to determine whether we observe a general relationship between risk preferences and adoption of solar PV. We do so in Figure 3. Most people in our sample, as in the underlying population, care about risk: risk averse households represent 70 % of our sample (Table S1). Figure 3 shows that this segment displays, in general, a lower-than-average intention to adopt solar. All else equal, risk averse households are less likely to invest in a solar PV system than individuals more prone to risk. This relationship is confirmed when only looking at the control group, to control for any effect of the treatment (Figure 4). The relationship between risk aversion and intention to invest in solar energy contributes to explaining why some people do not invest in solar PV systems, even when such systems are expected to be profitable (i.e. even when the expected monetary gain for the residential solar producer is positive).

[FIGURE 3 ABOUT HERE]

**Figure 3. Probability to invest in a solar PV system, by individual risk aversion**



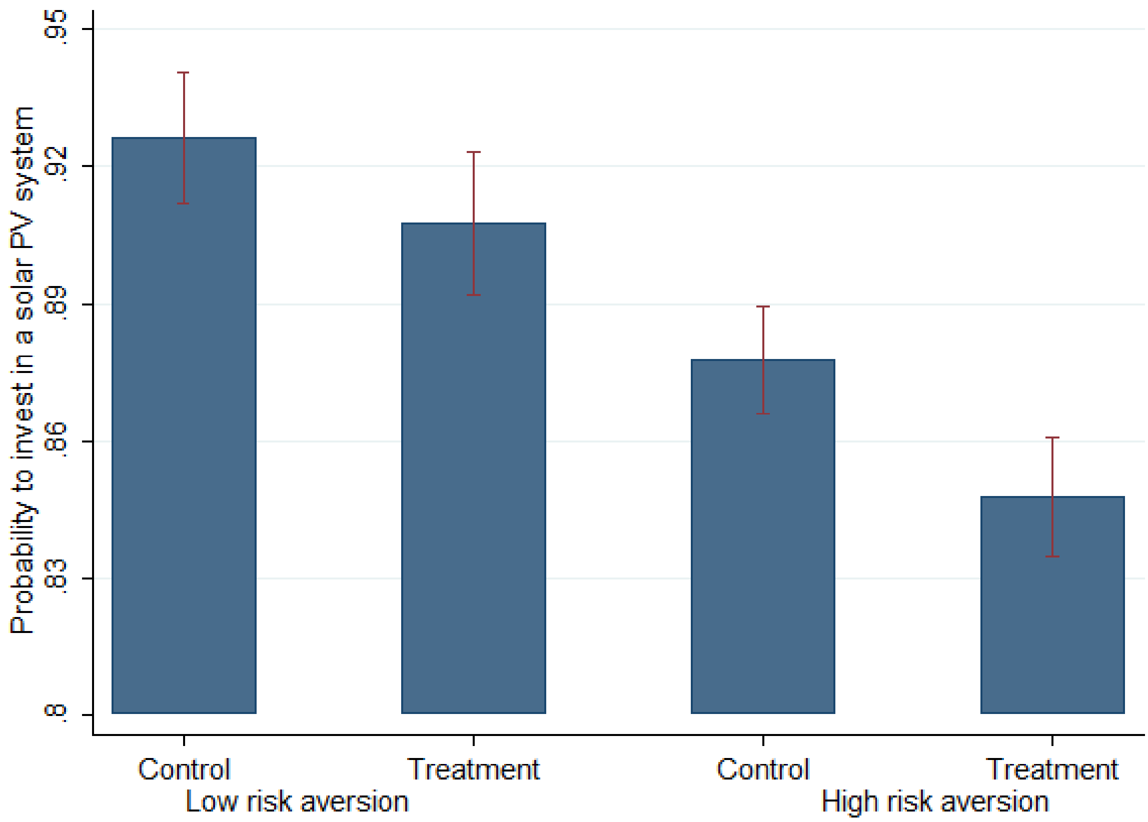

Probability to invest in a solar PV system is the frequency of not choosing the opt-out option (“NONE: I would not choose any of these options”) in the choice task. Whiskers represent 90 percent confidence intervals. Low risk aversion indicates individuals with a risk preference score equal to 5, 6, 7, or 8; high risk aversion indicates individuals with a risk preference score equal to 1, 2, 3 or 4. Risk preference score goes from 1 to 8, the higher the lower the risk aversion. See Table S1 for more details.

When we look at how our informational treatment affects people’s responses depending on their risk aversion (Figure 4), we observe, consistent with economic intuition, that for people who have low risk aversion, increasing the salience of policy risk does not reduce their intention to adopt solar. In contrast, highly risk adverse individuals react the most to the informational treatment: for them, revision of beliefs about policy risk is associated with a 5 % reduction (column 7 of Table 2).[8] That is, the average effect of 2.5 % is the sum of a relatively large reaction by individuals with high compared to individuals with low risk aversion. This finding about the relationship between risk preferences, revision of beliefs about policy risk, and intentions to invest in solar energy is qualitatively similar when we classify individuals into three categories for risk aversion, rather than two (Figures A1 and A2 in Appendix), and is robust to splitting the sample according to the strength of risk aversion (Table A1 in Appendix).

[FIGURE 4 ABOUT HERE]

[8] Note that the impact of the treatment is not significantly different between more and less patient households (Figure A4 in Appendix). This suggests that information we gave to the treatment group had the desired impact: making people aware of the risk that they will not receive the governmental subsidy, rather than making them simply aware that the reimbursement time becomes longer than what initially expected.

**Figure 4. Probability to invest in a solar PV system, by individual risk aversion and experimental group**




Probability to invest in a solar PV system is the frequency of not choosing the opt-out option ("NONE: I would not choose any of these options") in the choice task. Whiskers represent 90 percent confidence intervals. Estimates in the figure are comparable to intention-to-treat estimates. Low risk aversion indicates individuals with a risk preference score equal to 5, 6, 7, or 8; high risk aversion indicates individuals with a risk preference score equal to 1, 2, 3 or 4. Risk preference score goes from 1 to 8, the higher the lower the risk aversion. See Table S1 for more details.

Our analysis also shows that, when policy risk increases, regardless of its salience, the probability that a household invests in a solar PV system declines. The marginal effects for the "waiting time" attribute in Table 2 show that the longer the waiting time for receiving the grant is, the more households' likelihood to invest in solar declines. In particular, all else equal, when waiting time is undetermined, and therefore policy risk is at its maximum, the probability to invest drops by 15 %, as opposed to when reimbursement is immediate (or within one year) and hence policy risk is relatively low. Paying out the financial support within one year, instead of after an undetermined period of time, would have about the same positive impact on residential solar adoption as increasing the amount of financial support from 30 % to 40 %, or could compensate for a reduction in financial support from 30 % to 20%. This result is entirely consistent with the high discount rates observed in the literature.

We can attribute this effect to increasing policy risk connected to longer waiting time, rather than exclusively to households' time preferences, for two reasons. First, coefficients for the "waiting time" attribute do not change when controlling for time preferences (columns 5 and

6 in Table 2).[9] Second, coefficients for the "waiting time" attribute are only slightly different when considering only people with a low intertemporal discount rate (i.e. more patient individuals), compared to people with a high intertemporal discount rate (i.e. less patient individuals), as done in Table A3 in the Appendix. Even for the most patient households, having to wait for the subsidy payment for 1-2 years reduces intention to invest in solar by 7 %, compared to immediate subsidy payment, and not knowing when the subsidy is eventually paid reduces it by 15 %. By controlling for time preferences, we aim at isolating the impact of policy risk on willingness to invest from that of intertemporal discount rate (present bias). High observed implicit discount rates for solar subsidies reported in the literature (De Groote and Verboven 2018; Bollinger et al. 2018) seem therefore connected not simply to people preferring to receive financial incentives as early as possible, but also to people heavily discounting future payments due to the risk of policy changes.

The negative impact of a longer waiting time gets larger the stronger the household's risk aversion is (Table A1 in the Appendix). In particular, individuals with low risk aversion, in contrast to those with high risk aversion, tend to be indifferent between an immediate payment and a payment within one year. For more risk averse households, waiting for the subsidy for 1-2 years reduces intention to invest by 9 %, compared to a 6 % reduction for the less risk averse ones.

While policy risk matters to households, they do not seem to be very sensitive to market risk: a variable price for electricity sold to the grid does not reduce (or only reduces marginally) intention to invest in solar PV compared to a fixed price, unless the former foresees the possibility that reimbursement can go down to zero cents per kilowatt hour. When the interval for variable payment for surplus electricity includes zero, households are 5 % less likely to invest in solar PV compared to payment schemes that guarantee a positive price floor, no matter how volatile the payment is. The negative impact of the risk of feeding electricity into the grid for free holds true also for individuals who feature low risk aversion (Table A1 in Appendix), suggesting that market risk is largely not factored in across the board.

Our study is subject to some limitations, which can serve as starting points for further research. First, institutional features may matter for the formation of beliefs and their adjustment when new information is released. This study focuses on a single country, Switzerland, which shows a relatively high level of trust in the government. Extending our approach to other contexts would provide variation in terms of formal and informal institutions. Second, the point

[9] In line with economic intuition, the coefficient of the time preference score is positive and significant, implying that the more patient the household is, the more likely she is to invest in solar PV systems, as also confirmed by comparison of probability to invest between people with low and high intertemporal discount rate (Figure A3 in Appendix).

estimates provided in this study are conditional on the study design and, in particular, on the simulated range for market and policy risk. While the levels of the market and policy risk attributes in our DCE have been designed for the Swiss context, the level of risk faced by residential solar investors in other countries might actually be different. For instance, the regulatory framework might foresee negative prices for surplus electricity fed into the grid by solar producers. Experimenting with such range may be a promising avenue for future research. Third, we designed our experiment to carefully reflect the risks that residential investors are facing, but this specificity limits the extent to which our findings can be directly compared to prior research on other investor groups. Future research could try to simultaneously survey both residential and professional investors, applying the same measures for policy and market risk. Such a direct comparison would be beneficial for policymakers who are mindful about the way in which policy design influences the willingness of different investor groups to provide capital for low-carbon projects. Finally, our informational treatment works in one direction only, by making treated individuals aware of a material policy risk that could worsen their business case (limited fundings). The outcome of a different informational treatment, for instance signaling strong government climate commitments and low policy risk, could be potentially not symmetric to what we found; exploring this could be a promising avenue for future research.

## 5 Conclusions and policy implications

Households are important actors in the energy transition – not just as consumers, but also as investors. In fact, in an increasingly decentralized energy system, one of the most promising solutions for renewable electricity generation are solar photovoltaics (PV) systems installed on residential buildings. Recent policy developments in many countries have made the investment environment riskier for owners of residential solar PV systems. First, policy changes impacting the profitability of solar investments recently implemented in a number of countries have shown that policy risk is not negligible for solar producers. The increasing polarization of the climate change debate could make U-turns in energy and climate policy more likely, thereby increasing policy risk for investors. Second, in many jurisdictions, governments are phasing out policies that provide residential solar investors with long term secure revenues (e.g. feed-in tariffs), replacing them with policies that imply exposure to market risk.

In this risky environment, would households continue to invest in solar PV systems, and hence provide a key contribution to the decarbonization of the energy system? We investigated this question focusing on the context of Switzerland and measured Swiss households' intention to invest in a solar PV system for their house under different levels of policy and market risk. Stated preferences for investment in solar were obtained through a discrete choice experiment, which we coupled with a randomized informational treatment to examine the role of information asymmetries on the assessment of policy risk. Our study included a sample of 750 Swiss households, selected to represent a realistic segment of potential PV investors.

Households are sensitive to policy risk: their likelihood to invest in solar PV systems drops when policy risk increases. In fact, we find that upfront financial support is more conducive to residential solar investments than support spread over time, not just because households are impatient or liquidity constrained, but because households tend to heavily discount future payments to take into account that the government can cut support unexpectedly. Mitigating policy risk for residential solar investors could be a more effective approach to fostering investment decisions than increasing the level of financial incentives. In particular, paying out the full financial support to a residential solar producer within one year, instead of after an undetermined period of time – hence minimizing the materiality of policy risk – would have the same positive impact on residential solar adoption as increasing the amount of financial support from 30 % to 40 % of the initial investment, or could compensate for a reduction in financial support from 30 % to 20 %.

The negative impact of policy risk worsens if, at the time of their investment decision, households are especially aware of it. When policy risk becomes salient, in particular, the probability that a household decides to invest in solar PV drops by 2 %, all else equal, and the reduction is larger for risk-averse households (5 %). In such circumstances, households are less likely to adopt solar PV systems, suggesting that a salient policy risk may push some individuals to drop their intention to invest altogether, rather than reduce the size of their investment. Conversely, if the policy risk was not salient, households were willing to take more risk in investing in solar energy than they would have been comfortable with in hindsight if policy reversals occur.

While policy risk does matter for households, we show that, instead, households appear to be less sensitive to market risk. Compared to a fixed price for the electricity sold to the grid, only a payment that includes the possibility of remuneration dropping to zero significantly reduces the probability to invest in solar energy. Other types of variable remuneration do not deter households' investment decisions to a large extent, compared to the fixed price option. This turns out to be a substantial difference between households and professional investors: whereas previous studies show that market risk is one of the key deterrent factors in renewable investment decisions for professional investors, we find that volatile revenues from the sale of electricity are less of a concern for households investing in solar energy.

Our study informs policymakers in the developed world on options to maintain a sustained adoption of residential solar in a post-feed-in-tariff regime while correctly managing citizens' expectations. In particular, two main policy recommendations can be drawn from our findings.

First, policy design and communication strategies should correct for the potential detrimental impact of perceived policy risk on residential solar adoption decisions. Such options could include shorter waiting times for receiving financial support or upfront financial support. We also join a set of recent contributions suggesting that for residential investors, upfront one-off investment grants may be preferable to incentives spread over the life of the PV system (e.g. in the form of feed-in tariffs). As the impact of policy risk on investment decisions depends on the information that people receive, policymakers should signal clearly to prospective solar adopters their commitment not to worsen the business case for solar by changing the "rules of the game" retrospectively. In the European context, this could be done by informing prospective residential solar investors about an explicit ban for retrospective policy changes, as foreseen in the new European Union Renewable Energy Directive that shall be implemented by Member States by the end of 2021.

When governments have strong preferences against immediate payments, and are not willing to tie their hands across political cycles in the erogation of feed-in tariffs, they may incur a cost represented by the risk premium asked by households to compensate for their rational expectations of potential policy changes. This additional cost makes it harder to achieve renewable targets with a given budget. A solution to this source of inefficiency could be for other market participants, such as installers or local authorities, to offer pre-financing to households. This effectively reflects a risk transfer from residential solar investors to other players, the latter being willing to take on risk in exchange of a risk premium.

Second, our findings suggest that moving from a regulatory framework where households receive a fixed price for each kWh fed into the grid (e.g. feed-in tariffs) to one where remuneration is volatile and indexed to electricity market prices (e.g. feed-in premia), would not substantially reduce residential solar investors’s willingness to invest. However, setting a price floor for power purchase agreements that involve residential solar producers is likely to contribute to ensure sustained interest in residential solar adoption.

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## Supplementary material

### Table S1. Sample descriptive statistics and comparison with the Swiss population

| Variable name | Description | | % in sample | % in Swiss population | | Note |
|---|---|---|---|---|---|---|
| Household income | Household monthly income | | | | | |
| | | Up to CHF 6,000 | 12 | 30 | *** | (a) |
| | | CHF 6,001 to 9,000 | 26.1 | 25 | *** | (a) |
| | | CHF 9,001 to 12,000 | 26.4 | 19 | *** | (a) |
| | | More than CHF 12,000 | 25.2 | 27 | *** | (a) |
| Household assets | Household assets | | | | | |
| | | Up to CHF 100,000 | 44.9 | 65 | *** | (d) |
| | | CHF 100,001 to 500,000 | 29.2 | 22.6 | *** | (d) |
| | | CHF 500,001 to 1,000,000 | 6.8 | 6.7 | | (d) |
| | | More than CHF 1,000,000 | 8.4 | 5.7 | *** | (d) |
| Age | Age (years) | | | | | |
| | | 18-29 | 9.5 | 14.9 | *** | (b) |
| | | 30-44 | 18.5 | 17.1 | *** | (b) |
| | | 45-59 | 46.9 | 31.9 | *** | (b) |
| | | >59 | 25.1 | 36.1 | *** | (b) |
| Female | 1 if female, 0 if male | | 48.5 | 51.1 | *** | (b) |
| University degree | 1 if holds university degree, 0 otherwise | | 38.7 | 30.6 | *** | (b) |
| German-speaking region | 1 lives in German-speaking region, 0 otherwise | | 77.5 | 72.7 | *** | (b) |
| Environmental preferences | Environmental preference 5-level score, the lower the stronger the environmental preferences | | | | | |
| | | 1 | 32.5 | 27.5 | *** | (e) |
| | | 2 | 46.0 | 39.2 | *** | (e) |
| | | 3 | 18.4 | 30.4 | *** | (e) |
| | | 4 | 2.8 | 2.5 | *** | (e) |
| | | 5 | 0.3 | 0.3 | | (e) |
| "Techie" | 1 if reports being always among the first ones to buy new technologies | | 18.2 | 15.8 | *** | (c) |
| Political Party | Self-reported preference for political party (1) | | | | | |
| | | right-wing | 42.6 | 49 | *** | (a) |
| | | centre | 18.3 | 17 | *** | (a) |
| | | left-wing | 26.8 | 26 | *** | (a) |
| | | other | 12.0 | 8 | *** | (a) |
| Does not have solar peers | 1 if does not know or not aware of anybody among acquaintances and neighbors who has a solar PV system | | 8.5 | n.a. | | |
| Time preferences | Time preferences 8-level score, the higher the more patient | | | | | |
| | | 1 | 0.7 | n.a. | | |
| | | 2 | 1.6 | n.a. | | |
| | | 3 | 5.3 | n.a. | | |
| | | 4 | 10.4 | n.a. | | |
| | | 5 | 21.3 | n.a. | | |

| | | | |
|---|---|---|---|
| | 6 | 36 | n.a. |
| | 7 | 22.4 | n.a. |
| | 8 | 2.3 | n.a. |
| Low discount rate | 1 if individual intertemporal discount rate is low (time preference score higher than 4) | 82.0 | n.a. |
| High discount rate | 1 if individual intertemporal discount rate is high (time preference score lower or equal to 4) | 18.0 | n.a. |
| Risk preferences | Risk preferences 8-level score, the higher the more risk taker | | |
| | 1 | 3.1 | n.a. |
| | 2 | 15.1 | n.a. |
| | 3 | 24.5 | n.a. |
| | 4 | 27.1 | n.a. |
| | 5 | 19.7 | n.a. |
| | 6 | 8.3 | n.a. |
| | 7 | 2.0 | n.a. |
| | 8 | 0.3 | n.a. |
| Low risk aversion | 1 if risk aversion is low (Risk preference score higher than 4) | 30.3 | n.a. |
| High risk aversion | 1 if risk aversion is high (Risk preference score lower or equal to 4) | 69.7 | n.a. |

*, ** and *** imply statistically-significant differences in the proportion between our sample and Swiss population at 10%, 5%, and 1%, respectively. Due to missing data, some categories do not sum up to 100%
(a) Percentage in the fourth column refers to the Swiss population. Source: Swiss Federal Statistical Office (2017).
(b) Percentage in the fourth column refers to the population of Swiss homeowners. Source: Swiss Federal Statistical Office (2017).
(c) Percentage in the fourth column refers to the population of Swiss homeowners. Source: own estimate based on pool of 1,335 households how received survey invitations for this study.
(d) Percentage in the fourth column refers to the Swiss population. Source: Swiss Federal Department of Finance (2015). (e) Percentage in the forth column refers to the sample of the Swiss population of the World Value Survey, 5th Wave. Source: Kriesi and Hug (2007).
(f) Right-wing parties: SVP, FDP, BDP; Center parties: GLP, CVP, EVP; Left-wing parties: GPS, SP; declared no party preference and information intentionally not disclosed added to residual category (Other).

## Methodological note on risk and time preferences elicitation

Risk and time preferences were elicited through a combination of survey items, following the experimentally validated approach developed by Falk et al. (2016, 2018) for the Global Preference Survey.[10] This approach involves one qualitative item, relatively abstract and self-reported on a Likert-scale, and one quantitative item, which puts the respondent into a precisely defined hypothetical (i.e. non-incentivized) lottery/intertemporal choice sequence, using the staircase method. Following the procedure used for for the Global Preference Survey, resulting individual risk/time preference scores are a linear combination between the self-reported score and the quantitative item's outcome. The relative weight of the former is 47% and 71% for risk and time preferences. Applying this approach, we obtain an 8-level score for risk preferences (the higher the score the more risk taker the individual is) and an 8-level score for time

[10] Falk et al. (2018) report risk and time preference scores for 76 countries, including Switzerland, based on responses by representative population samples collected in 2012. For Switzerland the sample included 1000 respondents, who were interviewed by phone. The questionnaire was asked in German, French, or Italian, depending on the language region.

preferences (the higher the score the more patient the individual is). Categories for risk aversion used in the main body of this paper (including Figures 3 and 4) are defined as follows. “High risk aversion” indicates risk preference scores lower or equal to 4; “low risk aversion” indicates risk preference scores higher than 4.

### Methodological note on environmental preference elicitation

We measured individual environmental preferences through a standard survey item, using the exact wording (translations included) as in the $5_{th}$ wave of the World Value Survey(Inglehart et al. 2014): “Would you please indicate for the following description whether that person is very much like you, like you, somewhat like you, not like you, or not at all like you? Looking after the environment is important to this person; to care for nature and save life resources”.
Switzerland was included in World Value Survey 5th wave, ran in 2007, which allows comparing our sample with theirs.

**Table S2. Informational treatment: exact wording used in the questionnaire (translated to English)**

| | Treatment group | Control group |
|---|---|---|
| Information about financial support for solar PV systems provided in the survey | IMPORTANT: Since 2008, the Swiss Federal Government has been supporting solar PV systems through monetary incentives.<br><br>Until 2018 the Government offered the owners of solar PV systems a fixed monetary amount (“feed-in tariff”) for each kWh fed into the grid by their solar systems to be paid for 20 years.<br><br>With the new energy law, starting from January 2018 owners of small solar PV systems receive instead a one-off investment grant (“investment grant”) that covers a share of the system cost.<br><br>The investment grant is paid after the system is commissioned. The waiting time for the payment may exceed two years.<br><br>Note that if rules about incentives for solar PV systems change while one is still in the waiting list, the new rules may apply.<br><br>For instance, under the previous support scheme, the promised amount of support was reduced for PV project owners who entered the waiting list after 2012, due to a change in the law.<br><br>Recently, concerns have arisen about limited financial resources for the support of solar PV systems resulting in continuously growing waiting times for receiving the monetary support, as you can read in the newspaper article below. | IMPORTANT: Since 2008, the Swiss Federal Government has been supporting solar PV systems through monetary incentives.<br><br>Until 2018 the Government offered the owners of solar PV systems a fixed monetary amount (“feed-in tariff”) for each kWh fed into the grid by their solar systems to be paid for 20 years.<br><br>With the new energy law, starting from January 2018 owners of small solar PV systems receive instead a one-off investment grant (“investment grant”) that covers a share of the system cost.<br><br>The investment grant is paid after the system is commissioned. The waiting time for the payment may exceed two years. |

## Table S3. Balance of covariates: descriptive statistics by experimental group

| Variable name | Description | Sample mean or share of respondents for whom the variable takes value 1 | | |
|---|---|---|---|---|
| | | **Control group** | **Treatment group** | |
| Household income | Household monthly income, in 6 classes: 1: < CHF 3,000; 2: CHF 3,000-4,500; 3: CHF 4,501-6,000; 4: CHF 6,001-9,000; 5: CHF 9,001-12,000 CHF; 6: >CHF 12,000 | 4.6 | 4.7 | *** |
| Household assets | Household assets, in 4 classes: 1: <= CHF 100K; 2:CHF 101-500K; 3: CHF 501-1,000K; 4: > CHF 100K | 1.8 | 1.7 | *** |
| Age | Age (years) | 50.3 | 50.6 | ** |
| Female | 1 if female, 0 if male | 48% | 49% | |
| University degree | 1 if holds university degree, 0 otherwise | 40% | 37% | |
| German-speaking region | 1 lives in German-speaking region, 0 otherwise | 75% | 80% | *** |
| Time preferences | Time preference 8-level score, the higher the more patient | 5.6 | 5.6 | |
| Low risk aversion | 1 if risk aversion is low | 30% | 31% | |
| High risk aversion | 1 if risk aversion is high | 70% | 69% | |
| Environmental preferences | Environmental preference 5-level score, the lower the stronger the environmental preferences | 1.9 | 1.9 | |
| “Techie” | 1 if reports being always among the first ones to buy new technologies | 19% | 18% | |
| Right-wing voter | 1 if self-declared right party supporter | 42% | 43% | ** |
| Does not have solar peers | 1 if does not know or not aware of anybody among acquaintances and neighbors who has a solar PV system | 10% | 7% | *** |
| **Respondents** | | **373** | **377** | |

*, ** and *** imply statistically-significant differences in the mean/proportion between experimental groups at 10%, 5%, and 1%, respectively. We used two-tailed T- test for interval, ordinal and ratio variables; chi-squared test for binary variables.

## Table S4. Perceived policy risk by experimental group

| | Control | Treatment | |
|---|---|---|---|
| Certain or very likely | 59% | 45% | *** |
| Rather likely | 32% | 40% | *** |
| Rather unlikely or very unlikely | 9% | 14% | *** |
| Do not know | 1% | 1% | |

Row labels present possible answers to the survey question: “If you buy a solar system today and the federal government promises you to pay an investment grant after a certain waiting time, how likely you do you think it is that you are indeed going to be reimbursed?”
*, **, and *** imply statistically-significant differences in the proportion between experimental groups at 10%, 5% and 1%, respectively. We used chi-squared test.

### Figure S1. Example of a choice task screen

**If these were your only options, which of the following offers for a solar PV system for your house would you choose?**

Choose by clicking one of the buttons below:

(4 of 8)

| | | | | |
|---|---|---|---|---|
| **Investment cost** | CHF 15 000 | 20 000 CHF | 25 000 CHF | NONE: I wouldn't choose any of these. |
| **Own consumption** | Your production covers **50%** of your yearly consumption | Your production covers **25%** of your yearly consumption | Your production covers **50%** of your yearly consumption | |
| **Payment for surplus electricity** | Variable payment: ranging from 4 to 12 cent/kWh | Variable payment: ranging from 6 to 10 cent/kWh | Fixed payment: 8 cent/kWh | |
| **Investment grant** | The federal government will reimburse you 40% of the price | The federal government will reimburse you 20% of the price | The federal government will reimburse you 30% of the price | |
| **Waiting time for investment grant** | No waiting time (immediate payment) | Between 1 and 2 years | Undetermined | |

**IMPORTANT:** For additional information please scroll with the mouse over the corresponding property of the product (left column, bold text)

# Appendix

### Table A1. Choice experiment: estimated marginal effects from conditional logit model (high and low risk aversion subsamples)

| | | | High risk aversion | Low risk aversion |
|---|---|---|---|---|
| Waiting time | Immediate | (baseline) | | |
| | <1 year | | -0.05 | -0.01 |
| | | | (0.010)** | (0.02) |
| | 1-2 year | | -0.09 | -0.06 |
| | | | (0.010)** | (0.018)** |
| | Undetermined | | -0.17 | -0.15 |
| | | | (0.010)** | (0.017)** |
| Payment for surplus electricity | Fixed: 8 cent/kWh | (baseline) | | |
| | Variable: 6 - 10 cent/kWh | | -0.02 | -0.04 |
| | | | (0.01) | (0.018)* |
| | Variable: 4 - 12 cent/kWh | | -0.04 | 0.00 |
| | | | (0.011)** | (0.02) |
| | Variable: 0 - 16 cent/kWh | | -0.06 | -0.05 |
| | | | (0.011)** | (0.018)** |
| Investment cost | CHF 15,000 | (baseline) | | |

| | | | | |
|---|---|---|---|---|
| | CHF 20,000 | | -0.05 | -0.02 |
| | | | (0.011)** | (0.02) |
| | CHF 25,000 | | -0.10 | -0.10 |
| | | | (0.011)** | (0.019)** |
| | CHF 30,000 | | -0.18 | -0.14 |
| | | | (0.011)** | (0.019)** |
| Investment grant | 10 % | (baseline) | | |
| | 20 % | | 0.10 | 0.10 |
| | | | (0.013)** | (0.022)** |
| | 30 % | | 0.18 | 0.19 |
| | | | (0.014)** | (0.022)** |
| | 40 % | | 0.27 | 0.28 |
| | | | (0.015)** | (0.022)** |
| Self-consumption | 25 % | (baseline) | | |
| | 50 % | | 0.21 | 0.28 |
| | | | (0.018)** | (0.029)** |
| | 75 % | | 0.45 | 0.47 |
| | | | (0.016)** | (0.025)** |
| | 100 % | | 0.62 | 0.62 |
| | | | (0.014)** | (0.021)** |
| | Treatment | | -0.07 | -0.04 |
| | | | (0.014)** | (0.017)* |
| | Time preferences | | -0.01 | 0.00 |
| | | | (0.003)** | (0.00) |
| | Choice tasks | | 4184 | 1816 |
| | Respondents | | 523 | 227 |
| | Controls | | NO | NO |

Heteroskedasticity-consistent standard errors in parentheses. All models without case-specific constant term. Estimates report marginal effects (at means) from alternative-specific conditional logit model. Dependent variable is the probability to invest in solar PV system.
*** p<0.01, ** p<0.05, * p<0.1.

## Table A2. Selected investment options in the DCE by investment cost and experimental group (%)

| Investment cost (CHF) | Control | Treatment | Overall |
|---|---|---|---|
| 15,000 | 20% | 21% | 21% |
| 20,000 | 33% | 31% | 32% |
| 25,000 | 26% | 26% | 26% |
| 30,000 | 21% | 21% | 21% |

**Table A3. Choice experiment: estimated marginal effects from conditional logit model, by intertemporal discount rate**

| | | | Subsample 1: individuals with low intertemporal discount rate | Subsample 2: individuals with high intertemporal discount rate | Entire sample |
|---|---|---|---|---|---|
| Waiting time | Immediate | (baseline) | | | |
| | <1 year | | -0.02 | -0.05 | -0.02 |
| | | | (0.01) | (0.022)* | (0.010)* |
| | 1-2 year | | -0.07 | -0.10 | -0.07 |
| | | | (0.011)** | (0.021)** | (0.010)** |
| | Undetermined | | -0.15 | -0.16 | -0.15 |
| | | | (0.011)** | (0.020)** | (0.009)** |
| Payment for surplus electricity | Fixed: 8 cent/kWh | (baseline) | | | |
| | Variable: 6 - 10 cent/kWh | | -0.01 | -0.01 | -0.01 |
| | | | (0.01) | (0.02) | (0.01) |
| | Variable: 4 - 12 cent/kWh | | -0.02 | -0.02 | -0.02 |
| | | | (0.01) | (0.02) | (0.01) |
| | Variable: 0 - 16 cent/kWh | | -0.06 | -0.01 | -0.05 |
| | | | (0.011)** | (0.02) | (0.010)** |
| Investment cost | CHF 15,000 | (baseline) | | | |
| | CHF 20,000 | | -0.02 | -0.06 | -0.03 |
| | | | (0.01) | (0.022)* | (0.011)* |
| | CHF 25,000 | | -0.09 | -0.13 | -0.10 |
| | | | (0.012)** | (0.021)** | (0.010)** |
| | CHF 30,000 | | -0.14 | -0.19 | -0.15 |
| | | | (0.012)** | (0.023)** | (0.010)** |
| Investment grant | 10 % | (baseline) | | | |
| | 20 % | | 0.13 | 0.09 | 0.12 |
| | | | (0.015)** | (0.028)** | (0.013)** |
| | 30 % | | 0.21 | 0.17 | 0.20 |
| | | | (0.015)** | (0.031)** | (0.013)** |
| | 40 % | | 0.31 | 0.24 | 0.29 |
| | | | (0.015)** | (0.030)** | (0.014)** |
| Self-consumption | 25 % | (baseline) | | | |
| | 50 % | | 0.28 | 0.20 | 0.26 |
| | | | (0.020)** | (0.037)** | (0.017)** |
| | 75 % | | 0.51 | 0.41 | 0.49 |
| | | | (0.017)** | (0.035)** | (0.015)** |
| | 100 % | | 0.66 | 0.56 | 0.64 |
| | | | (0.014)** | (0.033)** | (0.013)** |
| | Treatment | | -0.01 | -0.07 | -0.025 |
| | | | (0.013) | (0.035)* | (0.012)* |
| | Choice tasks | | 4296 | 976 | 5272 |
| | Respondents | | 537 | 122 | 659 |
| | Controls | | YES | YES | YES |

Heteroskedasticity-consistent standard errors in parentheses. All models without case-specific constant term. Estimates report the marginal effects (at means) from alternative-specific conditional logit model. Dependent variable is the probability to invest in solar PV system. High intertemporal discount rate refers to individuals with a time preference score equal to 1, 2, 3 or 4. Low intertemporal discount rate refers to individuals with a time preference score equal to 5, 6, 7 or 8. Time preference score goes from 1 to 8, the higher the lower the individual intertemporal discount rate (i.e. the more patient the individual is). See Table S1 for more details.
*** p<0.01, ** p<0.05, * p<0.1.

## Table A4. Choice experiment: estimated marginal effects from conditional logit model (showing all control variables)

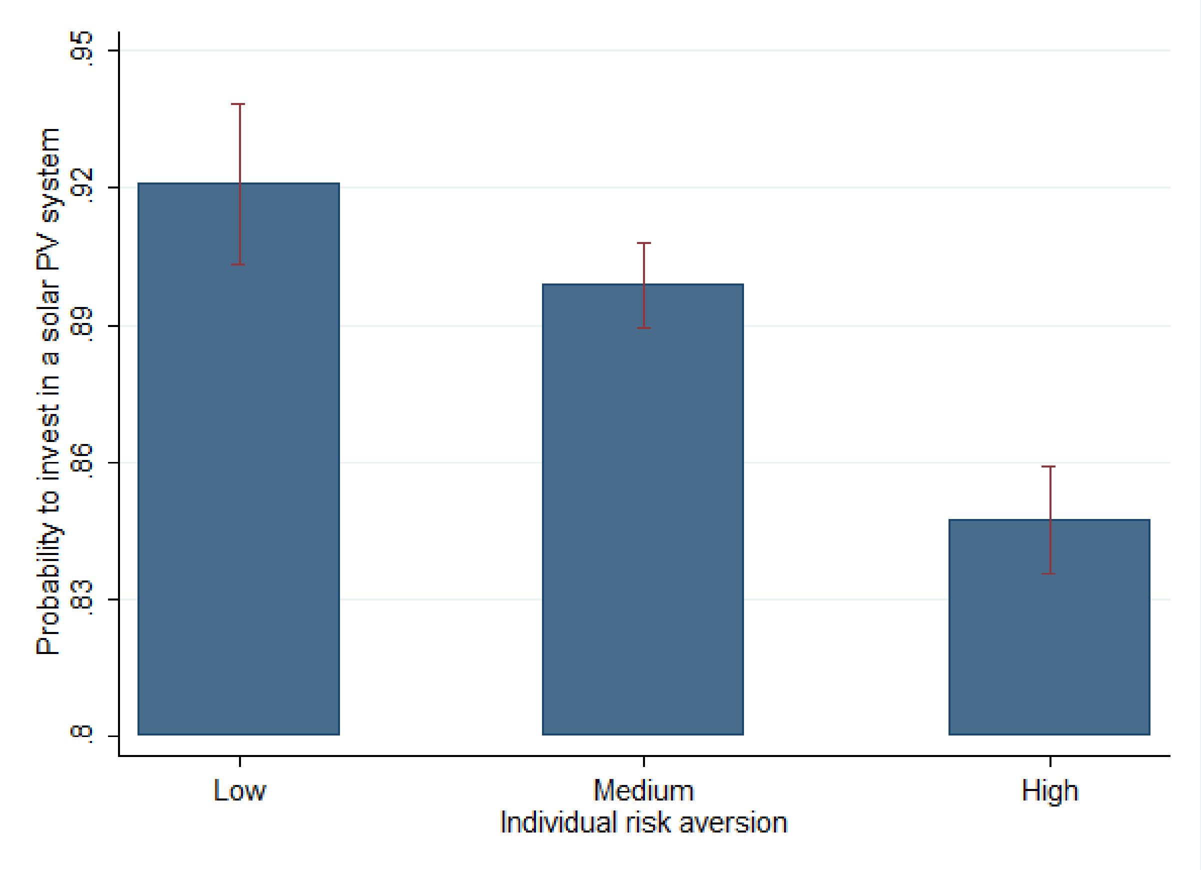
| | | | With controls | With controls, IV approach | With controls, time preferences | With controls, time preferences, IV approach | With controls, time preferences, and treatment/risk preference interaction | With controls, time preferences, and treatment/risk preference interaction, IV approach |
|---|---|---|---|---|---|---|---|---|
| Waiting time | Immediate | (baseline) | | | | | | |
| | <1 year | | -0.02 | -0.02 | -0.03 | -0.02 | -0.02 | -0.02 |
| | | | (0.010)* | (0.010)* | (0.010)* | (0.010)* | (0.010)* | (0.01) |
| | 1-2 year | | -0.07 | -0.07 | -0.08 | -0.07 | -0.07 | -0.07 |
| | | | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** |
| | Undetermined | | -0.15 | -0.15 | -0.15 | -0.15 | -0.15 | -0.15 |
| | | | (0.009)** | (0.009)** | (0.009)** | (0.010)** | (0.010)** | (0.010)** |
| Payment for surplus electricity | Fixed: 8 cent/kWh | (baseline) | | | | | | |
| | Variable: 6 - 10 cent/kWh | | -0.01 | -0.01 | -0.02 | -0.01 | -0.02 | -0.01 |
| | | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| | Variable: 4 - 12 cent/kWh | | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 |
| | | | (0.01) | (0.01) | (0.010)* | (0.01) | (0.010)* | (0.01) |
| | Variable: 0 - 16 cent/kWh | | -0.05 | -0.05 | -0.05 | -0.05 | -0.05 | -0.05 |
| | | | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** |
| Investment cost | CHF 15,000 | (baseline) | | | | | | |
| | CHF 20,000 | | -0.03 | -0.02 | -0.03 | -0.02 | -0.03 | -0.02 |
| | | | (0.011)* | (0.011)* | (0.011)** | (0.011)* | (0.011)** | (0.011)* |
| | CHF 25,000 | | -0.10 | -0.09 | -0.10 | -0.09 | -0.10 | -0.09 |
| | | | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** |
| | CHF 30,000 | | -0.15 | -0.15 | -0.16 | -0.15 | -0.16 | -0.15 |
| | | | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** | (0.010)** |
| Investment grant | 10 % | (baseline) | | | | | | |
| | 20 % | | 0.12 | 0.13 | 0.12 | 0.13 | 0.12 | 0.13 |
| | | | (0.013)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 30 % | 0.20 | 0.21 | 0.20 | 0.21 | 0.20 | 0.21 |
| | | (0.013)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** |
| | 40 % | 0.29 | 0.30 | 0.29 | 0.30 | 0.29 | 0.30 |
| | | (0.014)** | (0.014)** | (0.013)** | (0.014)** | (0.014)** | (0.014)** |
| Self-consumption | 25 % (baseline) | | | | | | |
| | 50 % | 0.26 | 0.27 | 0.26 | 0.27 | 0.26 | 0.27 |
| | | (0.017)** | (0.018)** | (0.017)** | (0.018)** | (0.017)** | (0.018)** |
| | 75 % | 0.49 | 0.50 | 0.48 | 0.50 | 0.48 | 0.50 |
| | | (0.015)** | (0.016)** | (0.015)** | (0.016)** | (0.015)** | (0.016)** |
| | 100 % | 0.64 | 0.65 | 0.64 | 0.65 | 0.64 | 0.65 |
| | | (0.013)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** | (0.013)** |
| Treatment | | -0.025 | | -0.027 | | 0.01 | |
| | | (0.012)* | | (0.012)* | | (0.02) | |
| Interaction between policy risk and treatment | | | -0.07 | | -0.14 | | -0.11 |
| | | | (0.016)** | | (0.019)** | | (0.020)** |
| Time preferences | | | | 0.03 | 0.04 | 0.02 | 0.03 |
| | | | | (0.004)** | (0.004)** | (0.004)** | (0.004)** |
| | | | | | | -0.05 | |
| Treatment and high risk aversion | | | | | | -0.05 | |
| | | | | | | (0.021)* | |
| Interaction between policy risk, treatment and high risk aversion | | | | | | | -0.02 |
| | | | | | | | (0.006)** |
| Household income | | 0.02 | 0.03 | 0.01 | 0.03 | 0.01 | 0.03 |
| | | (0.005)** | (0.006)** | (0.01) | (0.005)** | (0.01) | (0.005)** |
| Households assets | | 0.006 | 0.004 | 0.003 | -0.002 | 0.002 | -0.004 |
| | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Age | | -0.002 | -0.001 | -0.003 | -0.001 | -0.003 | -0.001 |
| | | (0.000)** | (0.000)** | (0.000)** | (0.000)** | (0.000)** | (0.000)** |
| University degree | | -0.02 | -0.01 | -0.02 | -0.02 | -0.02 | -0.02 |
| | | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Female | | -0.04 | -0.02 | -0.04 | -0.02 | -0.04 | -0.02 |
| | | (0.012)** | (0.01) | (0.012)** | (0.01) | (0.012)** | (0.01) |
| German-speaking region | | -0.01 | 0.00 | -0.03 | -0.02 | -0.03 | -0.01 |
| | | (0.01) | (0.01) | (0.013)* | (0.01) | (0.013)* | (0.01) |
| Environmental preferences | | -0.03 | -0.02 | -0.02 | -0.01 | -0.02 | -0.01 |
| | | (0.007)** | (0.008)* | (0.007)** | (0.01) | (0.007)** | (0.01) |
| "Techie" | | 0.04 | 0.04 | 0.03 | 0.04 | 0.03 | 0.04 |
| | | (0.015)* | (0.015)** | (0.015)* | (0.015)** | (0.02) | (0.015)* |
| Right-wing voter | | -0.03 | -0.03 | -0.03 | -0.03 | -0.03 | -0.03 |
| | | (0.012)* | (0.012)* | (0.012)* | (0.012)* | (0.012)* | (0.012)* |
| Does not have solar peers | | -0.03 | -0.03 | -0.04 | -0.04 | -0.04 | -0.04 |
| | | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Choice tasks | | 5272 | 5272 | 5272 | 5272 | 5272 | 5272 |
| Respondents | | 659 | 659 | 659 | 659 | 659 | 659 |
| Controls | | YES | YES | YES | YES | YES | YES |

Heteroskedasticity-consistent standard errors in parentheses. All models without case-specific constant term. Estimates report the marginal effects (at means) from alternative-specific conditional logit model. Dependent variable is the probability to invest in solar PV system.

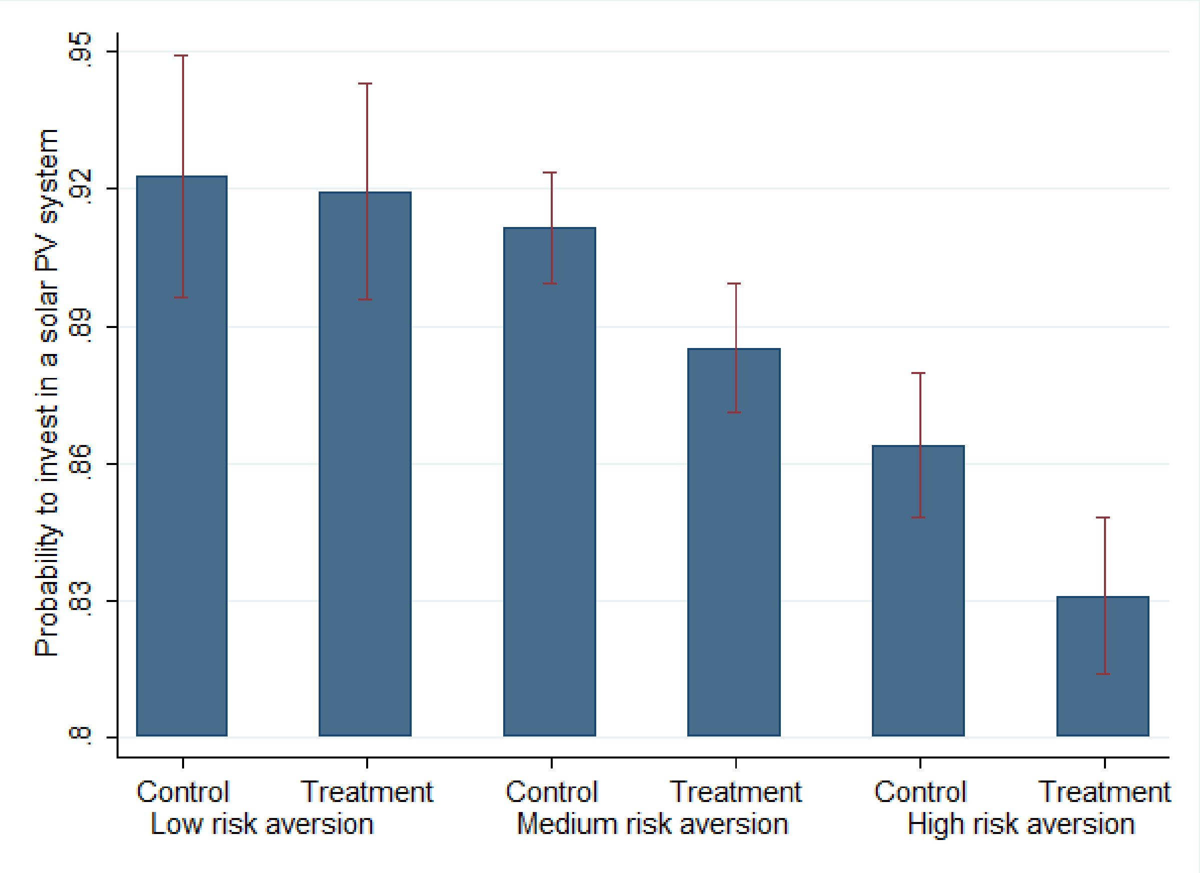
*** p<0.01, ** p<0.05, * p<0.1.

**Figure A1. Probability to invest in a solar PV system, by individual risk aversion (3 categories)**



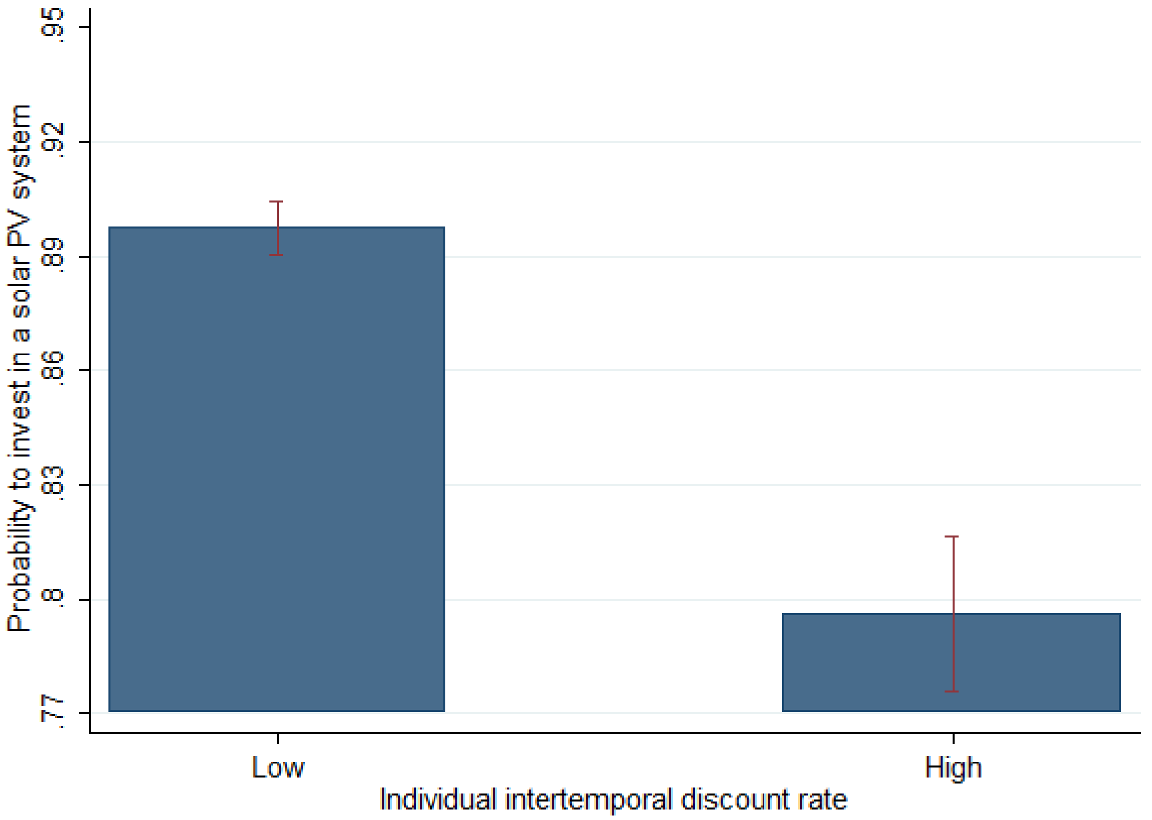

Probability to invest in a solar PV system is the frequency of not choosing the opt-out option ("NONE: I would not choose any of these options") in the choice task. Whiskers represent 90 percent confidence intervals. Low risk aversion indicates individuals with a risk preference score equal to 6, 7, or 8; medium risk aversion indicates individuals with a risk preference score equal to 4 or 5; high risk aversion indicates individuals with a risk preference score equal to 1, 2, or 3. Risk preference score goes from 1 to 8, the higher the lower the risk aversion.

**Figure A2. Probability to invest in a solar PV system, by individual risk aversion (3 categories) and experimental group**



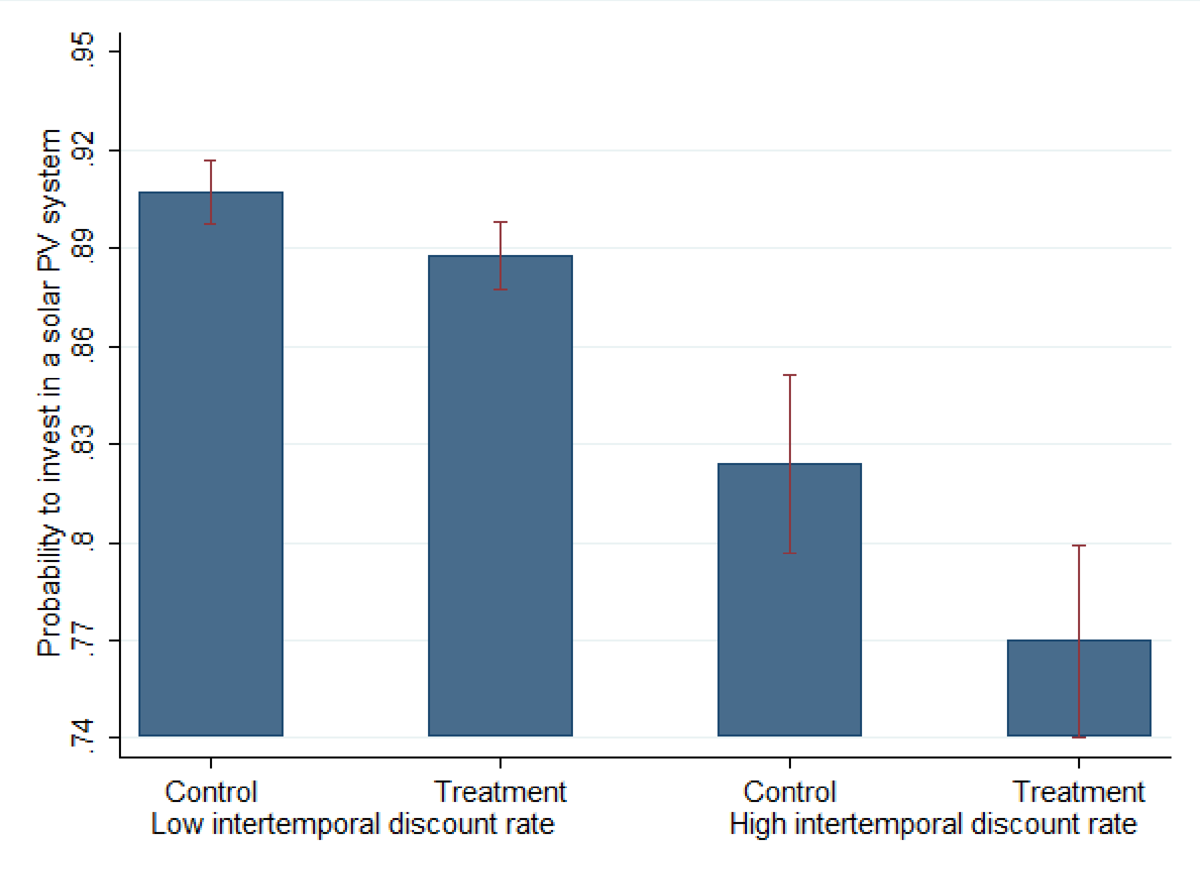

Probability to invest in a solar PV system is the frequency of NOT choosing the opt-out option ("NONE: I would not choose any of these options") in the choice task. Whiskers represent 90 percent confidence intervals. Estimates in the figure are comparable to intention-to-treat estimations. Low risk aversion indicates individuals with a risk preference score equal to 6, 7, or 8; medium risk aversion indicates individuals with a risk preference score equal to 4 or 5; high risk aversion indicates individuals with a risk preference score equal to 1, 2, or 3. Risk preference score goes from 1 to 8, the higher the lower the risk aversion.

**Figure A3. Probability to invest in a solar PV system, by individual intertemporal discount rate (2 categories)**



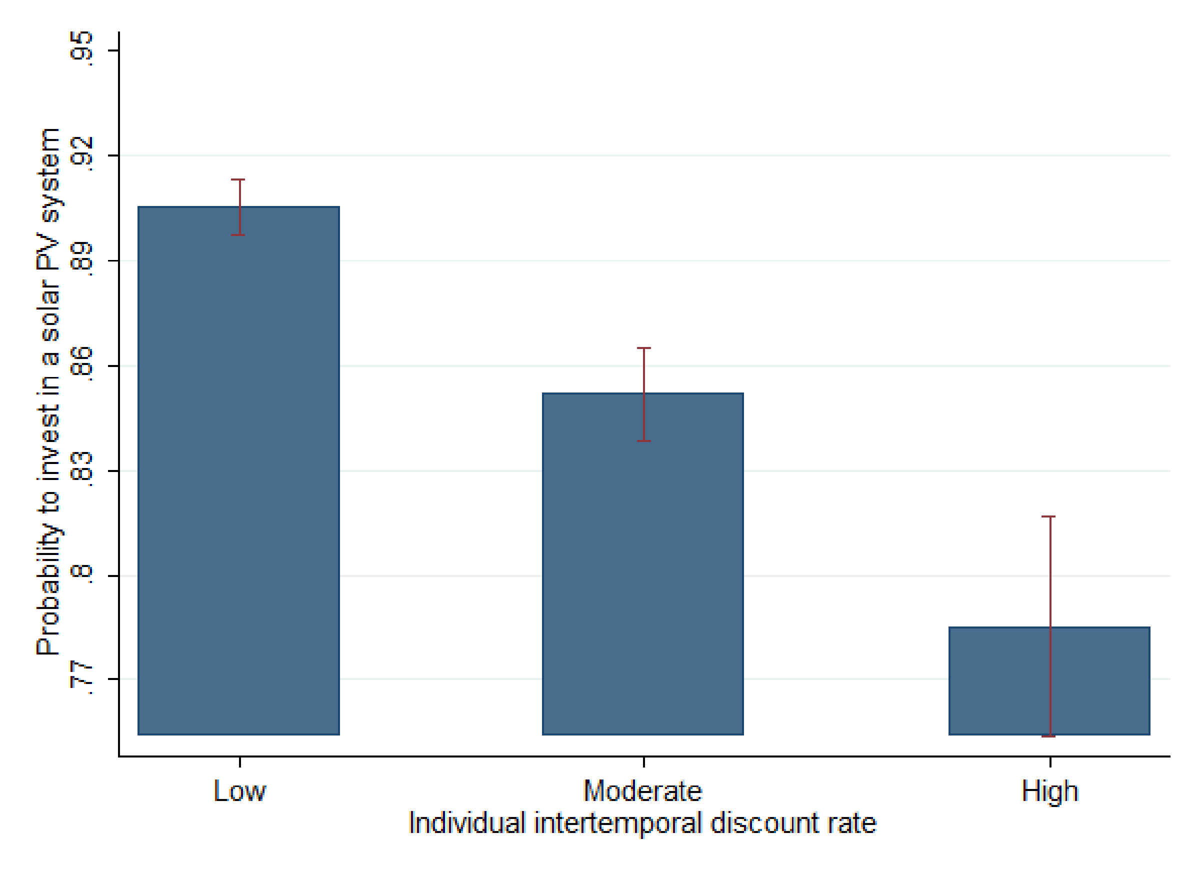

Probability to invest in a solar PV system is the frequency of not choosing the opt-out option ("NONE: I would not choose any of these options") in the choice task. Whiskers represent 90 percent confidence intervals. High intertemporal discount rate indicates individuals with a time preference score equal to 1, 2, 3 or 4; low intertemporal discount rate indicates individuals with a time preference score equal to 5, 6, 7, or 8. Time preference score goes from 1 to 8, the higher the lower the individual intertemporal discount rate (i.e. the more patient the individual is).

**Figure A4. Probability to invest in a solar PV system, by individual intertemporal discount rate (2 categories) and experimental group**



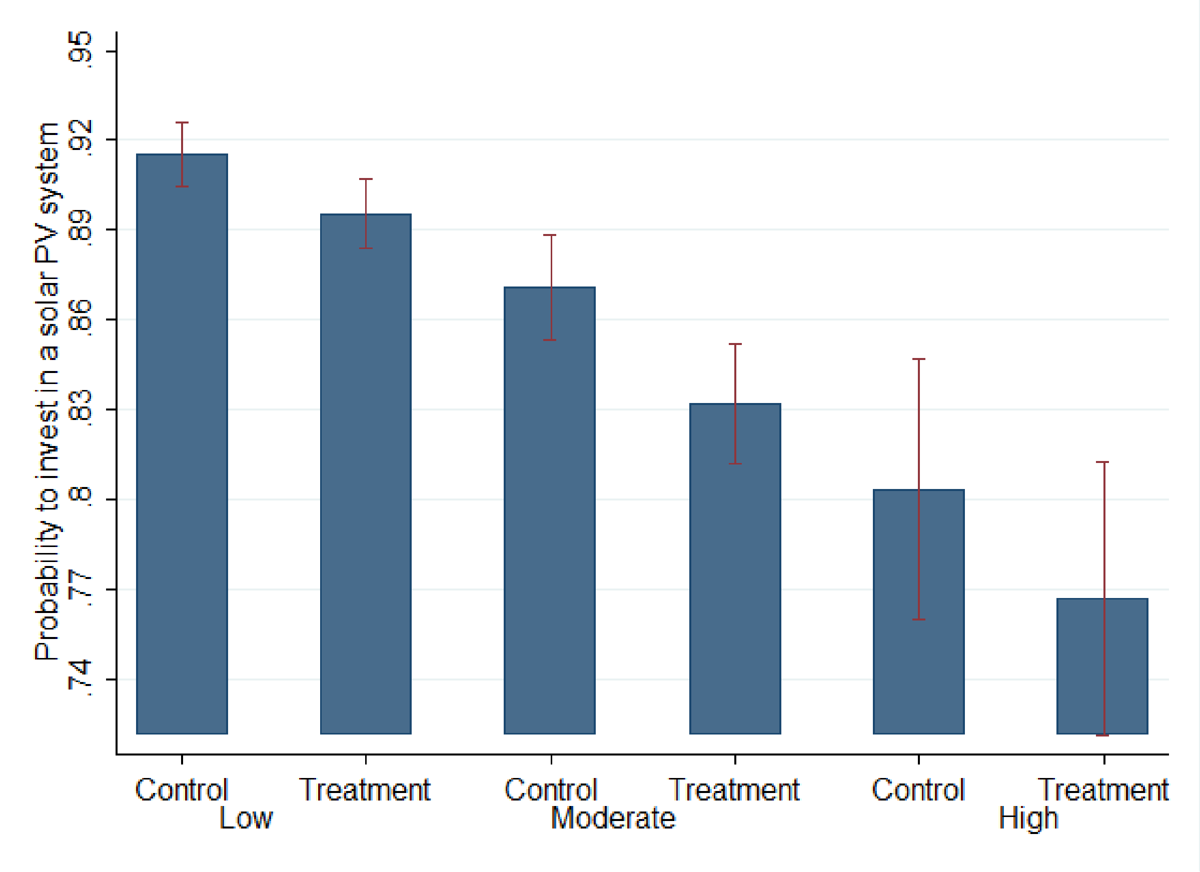

Probability to invest in a solar PV system is the frequency of NOT choosing the opt-out option ("NONE: I would not choose any of these options") in the choice task. Whiskers represent 90 percent confidence intervals. Estimates in the figure are comparable to intention-to-treat estimates. High intertemporal discount rate indicates individuals with a time preference score equal to 1, 2, 3 or 4; low intertemporal discount rate indicates individuals with a time preference score equal to 5, 6, 7, or 8. Time preference score goes from 1 to 8, the higher the lower the individual intertemporal discount rate (i.e. the more patient the individual is).

**Figure A5. Probability to invest in a solar PV system, by individual intertemporal discount rate (3 categories)**



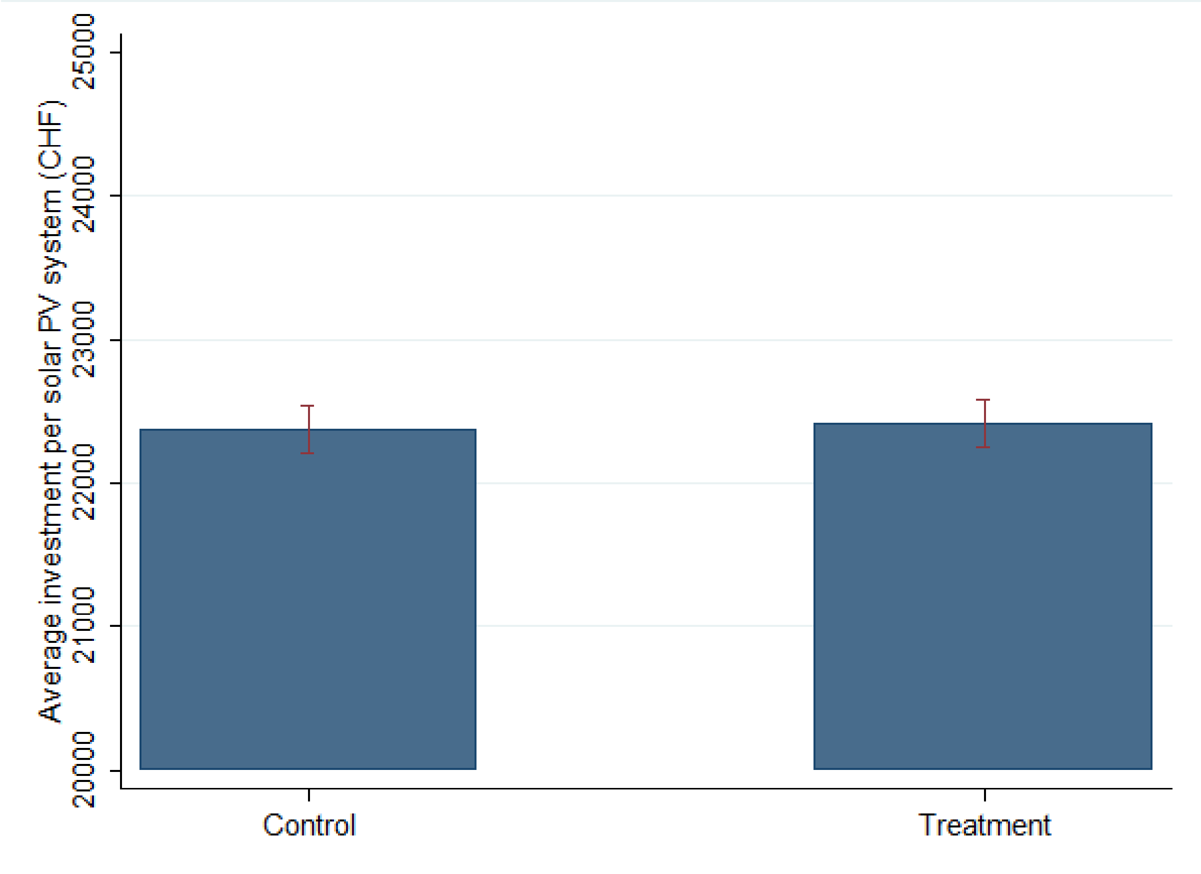

Probability to invest in a solar PV system is the frequency of NOT choosing the opt-out option ("NONE: I would not choose any of these options") in the choice task. Whiskers represent 90 percent confidence intervals. High intertemporal discount rate indicates individuals with a time preference score equal to 1, 2, 3 or 4; low intertemporal discount rate indicates individuals with a time preference score equal to 5, 6, 7, or 8. Time preference score goes from 1 to 8, the higher the lower the individual intertemporal discount rate (i.e. the more patient the individual is).

**Figure A6. Probability to invest in a solar PV system, by individual intertemporal discount rate (3 categories) and experimental group**



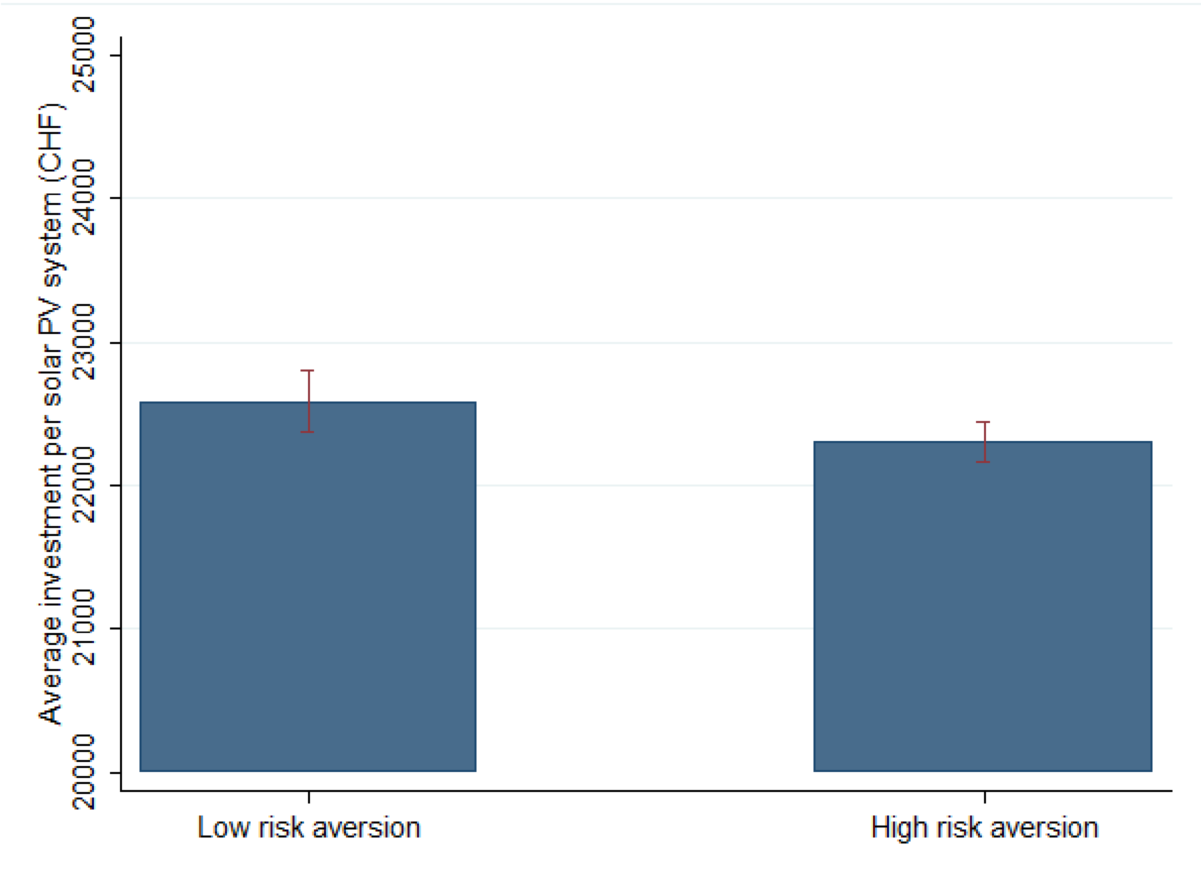

Probability to invest in a solar PV system is the frequency of NOT choosing the opt-out option ("NONE: I would not choose any of these options") in the choice task. Whiskers represent 90 percent confidence intervals. Estimates in the figure are comparable to intention-to-treat estimates. High intertemporal discount rate indicates individuals with a time preference score equal to 1, 2, 3 or 4; low intertemporal discount rate indicates individuals with a time preference score equal to 5, 6, 7, or 8. Time preference score goes from 1 to 8, the higher the lower the individual intertemporal discount rate (i.e. the more patient the individual is).

**Figure A7. Average investment per solar PV system, by experimental group**



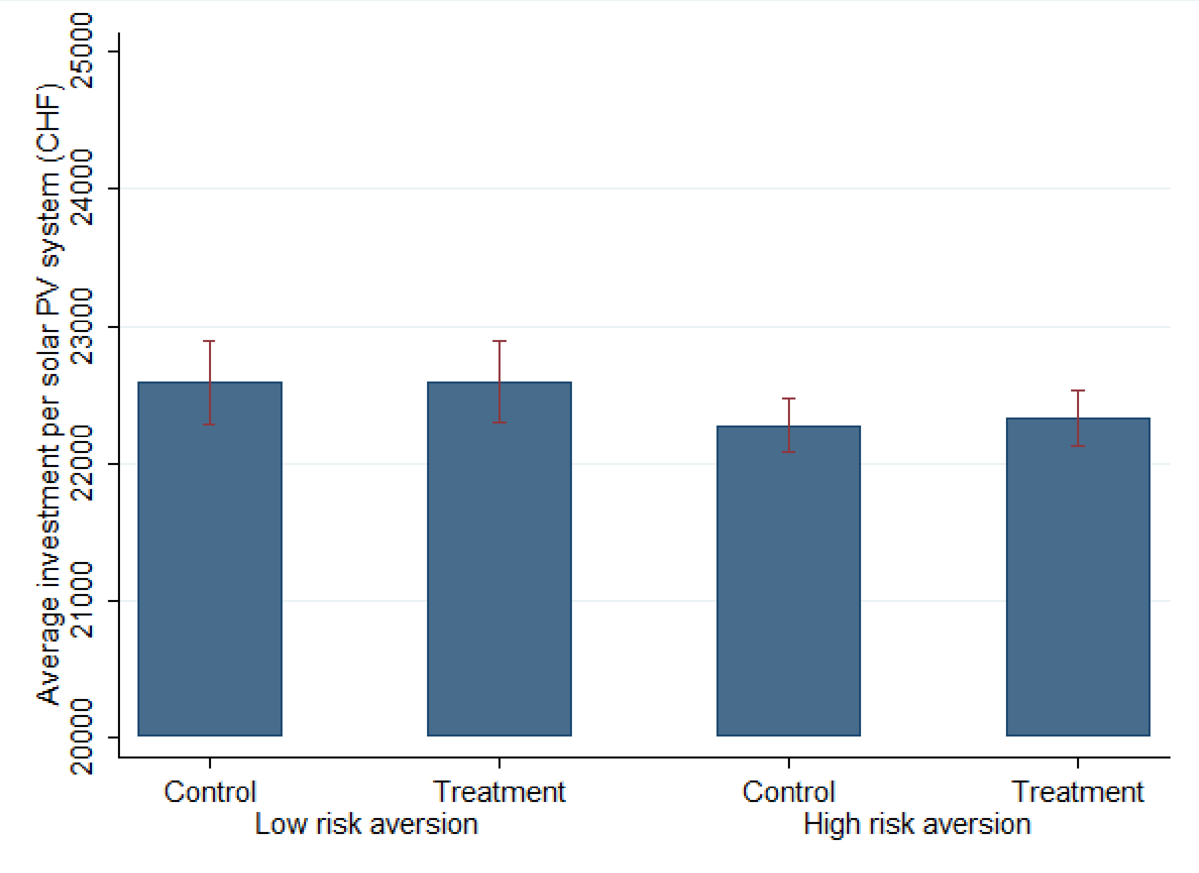

Whiskers represent 90 percent confidence intervals.

**Figure A8. Average investment per solar PV system, by individual risk aversion (2 categories)**



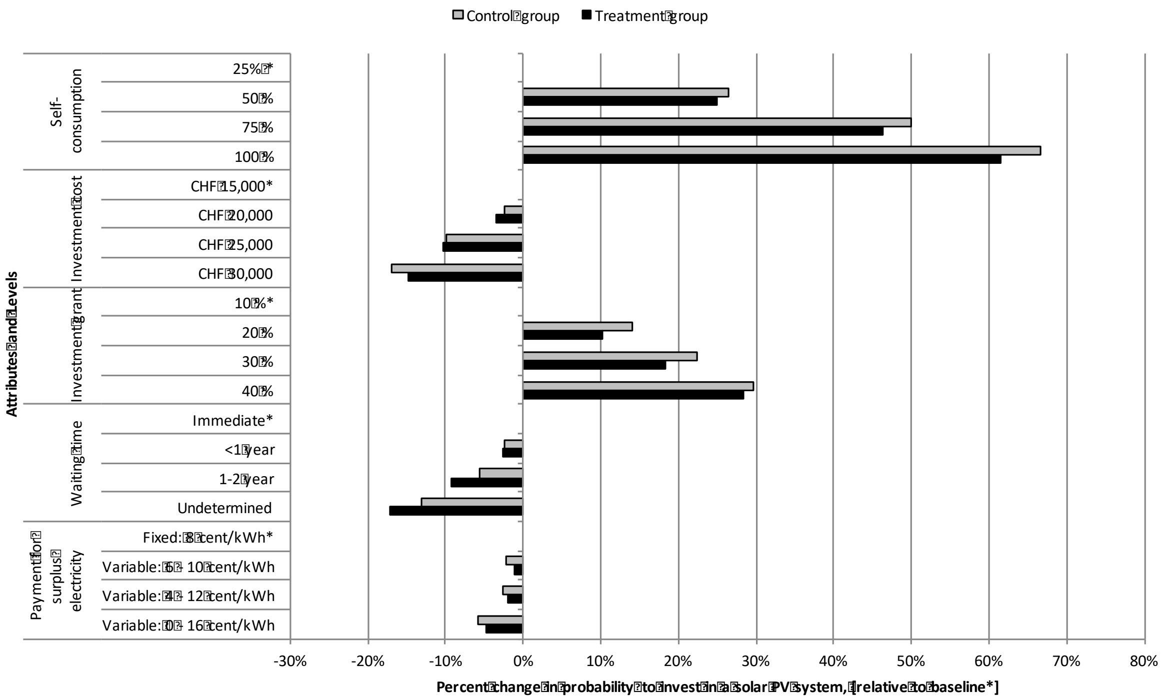

Whiskers represent 90 percent confidence intervals.

**Figure A9. Average investment per solar PV system, by individual risk aversion (2 categories) and experimental group**




Whiskers represent 90 percent confidence intervals.

**Figure A10. Impact of policy risk salience on the probability to invest in a solar PV system**




Estimates report the marginal effects (at means) from alternative-specific conditional logit model. Dependent variable is the probability to invest in solar PV system. Estimates in the figure are comparable to intention-to-treat estimates.

## Annex I Selection of attributes and levels

Attributes were limited to 5, in order to avoid cognitive overload for respondents. We selected attributes and levels after reviewing existing choice experiment studies analyzing other research questions on the purchase of residential solar PV systems (Islam 2014; Bao et al. 2017; Hille, Curtius, and Wüstenhagen 2018) and based on 10 semi-structured interviews conducted between July and October 2018 with solar PV experts, Swiss households who adopted solar, and solar PV installers. The resulting set of attributes and levels was pre-tested in a small pilot study with 30 Swiss homeowners declaring to be interested in installing solar PV systems in the next 5 years. The choice of each attribute and corresponding levels is discussed below.

**Investment cost.** This monetary attribute is the upfront total investment cost of the solar PV system including installation and grid connection and excluding any investment grant. Its levels reflect the observed price range for residential solar PV systems in Switzerland. In particular, according to the interviews with solar PV installers, in 2018 most residential installations are of 7-8 kW and the typical system cost was around CHF 20,000. Deviations from this amount are typically driven by the choice of installer, origin of modules, modules' color and type (building-integrated or building attached).

**Self-consumption.** This attribute states what share of the household's annual electricity consumption the PV solar system can cover on average. Based on interviews and the literature (Balcombe et al. 2014, Palm 2018), the possibility to produce own energy and be independent of incumbent utilities is something that may matter to many households. The attribute levels were linearly increased starting from an estimate of the standard yearly average level that a Swiss household can reach without self-consumption optimization, which is 25 %. Higher levels would be made possible by the so-called self-consumption optimization solutions (EnergieSchweiz 2017), ranging from: solutions that run electric appliances (e.g. heat pump, washing machine, tumble drier, dishwasher) according to when solar is produced; a combined solar-storage system; a solar system coupled with an electric vehicle domestic charging station; virtual storage (also known as "storage on the grid"). This attribute is typically strongly positively correlated with expected cost energy savings, even if regulation could substantially weaken this correlation.[11] In our design we ruled out the combination between the highest self-consumption level (100 %) and the lowest system cost's level (CHF 15,000). The constraint was introduced to rule out a combination that looked quite unrealistic, even in a 5-year horizon according to the literature review and the expert interviews.

[11] On-bill savings also depend on how grid fees are charged to prosumers and on the pricing of retail electricity, i.e. fix versus volumetric (Kubli 2018). For instance, energy cost savings would be null in a scenario, where, similarly to the telcom industry, electricity customers pay a fixed "all-you-can-eat" monthly amount for withdrawing electricity from the grid and residential solar PV producers do not go off-grid.

**Payment for surplus electricity.** In the choice experiment, the electricity-price driven risk is reflected in the attribute “payment for surplus electricity”, which features the following levels: fixed payment: 8 cents/kWh; variable payment: ranging from 6 to 10 cent/kWh, depending on electricity market price; variable payment: ranging from 4 to 12 cent/kWh, depending on electricity market price; variable payment: ranging from 0 to 16 cent/kWh, depending on electricity market price. The levels of this attribute have the same “certainty equivalent” (i.e. the same average value, assuming a normal probability distribution for the electricity market price) but different variability (in terms of min-max range). We assume that higher variability is associated with higher perceived market risk.

**Investment grant.** This attribute describes the share of the total investment cost reimbursed by the federal government, paid after the system is commissioned and possibly after a time lag, as detailed in the attribute “waiting time for investment grant”. The choice of simulating an investment subsidy, rather than a production subsidy (e.g. feed-in tariff), is consistent with the current policy environment in many developed countries, Switzerland included.

**Waiting time for investment grant.** In the choice experiment, the policy-driven risk is reflected by a longer waiting time for receiving the investment grant, which features the following levels: no waiting time (immediate reimbursement); shorter than 1 year; 1-2 years; undetermined. Such levels appeared realistic for Switzerland and are consistent with policy designs in many other developed countries.

## Annex II Questionnaire (translated into English)

Institute for Economy
and the Environment

University of St.Gallen

### Thank you for your participation.

This survey is part of a research project carried out by the University of St.Gallen in cooperation with the Swiss Federal Office of Energy.

This survey will take about 15 minutes of your time.

Your responses will remain anonymous, treated confidentially and used for research purposes only. For any questions, you could send an email to : energie@unisg.ch

Have you ever seen a house with a photovoltaic solar system* in your neighborhood?

- Yes
- Yes, I have installed a solar photovoltaic system on my house
- No

* A solar photovoltaic (PV) system generates electricity from sun’s energy

Houses with a solar PV system @ CC BY 2.0 Vicent Li ©IWÖ-HSG Luca Schmid

0% 100%

Would you consider installing a solar PV system in the next 5 years?

Please consider that the cost range for a typical solar PV system for a residential house in Switzerland is 15 000-30 000 CHF*.

- Yes
- Maybe
- No

* depending on capacity, preferred features, installer etc

0% 100%

**Please imagine you are considering purchasing a solar photovoltaic (PV) system for your house.**

Solar PV systems generate electricity from the sun's energy.

By purchasing a solar PV system for your house, you pay once and you will produce your own electricity for about 20 years.

You will use the electricity you produce for your needs, you will **buy less electricity from the grid**
and can save money on your future energy bills.

When your production is not sufficient to cover your consumption, you will buy electricity from the grid. When you produce more electricity than you need, surplus electricity will go directly into the grid and you will receive a **payment for the electricity you send to the grid**.

Even when your average yearly self-consumption is less than 100%, you will be able to sell electricity to the grid, e.g. on a sunny summer day.

0% 100%

**IMPORTANT:** Since 2008, the Swiss Federal Government has been supporting solar PV systems through **monetary incentives**.

Until 2018 the Government offered the owners of solar PV systems a fixed monetary amount (“feed- in tariff”) for each kWh fed into the grid by their solar systems to be paid for 20 years.

With the new energy law, starting from January 2018 owners of small solar PV systems receive instead a **one-off investment grant** (“investment grant”) that covers a share of the system cost.

The investment grant is paid after the system is commissioned. The **waiting time** for the payment may exceed two years.

Note that if rules about incentives for solar PV systems change while one is still in the waiting list, the new rules may apply. For instance, under the previous support scheme, the promised amount of support was reduced for PV project owners who entered the waiting list after 2012, due to a change in the law.

Recently, concerns have arisen about limited financial resources for the support of solar PV systems resulting in continuously growing waiting times for receiving the monetary support, as you can read in the newspaper article below.

Energie

# Jahrelange Wartezeit für Subventionen des Bundes für Solaranlagen

09:55 Uhr 04.12.2017 00:50 Uhr 05.10.2018

**Wer von einer Einmalvergütung des Bundes für eine Solaranlage profitieren will, muss künftig statt Monate Jahre auf das Geld warten. Die Wartefristen für kleine Anlagen steigen laut BFE auf mindestens zweieinhalb Jahre, für grosse Anlagen gar auf sechs Jahre.**

Es würden viel mehr Anlagen und auch grössere Anlagen von der Einmalvergütung profitieren können. Deshalb müsse man mit längeren Wartezeiten für die Auszahlung rechnen, erklärte Sabine Hirsbrunner, Sprecherin des Bundesamts für Energie (BFE), am Montag in der Sendung «Heute Morgen» von Schweizer Radio SRF.

Die längeren Wartezeiten sind die Folge der neuen Energiestrategie. Diese hatte das Volk im Mai mit 58 Prozent Ja-Stimmenanteil angenommen. Diese sorgt dafür, dass insgesamt mehr Fördermittel zur Verfügung stehen. Diese reichen aber nicht aus, um die Warteliste vollständig abzubauen.

**<u>IMPORTANT:</u>** Since 2008, the Swiss Federal Government has been supporting solar PV systems through **monetary incentives**.

Until 2018 the Government offered the owners of solar PV systems a fixed monetary amount (“feed- in tariff”) for each kWh fed into the grid by their solar systems to be paid for 20 years.

With the new energy law, starting from January 2018 owners of small solar PV systems receive instead a **one-off investment grant** (“investment grant”) that covers a share of the system cost.

The investment grant is paid <u>after</u> the system is commissioned. The **waiting time** for the payment may exceed two years.

0% 100%

In the next section, we'll be asking you to choose among a number of offers for a **solar PV system for your house**. Please assume that all the proposed solar PV systems can be installed on your house as it is.

**IMPORTANT**: **answer in the way you would if you were actually taking a REAL spending decision**, consistent with your budget constraint: the amount you spend for the PV system will not be available to you for other expenditures!

If you wouldn't purchase any of the offers shown, you can indicate that by choosing "None".

0% 100%

**If these were your only options, which of the following offers for a solar PV system for your house would you choose?**
Choose by clicking one of the buttons below:

**IMPORTANT:** For additional information please scroll with the mouse over the corresponding property of the product (left column, bold text)

(1 of 8)

| | | | | |
|---|---|---|---|---|
| **Investment cost** | 30 000 CHF | 20 000 CHF | 25 000 CHF | NONE: I wouldn't choose any of these. |
| **Own consumption** | Your production covers **50%** of your yearly consumption | Your production covers **100%** of your yearly consumption | Your production covers **75%** of your yearly consumption | |
| **Payment for surplus electricity** | Variable payment: ranging from 6 to 10 cent/kWh | Fixed payment: 8 cent/kWh | Variable payment: ranging from 0 to 16 cent/kWh | |
| **Investment grant** | The federal government will reimburse you **30%** of the price | The federal government will reimburse you **20%** of the price | The federal government will reimburse you **40%** of the price | |
| **Waiting time for investment grant** | Between 1 and 2 years | Shorter than 1 year | No waiting time (immediate payment) | |
| | ○ | ○ | ○ | ○ |

0% 100%

**If these were your only options, which of the following offers for a solar PV system for your house would you choose?**
Choose by clicking one of the buttons below:

**IMPORTANT:** For additional information please scroll with the mouse over the corresponding property of the product (left column, bold text)

(2 of 8)

| | | | | |
|---|---|---|---|---|
| **Investment cost** | CHF 15 000 | 30 000 CHF | 20 000 CHF | NONE: I wouldn't choose any of these. |
| **Own consumption** | Your production covers **25%** of your yearly consumption | Your production covers **25%** of your yearly consumption | Your production covers **75%** of your yearly consumption | |
| **Payment for surplus electricity** | Fixed payment: 8 cent/kWh | Variable payment: ranging from 4 to 12 cent/kWh | Variable payment: ranging from 4 to 12 cent/kWh | |
| **Investment grant** | The federal government will reimburse you **10%** of the price | The federal government will reimburse you **20%** of the price | The federal government will reimburse you **40%** of the price | |
| **Waiting time for investment grant** | No waiting time (immediate payment) | Undetermined | Between 1 and 2 years | |
| | ○ | ○ | ○ | ○ |

0% 100%

**If these were your only options, which of the following offers for a solar PV system for your house would you choose?**
Choose by clicking one of the buttons below:

**IMPORTANT:** For additional information please scroll with the mouse over the corresponding property of the product (left column, bold text)

(3 of 8)

| | | | | |
|---|---|---|---|---|
| **Investment cost** | 30 000 CHF | CHF 15 000 | 25 000 CHF | NONE: I wouldn't choose any of these. |
| **Own consumption** | Your production covers **100%** of your yearly consumption | Your production covers **75%** of your yearly consumption | Your production covers **25%** of your yearly consumption | |
| **Payment for surplus electricity** | Variable payment: ranging from 4 to 12 cent/kWh | Variable payment: ranging from 0 to 16 cent/kWh | Variable payment: ranging from 6 to 10 cent/kWh | |
| **Investment grant** | The federal government will reimburse you **30%** of the price | The federal government will reimburse you **10%** of the price | The federal government will reimburse you **10%** of the price | |
| **Waiting time for investment grant** | Shorter than 1 year | Undetermined | Shorter than 1 year | |
| | ○ | ○ | ○ | ○ |

0% 100%

**If these were your only options, which of the following offers for a solar PV system for your house would you choose?**
Choose by clicking one of the buttons below:

**IMPORTANT:** For additional information please scroll with the mouse over the corresponding property of the product (left column, bold text)

(4 of 8)

| | | | | |
|---|---|---|---|---|
| **Investment cost** | CHF 15 000 | 20 000 CHF | 25 000 CHF | |
| **Own consumption** | Your production covers **50%** of your yearly consumption | Your production covers **25%** of your yearly consumption | Your production covers **50%** of your yearly consumption | |
| **Payment for surplus electricity** | Variable payment: ranging from 4 to 12 cent/kWh | Variable payment: ranging from 6 to 10 cent/kWh | Fixed payment: 8 cent/kWh | NONE: I wouldn't choose any of these. |
| **Investment grant** | The federal government will reimburse you **40%** of the price | The federal government will reimburse you **20%** of the price | The federal government will reimburse you **30%** of the price | |
| **Waiting time for investment grant** | No waiting time (immediate payment) | Between 1 and 2 years | Undetermined | |
| | | | | |

0% 100%

**If these were your only options, which of the following offers for a solar PV system for your house would you choose?**
Choose by clicking one of the buttons below:

**IMPORTANT:** For additional information please scroll with the mouse over the corresponding property of the product (left column, bold text)

(5 of 8)

| | | | | |
|---|---|---|---|---|
| **Investment cost** | 30 000 CHF | 25 000 CHF | 20 000 CHF | NONE: I wouldn't choose any of these. |
| **Own consumption** | Your production covers **50%** of your yearly consumption | Your production covers **75%** of your yearly consumption | Your production covers **100%** of your yearly consumption | |
| **Payment for surplus electricity** | Variable payment: ranging from 0 to 16 cent/kWh | Variable payment: ranging from 6 to 10 cent/kWh | Variable payment: ranging from 0 to 16 cent/kWh | |
| **Investment grant** | The federal government will reimburse you **40%** of the price | The federal government will reimburse you **20%** of the price | The federal government will reimburse you **30%** of the price | |
| **Waiting time for investment grant** | Shorter than 1 year | Undetermined | No waiting time (immediate payment) | |
| | ○ | ○ | ○ | ○ |

0% 100%

**If these were your only options, which of the following offers for a solar PV system for your house would you choose?**
Choose by clicking one of the buttons below:

**IMPORTANT:** For additional information please scroll with the mouse over the corresponding property of the product (left column, bold text)

(6 of 8)

| | | | | |
|---|---|---|---|---|
| **Investment cost** | 30 000 CHF | CHF 15 000 | 20 000 CHF | NONE: I wouldn't choose any of these. |
| **Own consumption** | Your production covers **75%** of your yearly consumption | Your production covers **25%** of your yearly consumption | Your production covers **100%** of your yearly consumption | |
| **Payment for surplus electricity** | Fixed payment: 8 cent/kWh | Fixed payment: 8 cent/kWh | Variable payment: ranging from 4 to 12 cent/kWh | |
| **Investment grant** | The federal government will reimburse you **30%** of the price | The federal government will reimburse you **20%** of the price | The federal government will reimburse you **10%** of the price | |
| **Waiting time for investment grant** | Undetermined | Between 1 and 2 years | Between 1 and 2 years | |

0% 100%

**If these were your only options, which of the following offers for a solar PV system for your house would you choose?**
Choose by clicking one of the buttons below:

**IMPORTANT:** For additional information please scroll with the mouse over the corresponding property of the product (left column, bold text)

(7 of 8)

| | | | | |
|---|---|---|---|---|
| **Investment cost** | 30 000 CHF | 25 000 CHF | 25 000 CHF | NONE: I wouldn't choose any of these. |
| **Own consumption** | Your production covers **25%** of your yearly consumption | Your production covers **50%** of your yearly consumption | Your production covers **100%** of your yearly consumption | |
| **Payment for surplus electricity** | Variable payment: ranging from 6 to 10 cent/kWh | Variable payment: ranging from 0 to 16 cent/kWh | Variable payment: ranging from 6 to 10 cent/kWh | |
| **Investment grant** | The federal government will reimburse you **10%** of the price | The federal government will reimburse you **20%** of the price | The federal government will reimburse you **40%** of the price | |
| **Waiting time for investment grant** | Shorter than 1 year | No waiting time (immediate payment) | Undetermined | |

0% 100%

**If these were your only options, which of the following offers for a solar PV system for your house would you choose?**
Choose by clicking one of the buttons below:

**IMPORTANT:** For additional information please scroll with the mouse over the corresponding property of the product (left column, bold text)

(8 of 8)

| | | | | |
|---|---|---|---|---|
| **Investment cost** | 20 000 CHF | 20 000 CHF | CHF 15 000 | NONE: I wouldn't choose any of these. |
| **Own consumption** | Your production covers **75%** of your yearly consumption | Your production covers **100%** of your yearly consumption | Your production covers **50%** of your yearly consumption | |
| **Payment for surplus electricity** | Variable payment: ranging from 6 to 10 cent/kWh | Fixed payment: 8 cent/kWh | Variable payment: ranging from 4 to 12 cent/kWh | |
| **Investment grant** | The federal government will reimburse you **10%** of the price | The federal government will reimburse you **40%** of the price | The federal government will reimburse you **30%** of the price | |
| **Waiting time for investment grant** | No waiting time (immediate payment) | Undetermined | Shorter than 1 year | |
| | ○ | ○ | ○ | ○ |

0% 100%

**How do you see yourself: are you generally a person who is very willing to take risks or do you try to avoid taking risks?**

Please tick a box on the scale, from ‘not at all willing to take risks’ to ‘very willing to take risks’.

| | not at all willing to take risk | | | | | | | | | very willing to take risk |
|---|---|---|---|---|---|---|---|---|---|---|
| | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

0% 100%

Please imagine the following situation. You can choose between a sure payment of a certain amount of money, or a draw, where you would have an equal chance of getting 750 CHF or getting nothing.

We will present three different situations to you.

**First situation.** What would you prefer:

- receiving 400 CHF for sure
- a 50% chance of receiving 750CHF, and the same 50% chance of receiving nothing

0% 100%

**Second situation.** What would you prefer

- receiving 200 CHF for sure
- a 50% chance of receiving 750 CHF, and the same 50% chance of receiving nothing

0% 100%

**Third situation.** What would you prefer

- receiving 100 CHF for sure
- a 50% chance of receiving 750 CHF, and the same 50% chance of receiving nothing

0% 100%

**Second situation.** What would you prefer

- [ ] receiving 600 CHF for sure
- [ ] a 50% chance of receiving 750 CHF, and the same 50% chance of receiving nothing

0% 100%

**Third situation.** What would you prefer

◯ receiving 500 CHF for sure

◯ a 50% chance of receiving 750 CHF, and the same 50% chance of receiving nothing

0% 100%

**Third situation.** What would you prefer

- receiving 300 CHF for sure
- a 50% chance of receiving 750 CHF, and the same 50% chance of receiving nothing

0% 100%

**Third situation.** What would you prefer

- receiving 700 CHF for sure
- a 50% chance of receiving 750 CHF, and the same 50% chance of receiving nothing

0% 100%

**How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?**

Please tick a box on the scale, from ‘not at all willing’ to ‘very willing’.

| | not at all willing | | | | | | | | | very willing |
|---|---|---|---|---|---|---|---|---|---|---|
| | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

0% 100%

Suppose you were given the choice between receiving a payment today or a payment in 12 months.

We will now present 5 situations to you.

The payment today is the same in each of these situations. The payment in 12 months is different in every situation.

For each of these situations we would like to know which you would choose.

Please assume there is no inflation, i.e, future prices are the same as today's prices.

**First situation.** What would you

choose? ◯ 200 CHF today

◯ 308 CHF in 12 months

0% 100%

**Second situation.** What would you choose?

- 200 CHF today
- 370 CHF in 12 months

0% 100%

**Second situation.** What would you choose?

- 200 CHF today
- 251 CHF in 12 months

0% 100%

**Third situation.** What would you choose?

- 200 CHF today
- 403 CHF in 12 months

0% 100%

**Third situation.** What would you choose?

- 200 CHF today
- 338 CHF in 12 months

0% 100%

**Third situation.** What would you choose?

- ◯ 200 CHF today
- ◯ 278 CHF in 12 months

0% 100%

**Third situation.** What would you choose?

- 200 CHF today
- 412 CHF in 12 months

0% 100%

**Fourth situation.** What would you choose?

- 200 CHF today
- 421 CHF in 12 months

0% 100%

**Fourth situation.** What would you choose?

- ○ 200 CHF today
- ○ 386 CHF in 12 months

0% 100%

**Fourth situation.** What would you choose?

- 200 CHF today
- 354 CHF in 12 months

0% 100%

**Fourth situation.** What would you choose?

- 200 CHF today
- 323 CHF in 12 months

0% 100%

**Fourth situation.** What would you choose?

- 200 CHF today
- 293 CHF in 12 months

0% 100%

**Fourth situation.** What would you choose?

- 200 CHF today
- 265 CHF in 12 months

0% 100%

**Fourth situation.** What would you choose?

- 200 CHF today
- 238 CHF in 12 months

0% 100%

**Fourth situation.** What would you choose?

- 200 CHF today
- 212 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- 200 CHF today
- 429 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- 200 CHF today
- 412 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- 200 CHF today
- 395 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- ◯ 200 CHF today
- ◯ 378 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- 200 CHF today
- 362 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- 200 CHF today
- 346 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- 200 CHF today
- 330 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- 200 CHF today
- 315 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- 200 CHF today
- 300 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- 200 CHF today
- 286 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- 200 CHF today
- 271 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- ○ 200 CHF today
- ○ 258 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- 200 CHF today
- 244 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- 200 CHF today
- 231 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- 200 CHF today
- 218 CHF in 12 months

0% 100%

**Fifth situation.** What would you choose?

- 200 CHF today
- 206 CHF in 12 months

0% 100%

Do you know how much you spend monthly for electricity in your house?

- Yes
- I do not know, I would have to check

0% 100%

If yes, please indicate

- <50 CHF / month
- 50-100 CHF / month
- 100-150 CHF / month
- > 150 CHF / month

0% 100%

How would you describe the amount you pay for electricity:

- very high
- rather high
- fair
- rather low
- very low
- I do not know

0% 100%

Do you have a heat pump?

- yes
- no

Do you have an electric car?

- no, and I am not interested in buying one in the next 5 years
- no, but I am interested in buying one in the next 5 years
- yes

Please select the word "energy" from the list below

- environment
- energy
- politics
- building
- I do not know

Thank you, the third question was a little attention check.

0% 100%

What do you think about how **electricity prices for Swiss households** will develop over the next five years?

I think that the price of electricity for Swiss households..

. ◯ will go up

◯ will stay about the same as it is now

◯ will go down

◯ no idea

0% 100%

About how much do you think the price of electricity for Swiss households will increase during the next five years compared to now?

- It will raise sharply (increase by more than 10%)
- It will raise slightly (increase up to 10%)

0% 100%

About how much do you think the price of electricity for Swiss households will decrease during the next five years compared to now?”

- It will decrease sharply (decrease by more than 10%)
- It will decrease slightly (decrease up to 10%)

0% 100%

If you buy a solar system today and the federal government promises you to pay an investment grant after a certain waiting time, how likely do you think it is that you are indeed going to be reimbursed?

| | certain | very likely | rather likely | rather unlikely | very unlikely | I do not know |
|---|---|---|---|---|---|---|
| | ○ | ○ | ○ | ○ | ○ | ○ |

0% 100%

Do you think there will be more or less **government support available for solar systems** 5 years from now?

- Much more than today
- A little more than today
- The same as today
- A little less than today
- Much less than today
- I do not know

0% 100%

Would you please indicate for the following description whether that person is very much like you, like you, somewhat like you, not like you, or not at all like you?

**Looking after the environment is important to this person; to care for nature and save life resources**

- very much like you
- like you
- somewhat like you
- not like you
- not at all like you

How many of the people you know (**friends, family members, colleagues**) have already adopted solar system?

- none
- a minority
- about half
- the majority
- all
- I do not know

How many of **your neighbors** have already adopted a solar system?

- none
- a minority
- about half
- the majority
- all
- I do not know

0% 100%

One of the ways to increase the share of self-consumption is to combine solar PV system with battery storage. What do you think about battery storage?

I find **battery storage**…

| | fully agree | rather agree | rather not agree | not agree at all | I do not know |
|---|---|---|---|---|---|
| Not harmful for the environment | ○ | ○ | ○ | ○ | ○ |
| a mature technology | ○ | ○ | ○ | ○ | ○ |
| already a profitable investment today | ○ | ○ | ○ | ○ | ○ |

0% 100%

If you would like to gather information on buying a solar system, which **information channel** would be

reliable for you?

If you would not use the source, answer “not relevant”

| | not reliable at all | rather not reliable | rather reliable | very reliable | not relevant |
|---|---|---|---|---|---|
| Information event in your municipality | ○ | ○ | ○ | ○ | ○ |
| Swissgrid/Pronovo | ○ | ○ | ○ | ○ | ○ |
| Exhibition/Showroom/Shop | ○ | ○ | ○ | ○ | ○ |
| Cantonal/regional energy agency | ○ | ○ | ○ | ○ | ○ |
| Architect | ○ | ○ | ○ | ○ | ○ |
| Friends, colleagues or relatives who already have a solar system | ○ | ○ | ○ | ○ | ○ |
| Online search | ○ | ○ | ○ | ○ | ○ |
| SwissEnergy | ○ | ○ | ○ | ○ | ○ |
| Installer | ○ | ○ | ○ | ○ | ○ |

If you would use information channels different from those mentioned above, what are these? Please enter your answer below.

0% 100%

Please enter your **ZIP code**

Please indicate which is your **household monthly income**

(please note responses are completely anonymous and will be treated confidentially)

- less than 3'000 CHF
- between 3'000 and 4'500 CHF
- between 4'501 and 6'000 CHF
- between 6'001 and 9'000 CHF
- between 9'001 and 12'000 CHF
- more than 12'000 CHF
- No answer

What is the value of **your household's assets**?

(please note responses are completely anonymous and will be treated confidentially)

- less than 10'000 CHF
- 10'000 - 100'000 CHF
- 100'001 - 500'000 CHF
- 500'001 - 1'000'000 CHF
- 1'000'001 - 2'000'000 CHF
- over 2'000'000 CHF
- No answer

0% 100%

Thank you for your participation in this survey. We have just two short final questions for you.

Do you have any comments?

Please use the following box to share your **comments**

0% 100%

This is our last question.

Since you are interested in purchasing a solar system in the foreseeable future, we can redirect you to a non-for-profit platform, **SwissEnergy***, that allows you to receive three non-binding quotes for a solar installation, and compare them with the help of SwissEnergy's experts.

Would you like to be redirected to SwissEnergy's website?

- yes,please
- no,thanks

***EnergieSchweiz** is the platform for renewable energy and efficiency created by the **Swiss Federal Office of Energy.**

0% 100%

**Many thanks!**

Click HERE to open SwissEnergy's website in a new tab.


This survey was about solar PV systems and Swiss energy policy. If you are indeed interested in producing your own solar power, it might be important for you to know that the federal government has announced, in November 2018, that they are committed to reducing the waiting times for incentives for solar.

Please click HERE to terminate the survey.

If you have any questions, send an email to: energie@unisg.ch.

0% 100%

**Many thanks!**

Please click HERE to terminate the survey.

This survey was about solar PV systems and Swiss energy policy. If you are indeed interested in producing your own solar power, it might be important for you to know that the federal government has announced, in November 2018, that they are committed to reducing the waiting times for incentives for solar[12].

If you have any questions, send an email to: energie@unisg.ch.

0% 1

[12] From here, respondents could access the corresponding official press release issued on the 9th of November 2018 by the Swiss Federal Office of Energy (https://www.bfe.admin.ch/bfe/de/home/news-und-medien/medienmitteilungen/mm-test.msg-id-72851.html).

# Appendix 5

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

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

Martin Péclat[†‡§] and Stefano Carattini[¶‖**]

**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 are not only associated with 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 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 dataset of subnational subsidies for solar energy implemented between 2006 to 2017 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 the 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** Q42; Q48; Q58

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# 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 photovoltaics (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 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. 2017), and is supposed to be driven by imitation through social norms and information sharing, consistently with the abovementioned 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, 0.36 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 0.7 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 it decreases over time. These results are consistent with social contagion effects.

This paper contributes to three 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 \$1000 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. (2017) 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 the current assessments may underestimate the cost-effectiveness of policies promoting the adoption of renewable energy. 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, to the extent that our results are driven by social contagion, they point to the largely untapped potential of policies promoting social learning and imitation, within and across jurisdictions, which could further reduce the cost of implementing climate policy (see Carattini et al. 2019). Finally, they point to the need for several assessments, at different points in time, to account for effects arising after the policy is discontinued.

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).

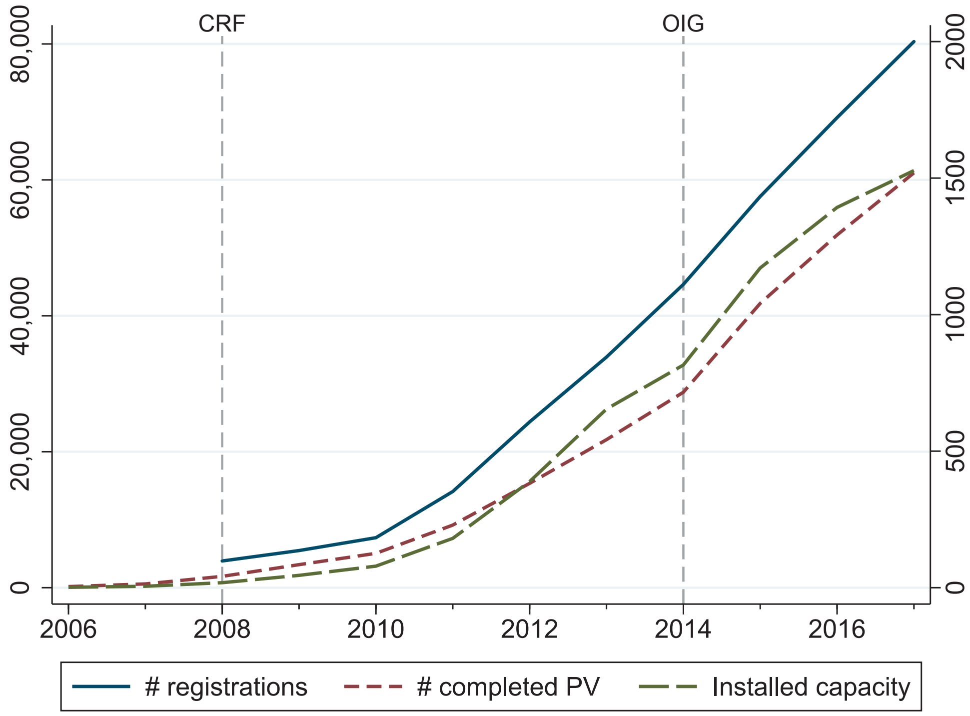
The CRF is exclusively financed by an electricity surcharge paid by Swiss electricity consumers. Demand for solar exceeded policymakers' expectations, leading promised subsidies to exceed the revenues collected through the electricity surcharge. While policymakers adjusted upward the electricity surcharge several times, such adjustments were not sufficient to close the gap, leading to the establisment 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 CFR, 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 2019), 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 to 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 jurisdicition, 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), 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).

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:

$$PVinstal_{mit} = \alpha_m + \beta PROD_{it} + \gamma INV_{it} + X_{mt}^{'}\delta + \mu_t + \varepsilon_{mit} \quad (1)$$

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 $\alpha_m$, and year fixed effects, denoted $\mu_t$. 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, $\varepsilon_{mit}$ 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., 2017), 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. We thus also use alternative specifications in which $T_{mt}$ is set to 1 not only when the subsidy in the closest canton is in force, but also 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 $t$.

## 3.2 Data

### 3.2.1 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.[1] 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.[2] 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.[3] Additional technical

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

[2]The SFOE data contain all solar installations that have applied for a federal subsidy. The vast majority of PV installations are covered, asthe 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 to 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.

[3]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. Obviously, GEOSTAT also provides the center of municipalities that resulted from a merge. 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

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.

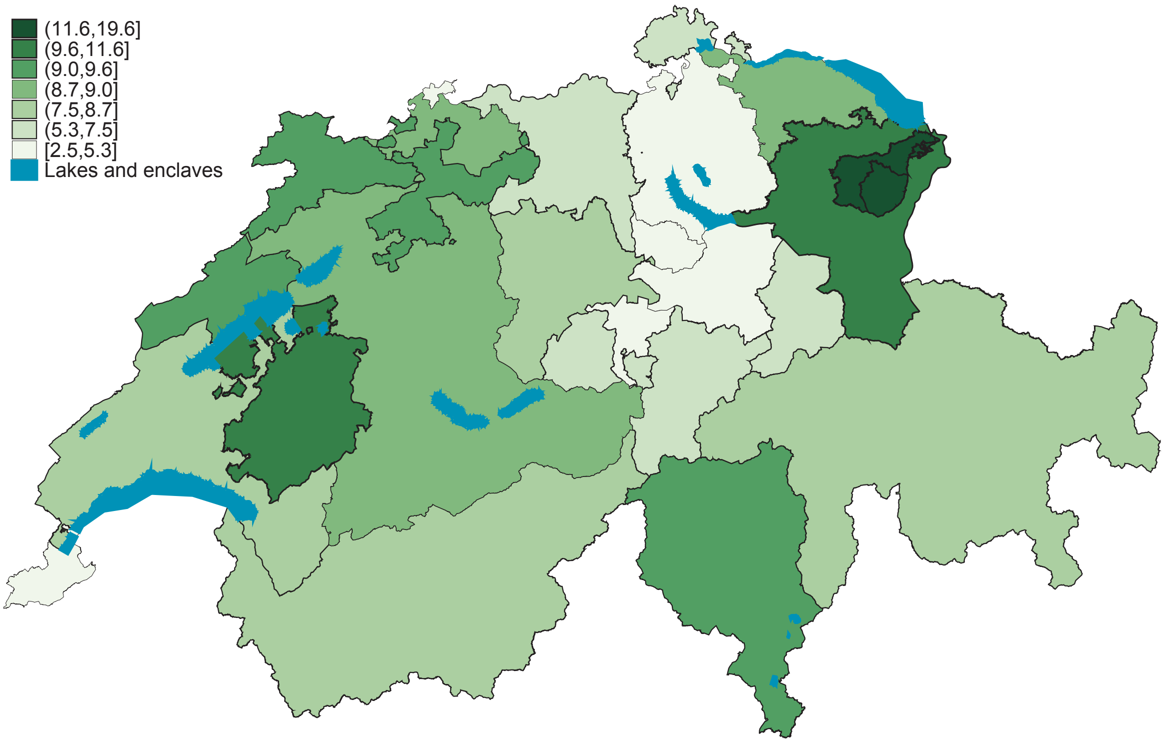
Regarding the time dimension, the date we use depends on the type of analysis. For the analysis of the effect of subsidies, we use the installation date because we aim to analyze whether the cantonal subsidies have achieved their objective, namely to increase the solar PV capacity. To answer this research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

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 installation (less than 0.01%). These are not included in the final sample.

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).

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 1000 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 on to the other, Appenzell Innerrhoden (mostly rural) and Zurich (mostly urban), we observe a sixfold difference in adoption per 1,000 inhabitants.

### 3.2.2 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 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 1$^{st}$ and terminated, if ever, on December 31$^{st}$.

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.

**Investment subsidies** In what follows, we shortly describe the main policies used by cantons. These are one-off investment subsidies and production-based subsidies.[4] We start with

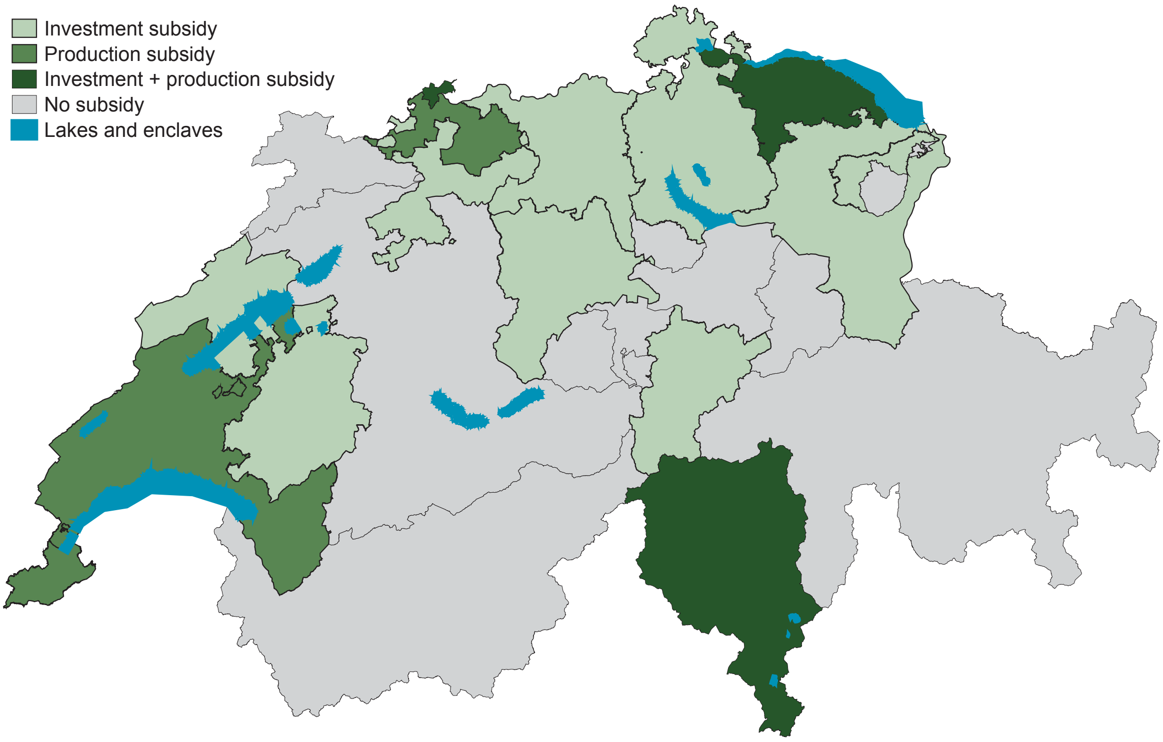
[4]Swiss cantons have also offered tax credits. In the Swiss federal system, the largest portion of income taxes is due to the canton where a person resides. Similar to federal tax credits in the United States, almost

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.

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).

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 over three 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 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

all Swiss cantons soon or later decided to make investments in solar energy tax deductible (the two exceptions being 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.

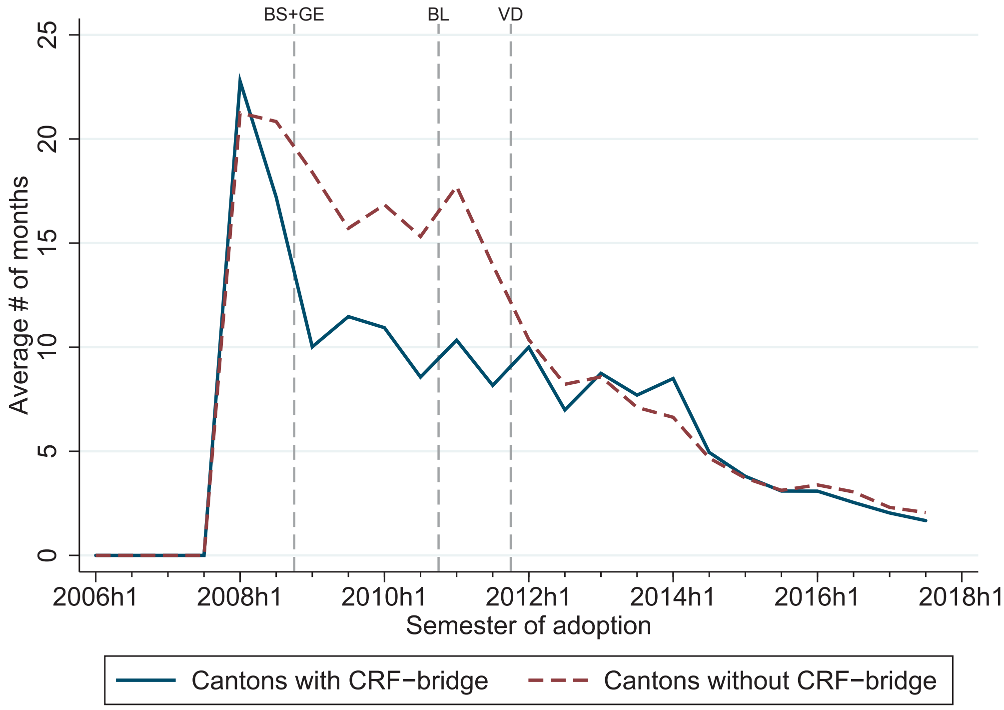
period through which the subsidy can be enjoyed, and hence the lower the overall subsidy. In presence of a waiting list, the CRF creates an incentive to register the intent to install solar as soon as possible, but also to postpone completion as much as possible. Cantonal schemes providing a bridge for 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.

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.

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 FIT, 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 end of the federal CRF. Under the scheme

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




implemented in Ticino, solar owners can apply to both the cantonal FIT and the federal OIG.

#### 3.2.3 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 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. (2017).

# 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, 0.542 (0.249) higher than in other municipalities. As an indication, a broad comparison of these figures with the average annual adoption rate, which is 1.44 PV installations per 1,000 inhabitants, suggests that cantonal subsidies are associated with an increase of about 17 to 37 % in PV installations. According to model 1, production subsidies are correlated with higher adoption than investment subsidies.

The positive association between subsidies and adoption 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.[5]

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

[5]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.

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 kW (1 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 installed capacity in levels as outcome variable, the effect of the production subsidies is no longer statistically significant.

Our results are robust to several changes in the baseline model. Table 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 543 local utilities active in Switzerland, interacted with year fixed effects.

## 4.2 Across jurisdictions

In the previous section, we provide evidence suggesting 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 5 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.

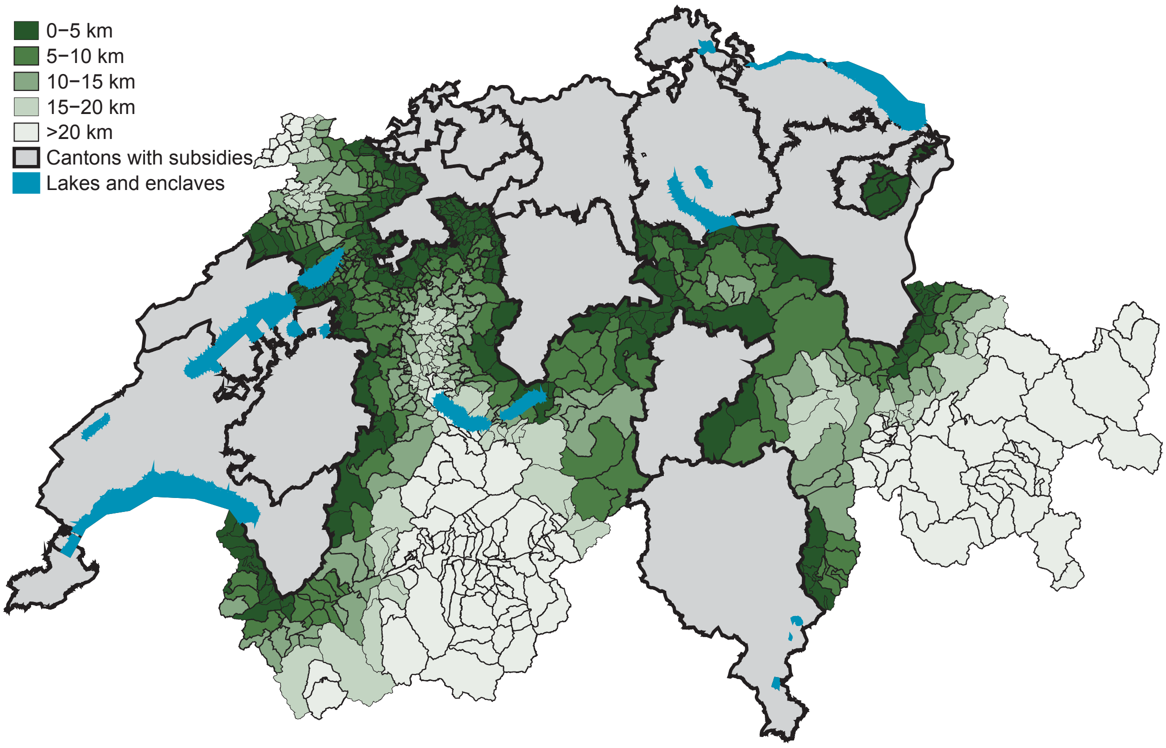
The closer a municipality in a canton without a subsidy is to a canton with a subsidy, the

Table 2: Production and investment subsidies and PV adoption

| | Number of installations | | | Installed capacity (kWp) | | |
|---|---|---|---|---|---|---|
| | | | | | <10 kWp adopt. | |
| | Rate OLS | Number Poisson | Number NB | Rate OLS | Rate OLS | Number OLS |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Production subsidy | $0.542^{***}$ | $0.219^{***}$ | $0.155^{***}$ | 8.605 | $2.961^{***}$ | 0.423 |
| | (0.072) | (0.047) | (0.040) | (8.153) | (0.332) | (0.675) |
| Investment subsidy | $0.249^{***}$ | $0.255^{***}$ | $0.245^{***}$ | $4.841^{*}$ | $1.032^{***}$ | $1.863^{***}$ |
| | (0.037) | (0.044) | (0.026) | (2.390) | (0.182) | (0.379) |
| Population | | | | | | $0.006^{*}$ |
| | | | | | | (0.003) |
| ln(Population) | | $3.306^{***}$ | $0.351^{***}$ | | | |
| | | (0.378) | (0.034) | | | |
| Density (population/ha) | $-0.427^{***}$ | $-0.051$ | $-0.020^{***}$ | $-8.950^{***}$ | $-1.585^{***}$ | $-0.923$ |
| | (0.039) | (0.031) | (0.003) | (1.375) | (0.146) | (1.549) |
| Pop. aged 30-44 (%) | 0.012 | $-0.023$ | $-0.028^{**}$ | 1.024 | $-0.152$ | $-0.219$ |
| | (0.022) | (0.013) | (0.009) | (0.781) | (0.085) | (0.117) |
| Pop. aged 45-64 (%) | 0.013 | $0.040^{**}$ | 0.006 | $3.041^{*}$ | $-0.177^{*}$ | $-0.403^{***}$ |
| | (0.021) | (0.013) | (0.008) | (1.520) | (0.078) | (0.098) |
| Pop. aged >65 (%) | $-0.017$ | $-0.024$ | $-0.037^{***}$ | $-0.358$ | $-0.146$ | $-0.417^{***}$ |
| | (0.025) | (0.015) | (0.007) | (0.860) | (0.095) | (0.121) |
| Taxpayers with income CHF 15-29.9k (%) | 0.044 | 0.027 | 0.009 | $-0.447$ | $0.236^{*}$ | $-0.070$ |
| | (0.036) | (0.016) | (0.009) | (1.475) | (0.107) | (0.120) |
| Taxpayers with income CHF 30-49.9k (%) | 0.024 | 0.012 | $-0.001$ | $-0.844$ | 0.194 | $-0.172$ |
| | (0.030) | (0.015) | (0.007) | (1.512) | (0.102) | (0.116) |
| Taxpayers with income CHF 50-74.9k (%) | 0.016 | $-0.007$ | $-0.016^{*}$ | $-1.230$ | 0.120 | $-0.272^{*}$ |
| | (0.029) | (0.015) | (0.007) | (2.135) | (0.108) | (0.118) |
| Taxpayers with income CHF >75k (%) | 0.041 | $-0.013$ | $-0.008$ | $-0.783$ | $0.203^{*}$ | $-0.356^{**}$ |
| | (0.027) | (0.016) | (0.007) | (1.574) | (0.102) | (0.122) |
| Green party share (%) | 0.005 | $-0.001$ | 0.004 | 1.082 | 0.004 | 0.069 |
| | (0.007) | (0.005) | (0.003) | (0.561) | (0.031) | (0.050) |
| Apartment buildings (%) | 0.006 | $-0.010$ | $-0.001$ | $1.125^{*}$ | $-0.006$ | 0.089 |
| | (0.009) | (0.010) | (0.004) | (0.503) | (0.043) | (0.086) |
| Buildings with apart. and other use (%) | $-0.061^{**}$ | 0.006 | 0.002 | $-0.114$ | $-0.043$ | $0.814^{***}$ |
| | (0.020) | (0.012) | (0.004) | (1.155) | (0.080) | (0.179) |
| Commercial/industrial buildings (%) | $-0.007$ | $-0.008$ | $-0.016^{*}$ | $-0.168$ | 0.062 | 0.029 |
| | (0.018) | (0.010) | (0.007) | (0.574) | (0.082) | (0.145) |
| Average # of rooms per dwelling | 0.299 | $0.676^{*}$ | 0.190 | 16.352 | 2.367 | $-4.030$ |
| | (0.352) | (0.271) | (0.143) | (16.025) | (1.719) | (5.085) |
| Average area per dwelling (sqm) | $-0.010$ | $-0.033^{***}$ | $-0.009^{*}$ | $-0.455$ | $-0.054$ | $-0.282^{*}$ |
| | (0.011) | (0.008) | (0.004) | (0.788) | (0.050) | (0.125) |
| Solar irradiance (in W/sqm) | $-0.005$ | $-0.002$ | $-0.007^{*}$ | $-0.104$ | $-0.032$ | $-0.115^{**}$ |
| | (0.006) | (0.004) | (0.003) | (0.288) | (0.024) | (0.044) |
| Constant | $-0.160$ | | $-1.866$ | $-15.695$ | $-0.053$ | $76.900^{**}$ |
| | (3.734) | | (1.102) | (152.480) | (13.541) | (23.563) |
| 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 |
| $R^2$ | 0.2150 | | | 0.0271 | 0.1592 | 0.2381 |

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

Figure 5: Distance to cantons with financial incentives for PV

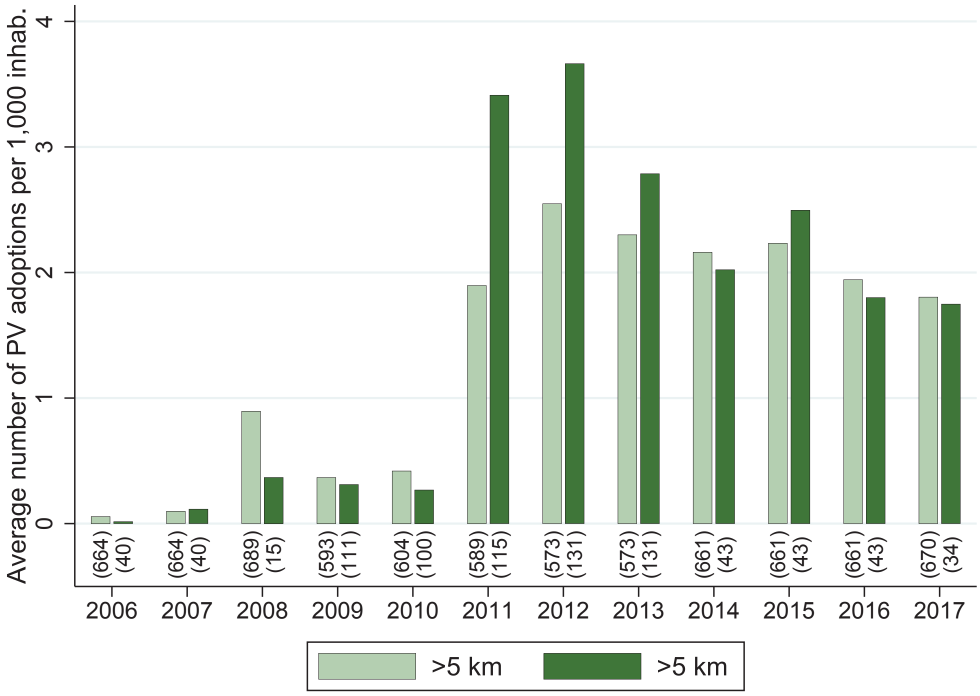



Note: Grey areas correspond to the cantons that have implemented a subsidy for PV between 2006 and 2017. Green shaded areas represent the distance between the municipalities located in cantons that have never implemented financial incentives for PV during this period and the closest canton that has implemented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

more its level of adoption could be influenced by cross-boundary effects. Figure 6 represents the average number of adoptions per 1,000 inhabitants for municipalities that are located within and beyond 5 km from the closest canton 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.

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

Figure 6: PV adoption rate within 5 km vs. beyond 5km from the closest canton with PV subsidies, 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 parenthesis 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 cantons without subsidies that are adjacent to cantons with subsidies.[6] Table 3 reports the results. Column 1 shows that municipalities sharing a border with a canton offering a subsidy experience, on average, 0.448 more PV adoptions per 1,000 inhabitants and per year than other, non-adjacent municipalities.

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 and 3 of Table 3. Column 2 shows the results when extending the treatment period to the year that follows the end of the subsidy. Column 3 assumes the treatment to be permanent from the moment a municipality is adjacent to a subsidized canton. Both columns show positive and significant effects, which are consistent with the results being driven by social contagion effects. Further, such effects decay with time, which is also consistent with the literature on social contagion in the adoption of solar energy (Graziano and Gillingham, 2015; Baranzini et al., 2017). 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.

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).[7] On average, municipalities located within 5 km from subsidized cantons experience 0.9 more PV adop-

[6] 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.

[7] Outlier municipalities, located very far away from all boundaries, are removed from the estimations in Table 4. Including these observations would not affect, qualitatively and quantitatively, our results.

Table 3: Cross-border effects

| | (1) | (2) | (3) |
|---|---|---|---|
| Adjacent | 0.448*** | | |
| | (0.145) | | |
| Adjacent [+1 year] | | 0.470*** | |
| | | (0.137) | |
| Adjacent [lasting] | | | 0.217* |
| | | | (0.119) |
| Constant | −8.847 | −8.614 | −8.734 |
| | (6.902) | (6.893) | (6.896) |
| Controls | Yes | Yes | Yes |
| Municipality FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| # Observations | 8,448 | 8,448 | 8,448 |
| $R^2$ | 0.1637 | 0.1640 | 0.1625 |

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. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

tions 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.

Heterogeneous effects can also be combined with the discontinuation of subsidies. We do so in Table 4 in the Appendix. We apply the same procedure as in Table 3, which consists in extending the processing period by one year (odd columns) and until the end of 2017 (even columns). 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 4, in which they can be seen in conjunction. As in 3, for any given cutoff distance, the

Table 4: Heterogeneous cross-boundary effects

| | (1) <5 km | (2) <10 km | (3) <15 km | (4) <20 km | (5) All |
|---|---|---|---|---|---|
| Distance × Treated | $-0.199^{*}$ | $-0.094^{***}$ | $-0.039^{**}$ | $-0.027^{***}$ | $-0.007^{***}$ |
| | (0.102) | (0.029) | (0.018) | (0.010) | (0.001) |
| Treated | $0.911^{***}$ | $0.711^{***}$ | $0.509^{***}$ | $0.396^{***}$ | |
| | (0.330) | (0.207) | (0.177) | (0.152) | |
| Distance | −0.003 | $-0.003^{*}$ | −0.001 | $-0.003^{*}$ | |
| | (0.002) | (0.002) | (0.002) | (0.002) | |
| Constant | −13.267 | −0.090 | −8.281 | −4.983 | −7.201 |
| | (16.301) | (10.811) | (11.173) | (8.678) | (6.844) |
| 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 |
| $R^2$ | 0.2356 | 0.2127 | 0.1894 | 0.1929 | 0.1646 |

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

coefficients are larger when only the following year is included in the treatment, while they are smaller (and sometimes non-significant) when all subsequent years are included.

# 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 60,000 solar installations, completed between 2006 and 2017. Among them, about 20,000 benefitted from a cantonal subsidy.

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, 0.36 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 0.7 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.

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# Appendix

Table 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., $<$10 kWp | 3.777 | 8.67 | 0.00 | 218.10 | 26,664 | SFOE |
| Number of PV adoptions | 2.630 | 4.75 | 0.00 | 58.00 | 8,448 | SFOE |
| Number of PV adoptions per 1,000 inhab. | 1.435 | 2.65 | 0.00 | 47.62 | 8,448 | SFOE |
| MAIN INDEPENDENT VARIABLES | | | | | | |
| Production subsidy | 0.105 | 0.31 | 0.00 | 1.00 | 26,664 | |
| Investment subsidy | 0.142 | 0.35 | 0.00 | 1.00 | 26,664 | |
| Adjacent | 0.077 | 0.27 | 0.00 | 1.00 | 8,448 | |
| Adjacent [+1 year] | 0.097 | 0.30 | 0.00 | 1.00 | 8,448 | |
| Adjacent [lasting] | 0.176 | 0.38 | 0.00 | 1.00 | 8,448 | |
| Treated ($<$20 km) | 0.376 | 0.48 | 0.00 | 1.00 | 8,448 | |
| Treated ($<$20 km) [+1 year] | 0.451 | 0.50 | 0.00 | 1.00 | 8,448 | |
| Treated ($<$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 15-29.9 k (%) | 13.207 | 4.46 | 0.00 | 72.62 | 26,664 | FTA |
| Tax payers with income CHF 30-49.9 k (%) | 29.102 | 7.34 | 0.00 | 66.67 | 26,664 | FTA |
| Tax payers with income CHF 50-74.9 k (%) | 27.111 | 4.41 | 0.00 | 50.00 | 26,664 | FTA |
| Tax payers with income CHF $>$75 k (%) | 28.199 | 11.50 | 0.00 | 72.00 | 26,664 | FTA |
| Green party 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 # or 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 2: Robustness checks on subsidies and PV adoption in the same jurisdiction

| | (1) Baseline | (2) Add lagged PV | (3) SE clustered by canton | (4) Replace mun. FE by DSO FE | (5) Replace mun. FE by DSO × year FE |
|---|---|---|---|---|---|
| Subsidies | 0.356*** | 0.358** | 0.356** | 0.360** | 0.243* |
| | (0.035) | (0.126) | (0.126) | (0.122) | (0.101) |
| Lagged PV count | | 0.015** | | | |
| | | (0.005) | | | |
| Constant | 0.160 | −0.013 | 0.160 | −1.997 | −2.814 |
| | (3.737) | (3.253) | (3.210) | (1.851) | (2.071) |
| 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 |
| $R^2$ | 0.2145 | 0.2150 | 0.2145 | 0.2481 | 0.4043 |

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 colomns 4 and 5. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 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 | 0.448*** | 0.455*** | 0.440*** | 0.490*** | 0.425*** |
| | (0.145) | (0.145) | (0.146) | (0.151) | (0.158) |
| Constant | −8.847 | −5.638 | −8.625 | −0.260 | −13.016 |
| | (6.902) | (8.526) | (11.010) | (10.850) | (16.762) |
| 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 |
| $R^2$ | 0.1637 | 0.1916 | 0.1882 | 0.2092 | 0.2305 |

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 4: Effect of distance and time in cross-border effects

| | <5 km | | <10 km | | <15 km | | <20 km | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Distance × Treated [+1 year] | $-0.221^{**}$ | | $-0.084^{***}$ | | $-0.034^{**}$ | | $-0.022^{**}$ | |
| | (0.090) | | (0.027) | | (0.016) | | (0.009) | |
| Treated [+1 year] | $0.896^{***}$ | | $0.675^{***}$ | | $0.500^{***}$ | | $0.394^{***}$ | |
| | (0.289) | | (0.190) | | (0.154) | | (0.130) | |
| Distance × Treated [lasting] | | −0.101 | | $-0.074^{***}$ | | $-0.025^{*}$ | | $-0.014^{*}$ |
| | | (0.076) | | (0.023) | | (0.013) | | (0.008) |
| Treated [lasting] | | $0.455^{*}$ | | $0.310^{**}$ | | 0.186 | | 0.061 |
| | | (0.231) | | (0.153) | | (0.133) | | (0.120) |
| Distance | $-0.004^{**}$ | $-0.007^{***}$ | $-0.003^{**}$ | $-0.007^{***}$ | −0.002 | $-0.005^{***}$ | $-0.003^{**}$ | $-0.006^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.001) | (0.001) |
| Constant | −11.995 | −12.269 | 1.005 | 0.550 | −7.712 | −7.880 | −4.647 | −4.495 |
| | (16.232) | (16.483) | (10.710) | (10.773) | (11.097) | (11.105) | (8.621) | (8.578) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Municipality FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| # Observations | 2,616 | 2,616 | 4,440 | 4,440 | 5,796 | 5,796 | 6,876 | 6,876 |
| $R^2$ | 0.2363 | 0.2313 | 0.2129 | 0.2106 | 0.1897 | 0.1881 | 0.1930 | 0.1921 |

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

# Appendix 6

# Short-term interventions for long-term change: Spreading stable green norms in networks

# Short-term Interventions for Long-term Change: Spreading Stable Green Norms in Networks *

Gwen Spencer†, Stefano Carattini‡§,and Richard B. Howarth¶

**Abstract**

Strong empirical evidence suggests that people infer prevailing pro-environmental norms based on the behavior of people they encounter and engage with. These norms seem to be adopted in response to both internal motivation and social pressure. To formalize such behavior, the economic literature has introduced theoretical models that include moral and social drivers. We complement this theoretical literature by analyzing the adoption of green behavior in presence of social networks. Leveraging insights from the network-science literature, we extend an existing model of socially contingent moral motivation to include characteristics of human social behavior that have been shown, empirically, to matter for green behavior, but which have been neglected by most theoretical models. Our network moral-motivation model leads naturally to spatial-heterogeneity in environmental norms. Consistent with non-network models, we show that temporary subsidy can lead to stable equilibria with positive adoption, even when the subsidy is discontinued. In our model, however, regulators can achieve significant savings by targeting subsidies. With our computational exercises, using small semi-realistic networks, we quantify the gains of targeting subsidies, or social interventions, towards optimal seed groups. These gains may be large compared to widespread subsidies, or random selection of seed groups, and depend on the society's structural characteristics. Hence, considering social networks may change radically the performance of initiatives aimed at promoting the adoption of green behavior.

## 1 Introduction

Addressing climate change is one of the most important challenges of this century. Transitioning to a low-carbon economy requires people to drastically change their behavior, and the adoption of climate-friendly technologies and habits to substantially increase. From an economic perspective, pricing carbon emissions would provide incentives to households and firms to adjust their behavior in accordance to the externality represented by climate change. Unfortunately, the political economy of carbon pricing remains often unfavorable to its implementation. As a result, many jurisdictions have opted for subsidies for renewable energy as well as hybrid and electric cars, along with bans on fossil fuel cars. These subsidies have however proved

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very costly (Marcantonini and Ellerman 2014; Marcantonini and Valero 2015; Crago and Chernyakhovskiy 2017; Borenstein 2017), and potentially also regressive.

More recently, a third way has emerged. This third way relies on the use of social norms. Increasing empirical evidence suggests that people tend to follow local social norms even when taking decisions that are relevant for climate change mitigation, a global dilemma (see Carattini et al. 2017 for a review). A growing literature shows that social contagion, or peer effects, drive the adoption of solar panels and hybrid cars (Bollinger and Gillingham 2012; Narayanan and Nair 2013; Graziano and Gillingham 2015; Rode and Weber 2016; Baranzini et al. 2017). Very localized network effects lead to higher adoption in some areas compared to others. Contagion effects decay very rapidly with distance, and become in most studies economically meaningless beyond the range of a neighborhood or block. Two channels are likely to drive this pattern: learning through word-of-mouth, and imitation of neighbors (social norms), especially when green behavior is particularly visible (Bollinger and Gillingham 2012). Disentangling econometrically the two channels may be especially hard. Recent evidence points, however, to the existence of both effects, which can have different strength depending on the context. Narayanan and Nair (2013) show, for instance, the presence of social contagion effects in the adoption of Toyota Priuses in California. Their data also allow them to study social contagion effects in the adoption of the Honda Civic Hybrid. The authors find none. Their explanation for this result is the following: since the Honda Civic Hybrid looks exactly the same as the conventional, gas driven, Honda Civic, people do not realize that the neighborhood is going green when people adopt the Honda Civic Hybrid. That is, in this context, social contagion effects seem to be driven mainly by visibility (imitation) effects. In the case of solar panels, Baranzini et al. (2017) analyze the spatial pattern of adoption for about 60,000 installations in Switzerland, belonging to households, businesses, and firms. They find that the adoption by businesses and farms is mainly influenced by other businesses, and farms, respectively, suggesting that learning may be driving adoption for these agents. However, they also find that households are particularly influenced by visible installations (building-integrated photovoltaic). Hence, very local social norms seem to matter for the adoption of green behavior.

Measuring social contagion effects is only a first step in this third way. The following step consists in leveraging these effects to spur adoption of climate-friendly behavior and technologies. Leveraging peer effects may be particularly important, but also challenging, for those behaviors that are minimally observable, such as the participation in green energy programs, the purchase of carbon offsets, or energy conservation. A large number of social interventions have already been implemented, often with a combination of descriptive and injunctive norms (Cialdini 2003). These type of interventions have contributed, for instance, to decrease energy consumption (Schultz et al. 2007; Allcott 2011), increase towel reuse in hotels (Goldstein et al. 2008), and increase participation in programs designed to prevent blackouts (Yoeli et al. 2013). These interventions provide information about the adoption of a given behavior by others, or make it salient, allowing people to observe the social norm and behave accordingly. The constructive, and destructive, power of social norms has been used also in other realms of environmental policy, including to affect littering behavior, as documented by Dur and Vollaard (2015) for the Netherlands, and McClure and Spence (2006) for Texas (for broader overviews, beyond the environmental arena, see Cialdini 2006; Thaler and Sunstein 2009; Jacquet 2016).

However, two important challenges limit the widespread adoption and generalization of these interventions. The first challenge is represented by the persistence of the behavioral changes generated by these interventions. The second, related, challenge concerns the cost-effectiveness of these interventions. Allcott and Rogers (2014) analyze the effectiveness of an intervention, realized by the firm Opower for several utilities in the United States, centred around the use of home energy reports. Energy reports provided information about the household energy use, the neighbors' energy use, as well as tips and suggestions to improve energy efficiency and reduce consumption. In a specific setting with different treatment groups with a staggered discontinuation of the treatment, the authors are able to analyze the "long-run" implications of the Opower intervention. While, after discontinuation of the home energy reports, energy consumption in the previously treated households does not converge to the higher level of the control group, a considerable portion of the energy conservation efforts observed during the treatment vanish. Even so, in this particular case, the authors find that the intervention was very cost-effective. However, the same may not apply in other contexts, such as Europe, where the starting level of energy consumption is already relatively low, as well as its carbon intensity. In this context, interventions seem to make sense if targeted to some groups of individuals, with a higher-than-average energy consumption (Andor et al. 2017).

Hence, the question for practitioners and policy-makers is how to best target interventions to improve their cost-effectiveness, and how to generate stable "green" norms. We argue that the use of social networks is crucial (cf. Videras 2013; Currarini et al. 2016). Field experiments in developing countries have already applied the lessons from social network theory to target the most influential members of a village and ensure that innovative behaviors spread fast across the community (Banerjee et al. 2014). The Solarize campaign in Connecticut, an initiative to increase the adoption of solar energy, has also recruited influential members of the towns in which the campaign was active to spur adoption. "Solar ambassadors" seem to have contributed to increased solar adoption (Kraft-Todd et al. 2018). Still in Connecticut, the Clean Energy Communities initiative also relied on neighbors teaming up to reach substantial levels of green energy adoption, as part of a campaign organized as a threshold public good game (Jacobsen et al. 2013).

Leveraging social networks may be a promising avenue for future interventions aimed at spurring the adoption of green behavior. However, to the best of our knowledge, no solid theoretical foundations exist on how pro-environmental behavior can be addressed in this context. Our paper aims to fill this gap. It extends the model of Nyborg et al. (2006), one of the most popular models of pro-environmental behavior, to include network structures and localized spillovers. The model of Nyborg et al. (2006) relies on beliefs about the adoption of a given behavior by others in society as one of the main determinants of pro-environmental behavior, also for morally-motivated individuals. In this model, if an individual perceives a personally-expensive (in terms of time, money) green behavior to be a normal part of good citizenship, then she can effectively be compensated for spending money or time engaging in the green behavior by the satisfaction of being a good citizen. The model is sophisticated enough to assume that individuals have imperfect knowledge about society-wide adoption rates. This noisy view of society is, however, the same for all individuals.

This latter constraint contrasts with the growing evidence on the role of very localized social spillovers. We respond by extending the model of Nyborg et al. (2006) to a framework in which individual behavior depends on the percentage of adoption among neighbors in the network. Each individual in the network has a threshold: if the percentage of their neighbors that adopt a green behavior is above the threshold, they also adopt the green behavior. The original model of Nyborg et al. corresponds to the special case of our network version in which the graph is complete.

In the model, adoption can occur in each period, when individuals can revise their beliefs on others' adoption. Our model also introduces time constraints, to analyze how convergence in adoption may occur when the relevant horizon is not infinite. There is some degree of urgency, for instance, related with the societal challenge of transitioning towards a greener economy and avoid severe interferences with the climate system. Hence, a long process of social contagion may not be ideal in this case, even if it, eventually, leads to a high degree of adoption.

This paper does not only contribute to a growing literature interested in the adoption of green behaviors. Our work also contributes to the growing exploration in the economic literature of how models may be extended to network settings (for example, the extensions of many game-theoretic notions to networks, as in Galeotti et al. 2010 and Ballester et al. 2006). Similar spread mechanisms in networks have been studied as “Complex Contagion" in sociology, and emerge naturally from models of repeated game play in networks (see Centola and Macy 2007a).

Our paper also provides a set of important policy implications. In the original model of Nyborg et al. (2006), a temporary subsidy could lead to a high-adoption equilibrium. While in classical models phasing out the subsidy would lead the pro-environmental behavior to vanish, in Nyborg et al. (2006) the high-adoption “green equilibrium” is stable. The same applies to our paper. Our focus is, however, on policy-making and social marketing in the presence of networks, where individuals have access to adoption information only among their neighbors. In this context, policy-makers, and practitioners, can create temporary targeted subsidies, or targeted public education campaigns, that normalize pro-environmental behavior. As in the original model, the goal is to convert the society to a stable “green equilibrium" characterized by high levels of pro-environmental behavior. To choose a good set of individuals to temporarily subsidize, we characterize the long-term effect of subsidy. This effect depends on a spatially-heterogeneous pattern of adoption that evolves according to a local update rules, in which, in every period, individuals revise their beliefs on whether to adopt a green behavior, based on the adoption of their neighbors. In this paper, we provide the necessary insights to define which individuals should be approached by policy-makers, and practitioners, with the option of subsidized adoption. While differentiated subsidies may not always be feasible in practice, information about temporary subsidies can be targeted at some groups, especially with the help of practitioners. Practitioners can also decide to adapt their pricing models, based on the insights of this model. For instance, with Solarize campaigns in the United States, discounts are often available for potential adopters of solar energy for the duration of the initiative, which in each state takes place in a selected number of towns.

Finally, our paper provides evidence, based on simulations, on how optimization could work in practice. Small examples are used to this end. Our simulations provide insights on the magnitude of the savings related with targeted subsidies, and show the impact on these gains of a set of relevant population-specific parameters. These computations complement the theoretical formalization and illustrate the functioning of real-world-like social networks in practice.

The remainder of the paper is organized as follows. Section 2 expands on the economic background. Section 3 presents the main features of our model. Section 4 provides mathematical results and compares with a network-free model. Section 5 adds insights from a series of computational exercises. Section 6 concludes.

## 2 Economic background

Explaining the private provision of public goods represents an intriguing challenge for economists. The emergence of experimental methods has contributed to shed new light on the magnitude of this facet of human behavior, an anomaly, cooperation, difficult to reconcile with standard economic models (Dawes and Thaler 1988; Ostrom 2000). As a result, several economic models tried to incorporate elements from the behavioral sciences to explain the puzzle of human cooperation. These models relied, for instance, on a “warm-glow” of giving (Andreoni 1990), on inequity aversion (Fehr and Schmidt 1999), or guilt (Kotchen 2009). In the environmental literature, an important strand of literature has focused on analyzing cooperation in local dilemmas, or commons (cf. Ostrom 1990; Poteete et al. 2010). Environmental dilemmas have become even more important with the increase in knowledge about the drivers, and implications, of climate change. Identifying ways to evolve, as a society, to cooperative equilibria preventing severe climate changes, is a challenge that is nowadays part of the research agendas of several disciplines (Tavoni and Levin 2014).

This paper extends the model of socially contingent moral motivation by Nyborg et al. (2006), a widely used model in the economics literature to explain a range of pro-environmental behaviors, which in turn builds on the early model of moral motivation by Brekke et al. (2003). We extend this model to include a social network approach. While other models of cooperative behavior (e.g. Dixit 2004; Tabellini 2008) include spatial elements in their formalization, our approach includes specific social networks, and leverages the tractability of Nyborg et al. (2006), in particular in what concerns the ability to provide policy recommendations.

The model of Nyborg et al. (2006) focuses on beliefs about others, which represent an important driver of behavior, as highlighted in the introduction, also for morally-motivated agents. While the adoption of some pro-environmental behaviors (like curbside recycling) may be actively encouraged by peer-observation, adoption of minimally-observable pro-environmental behaviors led economists to explore models that include utility derived from both “social” and “moral motivation.” In Nyborg et al. (2006), individuals experience utility when they act in accordance with a virtuous green norm. The model proposes that this utility benefit is non-decreasing in the percentage of adoption society-wide. Based on their model, the authors are able to address the following question: for settings where socially contingent moral motivation may apply, how can we best motivate many individuals to adopt green behavior?

Incentivizing early adoption is one of the main recommendations that the authors provide. The findings in Nyborg et al. (2006) predict that temporary periods of financial subsidy can cause migration from an equilibrium in which almost no members of the society adopt the pro-environmental behavior to an equilibrium in which a high percentage of the society adopts the behavior. The key to this result is that, in each period, a subset of individuals can revise their beliefs about others’ adoption. Once this favorable equilibrium is reached, the society accrues additional environmental benefits associated with widespread pro-environmental behavior. Thus, a planner may introduce a temporary financial subsidy (so that adopting the pro-environmental behavior is utility-maximizing regardless of adoption rates) until some critical level of society-wide adoption is reached. Once the critical level of adoption is reached, the egoistic utility benefit of conforming to the widely-adopted pro-environmental norm is sufficient to guarantee convergence to a high-adoption “green equilibrium." In contrast, classical models predict that when temporary subsidies are removed, participation in the pro-environmental behavior will disappear.

If people are influenced by others’ adoption, increasing the latter should have an impact on the former. At this stage, one spontaneous question arises: how can people observe the society-wide adoption rates? Especially for green behaviors such as energy conservation, or participation in green energy programs, it may be particularly hard for individuals to predict the average level of adoption in society. In contrast, people may have a general idea of how many people are adopting solar panels, or hybrid cars. Even for these goods, however, predictions are likely to be inaccurate. Nyborg and coauthors acknowledge this property of the real world, and in their model relax the assumption that individuals have perfect knowledge of society-wide adoption rates. They hence assume that knowledge of precise society-wide adoption is impacted by stochastic noise. However, every member of the society is assumed to be observing (and being influenced by) the same noisy picture of society-wide adoption. That is, while relaxing the assumption of perfect information makes the model more sophisticated, its realism is still somehow limited by the fact that all individuals have access to a symmetric global view of the society.

This limitation may be particularly relevant in some specific contexts. The abovementioned literature on social contagion suggests that social spillovers are active at a very localized level, such as the neighborhood level. In the experimental literature, repeated contacts with the same people (including face-to-face contact) are crucial in determining when individuals will be willing to cooperate (Frey and Stutzer 2006). Other examples pullulate the literature. Two of them are given in what follows. In Goldstein et al. (2008), different norm-based messages are used to test the impact of these local preferences on the reuse of towels by hotel guests. Switching from a standard door-hanger message about saving the environment to a message about other hotel guests reusing towels at a high rate resulted in a 26% jump in towel reuse. Replacing a message of the later type with a message that other hotel guests *in the same room* reused towels at a high rate resulted in a further 15% jump in towel reuse. Goldstein et al. describe their observations as the activation of a desire to conform to *provincial norms*. In Axsen and Kurani (2012), several frameworks are used to understand how positive views of plug-in hybrid electric vehicles (PHEVs) are shaped. A small group of eleven families test-drove PHEVs for a 4-6 week period. Their perceptions of the usefulness and convenience of the technology and their interactions with social contacts were tracked. Axsen and Kurani (p. 15) highlight "the existence of supportive pro-societal values within the household's social network," as one of three key factors that contribute to a high valuation of the benefits of PHEVs at the end of the trial.

Given this literature, our model pushes the boundaries even further towards a realistic depiction of reality, and extends the model of Nyborg et al. (2006) to include social networks. Given the importance of the model of Nyborg et al. (2006) in the environmental economics literature, and since it represents the starting point for our own model, we first guide the reader, in the next section, through the main elements of Nyborg et al. (2006).

# 3 The Socially-Contingent Moral-Motivation Model: Extending to Networks

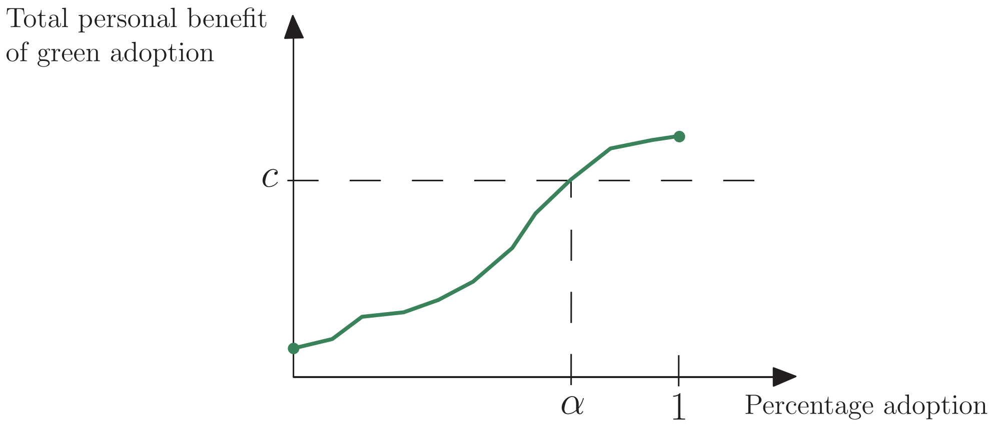
## 3.1 The Original Model of Socially-Contingent Moral Motivation

We first describe the basic moral-motivation model studied in Nyborg et al. (2006), then explain an equivalent threshold-based decision rule, then extend this decision rule to a network.

In Nyborg et al. (2006), each individual $i$ has a function $f_i(p) \geq 0$ of the fraction of society-wide adoption $p$ that describes the moral utility benefit they receive for adopting the green behavior. This is a non-decreasing function, as described in Figure 1.[1] The individual may also experience an environmental-quality benefit $\beta$ as a result of their green behavior choice (this is specified to be additive in Nyborg et al. (2006)). $\beta$ is, however, considered to be small, and even more so for global dilemmas. The sum of these benefits is weighed against the individual cost of adopting the green behavior $c$. This small environmental benefit $\beta$ from $i$ adopting is also accrued by all other members of the society. Figure 1 displays the functioning of the model. At the critical level of green adoption $\alpha$, the sum of the moral utility benefit and the personal environmental benefit of switching to green behavior overcomes the personal cost, $c$, associated with green behavior.

[1]This assumption makes quantitative Frey and Stutzer's (2006) observation that, "Individuals who believe that others will contribute to a public good tend to contribute more themselves." .

Figure 1: The original model of socially-contingent moral motivation




The focus in Nyborg et al. (2006) is to understand behaviors where both

- $f_i(0) + \beta < c$ : if no other members of society adopt the green behavior, then individual $i$ will not adopt the green behavior.
- For at least some individuals $f_i(1) + \beta > c$ : at a high rate of adoption at least some individuals will adopt even if they are not subsidized to do so.

A temporary intervention (like a subsidy of value $s$ for adopting green behavior), can be introduced so that $f_i(0) + \beta + s > c$. Thus, an individual will adopt the green behavior during the subsidy period. At the time the subsidy is removed there is some society-wide adoption rate $p'$. If $f_i(p') + \beta > c$ then $i$ will continue to engage in the green behavior. Otherwise, $i$ will stop engaging in the green behavior. When the subsidy is discontinued, individuals will repeatedly perform updates based on this decision-rule: some erosion of adoption rate may occur.

In Nyborg et al. (2006), dynamics are studied for the case of uniform $f_i(\cdot)$ under the assumption that individuals update in a random order. These assumptions give a system that conforms to replicator dynamics: the convergence rate is proportional to the net benefit associated with adoption. The replicator-dynamics convergence analysis in Nyborg et al. (2006) relies critically on the assumption that, under any current level of adoption, the personal benefit of adoption is identical for every individual.

### 3.2 Socially-Contingent Moral Motivation in Networks

We define an extended model that applies the local decision rule from Nyborg et al. (2006) to each individual in a network. We first introduce the ingredients of this extension, and then describe the dynamics and objective of our exercise. As is standard in social network analysis, individuals are represented as nodes (which are drawn as points). We note that a node may represent an individual person, or in some models, a larger unit, like a household. Each pair of nodes may either be linked by an edge or not. When an edge exists between a pair of nodes, the edge is drawn as a line segment connecting the pair. If two nodes are linked directly by an edge, then the two nodes are referred to as "neighbors." A graph is defined by a collection of nodes and a collection of edges that link specific pairs of nodes. A path from node $s$ to node $t$ is a sequence of edges that starts at $s$ and ends at $t$. For example, if nodes $s$ and $t$ have an edge between them (that is, $s$ and $t$ are neighbors in the graph), then the path length from $s$ to $t$ is one (a single edge), while if there is no *s*-to-*t* edge in the graph, then there may still be some longer path that connects *s* to *t* in the graph. Such a path passes through other nodes between the starting node *s* and final node *t*, and the length of this path is simply given by how many edges are traversed to arrive at *t*.

As a preliminary towards our computational experiments in Section 5, we remark that many measurements of a graph's structure can be computed. For example, suppose that a pair of nodes *q* and *r* is chosen uniformly at random from a graph *G*, and the length of the shortest path connecting *q* and *r* is computed. The expected value of this quantity is often called "the characteristic path length of *G*" or "the average shortest-path length of *G*." Given several graphs, their characteristic path lengths can be compared. In social network analysis, a common observation is that graphs that depict actual patterns of social interaction tend to have very small characteristic path length.

Another commonly observed property of graphs that represent real social networks is that they have high *clustering coefficient*. The clustering coefficient of a graph is a measurement that aims to describe how often two neighbors of a fixed node are also linked by an edge. Colloquially, the clustering coefficient quantifies the answer to the query, "Do friends of yours know each other?" In computing the clustering coefficient, first, for each node in the graph, the answer to this question is computed, and then these node-specific answers are averaged to give the clustering coefficient for the graph. Precisely, given a graph, for a single node *q*, suppose that it has edges to exactly $k_q$ neighbors: the maximum number of edges that could ever exist among *q*'s neighbors is $k_q(k_q-1)/2$. This number of edges would be correct if every pair of *q*'s neighbors were linked by an edge. In contrast, among *q*'s neighbors there is some actual number of edges, call it $A_q$. Then the clustering coefficient at node *q* is $A_q/(k_q(k_q-1)/2)$. The clustering coefficient for the graph is computed by averaging over such a quantity for all nodes in the graph.

- **Input:**
  A network (or "graph") consisting of nodes and edges, $G = (V, E)$. Each node in $V$ is in one of two states: *Green* or *Brown*. We associate the *Green* state with value 1, and the *Brown* state with value 0.

  Each node $i$ has a critical susceptibility fraction $\alpha_i$.[2] This fraction is the minimal percentage of the neighbors of $i$ that must be *Green* before $i$ will adopt the green behavior (without being subsidized), namely:

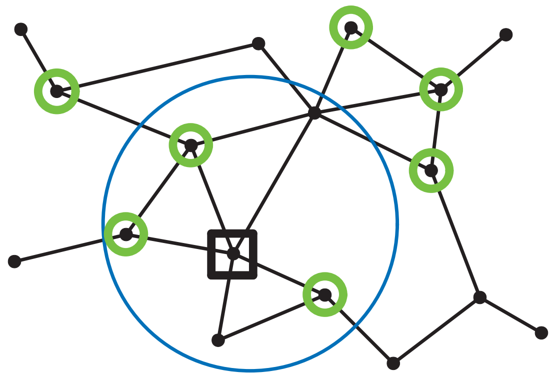
  $$\alpha_i = \text{argmin}_p\{p : f_i(p) + \beta > c\}.$$

  Notice that given $G$ and $\alpha_i$, we can immediately obtain a cardinality threshold, $b_i$, for adoption. Let $\delta(i)$ denote the set of $i$'s neighbors in G, so that $|\delta(i)|$ denotes the number of neighbors of $i$. Then round up $|\delta(i)|\alpha_i$ to obtain $b_i$, the minimum number of green neighbors that will ensure $i$ adopts when no subsidy occurs.

- **Dynamics:** for each time step $t$, every node $i$ checks how many of his neighbors are *Green*. If more than $b_i$ neighbors of $i$ are *Green*, $i$ is set to *Green* in time step $t+1$. Otherwise, $i$ is set to *Brown* in time step $t+1$. This update process iterates, giving a binary *adoption vector* $x(t) \in \{0,1\}^{|V|}$ that evolves deterministically in time. That is, $x(t)$ contains $|V|$ entries, each either 0 or 1, to indicate the state of every node at time $t$. Our choice of concurrent updating, rather than the randomly-ordered updating explored in Nyborg et al. (2006), follows the extensive body of work on repeated game play in network settings (cf. Nowak and May 1992 for an early study). Figure 2 displays the functioning of our extended model, in which adoption in a local neighborhood determines behavior in the next time step. Green adoption in the present time step is indicated by thick green circles. To decide adoption

[2] If $\alpha_i > 1$ we say $i$ is intransigent (following the statistical mechanics literature that considers individuals of fixed opinions, cf. Wu and Huberman 2004). Hence, $i$ will never adopt green behavior without subsidy.

Figure 2: The network model of moral motivation



in the next time step, each node checks the percentage of adoption within his set of neighbors. For example, the boxed node in Figure 2 will adopt in the next time step if he has threshold $\alpha \leq 0.6$.

- **Space of Actions:** Choose a set of nodes to temporarily subsidize (these nodes will be *Green* regardless of their neighbors behavior until the subsidy is removed). The set of nodes where a direct intervention will be targeted is often referred to as a *seed set* in the social networks literature.

- **Goal:** When the subsidy is removed, the long-term behavior of the adoption vector exhibits a high fraction of green behavior.

Suppose that the planner chooses a set of nodes to subsidize for $d$ consecutive time steps, then the subsidy is removed. When the subsidy is removed, nodes will continue to update their behavior according to the decision rules defined above for some finite period until behavior converges[3] to a permanent state for all future time steps (we call this the "long-term" behavior that results from the intervention). We formalize the two natural planning problems as follows.

- **Problem 1: Min-cost Complete Conversion (MCC)** What is the smallest number of nodes that can be subsidized to convert the entire network[4] permanently to *Green* behavior? [5]

- **Problem 2: Budgeted Maximum Conversion (BMC)** Given budget of $k$ nodes to subsidize, what is the maximum percentage of the network that can be permanently converted to *Green* behavior?

### 3.3 Stability

In networks, stability of adoption depends on spatial distribution. An important difference between the original moral-motivation model and our network version is in the ease of describing the long-term conversion achieved by subsidizing a particular set of nodes. In the non-network model, since individuals have uniform

[3]Theoretically, in some cases, behavior can converge to a 2-time step cycle rather than a steady state.

[4]Precisely, convert all nodes with $\alpha_i \leq 1$ permanently to green behavior; nodes with $\alpha_i > 1$ never adopt without direct subsidy.

[5]The assumption of uniform node-subsidy cost is adopted for ease of exposition, but our Integer Programs in Section A.2 can be trivially altered to accommodate non-uniform costs.

threshold ($\alpha_i$ is constant), the stability of conversion can be determined exactly by whether or not the critical level of adoption has been exceeded during the term of the subsidy. In the network model describing the long-term stability of a subsidy strategy, one must also consider the spatial distribution of the adopting nodes. A pattern of adoption and the configuration of network connections will together either maintain a high level of green behavior, or allow green adoption to slowly erode. This added complexity makes description of the long-term effects of a temporary subsidy significantly more challenging. The next section tackles this issue directly.

# 4 Mathematical Results: Contrasts with non-Network Socially-Contingent Moral Motivation

In Nyborg et al. (2006), the authors describe a number of properties of the original socially-contingent moral motivation model. In this section, we compare our network model with theirs, mathematically. As a preliminary, do note that our model contains the original model of Nyborg et al. (2006) as a special case: their non-networked model corresponds exactly to the special case of our model where $G$ is a complete graph.[6] Our model expands to the general case where the network $G$ has some more complex structure. How much can the properties of the model vary when the graph is not complete, that is, in our network socially-contingent moral motivation model? Our intent with such a comparison is to persuade the reader that adding the feature of network structure can lead to qualitative messages that can contrast strongly with the non-networked model of Nyborg et al. (2006). We emphasize that, in this section, we aim to show that *there exist* network structures for which wide departures are possible. In the next section, we go further by arguing that the flavor of departures for these carefully-architected examples is suggestive of findings for network structures that resemble real measured patterns of social interaction.

Before developing the consequences of our network model in detail, we provide a high-level summary of several of the striking contrasts between the consequences of the two model formulations. The first immediate consequence of the socially-contingent moral motivation model from Nyborg et al. (2006) is that the long-term adoption rate resulting from a subsidy depends only on the number of individuals subsidized. In contrast, under our network model, the long-term adoption rate resulting from a subsidy depends strongly the spatial placement of individuals targeted in the network. This contrast reflects one of the most fundamental insights in the study of social networks.In particular, under the Nyborg et al. (2006) model, if all members of society apply the same decision threshold $\alpha_i$, achieving $100\%$ green adoption requires subsidizing at least $\alpha_i|V|$ (rounded up) nodes. That is, for uniform $\alpha_i$, an intervention that targets less than the critical susceptibility fraction of the entire society cannot reach an all-green equilibrium. Under our network model, however, for societies structured in certain ways, targeting interventions at a much smaller subset of nodes can be sufficient to reach $100\%$ green adoption (and such examples exist even when all nodes apply the same decision threshold $\alpha_i$). For some societal network structures, it may be that effective seed sets are highly rare: even when a subsidy set $S$ achieves $100\%$ green adoption, almost every subsidy set of the same size can fail to do so.

Further, when nodes apply the same decision threshold, the Nyborg et al. (2006) model exhibits only two stable equilibria: no green adoption and $100\%$ green adoption. Heterogeneous stable equilibria can be obtained for the non-network model only when $\alpha_i$ is not uniform. That is, stable heterogeneous patterns of adoption can emerge in the non-network model only when some individuals are less morally-motivated

[6] The complete graph on a set of nodes $V$ has an edge between every pair of nodes in $V$. The complete graph on $|V|$ nodes is denoted $\mathbf{K}_{|V|}$.

than others or incur an inflated cost to engage in green behavior. In contrast, under our networked model, there can be *many* stable heterogeneous equilibria in addition to two homogeneous equilibria, even without assuming that non-adopters are inherently less morally-motivated. That is, stable heterogeneous patterns of green adoption and non-adoption can naturally result from imposing spatial structure on "equally moral" individuals.

To show how extreme these contrasts can become when subtle network structure is introduced, in the Appendix A.1 we describe carefully-designed families of networks. Below, we build intuition and motivate the character of these families. In the subsequent computational section, we will show that qualitatively-similar departures (between the original- and networked-moral-motivation models) hold even when the social network is not particularly carefully-chosen. That is, not only do *there exist networks* where the qualitative departures are quite extreme (our focus in this section), but in fact, the lack of agreement between the original- and networked-moral-motivation models should be considered a property that is typical and can *frequently arise*.

First, consider the magnitude of total spread that results from an intervention at a fixed number of nodes, $k$. Under our network model, the total impact of this intervention is not constant, as it depends strongly on the spatial placement of the $k$ interventions, i.e. on the specific nodes in the network that are targeted by the intervention. To see this, imagine two contrasting spatial placements of an intervention of a fixed size.

Suppose that the first intervention is placed at nodes that each have only very popular neighbors. Nodes targeted with direct intervention become early adopters. Next, neighbors observe these early adopters. Unfortunately, because each neighbor of an early adopter is popular, such neighbors each perceive adopters to be a very small fraction of their observed contacts. Thus, neighbors of early adopters under such an intervention will not modify their behavior, and no spread of adoption will occur. As a result, at the end of the intervention, early adopters will find that their neighbors never adopted, and will then be persuaded to return to a non-adopter status themselves. Under such an intervention, the long-term adoption is very small or 0.

In contrast, suppose that a second spatial intervention targets nodes with relatively unpopular neighbors. In this case, the neighbors of early adopters observe a high fraction of adoption among their contacts, so that they are motivated, based on our model, to become new adopters. The combination of these new adopters and early adopters is then observed by other nearby contacts, leading to an iterative cascade of adoptions spreading through the network. When the term of the intervention is over, adoption is already very widespread: most nodes observe high fractions of adoption among their contacts and thus choose to continue adopting as a result. So, the long-term rate of adoption is very high, even after the intervention has ended. In this way, widely-different rates of long-term stable adoption can result from interventions of the same size.

In Appendix A.1, we provide a class of examples (Class 1) that exaggerates the intuition above. Notably, our class of examples does not require nodes to apply different thresholds for deciding when to adopt: even when all individuals apply identical thresholds, considering their role in the network when designing an intervention can have a substantial impact on long-term adoption. This class of examples proves the following theorem.

**Theorem 1.** *Two intervention sets of the same size may have widely-different long-term adoption rates. This is true even when the $\alpha_i$ are uniform.*

Next, consider how many nodes must be targeted with the intervention to achieve a complete cascade in which all nodes become stable adopters of the green behavior. Under the original moral-motivation model, notice that if all nodes demand a uniform $\alpha_i < 1$ fraction of their neighbors to adopt before they will personally adopt, then the evolution of adoption behavior is extremely simple. First, if the intervention is at more than $|V|\alpha_i$ nodes (that is, at more than an $\alpha_i$ fraction of the whole society), then the number of early adopters convinces all other nodes to adopt. When direct intervention is discontinued, all nodes observe full societal adoption, and based on moral-motivation, continue to adopt, resulting in a stable full-adoption equilibrium.

Alternatively, if the initial intervention is at fewer than $|V|\alpha_i$ nodes, then the number of early adopters fails to convince any additional nodes to adopt. Thus, at the end of the direct intervention, the number of adopters is still fewer than $|V|\alpha_i$, so that no nodes, considering only moral-motivation benefits, continue to adopt. This results in a stable *0-adoption equilibrium.*

Thus, under the original moral-motivation model, the cost for the planner to cause complete conversion (Problem 1) is determined immediately by the size of the population and the value of $\alpha_i$. In contrast, for the network moral-motivation model, the structure of the network can play a significant role in determining this cost. In particular, if *G* contains every possible edge, then the cost to cause a complete cascade is still $|V|\alpha_i$, but if *G* has more subtle structure, then the cost to cause a complete cascade may be much lower if the spatial structure of the intervention is planned carefully.

To build intuition about this, consider a simple network that is composed of a line of ten nodes who each demand that an $\alpha_i = 0.4$ fraction of their neighbors adopt before they will be (morally) motivated to do so. Suppose that the planner intervenes at a single end-node of the line. The neighbor of the single early adopter perceives that half of his contacts are adopters, and accordingly, decides to adopt. Next, the neighbor of this newly-adopting neighbor perceives that half of his contacts are adopters, and thus decides to adopt. This process continues down the line until the entire line of 10 nodes adopts, driven by an initial intervention at *only one node* (rather than an intervention at $|V|\alpha_i = 10 * 0.4 = 4$ nodes, as a model ignorant of network structure suggests would be required).

The simple example above argues that the cost to cause complete conversion under the network model can be *less than one-quarter* of what is suggested by the non-networked model. Letting the line network contain 100 nodes, still with $\alpha_i = 0.4$, a similar example shows that the cost to cause complete conversion under the network model may *less than one-fortieth* of what is suggested by the non-networked model. By exaggerating this intuition, we present in Appendix A.1 a class of examples (Class 1) where the cost to cause complete conversion under the networked model is an arbitrarily-small fraction, $\epsilon > 0$, of the cost predicted by the non-networked model. Furthermore, there always exists such an example where all nodes apply the same threshold $\alpha_i$, proving the following theorem.

**Theorem 2.** *For any $\epsilon > 0$, there exists a network with some uniform $\alpha_i$ in which stable conversion to the $100\%$ adoption equilibrium can be accomplished by subsidizing at most $\epsilon|V|\alpha_i$ individuals.*

As we have explained above, under the original moral-motivation model, only two long-term states are possible when nodes apply a common value of $\alpha_i$: a *full-adoption equilibrium* or a *0-adoption equilibrium.* Heterogeneous equilibria can only be obtained under this model by assuming that some nodes apply higher $\alpha_i$ than others (that is, they are less susceptible to moral motivation or experience significantly different cost to adopt the green behavior). In contrast, in our networked model, a large number of different stable equilibrium are possible *due solely to the structure of the network.*

For example, consider a large network composed of many small communities. Within each small community, assume that there are many internal edges, and only a few edges connect nodes from different communities. If a single small community is at full adoption (and other communities contain no adopters), then every node in the adopting community perceives a high fraction of adoption among his neighbors, while nodes outside the adopting community perceive low or no adoption among their sets of neighbors. As such, under the moral motivation decision rule, nodes in the adopting community will continue to adopt, while nodes outside the adopting community will produce no new adoptions. This produces a stable heterogeneous pattern of adoption that results only from the structural form of the network. Any small community could be the "single adopting community," so immediately, there exist at least as many heterogeneous equilibria as the number of small communities in the network (in addition to full-adoption, 0-adoption, and perhaps other partial-adoption equilibria where a subset of the small communities adopt). Exaggerating this intuition, in Appendix A.1 we give a class of examples (Class 2) that proves the following theorem.

**Theorem 3.** *Even when $\alpha_i$ is uniform, networks can have at least $|V|/2$ stable equilibria (where two are homogeneous, and the rest are hetrogeneous).*

Our final theorem considers the efficacy of a *random guess* about where to apply intervention in the network. From Theorem 1, we are aware that different spatial placement of interventions may result in dramatically-different long-term adoption rates even if the number of individuals who receive direct intervention is the same. Given that total long-term adoption can be widely variable for fixed intervention size, does choosing to apply a randomly-spatially-placed intervention have a substantial probability of a good outcome? In particular, suppose that we have no information about the specific social network structure (for example, because the planner has not gathered data about relationships between individuals or households). Does this significantly compromise the potential impact of an intervention? Or, is it the case that is there a high probability that, by intervening spatially-at-random, the planner can achieve long-term adoption close to the optimal intervention that could be achieved based on full knowledge of the network structure?

The following theorem says that there exist networks where the probability of a sub-optimal guess can be arbitrariliy close to 1, even when all nodes apply the same $\alpha_i$. In particular, even when an intervention that reaches a full-adoption equilibrium exists, it can be the case that almost every spatial intervention of the same size fails to reach full adoption. By allowing nodes to apply variable $\alpha_i$, the efficacy of a randomly-spatially-placed intervention can be arbitrarily bad in expectation even when there does exist an intervention that reaches full-adoption.

**Theorem 4.**

- *Given any $\epsilon > 0$, there exists a network which can be converted to $100\%$ adoption by a set $S$ but where a randomly-selected set of size $|S|$ fails to achieve $100\%$ adoption with probability at least $1 - \epsilon$. This is true even when the $\alpha_i$ are required to be uniform.*
- *When the $\alpha_i$ are allowed to be non-uniform, given an additional parameter $\gamma > 0$, there exists a network where some subsidy set $S$ gives $100\%$ adoption, but the expected adoption resulting from a random $|S|$-size set is $< \gamma$.*

The first statement of this theorem is proved in Appendix A.1 by a class of examples (Class 1). The second statement is proved in Appendix A.1 by a different class of examples (Class 2).

### 4.1 The natural emergence of heterogeneous equilibria

In graphs that are not complete, the network moral-motivation model that we have described naturally gives rise to stable patterns of long-term heterogeneous behavior. That is, we obtain a society-wide fraction of adoption that is strictly greater than 0 but strictly less than 1, with spatial variation across the network (and furthermore, a single network and set of decision thresholds may give rise to many such heterogeneous equilibria). This is consistent with our observation of human behavior in the real world, in which behavior is not necessarily homogenous across individuals or geographic regions.

We remark that this realism is not an immediate consequence of the spatial network structure, but of the combination of network structure with the specific socially-contingent moral motivation model of Nyborg et al. (2006). Indeed, many models of behavior updating in networks fail to produce stable patterns of heterogeneous behavior. For example, the statistical mechanics literature has considered spread mechanisms in random networks where individuals are influenced by trends in adoption among their neighbors; if a high-percentage of their neighbors adopt a behavior, they are very likely to adopt it, and so on (e.g. López-Pintado 2008). The widely-studied version in Wu and Huberman (2004) relies on a probabilistic behavior update rule, according to which individuals periodically choose a random neighbor to emulate, following the assumption that these neighbors are always, in some sense, a representative sample of the society. This process gives a random walk on percentage of adoption, which must eventually converge to an adoption pattern that is totally homogeneous: either the entire society participates or no one participates. Concerned with the simplistic equilibrium behavior of population-level critical mass models, recent work of Centola (2013) manages to produce a partial-adoption equilibrium by assuming a secondary adoption threshold above which the sign of the benefits of adoption becomes negative. Such an assumption seems rather unnatural for describing norm spread.

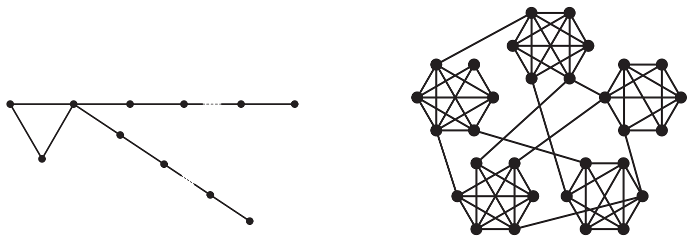
Even the heterogeneous equilibria that are possible under the non-network socially-contingent moral motivation model of Nyborg et al. (2006) achieve heterogeneity in a less-than-satisfying manner. In that model, partial-adoption equilibria can only be obtained by making some individuals more immune to moral motivation than others. That is, non-adopters are evenly mixed throughout the population, and are precisely those individuals that do not respond to the pressure to conform to norms at modest rates of society-wide adoption (or who, for some reasons, experience inflated costs to engage in green behavior). Those who ultimately act “virtuously” in such heterogeneous equilibria are just the individuals who were inherently more virtuous. Similarly, under the Bass model, heterogeneity prior to convergence to full adoption is achieved by defining two classes of individuals (“innovators” and “imitators”) that are inherently different (Bass 1969). In both models, every individual experiences a symmetric context: differences in the behavior of individuals is due simply to their inborn properties.

Our network model, on the other hand, allows stable adoption patterns that are not homogeneous without relying on the relative “moral callousness” of all non-adopters: stable pockets of non-adoption may easily occur when certain portions of the network mainly talk to themselves and not to other portions of the network in which adoption is higher. Non-adopters of green behaviors need not be fundamentally different than adopters: they are simply subject to a different incentive landscape, based on the environmental norms they observe among their peers. This speaks to the flavor of the famous work of Nowak and May (1992) on evolutionary games, where introducing a network structure to repeated game play gives rise to persistent spatial heterogeneity. Further, existence of heterogeneous adoption equilibria are not a “boundary case" in our model: in the computational section we observe that heterogeneous equilibria frequently arise in randomly-constructed graphs that are social-network-like under the spread process that we have described.

# 5 Computational Results: Exploring Additional Realism and Identifying Policy Recommendations

While the carefully-designed (or “pathological” in jargon) classes of examples used in the proofs of Theorems 1, 2, 3, and 4 are interesting in a mathematical sense, the question of much greater practical interest is whether these qualitative departures are significant for networks that resemble real social networks. In this section we provide insights from a computational exercise, showing that similar qualitative departures from the predictions of the non-networked model of Nyborg et al. (2006) hold for a range of social-network-like

Figure 3: Carefully-designed classes vs. realistic examples



examples that have high clustering and short average path length as demonstrated in Figure 3 (right panel). These departures are of milder, but still substantial magnitude.

Figure 3 illustrates the difference between pathological classes and realistic examples. We have shown that pathological networks, such as that on the left, produce messages that contrast severely with the findings of the non-networked model. The next step in our analysis consists in expanding our focus to more realistic examples, with the high-clustering and short average path length of social networks as displayed in the right-hand side of Figure 3. We are interested in whether departures from the predictions from the non-networked model can be also found in this type of social networks. To do this we will create a tool that allows precise measurement of optimal seed sets.

## 5.1 Towards networks that look like social networks

Consider again Figure 3. We argued that networks like that on the left produce messages that contrast severely with the findings of the original moral-motivation model. Do more realistic networks (with the high-clustering and short average path length of social networks) also exhibit strong contrasts?

In this section we focus on a specific range of network structures, with the aim of testing the relevance of our theory for real social networks. This section thus aims to address the following question: in networks which resemble real social networks, does considering network structure make a substantial difference in identifying strategies that could allow reaching a green equilibrium? Real social networks typically exhibit high levels of local density (or high “clustering coefficient") in combination with low average shortest-path length between randomly-selected pairs. This later property is often called the “small-world” property. The canonical work of Watts and Strogatz (1998) demonstrated that starting from uniform lattices (rings where each node has degree two, and square grids where each node has degree four), random “rewiring" of even a small percentage of the edges quickly gives rise to networks with these properties (qualitatively, even a very small percentage of random long ties results in a small world). Similar rewiring schemes have been widely used in the sociology literature to create test networks to examine the spread of complex contagion (see Centola et al. 2007 and Centola and Macy 2007b). In this section, we discuss computational observations for a class of networks with these properties. Figure 4 shows how the networks are constructed.

Our test networks will closely resemble the *stochastic block models* that have been widely-studied as a synthetic proxy for evaluating community-detection methods in the network science community (Holland et al. 1983). By randomly rewiring clusters, we explore a range of networks between dense local communities (small complete graphs) and a random network. We start with 5 complete graphs each containing 6 nodes. For each edge in the graph we “rewire" it with probability $p$: the edge is removed from the graph and replaced by a randomly-chosen edge between one of its endpoints and a random node from any community. We do this procedure for every edge in the leftmost figure. When $p = 0$, no edges are rewired: this gives the leftmost figure, composed of small highly-internally-connected communities. As $p$ increases, some local ties within communities are replaced by longer random ties to distant communities, reducing the average path-length between pairs of nodes, but maintaining fairly high clustering coefficient. That is, at modest rewiring probability, two friends of a common node are still highly likely to themselves be neighbors. When $p = 1$, the procedure will give a random graph with low clustering coefficient (so that two friends of a common node have a quite low probability of knowing each other), and the graph will have very low average path length. Exploring across a range of $p$ values will therefore explore a range of networks that exhibit properties considered to be typical of real observed social networks.

## 5.2 Policy implication I: what percentage of subsidy can convert the whole network?

Theorem 2 showed that for some carefully-designed classes of networks, subsidizing a very small fraction of the critical percentage of the network (a vanishingly-small percentage of $\alpha|V|$) would be sufficient to convert the entire network to adoption. A question follows from this theorem: for *networks that look like real social networks*, is there a very small set of individuals where an intervention at that set would convert the entire network to green behavior? Note that such a set of individuals where a direct intervention will be targeted is often referred to as a *seed set* in the social networks literature.

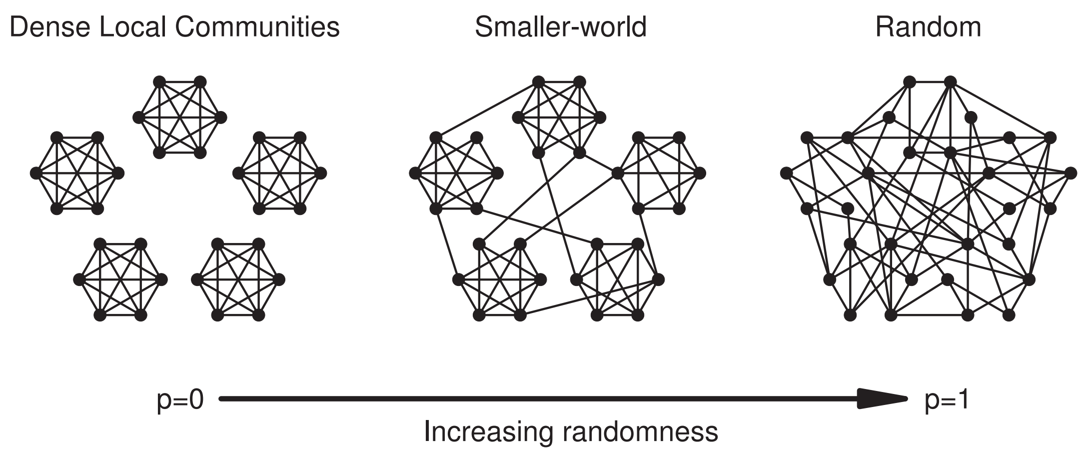
In our domain, however, it may make more sense to answer the following question: for networks that look like real social networks, is there a very small set of individuals where intervention will convert the entire network to green behavior *in a reasonable time frame?*

We consider this *time-constrained* modification for two reasons. First, in our context, each period represents an opportunity for each agent to revise her beliefs, as in the original Nyborg et al. (2006). In the case of climate change, for instance, time constraints are provided by the climate system, which responds to continuous anthropogenic forcing, and are translated into policies through emissions targets, also known as Nationally Determined Contributions, to which most world countries have committed at the 2015 Conference of the Parties, in Paris, France. Thus, there may be both ecological and policy imperatives to design interventions that succeed *in a reasonable time frame.*

Our second incentive for considering a time constraint is a technical point related to modeling. For some networks, the minimum-size intervention set may achieve 100% adoption very slowly via a very "long fuse" in which only a small number of new adoptions occur per time step (Easley and Kleinberg 2010). From an applications perspective, this is one of the least satisfying aspects of the model formulation: the solution which is declared optimal may rely on an incredibly long chain of events all proceeding in *perfect accordance* with the formal update rules. To exclude potentially brittle solutions of this type and produce intervention patterns more likely to be robust in real systems, we can limit our search to the minimum-size set that achieves 100% adoption by a specified time limit *t.*

We now show how to precisely formulate our model with time constraints. This formulation will allow us, for a fixed network and node thresholds, to make an exact measurement of the required intervention size to convert the entire network. For any limit $f$ on how many time steps of behavior-updating we allow until full-adoption is reached, we can compute the exact minimum-size intervention via the following Integer

Figure 4: Random-rewiring clusters



Program:

$$\text{minimize } q, \quad \text{subject to:}$$

$$\sum_{i \in V} y_i \leq q$$

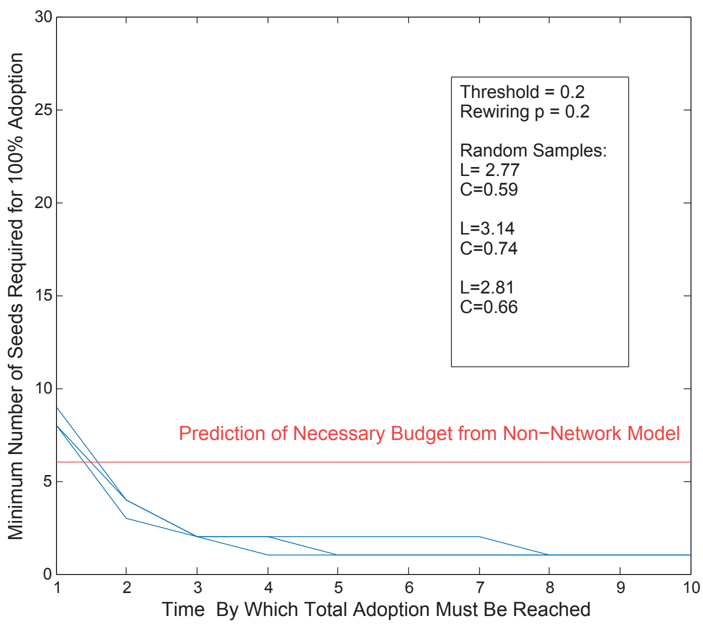
$$x_{it} \leq y_i + \frac{1}{b_i} \sum_{j \in \delta(i)} x_{j,t-1} \qquad \text{for } t \in \{0, 1, 2, ..., f\}, i \in V.$$

$$x_{i,f} \geq 1 \qquad \text{for } i \in V.$$

This Integer Program formulation assumes that we intervene to force adoption at a small set of nodes from time 0 to time $f$, and requires that full adoption is reached by time $f$. We solve these Integer Programs using off-the-shelf software (AMPL with CPLEX). A detailed explanation of this Integer Program formulation appears in Appendix A.2.

We use this Integer Program to calculate the optimal size seed set for a range of intervention time-limits $f = \{1, 2, ..., 10\}$. First, in Figure 5 we show results for $p = 20\%$ rewiring of the 30 node graphs described in the left-most panel of Figure 4, with uniform fractional thresholds of $\alpha = 0.2$. Figure 6 provides our main findings. It replicates Figure 5 over a grid of values in the (Rewiring Probability, Threshold Value)-parameter space. In Figure 5 we plot the number of nodes that must be targeted to reach the 100%-adoption equilibrium as a function of how quickly full adoption must be reached. We repeat this experiment three times for different social networks (three different rewirings of the initial dense communities). Each blue trajectory corresponds to one experiment run, and the network statistics for characteristic path length and clustering coefficient for each of the three networks are included in the figure. We note that the plotted relationship appears quite consistent despite some variation in the network statistics. The non-network socially-contingent moral motivation model predicts that $\alpha_i|V| = 0.2 * 30 = 6$ nodes must be targeted

Figure 5: Finding seed sets with time constraint



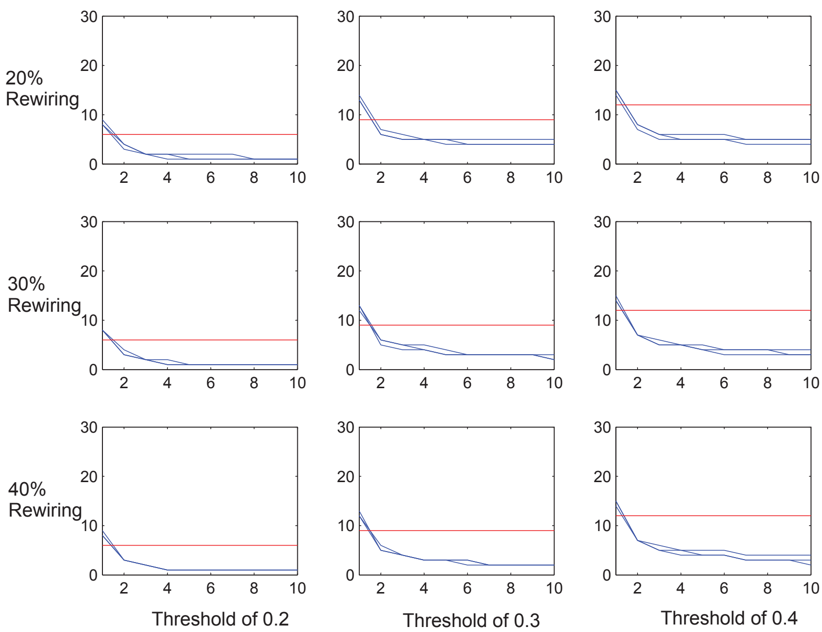
with intervention to reach $100\%$ adoption (this is depicted as a horizontal red line in Figure 5). Notice in Figure 5 that when norms are given a few time steps to operate, the number of seeds required to reach full adoption decreases dramatically from what is predicted by the non-network moral-motivation model. For example, when three time steps of norm updating are allowed, the required seed set size is less than half of the prediction from the non-network model for each of our three randomly-constructed sample networks. For this class of graphs, it appears that even imposing a quite restrictive limit of the “length of the fuse" that a solution can rely on, full adoption can be reached with a fairly small targeted intervention. That is, if local-norm spreading is given time to operate, the percentage of subsidy required to reach $100\%$ adoption decreases substantially from what is predicted by the non-networked moral-motivation model of Nyborg et al. (2006). Hence, targeted subsidies may allow the social planner to reach full adoption via a much smaller intervention if she is not subject to a very tight time constraint. Intuitively, the tighter the time constraint, the wider, and costlier, the intervention needs to be.

To show that the qualitative behavior observed in Figure 5 does not depend closely on the specific network statistics or node thresholds, we reproduce the experiment for a number of additional combinations in the parameter space. Figure 6 displays our findings. In the figure, each horizontal axis is the length of time allowed until full adoption must be reached. The size of the minimal seed set that causes full adoption is plotted on the vertical axis. The results from three randomly constructed graphs appear in each panel. Figure 6 shows that, unless we require total adoption to be reached very quickly, a targeted subsidy of at most $\frac{1}{2}\alpha n$ nodes appears more than sufficient to cause a full cascade in this parameter range. The number of seeds required appears quite consistent across the three trials for each parameter combination.

In Figure 6 we observe that across the (Random Rewiring, Threshold) parameter space, the required seed set size to reach the green equilibrium is only larger than the prediction of the non-network model when we insist that complete adoption has to be reached after only one time step of subsidy.

Hence, we can summarize our first policy implication as follows. Our model predicts that, with appro-

Figure 6: Finding smaller seed sets across parameter space



priate targeting, the cost to reach the green equilibrium may be substantially less than what is predicted by the non-networked model of Nyborg et al. (2006). This is not a highly-special property that holds only in carefully constructed classes of graphs: we have demonstrated this property in a class of highly-clustered, short-average-path length graphs that are randomly constructed and that mirror real-life social networks. In this class, we consistently observe that optimally-leveraging norm spread can reduce the number of nodes needed for seeding to reach green equilibrium by at least 50% (cf. Figure 6). This is true even when only seed sets that reach full adoption relatively quickly are considered. While the magnitude of the "savings" will vary by graph class and graph size, we hypothesize that qualitatively-similar results will hold for other social-network-like graph classes.

### 5.3 Policy implication II: how much does network-position-based targeting help?

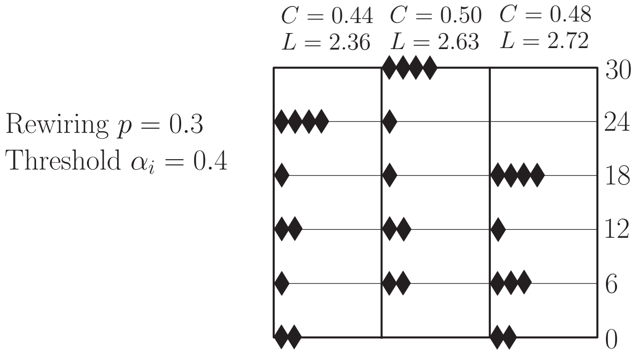
When individuals have uniform thresholds, the non-network moral-motivation model predicts that every set of seeds of the same size will have an identical long-term effect. Based on this prediction, if we had no specific knowledge about the social network, we might optimistically hope that a randomly-placed subsidy in the network would perform reasonably well compared to the best-targeted subsidy of the same size. Qualitatively, we are hoping that the information deficit (lack of knowledge of the social network) is not too costly in terms of the long-term adoption we are able to establish with our subsidy campaign.

In Theorem 4 we saw that for certain classes of specialized networks, even when a small set that can convert the entire network exists, a randomly-selected set of the same size could result in very low expected long-term adoption. Qualitatively, this means that in certain classes of networks, careful targeting gives substantial gains in long-term adoption.

We now want to simulate how large these gains are, and on what factors they depend. That is, we would like to disentangle the effect on adoption of having a non-homogenous social network, from the effect of optimizing the precise seed set that minimizes the subsidy cost to reach full adoption. The question that we are asking is thus the following: for networks that look like real social networks, if $k$ targeted subsidies are sufficient to convert the entire network, how much adoption results from a randomly-selected $k$-set?

To address this question, we compute the size of the exact-minimum-size seed set required to reach total adoption (within a "fuse" time limit of 5 periods). Then we compute the long-term number of adoptions that result from each of 10 randomly-chosen seed sets *of the same size as the optimal seed set*. Figure 7 displays our results. The Figure is constructed as follows. Each of the three columns corresponds to a random network on 30 nodes constructed with random rewiring parameter $p = 0.3$, and with uniform threshold 0.4. For each network, the column depicts the long-term performance of 10 randomly-chosen seed sets the same size as the minimum seed set capable of generating 100% adoption. The leftmost column shows that for a network with clustering coefficient $C = 0.44$, and shortest-average-path-length $L = 2.36$, the 10 random seed sets produced long-term adoption of $\{0, 0, 6, 12, 12, 18, 24, 24, 24, 24\}$ out of 30 nodes. That is, in Figure 7, the long-term performance of randomly-chosen seed sets for the first network is highly variable, ranging from 0% long-term adoption (0 nodes out of 30) to 80% long-term adoption (24 nodes out of 30). Some randomly-chosen seed sets result in high long-term adoption, while others result in very low long-term adoption. For this first network (leftmost column) the average long-term adoption over 10 attempts at random seeding is 14.4 nodes out of 30. That is, for the first network, attempting to plan an intervention without considering network structure appears to reduce the expected final level of green adoption by a factor of 2. For some networks (like that corresponding to the middle column of Figure 7), many randomly-chosen seed sets may actually match the behavior of optimal seed sets, while in other networks (rightmost column of Figure 7), randomly-chosen seed sets have particularly poor long-term behavior (averaging only 10.1 adopters out of 30 despite using an intervention size sufficient to convert the entire network, if strategically

Figure 7: Testing the long-term performance of randomly-chosen seed sets




targeted).

We then replicate this experiment across the (random rewiring, threshold)-parameter space. Figure 8 displays our results. In Figure 8, each panel reproduces the experiment from Figure 7 with different parameter combinations. When thresholds are very small, most nodes will become adopters if they observe any neighbor adopting. As a result, randomly-selected sets of the same size as the optimal seeding set result in $100\%$ long-term adoption (top row of Figure 8). Optimizing targeting based on social structure is not helpful here.When thresholds are slightly higher (so that many nodes can still be convinced to adopt by a single adopting neighbor), we again observe that the social planner derives little-to-no expected benefit from trying to target an intervention based on social structure. This message appears to hold despite some variation in network statistics as we increase $p$.

As thresholds increase, nodes need to observe more neighbors adopting for moral motivation to overcome the cost of engaging in green behavior, and Figure 8 shows that the average adoption resulting from a randomly-selected seed set decreases. For fractional threshold$\alpha_i = 0.3$, the average number of final adopters achieved by random-selected seed sets ranges from 1/3 to 2/3 of the adopters that could be achieved through careful intervention targeting. Table 1 provides the average values corresponding to each panel of Figure 8. In addition to poor average behavior, Figure 8 shows that when nodes apply higher thresholds, interventions that ignore spatial structure frequently fail "catastrophically": despite using an intervention size that is sufficient to reach $100\%$ adoption, random spatial placement of the intervention can result in zero long-term adopters. The frequency of "catastrophically" bad outcomes appears to be highest for the most rewired societies that we test (rightmost column of Figure 8). Even though Figure 8 shows that some "lucky guesses" are also possible, in this higher-threshold part of the paramter space, targeting based on social structure is critical and can help a social planner to achieve much better long-term outcomes.

Notice that in Figure 8 the performance of the randomly-selected sets often corresponds to multiples of 6: this is due to green-behavior stabilizing in several local communities but not being able to spread through the rewired ties into the remaining communities. In Table 1, we summarize the average values obtained in each panel of Figure 8. In sum, our computational results on the networked moral-motivation model predict that when thresholds are small, randomly-selected sets may perform similarly to the optimal seeding set. However, as thresholds increase, indicating that the percentage of local-adoption must be higher in order to surpass the personal cost of the green behavior, we observe that randomly-located subsidies are on average substantially less effective. Despite their low average performance, we observe high-variance: some randomly-chosen seed sets perform very well. Further, this set of experiments shows that random seed sets quite often settle at a long-term equilibrium which is heterogeneous for the class of graphs considered in

Figure 8: Testing the long-term performance of randomly-chosen seed sets with different parameters

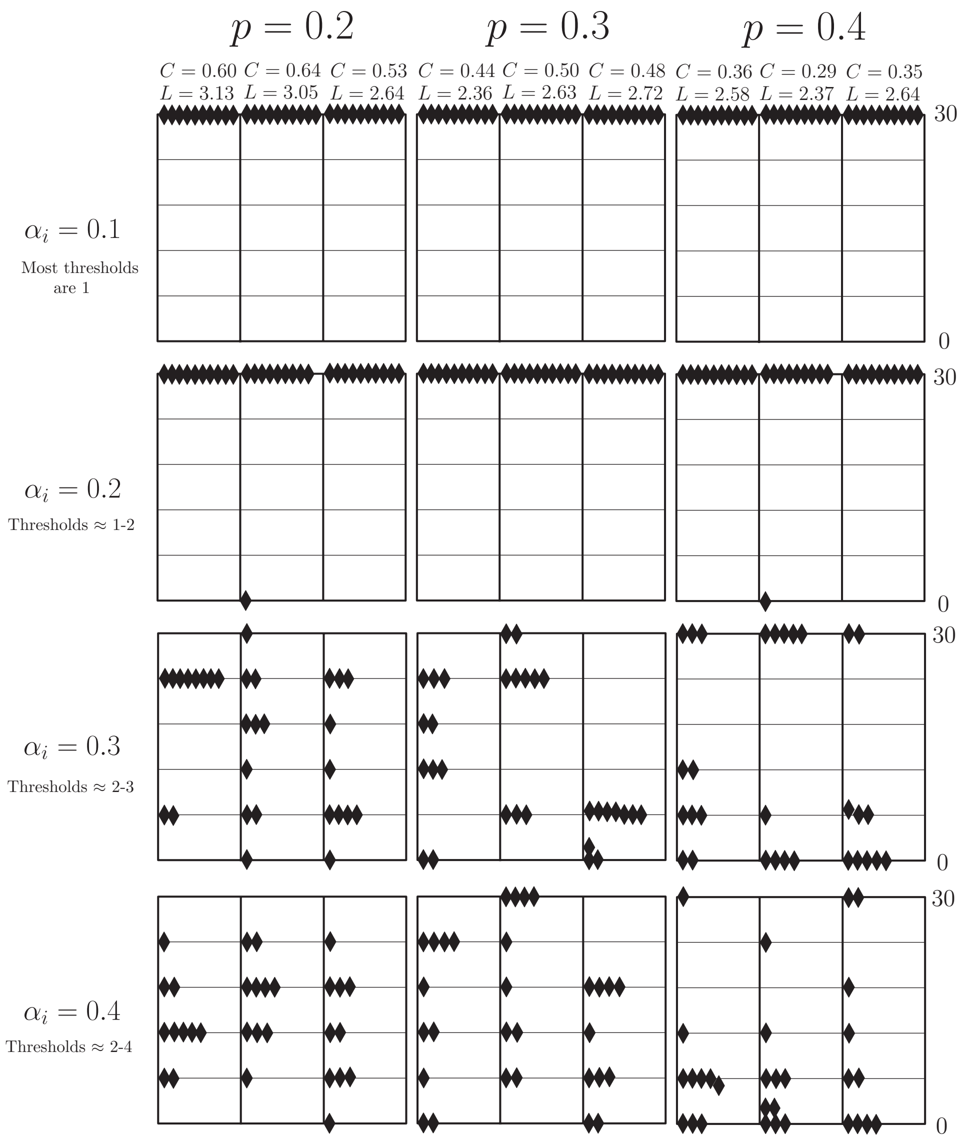


Table 1: Mean Performance Achieved by $k$ Random Seeds, where $k$ is sufficient for 100% adoption

| | Rewiring $p = 0.2$ | Rewiring $p = 0.3$ | Rewiring $p = 0.4$ |
|---|---|---|---|
| Fractional Threshold $\alpha_i = 0.1$ | (30,30,30) | (30,30,30) | (30,30,30) |
| Fractional Threshold $\alpha_i = 0.2$ | (30, 29, 30) | (30,30,30) | (30,29,30) |
| Fractional Threshold $\alpha_i = 0.3$ | (18.1, 15.6, 12.9) | (17.7, 19.8, 9.5) | (13.5,15.6, 10.7) |
| Fractional Threshold $\alpha_i = 0.4$ | (13.5, 16.3, 12) | (14.4, 19.9, 10.1) | (6.9, 6.3, 11.4) |

this paper. Qualitatively, green (or generally, virtuous) behavior may stabilize in small dense communities despite very low society-wide adoption.

## 6 Conclusion

Transitioning to a low-carbon society is one of the main challenges for our society. This challenge requires a widespread adoption of clean technologies and behavior. This paper provides the theoretical basis for a growing literature on the role of social networks in the adoption of clean goods and habits such as solar panels, hybrid cars, green energy programs, or energy conservation. It extends the socially-contingent moral motivation model from Nyborg et al. (2006) to social networks. In our model, individuals are influenced by behavior among a group of local neighbors. Individuals regularly update their beliefs about others' adoption of the green good, and, if adoption is sufficiently strong, decide to also go green. In our model, "others" does not refer to the society as a whole, for which adoption of most green behaviors would likely be unobserved. "Others" refer in our model to neighbors, and close individuals belonging to the same social network.

In a model of socially-contingent moral motivation, temporary subsidies can generate sufficient levels of adoption of green behavior, which are persistent over time. People are influenced by the behavior of others and if adoption is sufficiently widespread within society, discontinuing the subsidy may not lead adoption to drop, as it would be the case in a classical model. Increasing empirical evidence, reviewed in this paper, adds to that considered by Nyborg et al. (2006), and supports the relevance of this type of model. This empirical evidence, however, also suggests that people tend to pay attention to people very close to them, even when taking decisions that are related to a global dilemma.

Hence, from a policy perspective, exploiting social networks may allow targeting subsidies and other initiatives to a specific seed group. This would imply greatly increasing the cost-effectiveness of public interventions. In our model, we find that adoption of green behaviors may naturally be heterogeneous with stable pockets of adoption and non-adoption. When introducing external interventions into the model, we find that targeting subsidies based on the social network yields potentially important gains over strategies that specify only the size of the subsidized set. Our computational experiments, which use networks that replicate well the high clustering and short-average path lengths characteristic of real social networks, indicate that milder, but still substantial, advantages may be gained by careful subsidy targeting. Targeting subsidies based on knowledge of social-network structure could result in more long-term green adoption, or in substantial reduction in the costs of stabilizing wide-spread participation in pro-environmental behaviors. Two main elements determine the difference in cost-effectiveness between a standard subsidy, and a targeted subsidy. First, social networks need time to operate. If policy-makers, or practitioners, have sufficient time to allow individuals to update their beliefs, and for adoption to spread, targeted subsidies can be very effective. The more haste one has, the lower the benefit from targeting. This finding provides further support for the importance and cost-effectiveness of early action in addressing externalities, as for instance in the case of climate change. Second, people may be influenced by other people's adoption in different ways, in particular concerning the threshold of adoption after which one decides to follow her peers. Our paper shows that, in networks that resemble real social networks, the relative advantage of social-network-based targeting appears to increase as thresholds increase. The main take-home message from our model is that, for green behaviors where moral motivation applies, good information about social-network structure and targeted subsidies based on this information may increase long-term adoption and reduce the costs of subsidies, or public education campaigns, that aim to establish long-term participation in environmentally-friendly behaviors.

From a policy perspective, that temporary subsidy may be able to enforce a permanent change in behavior expands the range of possible settings in which subsidies, or targeted campaigns, are a rational approach. A subsidy is generally rational when the cost of providing the subsidy annually is outweighed by the benefits that result from the resulting behavior change annually. But if temporary subsidies can be used to cause a permanent shift in behavior, then the cost of imposing the temporary subsidies for some number of years should now be weighed against all benefits accrued during the term of the subsidies and *in the future* due to the behavior change that results from the temporary subsidies. In particular, in settings where moral motivation is in play, the size of investments in subsidies and public education campaigns that are "rational" may be much larger than when the future benefit of permanent behavior change is ignored. With our paper, we show that the cost-effectiveness of targeted interventions may be even higher, if these interventions leverage existing social networks. Also, if carefully designed, targeted interventions may also have the potential to reduce the occurrence of adverse distributional effects, which have been shown in presence of widespread subsidies for, for instance, solar panels.

In conclusion, we show that, if decision rules applied by individuals rely on local information, then the level of investment required to reach a green equilibrium may be much less than predicted by a non-network model. There indeed exist classes of networks where taking advantage of the network structure can significantly reduce the number of individuals that must be subsidized to reach a high-adoption equilibrium. Thus, the cost to reach a green equilibrium could be much lower than is predicted by a non-network model. As environmental and behavioral economists and sociologists work to understand why individuals adopt pro-environmental behaviors, and while the body of observable data about social networks continues to explode, leveraging network characteristics in considering the costs and benefits of encouraging behavior change could critically impact the cost-effectiveness of important policies and social interventions. Furthermore, we hope that our work can motivate study of how other influential decision models that describe the formation of social norms and the private provision of public goods translate to network settings.[7] Randomized controlled trials, in combination with social network analysis, are increasingly common in development economics. Applying the same tools to environmental economics would have, according to our model, high potential in terms of behavioral change. Finally, while in our context thresholds are treated exogenously, interventions that could lower them, or, equivalently, make the behavior of close ties more visible, could have important pay-offs as well.

[7] For example, Lindbeck et al. (1999) study political support for varying levels of public assistance based on individual tax-payers' perceptions of the number of claimants. Rege (2004) considers voluntary binary contributions to a public good based on social rewards and sanctions under viscous mixing where individuals have elevated probabilities of interacting with others whose behavior matches. It is not obvious, and would deserve careful attention, how the emergent behavior (e.g. the form of stable equilibria) of these models would be impacted if individuals' perceptions were based on local observations, rather than on a symmetric global view of behavior across the society.

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# Appendix

## A.1 Network moral-motivation model: severe departures from the $G = K_{|V|}$ case are possible.

To prove Theorems 1, 2, 3, and 4 we introduce several classes of networks.

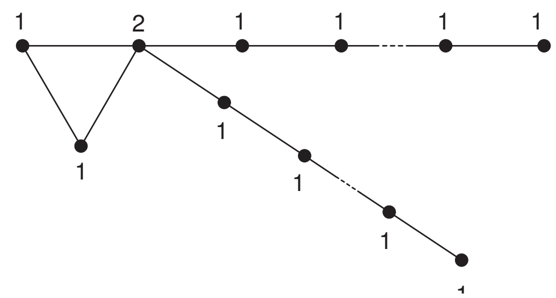


Figure A.1: ***Class 1:*** Resulting cardinality thresholds ($b_i$) are marked. Subsidizing any single node in the triangle for at least 3 time steps results in $100\%$ adoption, but subsidizing any single node not in the triangle (for any number of time steps) will result in long term adoption strictly less $50\%$.

***Class 1:*** $G$ is composed of a triangle on three nodes, with two “legs" each containing $n$ nodes (where the first such node in each leg is a common node from the triangle). Let $\alpha_i = 1/2$ for all $i \in V$ (see Figure A.1).

- *Proof of Theorem 1:* As explained in Figure A.1, two subsidy sets of size 1 have widely-different long-term adoption rates for Class 1 (which has uniform $\alpha$).
- *Proof of Theorem 2:* Regardless of the value of $n$, a network in Class 1 can be converted to $100\%$ adoption by subsidizing any single node in the triangle for at least three time steps. A network of Class 1 has $2n + 1$ nodes. Thus, for any $\epsilon > 0$, we can choose $n'$ sufficiently large so that $1 < \epsilon(2n' + 1)\frac{1}{2} = \epsilon|V|\alpha$. We obtain an infinite class of examples (for $n \geq n'$), which satisfy Theorem 2.
- *Proof of Theorem 4 (first half):* For a network in Class 1 there are three possible subsidy sets of size 1 which result in $100\%$ adoption if a subsidy is maintained for three timesteps. There are $2n - 2$ sets of size 1 that result in strictly less than $50\%$ adoption (regardless of how long the subsidy is maintained). Thus, while $100\%$ adoption is achievable by subsidizing a single node, for any $\epsilon > 0$, there exists sufficiently large $n$ so that the probability of randomly selecting a single node that achieves $100\%$ adoption is $3/(2n + 1) < \epsilon$.

***Class 2:*** $G$ is composed of a triangle on three nodes, with $n$ “legs" of length 3 attached to a common node of the triangle (the first node of each such leg is the common node in the triangle). All nodes of degree 1 or 2 have $\alpha_i = 1/2$. The node of degree $n+2$ has $\alpha = 2/(n+2)$. The class is presented in Figure A.2 below.

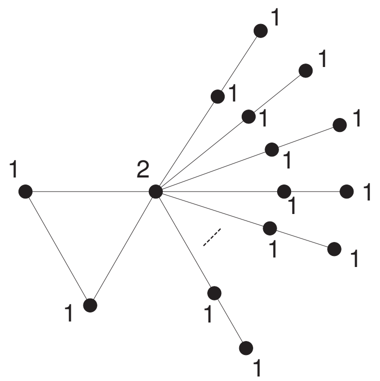


Figure A.2: ***Class 2:*** Resulting cardinality thresholds ($b_i$) are marked. Subsidizing any single node in the triangle for at least 3 time steps results in $100\%$ adoption, but subsidizing any single node not in the triangle (for any number of time steps) will result in long term adoption rate of at most $2/(2n+3)$.

- *Proof of Theorem 3:* For networks of Class 2 with $n \geq 1$, there are both homogeneous and heterogeneous stable equilibria. $100\%$ adoption is a stable equilibrium, $0\%$ adoption is a stable equilibrium, and there are $n$ stable heterogeneous equilibria of the form: the two outer nodes in a leg are adopters and no other nodes adopt.

- *Proof of Theorem 4 (second half):* For a network in Class 2 there are three possible subsidy sets of size 1 which result in $100\%$ adoption if subsidy is maintained for three timesteps. There are $2n$ sets of size 1 that result in $(2/(2n+3))$ adoption (regardless of how long the subsidy is maintained). Computing the expected adoption rate achieved by selecting a random set of size 1:

$$\text{Expectation } = \frac{3}{2n+3}(1) + \frac{2n}{2n+3}\left(\frac{2}{2n+3}\right) \leq \frac{10n+9}{(2n+3)^2}$$

  Thus, while $100\%$ adoption is achievable by subsidizing a single node, for any $\gamma > 0$, there exists sufficiently large $n$ so that the expected adoption rate achieved by selecting a random set of size 1 is strictly less than $\gamma$.

## A.2 An accurate tool for measurement: Integer Programs

In this section we define Integer Programs that perfectly calculate the optimal set of individuals (nodes) to subsidize. These Integer Programs (IP) can not be solved "efficiently" in a rigorous mathematical sense, but off-the-shelf solvers (e.g. CPLEX) running on a standard desktop allow us to make measurements in some small semi-realistic networks.

Let $\delta(i)$ denote the set of neighbors of $i$ in $G$. Recall the problem variants from Section 3.1.

### A.2.1 Min-cost Complete Conversion (MCC) for $d \geq |V|$

Decision variables:
*(Subsidy variables):* for $i \in V$: $y_i = 1$ if node $i$ is subsidized from time step 0 to $|V|$, and 0 otherwise.

*(Adoption variables):* for $i \in V, t \in \{0, 1, 2, ..., 2|V|\}$: $x_{it} = 1$ if node $i$ adopts at time $t$, and 0 otherwise.
*(Subsidy size):* a dummy variable $q$ describes the size of the subsidized set.

We wish to minimize $q$ subject to the following constraints. First, the number of nodes that are chosen for subsidy is at most $q$:

$$\sum_{i \in V} y_i \leq q$$

During the period of the subsidy, a node $i$ is allowed to be an adopter only if either it is subsidized, or if at least $b_i$ of its neighbors are adopters during the previous time step. Due to the integrality of the *Adoption* and *Subsidy* variables this condition is enforced precisely by the following inequality:

$$x_{it} \leq y_i + \frac{1}{b_i} \sum_{j \in \delta(i)} x_{j,t-1} \qquad \text{for } t \in \{0, 1, 2, ..., |V|\}, i \in V.$$

Assuming that the subsidy is maintained for $|V|$ time steps and is then removed gives the same behavior as if the subsidy is removed immediately after the first step in which no 0 to 1 conversions occur (that is, assuming subsidy is maintained for $|V|$ time steps perfectly emulates the conditions we defined for temporary subsidy). After the period of subsidy ends, a node $i$ is allowed to be an adopter only if at least $b_i$ of its neighbors are adopters during the previous time step:

$$x_{it} \leq \frac{1}{b_i} \sum_{j \in \delta(i)} x_{j,t-1} \qquad \text{for } t \in \{|V| + 1, |V| + 2, ..., 2|V|\}, i \in V.$$

Imposing the above condition for $|V|$ time steps after the subsidy is removed ensures that the process will have converged to a stable adoption vector. Forcing the adoption variables for the final time step to 1 ensures we only consider solutions which result in $100\%$ adoption. This is enforced by requiring that for all $i \in V$: $x_{i,2|V|} \geq 1$.

Combining these constraints we obtain the following IP that computes the smallest subsidy set which permanently converts the entire network.

$$\begin{aligned}
&\text{minimize } q \\
&\text{subject to} \\
&\quad \sum_{i \in V} y_i \leq q \\
&\quad x_{it} \leq y_i + \frac{1}{b_i} \sum_{j \in \delta(i)} x_{j,t-1} \qquad \text{for } t \in \{0, 1, 2, ..., |V|\}, i \in V. \\
&\quad x_{it} \leq \frac{1}{b_i} \sum_{j \in \delta(i)} x_{j,t-1} \qquad \text{for } t \in \{|V| + 1, |V| + 2, ..., 2|V|\}, i \in V. \\
&\quad x_{i,2|V|} \geq 1 \qquad \text{for } i \in V.
\end{aligned}$$

***A technical note:*** A sequence of adoption variables that constitute a feasible solution for the IP may not perfectly match the evolving adoption vector of the process. In particular, a set of adoption variables may “lag" the true adoption vector: the process effectively turns on (from 0 to 1) a node as soon as possible, while we only require that the IP do not turn on (from 0 to 1) a node if it is not justified in doing so (the second and third sets of constraints ensure this). At a first glance, this discrepancy might seem disconcerting; we might worry that the IP could gain some advantage by lagging the process, and thus produce a subsidy solution that is apparently the best but in fact performs badly with respect to the true adoption-evolution process. The answer to this concern is given by the lemma on the monotonicity of this update rule from Spencer (2016): when our goal is enlarging the set of adopters, there is never an advantage in delaying turning a node from 0 to 1.

### A.2.2 Budgeted Maximum Conversion (BMC) with $d \geq |V|$

Decision variables:
*(Subsidy variables):* for $i \in V$: $y_i = 1$ if node $i$ is subsidized from time step 0 to $|V|$, and 0 otherwise.
*(Adoption variables):* for $i \in V, t \in \{0, 1, 2, ..., 2|V|\}$: $x_{it} = 1$ if node $i$ adopts at time $t$, and 0 otherwise.

$$\text{maximize} \sum_i x_{i,2|V|}$$

$$\text{subject to}$$

$$\sum_{i \in V} y_i \leq k$$

$$x_{it} \leq y_i + \frac{1}{b_i} \sum_{j \in \delta(i)} x_{j,t-1} \qquad \text{for } t \in \{0, 1, 2, ..., |V|\}, i \in V.$$

$$x_{it} \leq \frac{1}{b_i} \sum_{j \in \delta(i)} x_{j,t-1} \qquad \text{for } t \in \{|V| + 1, |V| + 2, ..., 2|V|\}, i \in V.$$

### A.2.3 Min-cost Complete Conversion (MCC) for $d < |V|$

Decision variables:
*(Subsidy variables):* for $i \in V$: $y_i = 1$ if node $i$ is subsidized from time step 0 to $d$, and 0 otherwise.
*(Adoption variables):* for $i \in V, t \in \{0, 1, 2, ..., (d + 2|E| + |V|)\}$: $x_{it} = 1$ if node $i$ adopts at time $t$, and 0 otherwise.
*(Subsidy size)* a dummy variable $q$ describes the size of the subsidized set.

$$\text{minimize } q$$

$$\text{subject to}$$

$$\sum_{i \in V} y_i \leq q$$

$$x_{it} \leq y_i + \frac{1}{b_i} \sum_{j \in \delta(i)} x_{j,t-1} \qquad \text{for } t \in \{0, 1, 2, ..., d\}, i \in V.$$

$$x_{it} \leq \frac{1}{b_i} \sum_{j \in \delta(i)} x_{j,t-1} \qquad \text{for } t \in \{d + 1, d + 2, ..., (d + 2|E| + |V|)\}, i \in V.$$

$$x_{i,(d+2|E|+|V|-1)} \geq 1 \qquad \text{for } i \in V.$$

$$x_{i,(d+2|E|+|V|)} \geq 1 \qquad \text{for } i \in V.$$

### A.2.4 Budgeted Maximum Conversion (BMC) for $d < |V|$

Decision variables:
*(Subsidy variables):* for $i \in V$: $y_i = 1$ if node $i$ is subsidized from time step 0 to $d$, and 0 otherwise.
*(Adoption variables):* for $i \in V, t \in \{0, 1, 2, ..., (d + 2|E| + |V|)\}$: $x_{it} = 1$ if node $i$ adopts at time $t$, and 0

otherwise.

$$
\begin{aligned}
&\text{maximize } \frac{1}{2}\Big(\sum_{i\in V} x_{i,(d+2|E|+|V|)} + \sum_{i\in V} x_{i,(d+2|E|+|V|-1)}\Big)\\
&\quad\text{subject to}\\
&\qquad \sum_{i\in V} y_i \le k\\
&\qquad\quad x_{it} \le y_i + \frac{1}{b_i}\sum_{j\in\delta(i)} x_{j,t-1} \qquad \text{for } t\in\{0,1,2,...,d\}, i\in V.\\
&\qquad\quad x_{it} \le \frac{1}{b_i}\sum_{j\in\delta(i)} x_{j,t-1} \qquad \text{for } t\in\{d+1,d+2,...,(d+2|E|+|V|)\}, i\in V.
\end{aligned}
$$

### A.3 Technical note: intransigent individuals, weighted neighbors, differential costs of subsidy

***Intransigence:*** The model can describe *intransigent individuals* by letting the cardinality threshold, $b_i$, exceed the degree of the node, $|\delta(i)|$. This threatens to make our Min-cost Complete Conversion Problems infeasible: intransigent individuals will clearly violate the constraint that they be adopters in the final time step. By doing a simple iterative search in the network, it is easy (and efficient) to identify a set of nodes that are explicitly intransigent or implicitly intransigent (they are intransigent once all explicitly intransigent nodes are removed from the network, or once other implicitly intransigent nodes are removed, etc). This gives a *network of intransigence*: the planner can never hope to influence these nodes to adopt without direct indefinite subsidy. Removing the final time step constraint for nodes in this *network of intransigence* gives a variation of Min-budget Complete Conversion in which we can compute the minimum-size subsidy set that permanently converts all nodes which are not in the *network of intransigence*.

***Weighted neighbors:*** Suppose that the adoption of some set of $i$s neighbors is more important to $i$ than the adoption of other sets of $i$s neighbors. We might model this by weighting each neighboring adoption status (0 or 1) by a scalar before comparing to a threshold $b_i$. In particular, when symmetric weights are used to describe homophily of individuals (how alike a pair of individuals are) and weights are chosen from the set of integers $\{1, 2, ..., k\}$ for some constant $k$, nearly all our results go through immediately (with somewhat diluted, but still linear, upperbounds on convergence time for the fixed duration case). We mention this in reference to recent work in the mathematical sociology literature on how homophily appears to contribute substantially to increased rates of healthy-behavior transmission in social networks (cf. Centola 2011).

***Differential costs of subsidy:*** None of our tools require that the cost of subsidizing nodes is uniform. Trivial alteration of the Integer Programs specified allows perfect computation in the non-uniform case.