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

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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

[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.

support the adoption by residential owners, but also by the private sector.

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,

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

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 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 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

[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.

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 ($AveragePV_{i,t}$), 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 ($\mathit{\Delta} PV_{i,t}$) 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:

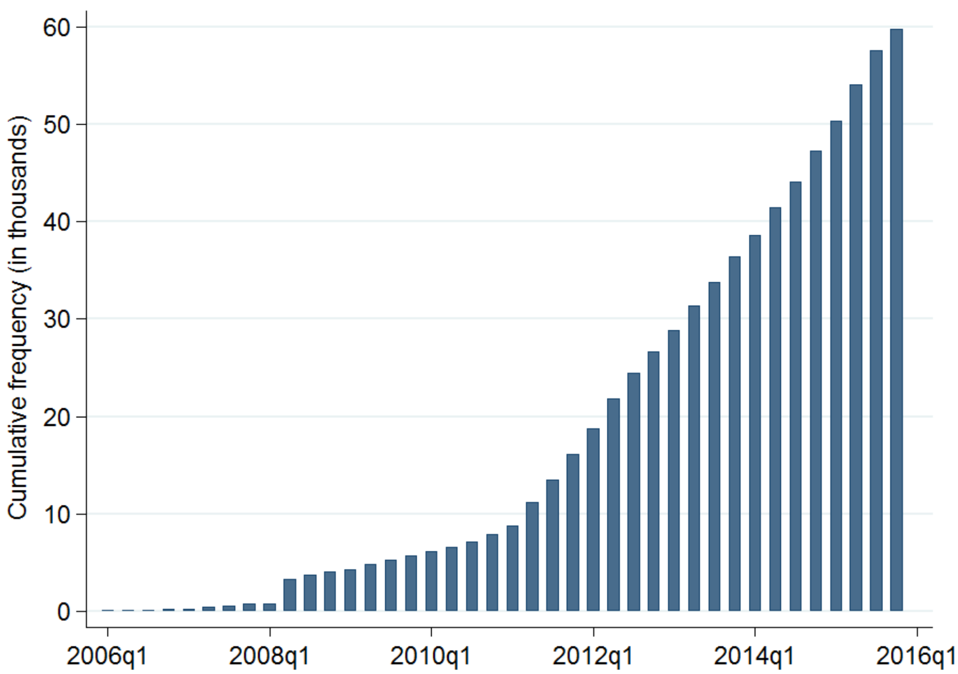
$$\mathit{\Delta} PV_{i,t} = \alpha + \beta Average\,PV_{i,t} + \gamma C_{i,t} + \phi_i + \mu_t + \lambda_{c,t} + \varepsilon_{i,t} \tag{2}$$

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, ϕ_i represents municipality-specific fixed effects controlling for time-invariant unobserved heterogeneity, μ_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 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).

[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.

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.

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

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

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.

which data are available is the municipality, and data are typically provided on an annual basis. We hence collect the relevant variables and, for each of them, we create a panel dataset at the municipality level for every year of the period 2006-2015.[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

[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.

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 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 β. 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 installations that are closer to the adopter. This finding is in line with previous studies on social contagion in the diffusion of PV technology, suggesting that social contagion is a localized phenomenon, whose effects are strong in a limited geographical 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.

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.

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

Table 4: Main specifications focusing on size

	(1) All adopt.	(2) <10 kWp adopt.	(3) 10-29.9 kWp adopt.	(4) 30-99.9 kWp adopt.	(5) >100 kWp adopt.
Average PV, <10 kWp	0.127***	0.106***	0.0845***	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.

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 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

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.

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 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.

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

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.

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

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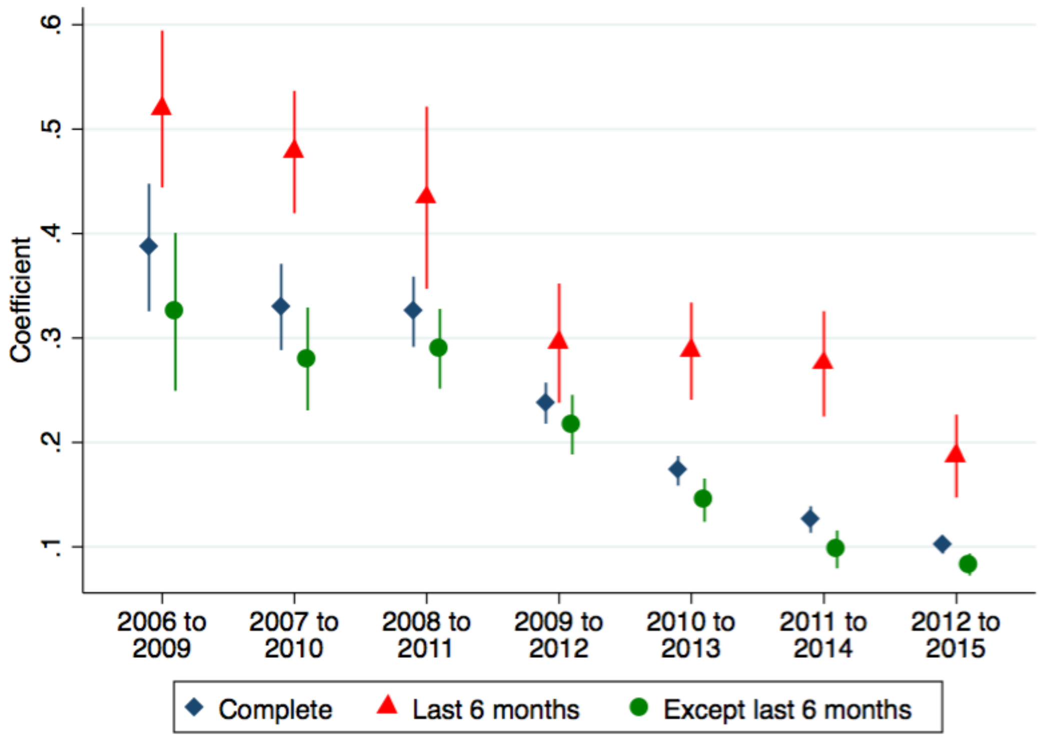
Appendix

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)	(2)	(3)	(4)
	Complete	6 months	12 months	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) HH adopt.	(2) Firm adopt.	(3) Farm adopt.	(4) HH adopt.	(5) Firm adopt.	(6) 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.