Do peer effects matter? Assessing the impact of causal social influence on solar PV adoption

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ABSTRACT

In this paper an assessment is made of the impact of causal peer effects found in a recent paper by Bollinger and Gillingham, simulating solar adoption over many markets in the presence of a causal peer effect. Heterogeneity in both the peer effect and the baseline adoption rate is introduced and their interaction assessed. The nature of the heterogeneity and the size of the peer effect both have implications for the resulting diffusion process. Causal peer effects have implications for firms and policymakers, who have the ability to utilize social spillover effects in their marketing activities in order to increase and expedite solar adoption.

Introduction

If I install a solar panel, are my neighbours more likely to install one too? A household's decision on whether or not to adopt a solar panel is determined by its preferences, the costs and benefits of the technology, and the state of the household's information regarding the technology. But it turns out that social contagion could also play a role. In Bollinger and Gillingham's 2012 Marketing Science paper [1], hereafter referred to as 'BG', the authors found evidence of causal 'peer effects' in the diffusion of solar PV panels, indicating that if there are multiple adopters in the same localized geographic area, one household's choice to adopt is influenced by others' decisions. These effects may occur as a result of information sharing or of even 'image motivation' from the conspicuous consumption of environmentally friendly goods. The causal nature of peer effects influencing the diffusion of solar PV technology is of critical interest to policymakers concerned about reducing greenhouse gas emissions to mitigate the potential consequences of global climate change. Furthermore, firms may be able to leverage these peer effects to expedite or increase the overall level of solar adoption by utilizing the social spillovers.

"If there are multiple adopters in the same localized geographic area, one household's choice to adopt is influenced by others' decisions."

This paper uses the results from BG to assess the magnitude of the estimated peer effects on the diffusion of solar PV panels in California, USA. Counterfactual simulations are performed to determine how the adoption rates and cumulative levels of adoption would change if firms or policymakers were able to increase the peer effect by 10%.

Background

There has been a long history of government support for solar energy, both in the United States in general and in California specifically. At the federal level, solar incentives date back to the Energy Tax Act (ETA) of 1978. More recently, the Energy Policy Act of 2005 created a 30% tax credit for residential and commercial solar PV installations, but with a $2000 limit. The Energy Improvement and Extension Act of 2008 removed the $2000 limit, and the American Recovery and Reinvestment Act of 2009 temporarily converted the 30% tax credit to a cash grant.

California's activity in promoting solar pre-dates the federal activity, with efforts beginning as early as the creation of the California Energy Commission (CEC) in 1974. For several decades much of the emphasis was on larger systems, and the interest in distributed-generation solar PV did not pick up until the late 1990s. In 1997, California Senate Bill 90 created the Emerging Renewables Program, which directed investor-owned utilities to add a surcharge to electricity bills to promote renewable energy. The proceeds of this surcharge supported a $3/W rebate for solar installations, a major step in California support for the solar industry [2]. This support was built upon in the following years with the addition, in 1998, of 'net metering' (allowing owners of solar PV systems to receive credit for electricity sold back to the grid), and a state tax credit of up to 15% for solar PV installations starting in 2001, as reported in the 2009 California Public Utilities Commission (CPUC) report [3]. The state tax credit remained in place to the end of 2005.

While the California incentive programme that was put in place in 1997 was substantial, it was renewed on a year-by-year basis, leading to much uncertainty in the solar market. The elements for a longer-term, more predictable policy were put in place in California in August 2004, when Governor Schwarzenegger announced the 'Million Solar Roofs Initiative', setting a goal of one million residential solar installations by 2015. In January 2006, the CPUC established the California Solar Initiative (CSI), a $3.3 billion, 10-year programme aiming "to install 3000MW of new solar over the next decade and to transform the market for solar energy by reducing the cost of solar" [3]. The solar PV industry in California has grown dramatically over the past decade, at least in part because of declining costs and government subsidy programmes, but also in part because of social contagion effects.

Analysis

Measurement of the peer effect

The methodology used in BG isolates the causal effect of nearby installations on the adoption rate of solar PV panels by using a first-differences approach. The model of household adoption is given by:

$$Y_{zt} = \alpha + \beta b_{zt} + \gamma' X_{zt} + \eta_{zq} + \xi_t + \varepsilon_{zt} \quad (1)$$

where Y_{zt} is the fraction of owner-occupied households in zip code z that had not previously adopted solar and decide to adopt solar on day t; η_{zq} are zip code-quarter fixed effects (q denotes a quarter); ξ_t are time indicator variables,

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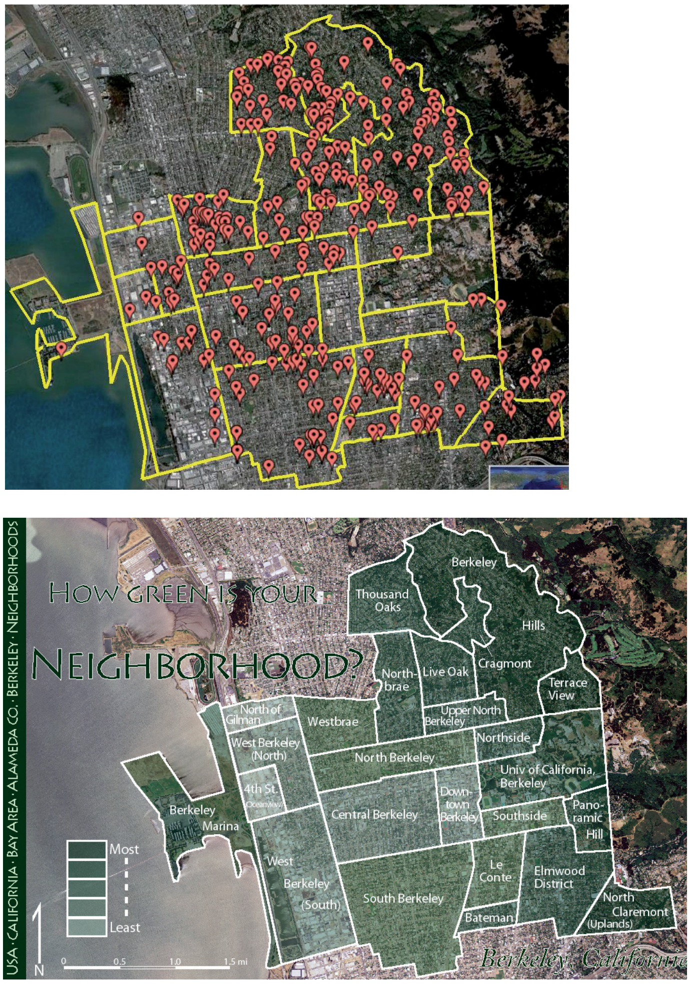

Figure 1. Google Earth view of Berkeley installations by neighbourhood 2001–2006: (a) Berkeley installations; (b) Berkeley neighbourhoods (created by Factle Maps [5]).

including year-month, day of the month and day of the week indicators; and ε_{zt} is a mean-zero stochastic error. X_{zt} contains additional explanatory variables that may vary over time, such as indicator variables for different levels of subsidy available for adopting solar.

The equation used for estimation is:

$$(Y_{zt} - Y_{zt-1}) = \beta(b_{zt} - b_{zt-1}) + \gamma'(X_{zt} - X_{zt-1}) + (\xi_t - \xi_{t-1}) + (\varepsilon_{zt} - \varepsilon_{zt-1}) \quad (2)$$

where BG dropped the first adoption in each zip-quarter so that the zip-quarter effects drop out of the estimation equation. BG estimated how a *change* in the installed base leads to a *change* in the adoption rate. The identifying assumption is that new installations do not contribute to the peer effect until they are completed, whereas the decision to adopt occurs before that, when the installation is first requested. These assumptions ensure that there is no correlation of the first-differenced error term with the first-differenced installed base, so β can be consistently estimated. This contrasts with traditional mean-differenced fixed effects estimation, in which there is a correlation of the mean-differenced error with the installed base by construction [1,4], so ordinary least-squares estimation results in biased estimates of the peer effect.

The size and nature of the peer effect

BG found that an extra installation in a particular zip code increases the daily household probability of an adoption by $\beta = 1.567 \times 10^{-6}$. This translates to an increase in the zip code adoption rate by 0.78 percentage points for those zip codes with the average number of owner-occupied homes. In addition, by assessing and finding a positive impact of previous installations on a street with the probability that more households on the same street adopt later, BG found that the peer effects operate at more localized levels.

> "Solar PV adoption rates are higher in zip codes where people have stronger preferences for environmentally friendly goods."

BG showed that solar PV adoption rates are higher in zip codes where people have stronger preferences for environmentally friendly goods, proxied for by the fraction of vehicle adoptions between 2001 and 2009 that were hybrids. Fig. 1(a) shows the exact locations of solar installations in neighbourhoods of Berkeley, California, between 1999 and 2006; Fig. 1(b) shows a map, created by Factle Maps [5], of how 'green' the neighbourhoods are. The greenest neighbourhoods are less populous yet have a high density of solar installations. Interestingly, while some clustering of installations appears to occur because of environmental preferences, BG found that there is clear evidence of clusters of solar panels, even after controlling for factors such as environmental preferences.

However, the magnitude of the clustering effect and how it influences the speed of adoption of solar panels depends on other demographic variables. BG found that zip codes with larger household sizes and the fraction of people with more than a 30-minute commute have larger peer effects, while zip codes with higher median household income and more people who carpool have smaller peer effects. Larger household sizes are associated with larger peer effects, perhaps indicating that the more the panels are seen, the greater the effect will be. If this is the case, more visible installations should have more of an effect as well. BG tested for this by measuring how the peer effect depends on the size of the installations. They found evidence that larger installations do have a larger impact on the peer effect. Since visibility appears to enhance the peer effect, increasing the visibility of adoptions would be expected to increase the rate of adoption. Indeed, this strategy can be seen with several installers putting up signs indicating that a solar PV panel has been installed.

> "The size of installations increases with the size of the zip code installed base."

While this evidence supports the notion that visibility of installations plays a role in the size of the peer effects, BG also found evidence that the peer effects may lead to reduced uncertainty in how consumers value the solar installations. It is hypothesized that if larger installed bases lead to less uncertainty in the per watt value of an installation, larger installed bases should also lead to larger installations, since the value of decreasing the risk is greater for larger installations. This is exactly what BG found – the size of installations increases with the size of the zip code installed base.

This result is consistent with the latest developments in the solar PV market. Companies such as SolarCity and Sungevity have recognized that reducing the consumer uncertainty about installing solar is critical to expanding the market. These companies lease solar panels to consumers; they perform the installation for free and take care of all the maintenance, and they then guarantee the system will perform as promised or they will pay the consumer the difference. By transferring the risk of installation to the installer, this may reduce moral hazard issues and lead to the installation of larger (and riskier) installations.

The finding that a larger installed base in a zip code leads to larger installations also suggests that other methods of information provision may also lead to increased adoption levels. The use of demonstration sites has been shown to have positive effects on the adoption of green technologies [6], although Kalish & Lilien [7] caution that such demonstrations for solar PV should only be used when the information to be learned is positive. Programmes such as PG&E's 'Neighborhood Solar Champions' training programme (Fig. 2) aim to leverage peer effects to provide such positive information to neighbours. "Solar can grow through trust and social dynamics like keeping up with the Joneses," says Sungevity's CMO Patrick Crane, formally of LinkedIn; indeed much of Sungevity's marketing strategy is now based on social interactions, beginning of course with the provision of an excellent customer experience in order to leverage such interactions [8].


Neighborhood Solar Champions

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Figure 2. Solar Champions Flyer.

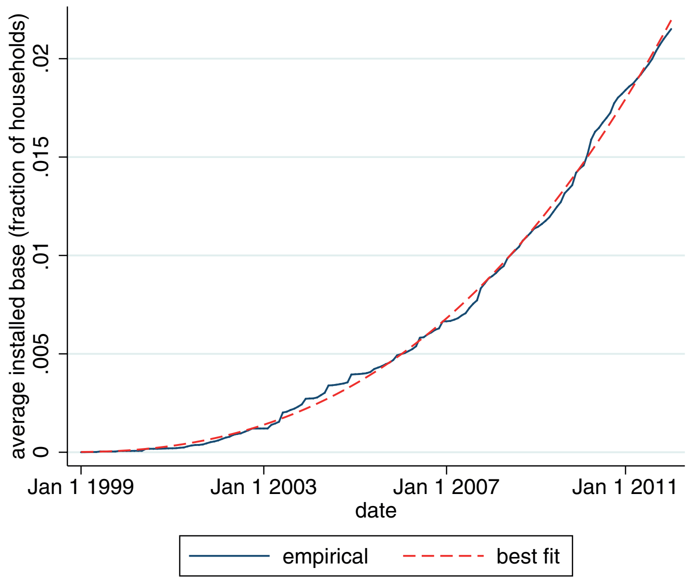

Figure 3. Zip code installed base.

Simulations

These findings have clear implications for marketers who are striving to reduce the high cost of consumer acquisition in the solar PV market. One of the findings in BG was that the peer effect may have increased slightly over time, which would support the notion that firms and policymakers in general are learning to utilize the peer effects in their marketing strategies. To assess the value of being able to leverage these peer effects, and to assess whether the magnitude of our statistically significant peer effect has any meaningful impact on the level of adoption, the diffusion of solar PV over twelve years is simulated using the estimated household-level peer effect of 1.567×10^{-6} and also using a peer effect 10% larger in size. Fig. 3 shows the actual average zip code installed base in the data, measured as the fraction of households in the zip code that have adopted.

For the simulations, 1000 identical zip codes with 1000 households apiece are considered, all of which have zero panels currently installed. The zip code sizes are normalized because it is desired to get an intuitive idea of the influence of an increased peer effect, as well as the presence of heterogeneity in the base adoption rate and the peer effect, without the further interactions with the zip code sizes. The normalization also makes the interpretation easier, since it does not matter whether the impact on adoption is measured in number of installations or in fraction of households who have installed. A baseline daily household adoption rate of 1×10^{-7} with an additive log exponential stochastic term multiplied by 1×10^{-8} is included. To allow for heterogeneity in both the peer effect and the baseline adoption rate, specifications are used in which the base rate and/or peer effect are heterogeneous, distributed normally with the means stated above, and standard deviations equal to half the means. Heterogeneity is important to include, since there may be large ramifications of heterogeneity for the overall levels of adoption. Moreover, if both the base adoption rate and the peer effect are heterogeneous, then whether they are positively or negatively correlated is crucial.

The simulations were performed 100 times and the mean results are reported here. Fig. 4(a) shows the average of the simulated installed bases (as a fraction of the owner-occupied homes) over twelve years, comparing what would happen with our estimated peer effect and with a peer effect 10% larger, with and without zip code heterogeneity in the base adoption rate. With homogeneous base rates, the 10% increase in the peer effect increases the average fraction (number) of households adopting (assuming homogeneous zip codes) from 0.0416 to 0.0579, an increase of 39%. With heterogeneous base rates, the increase is almost exactly the same, from 0.0416 to 0.0578. The addition of heterogeneity in the base rate has virtually no effect on the level of adoption, but the increase in the size of the peer effect has a large effect on overall adoption. These are our baselines for comparisons.

"The addition of heterogeneity in the base rate has virtually no effect on the level of adoption, but the increase in the size of the peer effect has a large effect on overall adoption."

Fig. 4(b) shows simulations with heterogeneity in the peer effect instead of the baseline adoption rate. Heterogeneity in the peer effect leads to an increase in the fraction of households adopting by 15.9%, from 0.0416 to 0.0482. The presence of heterogeneity leads to a smaller relative gain due to the 10% increase in the size of the peer effect, increasing adoption from 0.0482 to 0.0635, an increase of 31.7%. This level of adoption is, of course, higher since both the heterogeneity and increase in the peer effect lead to more adoption, and the absolute gain in the number of adoptions is (on average) 153, which is only slightly smaller than the increase of 163 for the homogeneous zip codes.

Fig. 4(c) includes perfectly positively correlated heterogeneity in both the peer effect and baseline adoption rate. The effect of the heterogeneity increases adoption from 0.0416 to 0.0545, an increase of 31.0%. Clearly, the correlation

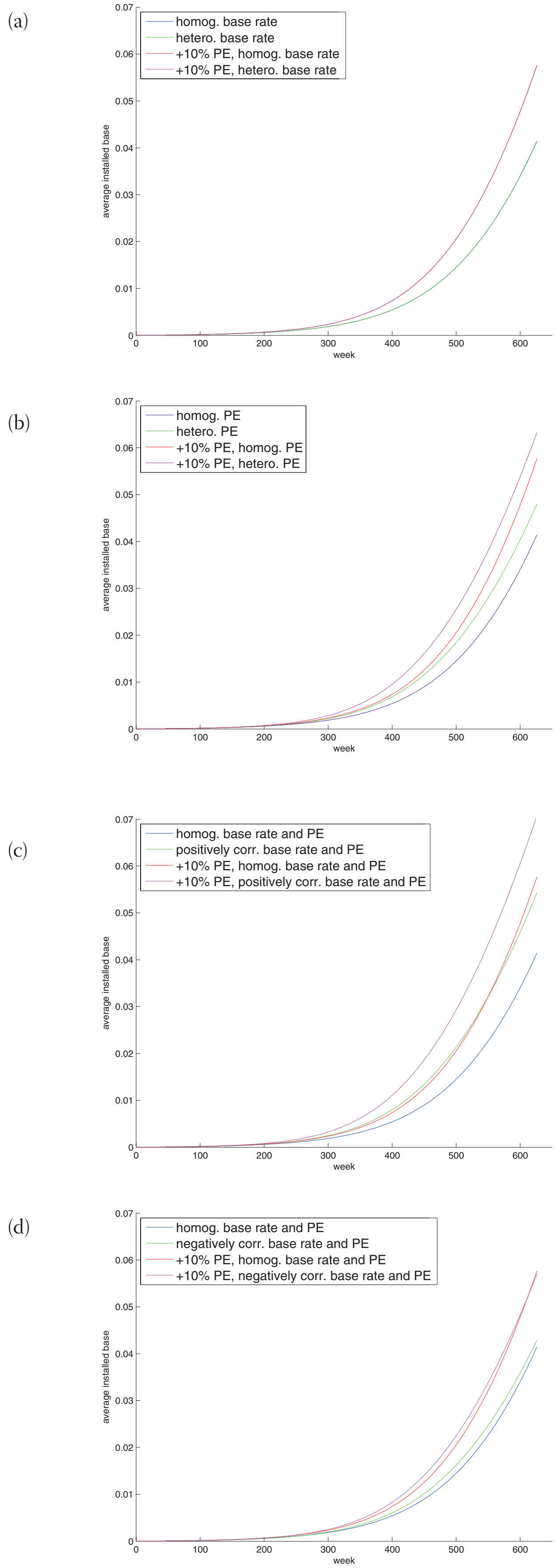

Figure 4. Simulation results: (a) heterogeneity in baseline adoption; (b) heterogeneity in peer effect (PE); (c) positively correlated heterogeneity in baseline adoption and PE; (d) negatively correlated heterogeneity in baseline adoption and PE.

in the heterogeneity helps to drive adoption. The 10% increase in the size of the peer effect leads to an increase in the installed base after twelve years from 0.0545 to 0.0710, an increase of 30.3%. The relative size of the increase in the peer effect is smaller than in the previous two simulations, but this is partly due to the fact that the correlated heterogeneity has already led to significantly more adoption.

In contrast, Fig. 4(d) includes perfectly negatively correlated heterogeneity in both the peer effect and the baseline adoption rate. When the peer effect heterogeneity is negatively correlated with the heterogeneity in the baseline adoption rate, the presence of heterogeneity increases adoption to only 0.0431, an increase of 3.6%. The increase in the peer effect further increases adoption to 0.0572, an increase of 32.7%. Adoption with perfectly negatively correlated heterogeneity leads to slightly less adoption than the scenario with heterogeneity on the base rate only (a decrease of 1.0%), and significantly less than when there is heterogeneity on the peer effect only (a decrease of 9.9%). Therefore, while heterogeneity leads to more adoption, negative correlation in the base rate and peer effect reduces adoption and can lead to a negative effect of heterogeneity on adoption. Since the relative gain from the increased peer effect is about the same, this also reduces the effectiveness of peer effect increases.

Discussion

The simulation results have some interesting implications for practitioners. The installation elasticity of the peer effect is approximately three, depending on the nature of the heterogeneity in baseline adoption rates and the peer effect. There is more value in increasing the peer effect in areas with high adoption rates (at least in this period where markets are far from saturated) but this may pose a challenge. Areas with high adoption rates may in fact be less likely to exhibit large peer effects if the mechanism behind the peer effects is the provision of information, and households in these areas are already informed regarding the benefits of solar.

It should be noted that the estimated peer effect in BG is not a structural estimate. While significant care was taken to establish the causality of the effect, one of the results is that the peer effect was estimated with limited structure imposed in the estimation. Thus, if market conditions change dramatically, it is entirely possible that the peer effect could change as well. While this can be a positive for marketers since there is scope for increasing the size of the peer effect, it also means that the peer effect may decrease as a result of other policies and marketing efforts used to increase solar adoption. This is an area worth further exploration.

Conclusion

BG established the existence of causal peer effects in the diffusion of solar panels, in addition to providing some suggestive evidence regarding some of the potential mechanisms underlying these social interaction effects. Visibility of installations seem to play a role in the size of the peer effect, which would be the case if there are image motivation effects, since the adoption of solar panels is an effective way of demonstrating 'greenness' through the conspicuous consumption of an environmentally friendly technology. In addition, transfer of information through word of mouth may also play an important role, supported by the fact that areas with larger installed bases have larger new installations, and larger installations are those that benefit the most from uncertainty reduction in the value of installing solar, made possible through information transfer via word of mouth. However, while BG found evidence that visibility and the transfer of information may both play a role in the mechanism behind the peer effects, more research is needed to establish their respective contributions.

> "The adoption of solar panels is an effective way of demonstrating 'greenness' through the conspicuous consumption of an environmentally friendly technology."

Finally, it would be useful to study how traditional marketing tools, as well as marketing intended to leverage peer effects, amplify and interact with social influence in the diffusion of solar panels and other green technologies. As this paper demonstrates, heterogeneity in the peer effect and baseline adoption rates also have significant effects on adoption, as would their interactions with such marketing tools. A better understanding of these interactions will help in determining how useful peer effects can be in expediting and increasing the overall adoption of solar.

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