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

Stefano Carattini†‡§, Martin Péclat¶‖, Andrea Baranzini‖

November 5, 2018

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.

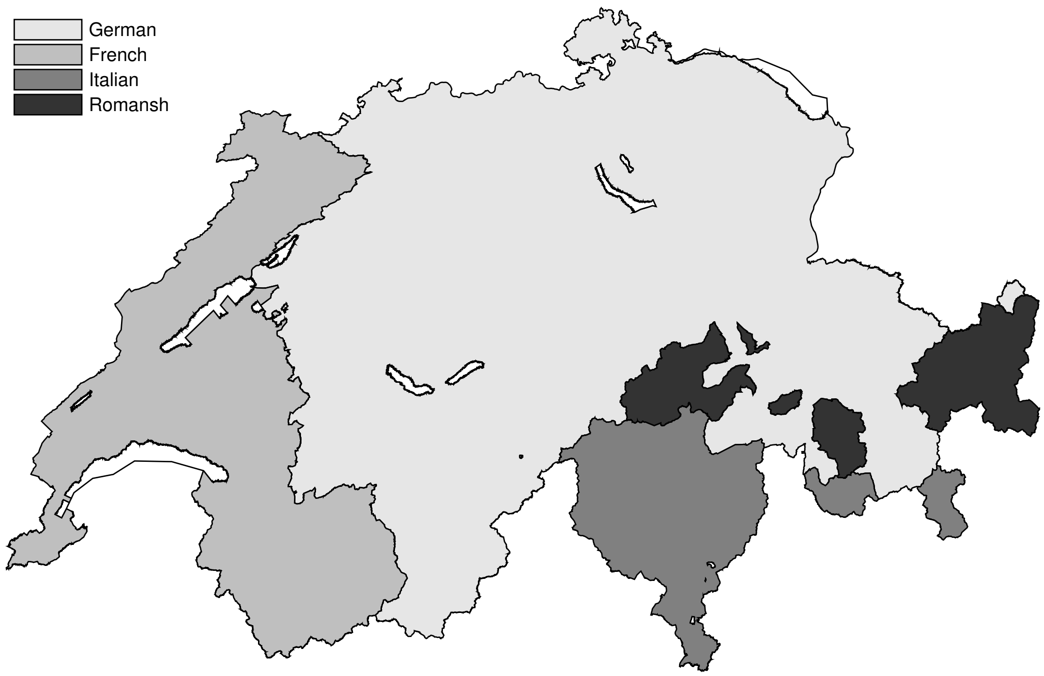
The second set of variables measures contextual factors that may be linked to the feasibility and profitability of PV installations. We use variables characterizing the type of building and solar irradiance. Building characteristics are of particular relevance, although in existing studies those data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

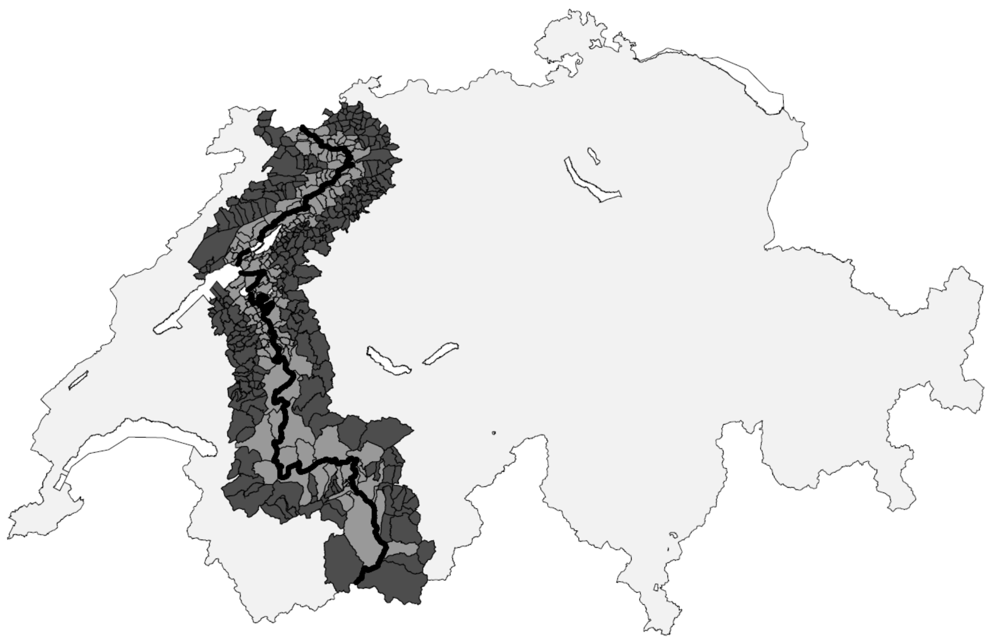
To perform our analysis of the impact of the border on PV adoption, we first need to precisely identify the location of the language border. Then, we compute the distances of each PV installation to the border. For reasons of political sensitivity, no official source provides precise geographical data 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 β coefficient. Everything else equal, the further we go from the language border, the higher the level of adoption. The objective of this first analysis is to determine whether there is a common pattern that is compatible with the language border being an obstacle to social spillovers. There is no ambition, at this stage, to deliver causal estimates on the effect of the border.

To further investigate if the presence of a language barrier may result in lower social spillovers, we test whether the release of important information on solar PV has a differentiated impact depending on the distance from the language border. To this end, we exploit the quasi-natural feature of the implementation, in 2008, of a countrywide feed-in tariff (FIT), which changed dramatically the profitability of solar installations in Switzerland.[4] With the FIT, the remuneration for each kWh injected into the electricity grid jumped from 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 ΔPV_{it} is the number of new adoptions in a municipality i during the year t and ϵ_{it} is the i.i.d. error term, clustered at the municipality level. The main coefficient of interest is given by $FIT \times distance_{it}$, which is an interaction term between the

[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, α_i, to capture potential time-invariant unobserved heterogeneity, and year-specific time dummies, μ_t, to capture time-varying factors potentially affecting the adoption rate over the whole region.[6]

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

[6] OLS is used in all specifications. Fixed effects are justified by a χ^2 (27) of 184.51 (p > $\chi^2(27)$ = 0.0000) in the Hausman test for model (1) of Table 2. The Hausman test supports the use of a fixed-effect model also in all other specifications. For each control variable in X_{it}, we test whether its level in 2008, and its evolution between 2008 and 2015, is related 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 β units per municipality, on average, installed between 2006 and 2015. The coefficient for column (1), for instance, suggests that the region within 5 km from the border experiences

[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

Model	km	Period	Per municipality: Per km and year	Per km	Total	All municipalities: 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.

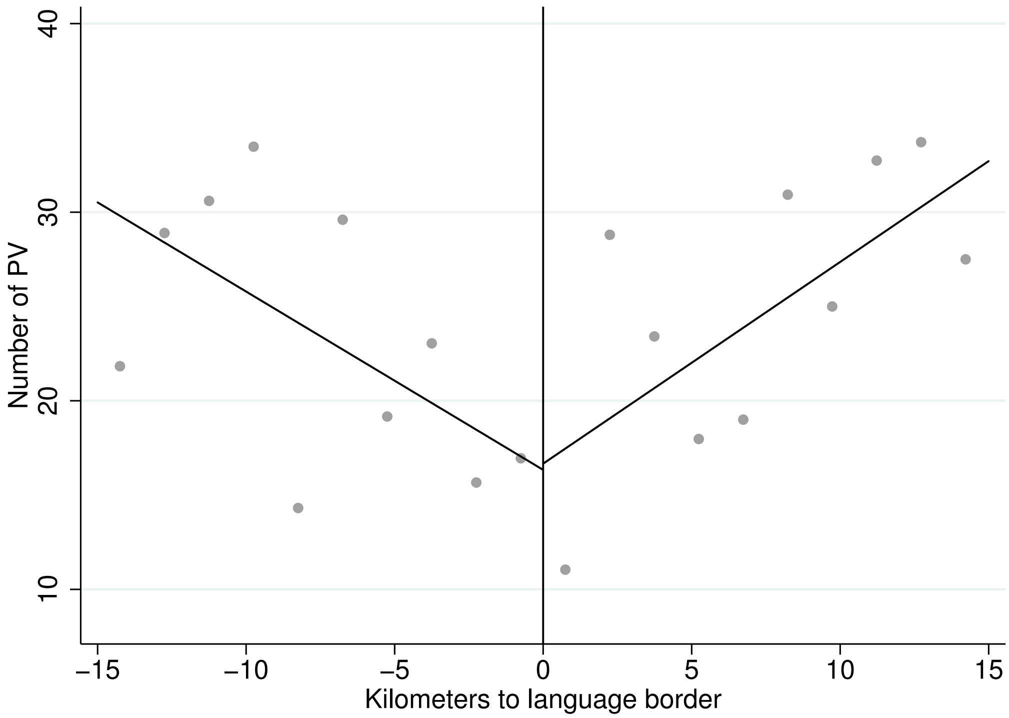
Table 4 quantifies the effects illustrated by Figure 3. Column (1) of Table 4 shows that the discontinuity in culture is associated with no significant change in the rate of adoption of solar PV. Columns (2) and (3) measure the slope of adoption, as a function of distance from the border, for the Western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

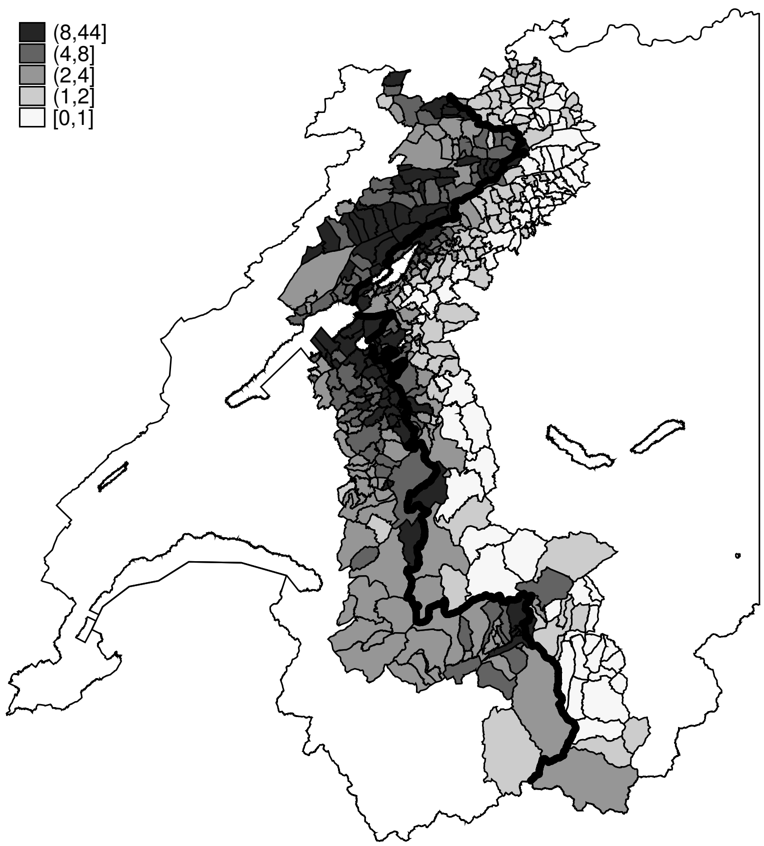
	RD	West	East
	(1)	(2)	(3)
RD estimate	0.329		
	(3.959)		
Distance		-0.945**	1.069***
		(0.406)	(0.361)
Constant		16.338***	16.667***
		(2.873)	(2.725)
N	436	188	248
R^2		0.0198	0.0362

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

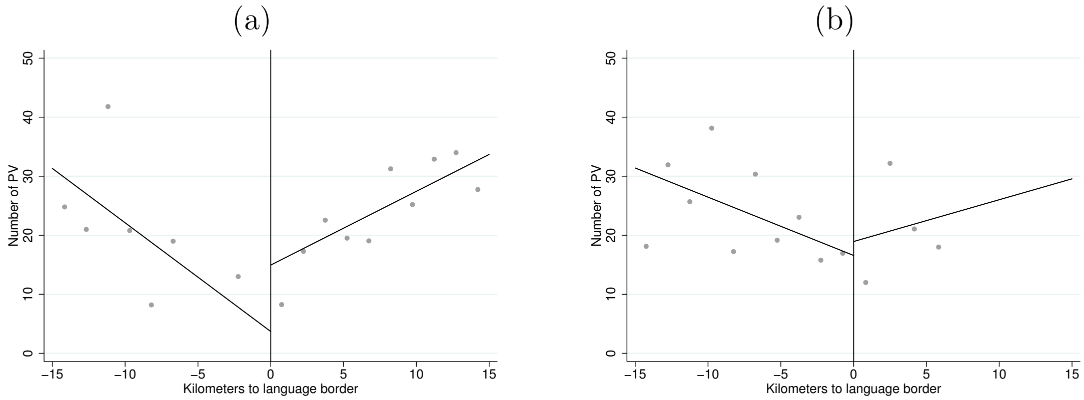
[11]The smaller number of observations on each side of the border, after the separation of the municipalities in two groups based on the median fluency, makes the results rarely statistically significant with bandwidths smaller than 15 km. However, regardless of the level of fluency, we always observe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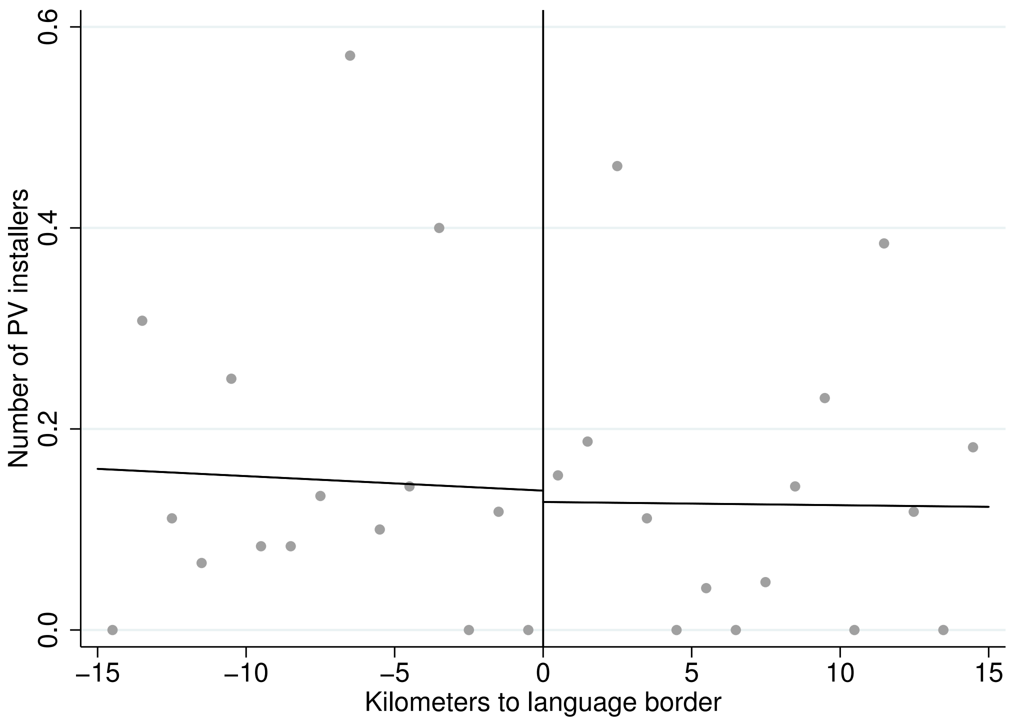
Appendix

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	

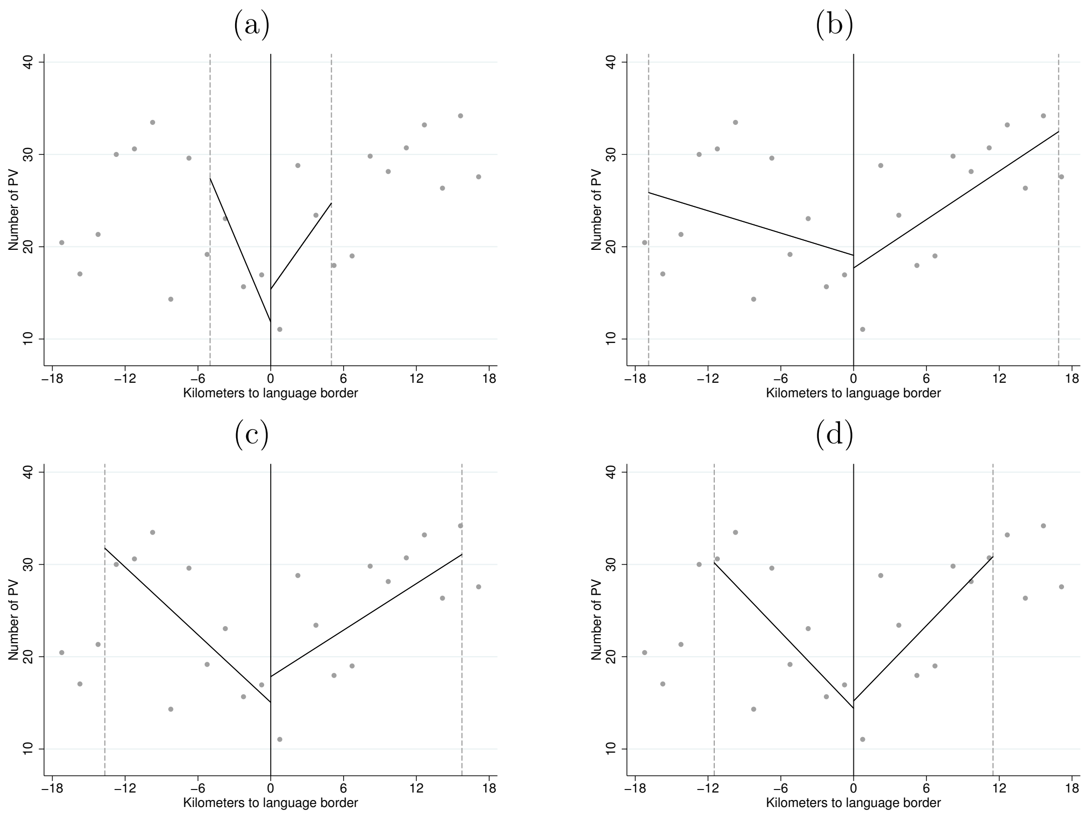
Note: Heteroskedasticity-consistent standard errors in parentheses. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. The dependent variable is the total number of PV system adoptions in a municipality by the end of 2015.

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 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.