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Motivation Crowding in Peer Effects: The Effect of Solar Subsidies on Green Power Purchases

Abstract

I test whether economic incentives dampen peer effects in public-good settings. I study how a visible and subsidized contribution to a public good (installing solar panels) affects peer contributions that are neither subsidized nor visible (electing green power). Exploiting spatial variation in the feasibility of installing solar panels, I find that panels increase voluntary purchases of green power by neighbors. However, using sharp changes in government incentives over time, I find that the magnitude of the spillover depends on the level of subsidies to solar. The results support the hypothesis that signals drive peer responses to visible public-good contributions and that economic incentives blur those signals.

Keywords: motivation, public goods contribution, solar panels, green energy, environmental public goods.

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1 Introduction

Despite the economic incentive to free ride, public-good contributions are common. Individuals routinely give to charity, purchase ethical products and restrain their consumption of goods with negative externalities. The discrepancy between economic incentives and observed levels of prosocial behavior motivates research that aims to generate better predictions of policy such as tax rebates and subsidies on public goods.

From a theoretical standpoint, high rates of prosocial behavior challenge traditional models, and motivate the search for alternatives. One such alternative incorporates the notion of intrinsic, extrinsic and image rewards. Intrinsic rewards are the value to the individual of being prosocial. Extrinsic motivations are material or monetary rewards while image rewards are those that an individual gains from other people's perception of them as a prosocial type. Motivation crowding theory suggests that extrinsic incentives may crowd out both intrinsic and image motivations. This theory is supported by empirical evidence that in some circumstances, economic incentives discourage prosocial behavior (Gneezy and Rustichini, 2000a,b; Mellström and Johannesson, 2008).

Bénabou and Tirole (2006) argue that economic incentives may reduce prosocial behavior because the image value of a prosocial action is linked to intrinsic motivations and the signal that the giver is intrinsically motivated is compromised by an extrinsic motivation. So if economic incentives make it more likely an action is interpreted as arising from extrinsic motivation, then the actor is seen as behaving less prosocially. In support of this mechanism, there is evidence from the lab and the field that, when a giver's actions are observable, visible economic incentives reduce their charitable contributions (Ariely et al., 2009).

This paper explores a new mechanism by which economic incentives may reduce contributions to public goods: peer behavior. Theories of conditional cooperation suggest that people are more willing to act prosocially when others do so. These theories are supported by evidence both from the lab and the field that peers affect charitable donations (Frey and Meier, 2004; Alpizar et al., 2008; Shang and Croson, 2009; Meer, 2011; Jack and Recalde, 2015; Smith et al., 2015; Archambault et al., 2016; Kessler, 2017).

Less is known, however, about the role of perceived motivation in generating these peer effects. If economic incentives compromise the signal that a contributor is intrinsically motivated, and peers are more likely to respond to intrinsically-motivated giving, then they may also reduce peer contributions. Signaling intrinisc motivation may encourage peer contributions, for example, by establishing norms for prosocial behavior or by creating peer pressure. Economic incentives may therefore weaken the social norm or lower peer pressure. The lack of a clear signal regarding motivation may also act as a kind of excuse which enables peers to avoid feeling bad about a decision not to contribute. This would be consistent with the literature documenting that providing excuses and allowing decision makers to avoid high-pressure settings lowers charitable giving and results in more self-serving behavior (DellaVigna et al., 2012; Andreoni et al., 2017; Dana et al., 2007; Exley, 2015a,b).

If economic incentives do affect peer responses to prosocial behavior, then on net it is possible that they decrease contributions. From a policy perspective, economic incentives such as subsidies may have a direct effect of increasing pro social behavior, however these incentives may also crowd out peer responses to those contributions. If that crowding out reduces contributions by more than the subsidies increase them, then the net impact of a policy could in fact be negative.

In this paper, I test whether the presence of economic incentives compromises prosocial spillovers in public-good settings. I study whether a visible contribution to a public good (installing solar panels) crowds in unobserved, unsubsidized contributions from neighbors (buying greener electricity) and whether the peer response depends on the magnitude of economic incentives to the visible contribution. Critically, the installation of solar panels lowers the carbon intensity of the electricity grid, is visible, and is heavily subsidized so that the decision to install could be driven by a combination of extrinsic, intrinsic and image rewards. In addition, subsidies provided to the installers of solar panels fall dramatically over time so that the value of extrinsic rewards and therefore the signaling value of an installation changes sharply at discrete points in time. On the other hand, opting in to a green power program (a voluntary program designed by government to increase the volume of renewable energy at the wholesale level) is neither subsidized nor visible and therefore is not motivated by extrinsic or image rewards.

The primary data source is an inventory of customer contracts for an electricity retailer in the state of Victoria, Australia over the period 2009 to 2016. I match each contract to the number of solar panels installed in that postcode in the quarter the contract was signed using installation data from the Clean Energy Regulator. These data are well suited to exploring the interaction between economic incentives and peer behavior. Australia is the largest per capita market for rooftop solar in the world, with approximately one in six dwellings having panels by the end of the sample period. In addition, there is substantial variation across time and space in solar panel installation and the sample period covers several sharp changes in the subsidies available. Critically, changes in the subsidies were extremely well covered by major news outlets and further publicized by significant marketing campaigns undertaken by solar installers.

The empirical strategy is two fold. The first objective is to establish whether on average, an additional solar panel in a neighborhood increases the probability that a customer opts in to a green power plan. I exploit differences in the visibility of solar panel adoption relative to green power contracting to overcome the classic problem of reflection in the estimation of peer effects. I then combine cross-sectional variation in the cost of installing solar panels across houses with different roof materials, with time-varying shocks in the global price of solar panel modules to develop an instrument for neighborhood level installation. Specifically, I use variation across postcodes in the ratio of metal to tile roofs and interact this with the inverse of a global solar module price index. Using data from a pre period before the mass uptake of solar, I show that there are parallel trends in green power purchasing in postcodes with above and below median metal to tile roof ratios. I also show evidence for parallel trends in house prices across postcodes by roof ratio.

I find that, on average over the sample period, solar panel installation increases the fraction of new contracts that are green power. An additional 100 dwellings with solar panels increases the share of non-solar customers signing new green power contracts by 0.002 (mean share of green power contracts is 0.02). Thus a private, unobserved contribution to a public good is crowded in by a visible peer contribution. There are two main threats to identification. The first arises from differential trends across neighborhoods via processes such as gentrification. A series of empirical exercises controlling flexibly for heterogeneous time trends suggest that the results are robust to this possibility. The second threat to identification comes from the possibility that the firm markets its products differently across postcodes, for example, by targeting green power deals at customers in neighborhoods with high solar penetration. I show however that differences in marketing effort across postcodes do not explain the relationship between solar panel installations and green power sign ups.

I next establish that economic incentives interact with peer effects. To do so, I test whether the impact of an additional solar panel in a high-subsidy period is different to the impact of an additional solar panel in a low-subsidy period. The identification strategy is an event study design that relies on multiple sharp changes in subsidies over the period of the sample. In event time, "high" subsidy periods are periods immediately after a subsidy increase or before a subsidy decrease, and "low" subsidy periods are those immediately before a subsidy decrease or after a subsidy increase.

I find that solar panels have a smaller crowd-in effect in high-subsidy periods relative to solar panels in low-subsidy periods. This is consistent with the idea that extrinsic incentives affect the signaling value of a prosocial action, and that this in turn drives peer behavior.[1] The results survive robustness checks that include adding controls, using differences in roof type as an instrument, redefining the event window, dropping early observations and restricting the sample to outer suburbs of the capital city. I also undertake a series of three placebo tests to demonstrate that the event study effects are not spurious.

The primary contribution of this paper is to study whether economic incentives at-

[1] An alternative signaling explanation would be that during a high-subsidy period a solar panel sends a poorer signal about the installer's belief about the quality of the public good (in this case, the importance of reducing emissions to abate climate change). However, the size of the subsidy is itself a quality signal.

tenuate peer effects in public-good settings. In doing so, it connects two related but separate branches of literature on prosocial behavior. The primary concern of the first branch of literature has been to establish the role of motivation, and in particular the role of economic incentives in an individual's propensity to act prosocially. While there are settings in which economic incentives are found to lower prosocial behavior, there are also many settings where incentives have no negative effect (see, for example Ariely et al., 2009; Lacetera et al., 2012; Ashraf et al., 2020; Lacetera et al., 2014; Rommel et al., 2015). Other contributions focus explicitly on identifying the role of signaling in motivating prosocial behavior (Sexton and Sexton, 2014; Dubé et al., 2017). I add to this literature by considering how extrinsic incentives may also affect the actions of this individual's peers, who are implicitly the recipients of any prosocial signals that are sent. The effect of peer behavior on contributions is the focus of the second branch of literature.[2] I demonstrate that the strength of the prosocial signal delivered by a public-good contribution affects the magnitude of the subsequent peer effect.

This paper also studies contributions to environmental public goods and in particular the effects of government incentives for environmentally friendly technologies.[3] Outside of charitable donations, little is known about how peer behavior affects private, un-solicited contributions to public goods. Bollinger and Gillingham (2012) and Kraft-Todd et al. (2018), among others, find evidence that peers influence the diffusion of solar panels. This diffusion could be the result of crowding in but it could equally reflect social learning about the private benefits of solar panels. Indeed Bollinger et al. (2020) show that diffusion of

[2]This literature is fairly extensive but see, for example as cited above: Frey and Meier (2004); Alpizar et al. (2008); Shang and Croson (2009); Meer (2011); Jack and Recalde (2015); Smith et al. (2015); Archambault et al. (2016); Kessler (2017)

[3]Both solar panels and green power can be characterised as "impure" public goods, from which consumers obtain utility from both a private characteristic and a public characteristic. The theory of "impure" public goods was originally developed by Cornes and Sandler (1984, 1994) and applied to environmental public goods in Kotchen (2005, 2006). Kesternich et al. (2016) is a recent empirical investigation of demand for impure public goods.

dry landscaping for water conservation is stronger when there are financial incentives to reduce water consumption.[4] The effect of neighborhood solar installation on peer green power purchases is not influenced by learning about private benefits of green power, and is therefore more likely to be a pure prosocial spillover. Spillovers from solar panel installation to intermediate outcomes such as votes for green parties and belief in climate change have also been found in the literature (Comin and Rode, 2013; Beattie et al., 2019).

Finally, many papers study the effect of incentives on adoption of environmentally friendly technologies (see Sallee, 2011; Huse and Lucinda, 2014; Boomhower and Davis, 2014; Hughes and Podolefsky, 2015, for example). In contrast to this literature, the focus here is on how these incentives affect the prosocial contributions of an adopter's peers. From a policy perspective I show that accounting for peer responses decreases the cost effectiveness of subsidies as a policy mechanism. I also demonstrate that subsidies may not increase contributions to a public good even if adopters are marginal and that when adopters are inframarginal, subsidies decrease contributions.

The remainder of the paper is structured as follows. Section 2 provides context for the study before Section 3 outlines the data in detail. Section 4 investigates whether there is an average spillover from solar panels to green power adoption before Section 5 tests whether any spillover is affected by available subsidies. Section 6 discusses policy implications and Section 7 concludes.

2 Background

The setting for this study is the state of Victoria in Australia over a period covering the rapid adoption of rooftop solar. Figure 1 shows aggregate (state-level) trends in

[4] A related literature in environmental economics studies the role of social norms and peer comparisons in energy and water consumption (Allcott, 2011; Ferraro and Price, 2013; Byrne et al., 2017). Relevant papers in this literature study the interactions and relative effectiveness of price vs social norm treatments (Pellerano et al., 2017; Ito et al., 2017) and the role of observability (Delmas and Lessem, 2014).

rooftop solar using data from the Clean Energy Regulator.[5] At the start of the sample period there was very little solar installation. By the end of 2015, approximately one in six households had installed solar panels on their roof. There are several reasons for this rapid adoption including rising electricity prices, high levels of irradiance and the subsidies available to installers.

Table 1 reports the subsidies available over the study period. Explicit incentives to install solar were provided by both federal and state governments.[6] The federal government used two different mechanisms to subsidize rooftop solar. Initially, subsidies took the form of a fixed rebate. In 2009, the government instead granted solar installers the right to create Renewable Energy Certificates that obligated parties could use to demonstrate compliance with the Mandatory Renewable Energy Target.[7] As with grid scale renewable energy installations, the number of certificates that could be created by a solar installation was based on production potential. However to specifically support small-scale installations, the government introduced a small scale multiplier for the first 1.5kW of capacity. From June 2009 to June 2011 this multiplier was 5. The multiplier was reduced from 5 to 3 in July 2011, from 3 to 2 in July 2012 and was eliminated in 2013.

State governments also provided incentives to install solar panels by guaranteeing a set feed-in tariff for electricity sold to the grid.[8] Households are typically guaranteed

[5]The Clean Energy Regulator is the Australian Government agency that administers the Renewable Energy Target. The data represent all solar panel installations claiming subsidies under Federal Government programs.

[6]Solar installers are also implicitly subsidized by avoiding some of the costs of the distribution network that are recovered by per kWh charges on electricity consumption.

[7]This scheme would be called a Renewable Portfolio Standard in the United States. The scheme is designed to add renewable generation capacity to the grid. Obligated parties (retailers of electricity) are required to surrender Renewable Energy Certificates equal to a proportion of their sales of electricity. Renewable Energy Certificates can be created by eligible new renewable energy generators.

[8]These feed-in tariffs are referred to locally as *net* feed-in tariffs because they pay households for

these feed-in tariffs for a fixed period of time, e.g. 10 years. Before 2009, the feed-in tariff was a 1:1 match with the retail cost of electricity. From November 2009 the guaranteed feed-in tariff increased to 60c/kWh, or roughly three times the retail cost of electricity at the time. This feed-in tariff was reduced to 25c/kWh in late 2011, and reduced further to 8c/kWh and then 6c/kWh in 2013 and 2014 respectively.

Figure 2 shows a back of the envelope net present value (NPV) calculation for a 3kW solar installation over the study period assuming a 5% discount rate.[9] In particular, it shows a period where solar panels were a relatively attractive investment and large changes in the private return to installing solar when subsidies change.

The study period also coincides with a steep decline in sales of green power. Alongside the growth of rooftop solar, Figure 1 plots aggregate trends in green power purchases over the sample period using data from the National Green Power Accreditation Program.[10] In Australia, customers can elect to purchase a green power product in a relatively mature retail market for electricity. In this sector, retailers compete for customers by offering a variety of plans, including the option of purchasing a green power product that is accredited by government. These products guarantee that a fixed amount, or stipulated percentage of the consumer's electricity consumption, will be sourced from renewable electricity generators. Accredited green power products ensure there is no double counting across mandatory and voluntary green power programs and use the "GreenPower" logo.[11] Most retailers carry an accredited green power product.

electricity produced, net of the household's own simultaneous consumption.

[9]I take the calculations of NPV for installation of a solar panel in Victoria in 2015 in Wood and Blowers (2015), and adjust it for changes in solar panel installation prices from the Australian Photovoltaic Institute along with changes in subsidies. See Appendix B for further details on this calculation.

[10]This program, administered by the New South Wales Government, is a joint government initiative to promote renewable energy by increasing consumer confidence in accredited green power products.

[11]In practice, to sell an accredited green power plan, retailers must demonstrate that they have purchased sufficient Renewable Energy Certificates to cover their sales of green power products in addition to their mandatory obligations.

Figure 1 shows a strong correlation between the rise of rooftop solar, and the drop in household purchases of green power. There are several reasons that this correlation might be observed. First, households may substitute from purchasing green power to installing solar panels. Second, high levels of solar panel installation may crowd out public-good contributions previously made by green power customers. Finally, the correlation may be spurious or driven by some other time varying factor. Figure 1 also shows that at the start of the sample period, when subsidies to solar panels are highest (2009-2011), the decline in green power purchases is steepest. This is suggestive evidence that subsidies to solar may also play a role in the declining popularity of green power. In the remainder of the paper I outline an empirical strategy to identify the causal effect of neighborhood installation on green power sign ups, and the causal effect of subsidies on the size of this spillover.

For subsidies to solar panels to have an impact on green power purchases, it must be that prospective green power purchasers (or at least some of them) were aware of these subsidy changes. During the period of study climate change policy, renewable energy and electricity prices were a frequent feature of news coverage and numerous media reports at the time suggest that these subsidy changes were well publicized.[12]

3 Conceptual Framework

To consider the overall impact of subsidies on the public good of emissions reductions, consider a simple model of the emissions of an individual (E_i) who consumes k_i kiloWatt hours (kWh) of electricity. Assume this individual can make two choices to affect their overall emissions: they can either purchase green power (g_i), or they can choose to install solar panels (s_i). For simplicity consider the case where each decision is binary such that

[12]See for example the following articles published in national media outlets over 2010-2012: Sid Maher 'Greg Combet takes heat out of solar scheme', *The Australian December 1 2010*; Sid Maher 'Combet cools on solar credits' *The Australian May 5 2011*; Naomi Woodley, 'Government reducing solar subsidies' *ABC Dec 1 2010*; ABC NEWS, 'Solar panel subsidies scrapped early' *ABC 16 Nov 2012*

$(g_i, s_i \in \{0, 1\})$:

$$E_i = (1 - \gamma g_i)\beta k_i - \psi s_i$$

where β is the average emissions intensity of the grid, γ is the proportion of the consumer's electricity that is procured as green power, and ψ is the average emissions displaced by a solar panel installation. We wish to understand how this consumer's emissions change as the subsidy for solar panel installation changes, i.e. we wish to understand $\frac{\partial E_i}{\partial f}$ where f is the subsidy to solar installers. This subsidy has three potential impacts. First, it will affect the likelihood of the consumer adopting panels. Second, if adopting solar panels and purchasing green power are substitutes, then the subsidy will also have an effect on green power purchases via this substitution. Finally, if there are spillovers, or peer effects, the subsidy may have additional effects on the consumer via the installation decisions of others. To formalize, suppose that the green power decision depends on an individual's own solar adoption choice, the adoption choice of their neighbors, and the subsidy, and takes the following form:

$$g_i(f_i) = h(s_i(f)) + \rho(f) \times l(s_{-i}(f))$$

where s_{-i} are the installation decisions of neighbors and $\rho(f)$ allows the spillover from a neighbor's installation to be a function of the subsidy level. Then the quantity of interest is:

$$\frac{\partial E_i}{\partial f} = -\beta\gamma k_i \left[h'(s_i)s_i'(f) + \rho'(f)l(s_{-i}(f)) + \rho(f)l'(s_{-i}(f))s_{-i}'(f)\right] - \psi s_i'(f)$$

Re-arranging:

$$\frac{\partial E_i}{\partial f} = \underbrace{-s_i'(f)\left[\beta\gamma k_i h'(s_i) + \psi\right]}_{\text{Substitution effect}} - \underbrace{\beta\gamma k_i \left[\rho'(f)l(s_{-i}(f)) + \rho(f)l'(s_{-i}(f))s_{-i}'(f)\right]}_{\text{Crowding effect}}$$

The first term is the net impact of substitution within the household from green power to solar panels. Substitution implies that $h'(s_i) < 0$. The second term is the net impact of crowding, its sign depends on the elasticity of solar installation to the subsidy ($s'_{-i}(f)$) and the change in the spillover due to the subsidy ($\rho'(f)$). The aim of this paper is to provide empirical evidence for the sign and magnitude of $\rho'(f)$. If it is negative then higher subsidies reduce the spillover effect. The average crowding effect then depends on relative magnitudes.[13]

In general, if technology adopters are marginal to subsidies, i.e. subsidies *cause* a substantial portion of adoption, then they are less likely to eliminate positive spillovers to public-good contributions. On the other hand, if adopters are inframarginal, such that they would have adopted in the absence of the subsidies (i.e. $s'_{-i}(f) = 0$), then subsidies on net have a negative impact on public-good contributions. Boomhower and Davis (2014) suggest that a non-negligible number of technology adopters may be inframarginal. Even in the absence of spillovers, inframarginal adopters can compromise program cost-effectiveness. If they also lead to crowd out, subsidies would become even less cost-effective. Further, even if the crowding effect at the individual level is small, if the peer group is large, the net impact of crowding may be substantial. This consideration is particularly important in a policy environment that appears to favor policies such as technology subsidies over externality pricing. The results also have implications for the charity sector, and in particular for fundraising that rewards donors for their contributions with gifts. If these gifts are seen as a valuable private benefit associated with the contribution, they may in turn lower peer contributions.

4 Data

To identify the causal relationship between solar panels and green power purchases I use customer-level data on plan choice for a small-medium size electricity retailer in the

[13]In practice the literature on peer effects suggests that there are spillovers from solar adoption to peer solar adoption (Bollinger and Gillingham, 2012). These spillovers are also feasibly related to the size of subsidies (Bollinger et al., 2020).

contestable retail market in the state of Victoria. The data contain the full inventory of customers over the period 2006-2016. For approximately 300,000 the data include plan choice, contract start dates, and billing data. I exclude customers who have or adopt solar panels at any point from 2006-2016 and use billing and plan choice data to identify whether a household purchases green power.[14] The distribution of customers at the postcode level over the state and within the capital city Melbourne is shown in Appendix Figure A1. The sample is drawn from across the state with more customers in the more densely-populated region of Melbourne.

I aggregate the customer data to the postcode-quarter level then match it to solar penetration data from the Clean Energy Regulator. I also match postcodes to 2006, 2011 and 2016 census data from the Australian Bureau of Statistics[15] and postcode-quarter house and unit sales data for 2000-2016 from the Victorian Government Department of Environment, Land, Water and Planning. To construct the instrument I use a time invariant measure of roof materials by postcode from GeoScience Australia. Roof material data come from the National Exposure Information System (NEXIS). GeoScience Australia collects data for NEXIS from Local Government Authorities, the Victorian Census of Land Use and Employment, Victoria's Office of the Valuer-General and GeoScience Australia building and disaster surveys.[16] The instrument also uses a global price index for solar modules from Bloomberg New Energy Finance.[17] Appendix Figure A2 plots the value of this index during the sample period.

[14]Including solar adopters and controlling for their adoption decision does not however change the results. As the vast majority of green power customers opt for the lowest level of green power I analyze the extensive rather than the intensive margin.

[15]Census data are interpolated to construct variables at the quarterly frequency.

[16]GeoScience Australia states that where building specific data are not available it is predicted based on settlement type.

[17]To construct this index, Bloomberg collects quotes from buyers, sellers and traders of modules and module components such as silicon. Following a quality control process, these data are then averaged and published as an Index.

Table 2 provides summary statistics of the key variables of interest over the study period. As the module price index is only available from 2009, the study period is 2009-2016. Appendix Table A1 provides summary statistics for the same variables over the full period 2006-2016. The share of customers signing green power contracts over 2006-2009 is significantly higher than the later period, reflecting trends in green power purchasing over time. In the following section, trends in green power purchases prior to 2009 will be used to provide evidence for identification.

Appendix Figure A3 shows the distribution of green power and solar panels in the sample across the state while Appendix Figure A4 shows the distribution within the capital city Melbourne. Unsurprisingly, solar panels are least prevalent in the city and in particular in the denser inner suburbs where shading and smaller roof sizes make them less suited to solar panel installation.

Figure 3 plots the share of new contracts that are green power for the sample used in this paper. The trends are very similar to the aggregate (state level) trends in Figure 1. As noted, this sample excludes solar households. Hence among non solar households for this single retailer, and among customers signing new contracts, there is still a strong correlation between the rate at which customers sign contracts for green power, and the rate at which new solar panels are installed. If this relationship were causal, it would suggest that solar panels crowd out public-good contributions via a reduction in the number of consumers willing to purchase green power. However other time-varying factors, such as trends in the cost of purchasing electricity and reductions in solar module costs, may be driving this correlation. Again, the figure also provides suggestive evidence for the relationship between economic incentives and spillovers. In particular, the decline in green power purchases is steepest at the time that subsidies are highest.

To identify the causal impact of solar panels on green power purchases I use cross-sectional variation in the feasibility of installation, along with plausibly exogenous time variation in the cost of modules. This research design exploits the fact that solar panel installation is more feasible in neighborhoods that contain more houses with metal roofing materials as installing panels on metal sheeting is both easier and less costly than other materials such as tile.

Figure 4 shows the difference in solar panel adoption and green power purchases across postcodes with above vs below median number of houses with metal relative to tile roofs. At the start of the sample, there is no difference in the number of solar installations, by the end of the sample they have more solar installations. At the start of the sample, the percentage of customers in these postcodes opting in to green power is also lower (though noisy) and by the end of the sample the gap in green power purchases has disappeared.

5 Do Solar Panels Affect Neighbors' Green Power Choice?

5.1 Empirical Strategy

The first empirical objective of this paper is to establish whether an additional solar panel in a postcode impacts the probability that a non-solar customer in that postcode signs a contract for greener electricity. Hence at the postcode level I wish to identify β in the following regression:

$$Green\ Power_{it} = \alpha_i + \rho_t + \beta Solar\ Rooftops_{it} + \epsilon_{it} \tag{1}$$

where $Green\ Power_{it}$ is the proportion of households in postcode i that commence a contract in period t that opt in to green power, α_i are postcode fixed effects, ρ_t are quarter-year fixed effects and $Solar\ Rooftops_{it}$ is the number of solar panels installed in postcode i by time t. The parameter of interest β measures the effect of an additional solar installation on the fraction of new contracts in a postcode that opt in to green power.

The parameter β is a peer effect. Ordinarily, identification of peer effects is complicated by the reflection problem, or an inability to distinguish the direction of influence between peers (Manski, 1993). Here, I exploit differences in the visibility of actions to argue that the direction of causality runs from $Solar\ Rooftops_{it}$ to $Green\ Power_{it}$ and not the reverse. Unlike solar panels, decisions to sign up to green power are private, and not observed by neighbors. It is therefore unlikely that one neighbor's choice to buy green power influences another's choice to install solar panels. On the other hand, solar panels have been shown to affect neighbor's beliefs in climate change, and their likelihood of voting for a green party (Comin and Rode, 2013; Beattie et al., 2019). In addition, there is a considerable lag between the decision to adopt solar and the installation of solar panels. This lag suggests that solar panels observed at time t are unlikely to be influenced by green power sign ups at time t.

A remaining concern with estimating equation 1 is that $Solar\ Rooftops_{it}$ is not randomly assigned across postcodes. An OLS estimate of β may therefore suffer from omitted variable bias for example due to unobserved shocks to environmental preferences arising from something like a local campaign that lead to both solar installation and green power purchases. To address this identification problem, I exploit variation across neighborhoods in how feasible it is to install solar panels based on the average type of roofing in a postcode.

In Australia, approximately 75% of houses have roofs made of metal sheeting, 20% have roofs of tile (either concrete or terracotta) and the remainder use materials such as concrete or fiber cement. I exploit postcode level differences in the number of metal roofs relative to the number of tiled roofs. The logic of the research design is as follows: suppose there are two similar neighborhoods, however one has relatively more houses with tiled roofs (control) and the other has relatively more houses with roofs of metal sheeting (treatment). Because it is cheaper to install solar panels on roofs with metal sheeting, it is more suited to solar panel installation. Identification then relies on there being no unobserved time-varying differences across these two neighborhoods that are correlated with changes in environmental preferences that might simultaneously drive solar panel installation and green power purchases.

The fact that the decision of roofing material is a long term investment suggests that average roofing materials in a neighborhood are unlikely to respond to short term fluctuations in neighborhood composition. The decision of roofing material is also itself unlikely to be driven by trends in environmental concern or by factors correlated with environmental concern. For example, if metal roofs were substantially more thermally efficient we might expect suburbs with greener preferences to have a higher proportion of metal roofs. However neither roofing material has significant thermal insulation properties. Further, on average, the lifetime costs of metal and tiled roofs do not differ substantially.[18] While metal roofing has greater fire safety and is a more versatile roofing material than tile it is also noisier and less durable. It therefore seems plausible that there is no causal relationship between shocks environmental preferences and average neighborhood roofing materials.[19]

Even if there is no causal relationship between environmental preferences and roof type, it is still possible that roofing materials are correlated with unobserved changes in environmental preferences. This might be the case, for example, if tiled roofs are more popular in suburbs with older houses, and neighborhoods with older houses are more likely to undergo gentrification as they are closer to the inner city. In practice both roofing materials have been in common use since the 1850s, or shortly after the capital city of Melbourne was founded. Appendix Figure A5 shows examples of the mixed use of tile and metal sheeting within classic inner city Victorian terraces and within more modern suburban developments. Nevertheless, to address the concern about vintage and gentrification within the inner city, I separate the sample by distance from the center of the city, and re-estimate the parameters for inner, middle and outer suburbs of Melbourne.

I use a measure of neighborhood roof suitability to develop an instrument for the change over time in the number of solar installations in a postcode. To construct the

[18] The installation costs of concrete tile are generally lower than that of metal sheeting which are in turn lower than terracotta tile.

[19] It is also possible that people choose to install panels when they put on a new roof, and given the cost differences in panel installation across metal and tile, they may choose to install a metal roof. If solar panel installation causes roof type then roof type is not a valid instrument. Ideally I would therefore use differences in roof type *before* 2009. Unfortunately the NEXIS data do not provide any information on the vintage of roofs in a suburb. However roofs can last up to 50 years so re-roofing is a fairly rare event. In addition, I exploit a time invariant measure of roof type at the neighborhood level so that identification does not come from changes in roof type over the sample period.

instrument I interact a time-invariant variable at the local level (cross-sectional variation in roof type) with a common trend variable (time variation in the cost of solar panel modules). To account for differences in scale, I multiply the ratio of metal to tile roofs by a time invariant measure of the number of dwellings.[20] The instrument Z_{it} is defined in equation 2.

$$Z_{it} = \frac{Metal_i}{Tile_i} \frac{Roofs_i}{Module\ Price_t} \tag{2}$$

where $\frac{Metal_i}{Tile_i}$ and $Roofs_i$ are time-invariant measures of the ratio of metal to tile roofs and the number of roofs in postcode i respectively. The distribution of the time invariant component of the instrument is plotted in Appendix Figure A6. The top map shows variation across the state. The bottom map shows variation in the capital city Melbourne, where over 75% of the state's population reside. There is considerable variation in the value of the instrument across the state, within the capital city, and within suburbs that are approximately equi-distant from the center of the capital city. The time varying component of the instrument, $Module\ Price_t$, is the global solar panel module price index at time t and is plotted in Appendix Figure A2. I use the inverse of the module price to ensure that increases in the value of the instrument are associated with increases in the endogenous variable $Solar\ Rooftops_{it}$.

[20] Accounting for scale improves the strength of the instrument because the endogenous variable is cumulative solar rooftops. The construction of the instrument effectively penalizes suburbs with the same number of metal roofs, but a higher number of tile roofs, and also penalizes suburbs with the same ratio of metal to tile roofs but a smaller number of total roofs. Using the percentage or number of metal roofs leads to similar conclusions, but the instrument is weaker.

5.1.1 Testing for Parallel Pretrends

The exclusion restriction requires that there is no direct effect of postcode average roofing material on the probability that a customer without solar panels signs up to green power.[21] This would appear to be a plausible assumption. Identification also relies on shocks to environmental preferences being orthogonal to the ratio of metal to tile roofing in a neighborhood. If neighborhoods with a high metal to tile ratio differ due to time invariant characteristics, then these are captured in postcode fixed effects α_i. However, if time-varying processes such as uneven gentrification are more likely to occur in postcodes with a high number of metal roofs and these processes cause an increase in green power purchases then the estimates would be biased.

The key identifying assumption is parallel trends in green power purchasing across neighborhoods with different roof ratios. Column (1) of Table 3 shows that in the period before the uptake of solar panels (2006-2009), there is no evidence of differential trends across postcodes with more metal roofs. Column (2) shows that in the period after the rapid uptake of solar panels, green power purchases increased in postcodes with a high proportion of metal roofs relative to those with a high proportion of tile roofs. This is consistent with a crowd in effect and also evident in the trend in Figure 4. Column (3) shows average trends over the period 2009-2016 while Column (4) shows trends by period and roof ratio in a fully interacted model over the period 2009-2016. Again, there is no evidence for differential trends in green power purchasing prior to 2009, when solar panel penetration began to rise more significantly in postcodes with a higher metal roof ratio.

Appendix Table A2 also demonstrates that there are no differential trends in other

[21]If solar and green power are substitutes it is possible that households in neighborhoods that are less suited to solar panel installation are more likely to purchase green power. This would cause a negative correlation between roof ratio and green power purchases and go against finding a crowd in effect. I explore this possibility below and show in Appendix Table A13 that accounting for households who switch to solar does not change the effects. For reference Table A5 shows the results at the household level excluding solar households.

characteristics of electricity contracts across neighborhoods with different roof ratios. Column (1) shows that there are no differences in trends in the share of customers who elect to pay their bill manually (the alternative being an automatic debit). Column (2) shows that there are no differences in the share of customers that are eligible for a low income concession.

One concern with this evidence is that there is limited pre-period data available for testing pre-trends. As further supporting evidence therefore, Figure A7 plots the difference in house price from 2000-2015 across neighborhoods with a relatively high versus low metal to tile roof ratio. There is no statistically significant difference in house prices. Appendix Table A3 reports estimated trends in house prices in the pre and post 2009 period by metal roof ratio. Again, there is no evidence that there are differential trends. In the analysis I also demonstrate that changes to the set of time-varying controls X_{it} that would be correlated with time-varying processes such as gentrification do not significantly affect the magnitude of the estimate of β. As outlined below, I also allow for flexible time trends by distance from the center of the city and restrict the sample based on distance from the city, a proxy for vintage of houses and gentrification.

5.2 Results

Table 4 reports estimates of the average effect of neighborhood level solar panel installation on green power purchases using a straight fixed effects model. All standard errors are clustered at the postcode level and the regression is weighted by number of customers to account for aggregation. I find that an additional 1000 solar panels increases the fraction of new contracts in a postcode that opt in to green power by approximately 0.02. In Column (2) I use a LASSO to select observable neighborhood characteristics as controls. The LASSO selects four out of nine covariates: median income, median mortgage payment, percentage with a bachelor's degree and percentage employed full time. The estimated effect is no different to the effect in Column 1.

Equation 1 imposes a linear relationship between the number of solar panels in a postcode and the share of new contracts that contain green power, yet there is no clear theoretical or empirical reason why the relationship should be linear, or that panels outside the arbitrary borders of a postcode but nearby would not have an impact on the share of customers electing to purchase green power. Columns (3) - (6) impose alternative assumptions on the relationship between solar panels and green power purchases. Regardless of the model of behavior assumed, on average a solar panel continues to have a positive effect on green power sign ups. For example, Column (3) allows the effect of solar rooftops to be nonlinear, demonstrating a diminishing effect as the installed base increases, though the average effect of a solar panel is approximately unchanged from the linear specification. Columns (4) and (5) report results of alternative models where the measure of exposure to solar panels is panels per rooftop (Column (4)) and where the measure of exposure to solar panels is panels per unit area (Column (5)). Once again, I find a significant crowd in effect. Finally in column (6) I explore whether panels in a municipality (but not in the postcode) also have a small crowd in effect on green power purchases. I approximate municipality using the Statistical Area Level 3 (SA3) identifier from the Australian Bureau of Statistics (ABS) Statistical Geography.[22] I find that panels within the municipality do crowd in green power purchases though this effect is much smaller than the effect of within-postcode panels. This result is also comforting for identification, as it suggests that the estimates are not driven by confounding trends at the municipality level.

So far the relationship between solar panels and green power has been estimated in a fixed effects setting. Table 5 reports estimates employing the instrument based on roof ratio. Exploiting variation based on roof type does very little to change the magnitude of the estimated impact of a rooftop solar panel. In Column (1) the estimated effect is 0.029, which is statistically indistinguishable from the estimate in Column (1) of Table 4. Controlling for neighborhood characteristics (Column (2)) again does not change the estimated effect. Table 5 also reports F statistics for the first stage regressions, demonstrating that the instruments are strong. First stage coefficients are reported in Appendix Table A4.

[22]An SA3 consists of between 30,000 and 130,000 people and aligns closely to municipal boundaries.

There are two main threats to identification in the instrumental variables model. The first comes from the possibility of non-parallel trends, or persistent shocks to green-power purchases in postcodes with high metal to tile roof ratios, for example trends arising from gentrification. To account for threats such as gentrification, I explore the robustness of the results to the inclusion of a series of flexible time effects at the yearly level. First, Column (3) of Table 5 reports results employing year by region fixed effects, where region is again SA3 from the ABS. The results are robust to the inclusion of these fixed effects and therefore to flexible time trends at the municipal level.

Columns (4)-(6) of Table 5 reports results allowing for a number of other flexible time trends. In Melbourne, gentrification is most likely to occur in inner city suburbs. Distance to the city center is therefore a proxy for likelihood of gentrification. Column (4) of Table 5 demonstrates robustness to controlling for linear distance from the Melbourne General Post Office in the city center separately for each year. Column (5) shows that the effect of solar panels on green power purchases is robust to including an interaction between Year fixed effects and an indicator for above median roof ratio, while column (6) shows that the effect is robust to an interaction between Year fixed effects and quintiles of roof ratio.

Finally Table 6 reports results from restricting the sample to Melbourne (column 1) and then restricting to the inner city, middle suburbs, and outer suburbs of Melbourne. Inner city suburbs are those within 5km of Melbourne General Post Office, middle suburbs are between 5 and 20 km and outer suburbs are those greater than 20 km but still within the borders of the city according to the Australian census boundaries. Appendix Figure A8 maps these sample restrictions and the distribution of the time-invariant (scaled roof ratio) component of the instrument. There are no significant effects either for the inner or outer suburbs, however the effect for middle suburbs is positive and statistically significant. Thus most of the average effect seems to be driven by the behavior of those residing in the middle suburbs of Melbourne, suburbs that are unlikely to be experiencing the kind of gentrification that is a threat to identification.

The second main threat to identification comes from the possibility that the firm engages in differential marketing activities across postcodes that are correlated with solar panel installation. For example, if the firm takes observable solar panel installation as a signal of the green preferences of people in a neighborhood, they may target green power plans at households in that neighborhood. Then the observation that the share of green power is higher in neighborhoods with more solar panels is in part driven by differences in marketing. Several facts suggest that this is not a strong possibility: I find that the results are robust to a variety of rich fixed effects including municipality $\times$ year effects and to controls for distance from the city $\times$ year effects. To confound these estimates, marketing efforts would have to be both be postcode specific and changing over time with the installed solar base. This level of targeting does not seem consistent with the marketing strategies of electricity retailers in the state, who, anecdotally, tend to target larger geographic areas such as the "South East".

To address any remaining concern presented by differential marketing efforts, I exploit unique data on how customers were acquired by the company. In the customer inventory, for the vast majority of customers (98%) I observe whether new contracts are the result of telesales, door-to-door sales, a price comparison website, connection service or whether the customer is renewing an existing contract. I group sales channels into three categories: sales driven acquisitions (e.g. door-to-door sales which are the result of heavy and targeted marketing effort), customer driven acquisitions (e.g. customers signing contracts via a price comparison website who may be responsive to indirect marketing but were not acquired by direct marketing efforts) and renewal customers.[23] In Table 7 I show that the results are robust to controlling for the share of customers in a postcode acquired via these direct ("Sales Driven Acquisition") and indirect ("Customer Driven Acquisition") marketing efforts. Relative to renewal customers, a higher share of customers acquired via direct or indirect marketing efforts is associated with a higher share of green power contracts, however the effect of solar panels on green power purchases is unchanged.

[23] Appendix Figures A9 show the proportion of all new contracts by channel, and the total number of new contracts by channel over the sample period

6 Do Incentives Attenuate Peer Effects?

6.1 Empirical Strategy

Overall, the results summarized in the previous section suggest that a solar panel in a neighborhood increases the likelihood that non-solar peers sign up to a green power contract. The second empirical objective of this paper is to identify whether economic incentives, or extrinsic motivations, have an impact on the peer effect from solar panel installation to green power purchasing. To do so, I exploit sharp changes in solar subsidies to test the hypothesis that peer effects depend on the level of subsidies available to solar installers. I use these changes in subsidies in two ways. First, I separate the sample period into three periods representing a high-subsidy period (up to the first quarter of 2011), a period in which subsidies were falling (from the first quarter of 2011 to the first quarter of 2013), and a low-subsidy period (after the first quarter of 2013). I then estimate the effect of a solar panel in each of these periods by interacting an indicator for subsidy period with the number of solar panels in equation 1.

The second approach is to use an event study framework. In this approach I will estimate the following equation at the postcode level:

$$Green\ Power_{it} = \alpha_i + \rho_t + \sum_{\tau=-W}^{W} \theta_\tau (Solar\ Rooftops_{i\tau} \times Event\ Period_\tau) + \epsilon_{it} \qquad (3)$$

where $Solar\ Rooftops_{i\tau}$ is the number of solar rooftops in event period τ and $Event\ Period_\tau$ is an indicator for being event period τ within the event window W. I normalize event time such that $\tau \geq 0$ are high-subsidy periods and $\tau < 0$ are low-subsidy periods. Thus the quarter immediately before a subsidy increase is event period $\tau = -1$ and the quarter immediately after a subsidy increase is event period $\tau = 1$. Because there are both increases and decreases in subsidies observed within the sample, the quarter immediately before a subsidy decrease is also event period $\tau = 1$. Because the events are overlapping within the event window, an individual quarter may be both two periods before a subsidy decrease, and one period after a subsidy increase. In this case, event indicators

$Event\ Period_{\tau=2}$ and $Event\ Period_{\tau=1}$ are "switched on".[24] Coefficients θ_τ therefore measure the effect of an additional solar panel on purchases of green power in low ($\tau < 0$) and high ($\tau > 0$) subsidy periods relative to periods outside the event window.[25]

To estimate the impact of subsidies, I compare θ_τ coefficients in periods immediately before and immediately after a subsidy change.[26] If incentives do attenuate the peer effect then $\theta_{\tau|\tau<0} > \theta_{\tau|\tau>0}$. The identifying assumption is that other unobserved time-varying factors that affect green power purchases and that are correlated with solar installation do not change sharply with subsidies for solar panels. For the results to be spurious, some other factor would have to cause the same pattern of changes in green power purchases at exactly the same points in time as subsidy changes.[27] Note also that although event time is coded as positive for high-subsidy periods, subsidies are declining over the period of the sample. This, and the fact that $Solar\ Rooftops$ is a cumulative variable, ensures that the specification is not conflating the impact of a higher subsidy on the peer effect with a non-linearity in the effect of $Solar\ Rooftops$ on green power purchases. Furthermore controlling for a quadratic in $Solar\ Rooftops$ does not change the main findings.

To lend support to the results I employ two additional strategies. First, I include time-varying controls in the event study estimation and demonstrate no change to the main findings. Second, I also instrument for solar rooftops with the same instrument as

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[24] Appendix Figure A10 shows that the share of observations in each Event Period is relatively constant. Appendix Table A6 shows that the number of observations that coincide with more than one Event Period.

[25] Appendix Table A6 shows that 20% of observations are outside the Event Window. Observations outside the window are from first quarter of 2015. Dropping these observations does not change the conclusions.

[26] There is no cross-sectional variation in available subsidies, instead, cross-sectional variation comes from differences in the number of solar rooftops in a postcode

[27] Mian and Sufi (2012) use a similar research design to identify the effects of the Cash for Clunkers stimulus program on auto purchases. They measure exposure to the program as the number of "clunkers" (less fuel efficient vehicles eligible for trade-in subsidies) in a city before the stimulus came into effect.

above where for each event interaction ($Solar\ Rooftops_{i\tau} \times Event\ Period_\tau$) I construct an instrument ($Z_{i\tau} \times Event\ Period_\tau$).

6.2 Results

Figure 5 shows how the effect of solar panels on the likelihood a customer signs a green power contract depends on subsidies in the quarter in which the contract is being signed. In particular, it shows that an additional solar panel crowds in purchases of green power when subsidies are low or declining, but an additional solar panel crowds out purchases of green power when subsidies are high.

I next estimate equation 3 employing an event window of 18 months (9 months or 3 quarters on either side of the event). Coefficients and 95% confidence intervals for $\hat{\theta}_\tau$ in the linear fixed effects model are plotted in Figure 6 while coefficients and standard errors are reported in column (1) of Table 8. As with the average effect estimates, regressions are weighted by number of customers and standard errors are clustered at the postcode level. The coefficients for $\tau < 0$ are the effect of a solar panel in a low-subsidy period. Similarly, the coefficients where $\tau > 0$ are the effect of a solar panel in a high-subsidy period. On average, I find that the effect of an additional solar panel during a high-subsidy period is lower than the effect of an additional solar panel in a low-subsidy period.

I find very similar results when using the roof ratio instrument, and adding controls. Figure 7 plots the reduced form and instrumental variables estimates for the event study coefficients employing the roof ratio instrument interacted with event study indicators as instruments. Figure 10 shows the reduced form and instrumental variables estimates when controlling for the same time varying coefficients as Table 4. Coefficients and standard errors for these event study coefficients are reported in Table 8.

Across all columns of Table 8 I find that the effect of a solar panel in a low-subsidy period ($\tau < 0$) is positive and significant. The effect of a solar panel in a high-subsidy period ($\tau > 0$) is on average negative and significant while individual event period estimates are either statistically indistinguishable from zero or negative and significant. Across all columns the null hypothesis that the effects are the same in high and low-subsidy periods is rejected.

To summarize, across both fixed effect and instrumental variable models, I find that subsidies, a financial or extrinsic incentive, interact with peer effects that are generated from visible prosocial behavior. This finding is broadly consistent with the theory of motivation crowding and the idea that the social pressure that generates peer responses to prosocial behavior depends on the strength of the prosocial signal.

The event study analysis is robust to a range of specifications. In Figure 8 I first demonstrate that the results are consistent when I add time-varying controls. I next present results restricting the earliest date in the sample to be the first quarter of 2010 and thus removing the period surrounding a large increase in the feed-in tariff subsidy available to solar installers (see Table 1). Figure 9 demonstrates that this single increase in subsidies during the sample is not driving the results. In the same figure I also show results restricted to after the first quarter of 2011. There is still strong evidence that higher subsidies reduce the size of peer effects.

I also show that the conclusions are not sensitive to the choice of event window. The left hand panel of Figure 10 restricts the event window to six months before and after a subsidy change while the right hand panel widens the window to include a full year before and after the subsidy change (the top row of Figures shows fixed effects estimates while the bottom row of Figures shows instrumental variables estimates). Once again, although magnitudes differ, the coefficients support the conclusion that incentives for prosocial behavior reduce the size of peer effects. I also show in Appendix Figure A11 that the results are consistent when restricting the sample to suburbs of Melbourne and by distance from the center of the city.

One concern with the estimates may be that they are an artefact of disproportionate solar adoption among green power customers. As noted, because the focus of the paper is on the spillover from solar panels to green power purchases, the sample of interest is those households who are not observed to install panels. This could generate selection problems if solar households are disproportionately more or less likely to have been green power purchasers. Suppose for example that households choose either to purchase green power or install solar panels. In suburbs where solar panel installation is not feasible, we will observe a high share of green power purchases in the non-solar sample. In suburbs where solar panel installation is feasible we will observe a low share of green power purchases in the non-solar sample. This would generate a spurious result of crowding out. If the reverse is true, that solar and green power households are different types of households, then the opposite spurious result would occur. The key assumption is that solar households have the same ex-ante probability of being green power as households that do not choose to install panels over the sample period.

Appendix Table A11 shows that solar households have a lower ex-ante probability of being green power customers. The Table reports results of a linear regression using individual data from the full period 2006-2016. The dependent variable is whether a new contract includes green power. *Pre solar adoption* is an indicator for the customer will install solar panels in the future. *Post solar adoption* is an indicator for the customer has installed solar panels. *Always solar* is an indicator for the customer is only observed with solar panels. The coefficients on *Always solar* and *Post solar adoption* demonstrate that customers who have solar panels have a lower probability of signing a green power contract. This could be because they switch from green power to solar, or because they were less likely to purchase green power in the first place. Table A11 suggests that both are occurring. The coefficient on *Pre solar adoption* suggests that on average, prior to adoption, solar households have a lower probability of signing green power contracts than households who do not adopt solar. The larger magnitude of the coefficients on *Pre solar adoption* and *Post solar adoption* suggests that there is also substitution.

To ensure that the results are not driven by this form of sample selection, Table 9 reports event study coefficients including solar households in the sample at the customer level. In this case, $SolarRooftops_{i\tau}$ is now *peer* solar rooftops, solar rooftops excluding an adopter's solar panel. Column 1 reports coefficients from the basic event study specification. Column 2 includes an indicator variable for households have solar panels. The results do not differ substantially across columns, nor do they differ to the main postcode level results reported in Table 8 or the individual level results excluding solar households entirely (see Appendix Table A12). For reference and comparison with Table 4, Appendix Table A13 reports the average effect results at the customer level inclusive of solar households.

As further supporting evidence, I present the results of three placebo or falsification tests. In the first placebo exercise, I randomly re-assign event date indicators and re-estimate the event study coefficients. To generate a distribution, I replicate the exercise 1000 times. Figure 11 displays the results of this placebo exercise. Unlike the clear pattern of coefficients in Figure 6, I find no evidence of a reduction in the magnitude of the estimated peer effect during false 'high' subsidy periods, indeed the average effect is positive for all event periods, which is consistent with the results reported in Table 4.

The remaining three placebo exercises demonstrate that there are no effects of changes to solar subsidies on other features of new electricity contracts. Figure 12 plots coefficients from the main event study specification (Equation 3) where the dependent variable is in order of the figure panels: (a) the share of new contracts that select Manual Payment (b) the share of new contracts that receive a low income concession discount (c) the price of green power plans. The lack of significant effects demonstrates that the main event study results are not an artefact of changes in the composition of customers or of changes in available plans that coincide with changes in subsidies to solar panels.

7 Conclusion

This paper delivers two main results. First, that on average rooftop solar panel installation crowds in public-good contributions of neighbors via greater green power plan uptake. Second, that this peer effect depends on the level of subsidies available to install solar. When subsidies are high, a solar panel reduces the likelihood that non-solar neighbors adopt green power.

These findings are consistent with the idea that extrinsic incentives for visible prosocial actions compromise the image value of those actions and so dilute the prosocial signal, or the amount of peer pressure, that is sent. Previous literature has focused on the impact of extrinsic incentives on the likelihood an individual engages in a visible prosocial activity. I exploit differences in visibility and private benefits across two related prosocial actions to demonstrate that extrinsic incentives also affect the behavior of the individuals receiving those signals.

These results suggest some caution in evaluating the impacts of subsidies on environmental outcomes based purely on adoption. On the one hand solar panels increase purchases of green power among those households not choosing to install solar. On the other hand, subsidies to the installers of panels reduce green power purchases. The net effect of the subsidy therefore could be to lower contributions to the public good.

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Figures

Figure 1: State Trends in Residential Solar and Green Power

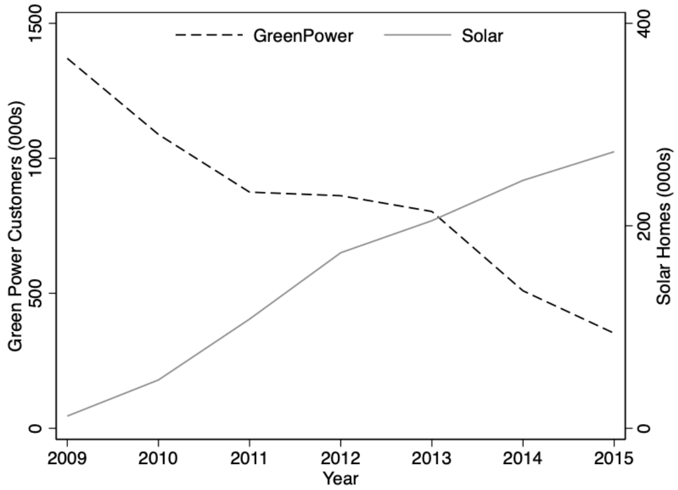


Figure plots the number of rooftop solar panel installations and residential green power customers for the state of Victoria. Green power data are sourced from the National Green Power Accreditation Program. Solar installation data are from the Clean Energy Regulator.

Figure 2: Net Present Value of Solar Installation

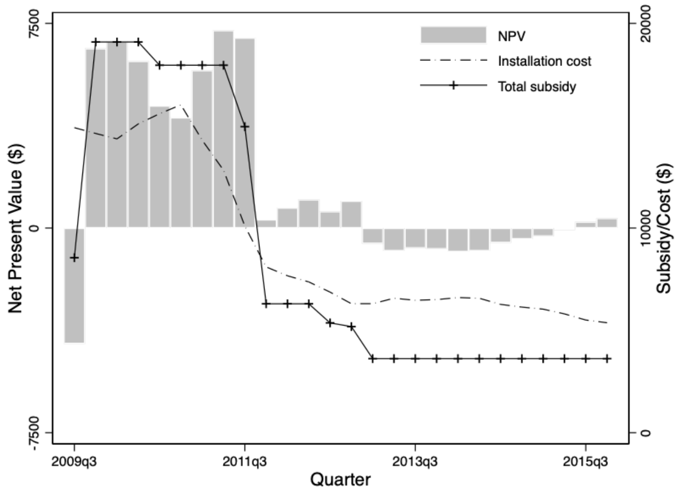


Figure shows back of the envelope calculations of the net present value of solar panel installation following Wood and Blowers (2015). See Appendix B for details of the calculations and data sources.

Figure 3: Sample Trends in Residential Solar and Green Power

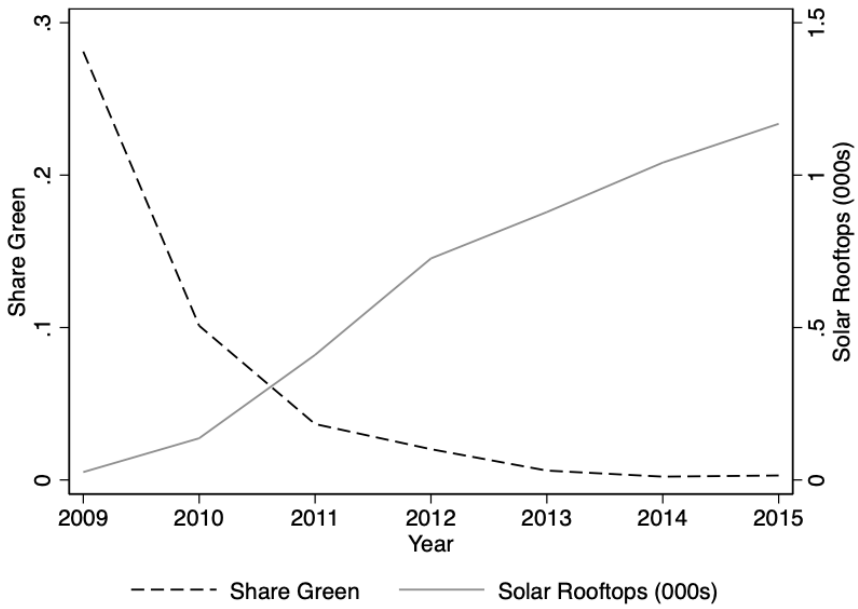


Figure plots trends in the share of new contracts in a postcode that opt in to green power and the number of solar panel installations in those postcodes for the sample used in this paper. Data weighted by number of customers.

Figure 4: Variation Within and Across Time in Solar Installation and Green Power Purchases

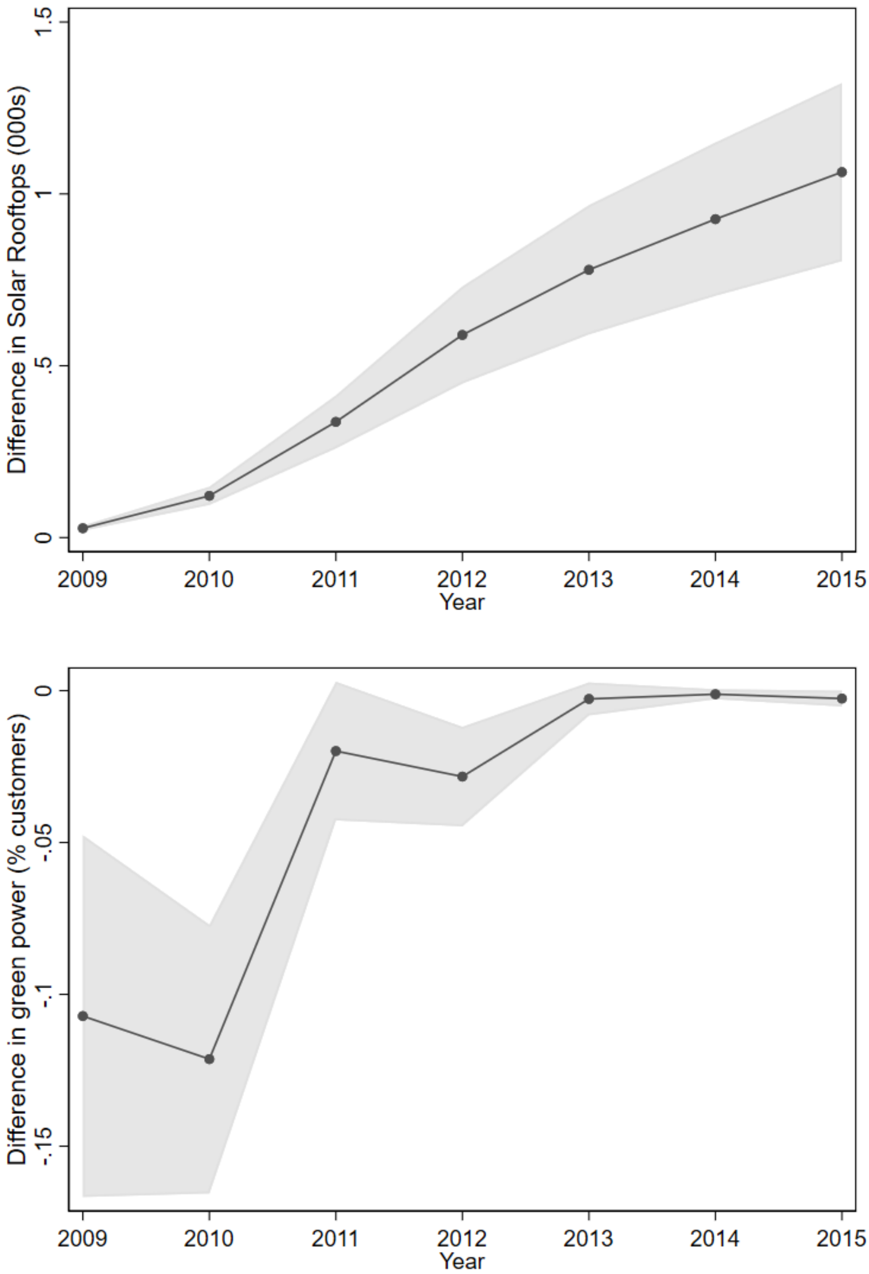


Figure shows the difference in the share of green power customers and solar installations across postcodes with above versus below median scaled roof ratio. Data weighted by number of customers.

Figure 5: Incentives and Peer Effects: High-Subsidy, Subsidy-Change, Low-Subsidy Periods

(a) Fixed Effects

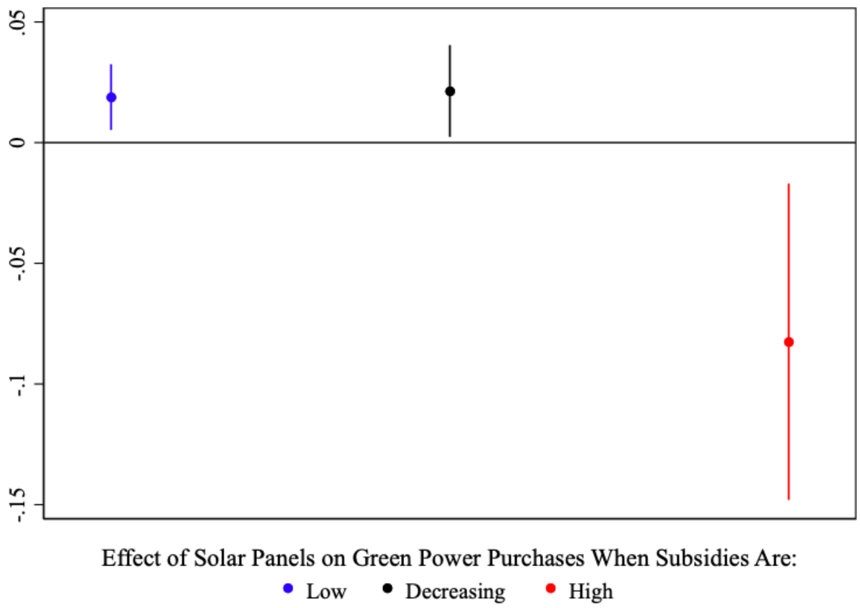


Figure plots coefficients and 95% confidence intervals for estimates of β by period where quarters are divided into high (prior to 2011q1), decreasing (2011q1-2013q1) and low (after 2013q1) subsidy intervals. Coefficients are the effect of a solar panel in a neighborhood on the share of customers signing a green power contract. Standard errors are clustered at the postcode level. Regression weighted by number of customers.

Figure 6: Incentives and Peer Effects: Event Study

(a) Fixed Effects

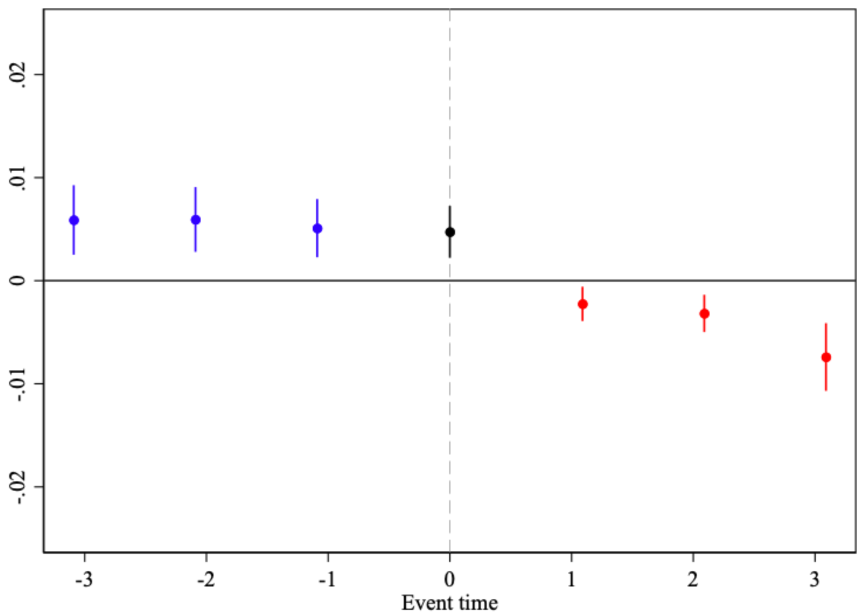
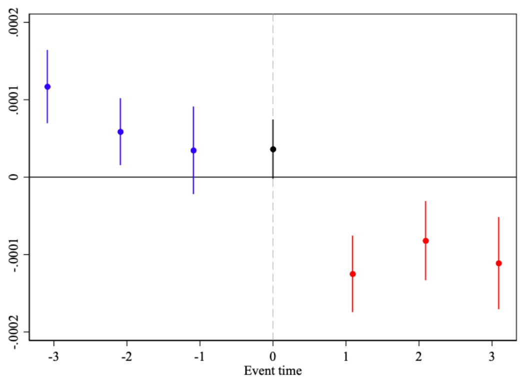


Figure plots coefficients and 95% confidence intervals for θ_τ where τ denotes event time. Coefficients are the effect of a solar panel on the likelihood an individual signs a green power contract during an event period. Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high-subsidy period and $\tau < 0$ being a low-subsidy period. Standard errors are clustered at the postcode level. Regression weighted by number of customers.

Figure 7: Instrumental Variables Estimates: Incentives and Peer Effects - Event Study


(a) Reduced Form

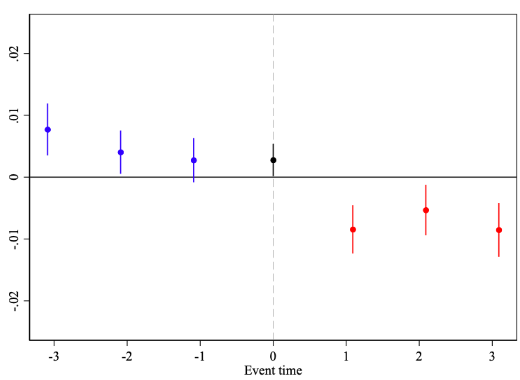

(b) Instrumental Variables

Figure plots coefficients and 95% confidence intervals for θ_τ where τ denotes event time. Coefficients are the effect of a solar panel on the likelihood an individual signs a green power contract during an event period. Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high-subsidy period and $\tau < 0$ being a low-subsidy period. Panel (a) is the reduced form for panel (b) where the instrument is an interaction between the scaled roof ratio and global solar module price index. Panel (b) coefficients are the instrumental variables estimates of the effect of solar panel installation on the likelihood an individual signs a green power contract. Regressions weighted by number of customers. Standard errors are clustered at the postcode level.

Figure 8: Instrumental Variables Estimates with Controls:
Incentives and Peer Effects

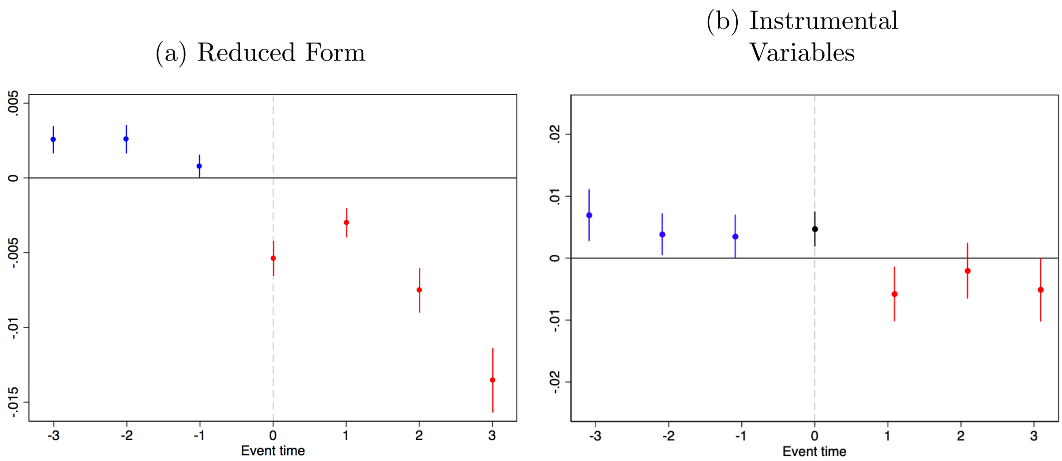
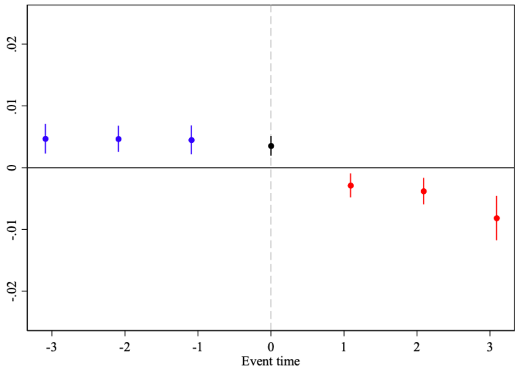


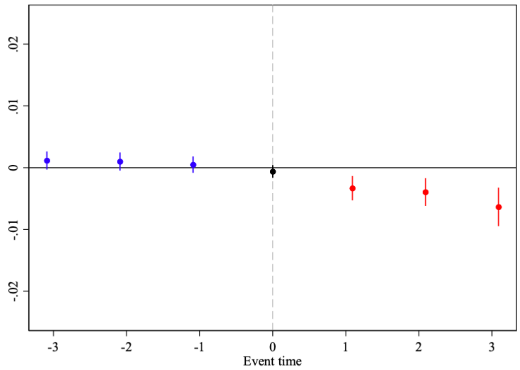
Figure plots coefficients and 95% confidence intervals. Coefficients in the left hand panel are the reduced form coefficients for the instrumental variables model from the right hand panel. In the left hand panel the estimates are θ_τ where τ denotes event time and coefficients are the estimates of the effect of solar panel installation on the likelihood an individual signs a green power contract during an event period. Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high-subsidy period and $\tau < 0$ being a low-subsidy period. The instrument is an interaction between the scaled roof ratio and global solar module price index. Specification includes controls. Regressions weighted by number of customers. Standard errors are clustered at the postcode level.

Figure 9: Restricted Sample in Time: Incentives and Peer Effects

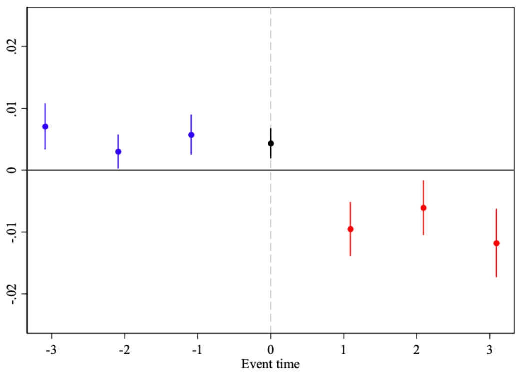
(a) Fixed Effects
post 2010



(b) Fixed Effects
post 2011



(c) Instrumental
Variables post 2010



(d) Instrumental
Variables post 2011

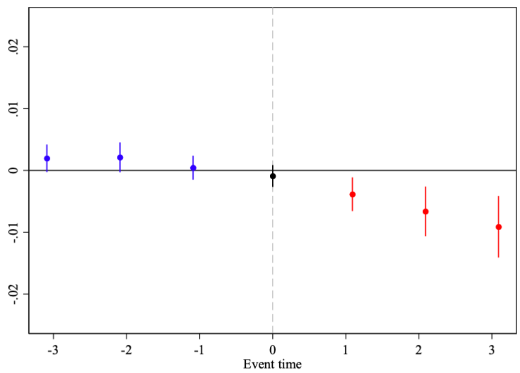
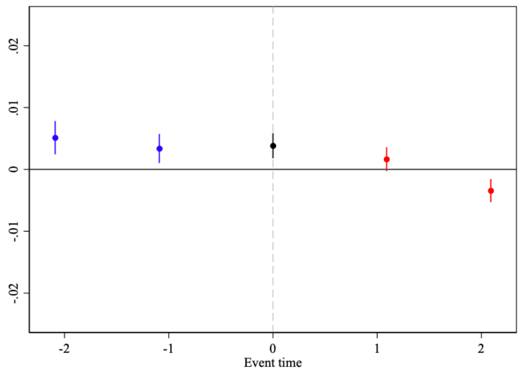


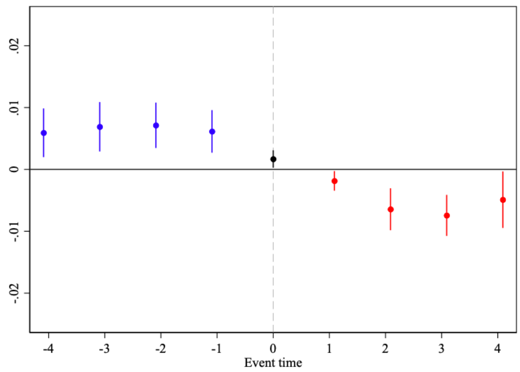
Figure plots coefficients and 95% confidence intervals for θ_τ where τ denotes event time. Coefficients are the effect of a solar panel on the likelihood an individual signs a green power contract during an event period. Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high-subsidy period and $\tau < 0$ being a low-subsidy period. Panels (a) and (b) are fixed effect estimates. Panels (c) and (d) are instrumental variable estimates. Panels (a) and (c) use the sample restricted to after first quarter of 2010. Panels (b) and (d) use the sample restricted to after first quarter 2011. The instrument is an interaction between scaled roof ratio and global solar module price index. Standard errors are clustered at the postcode level. Regressions weighted by number of customers.

Figure 10: Alternative Event Windows: Incentives and Peer Effects

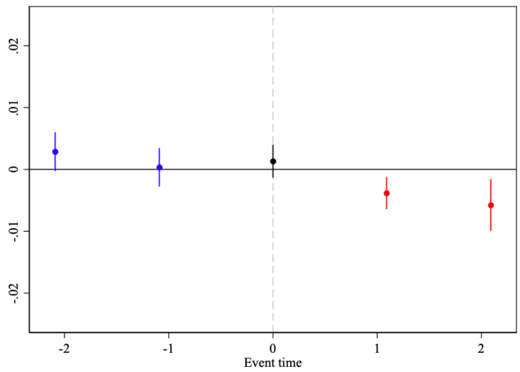
(a) Fixed Effects



(b) Fixed Effects



(c) Instrumental Variables



(d) Instrumental Variables

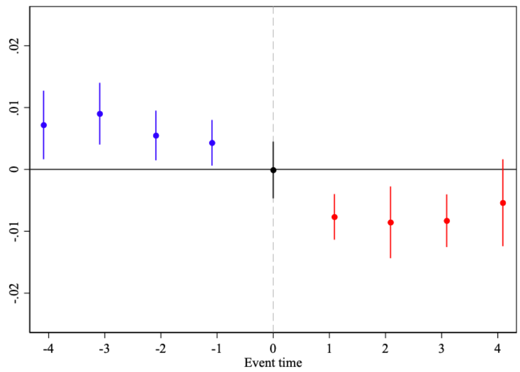


Figure plots coefficients and 95% confidence intervals for θ_τ where τ denotes event time. Coefficients are the effect of a solar panel on the likelihood an individual signs a green power contract during an event period. Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high-subsidy period and $\tau < 0$ being a low-subsidy period. Panels (a) and (c) restrict the event window to 6 months (2 quarters) on either side of an event. Panels (b) and (d) expand the event window to 12 months (4 quarters) on either side of an event. Panels (a) and (b) are fixed effect estimates. Panels (c) and (d) are instrumental variables estimates. Instrument is an interaction between scaled roof ratio and a global solar module price index. Standard errors are clustered at the postcode level. Regressions weighted by number of customers.

Figure 11: Placebo Test: Incentives and Peer Effects

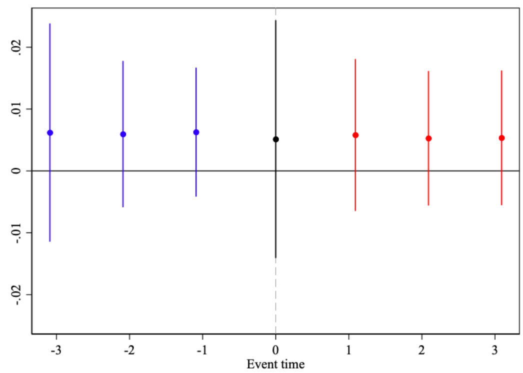
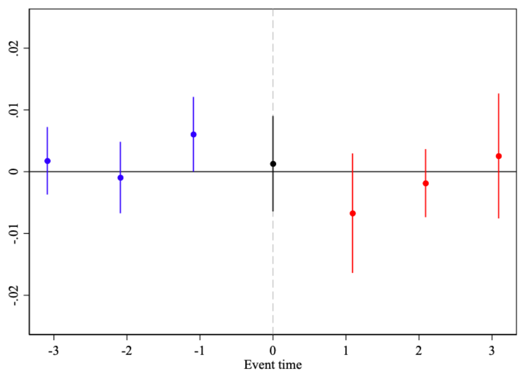


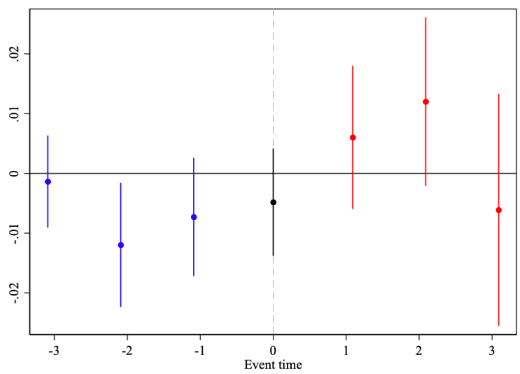
Figure plots coefficients and 95% confidence intervals for the estimate of θ_τ from a placebo exercise re-assigning subsidy changes to random dates throughout the sample with 1000 replications. Coefficients are from a fixed effects model and measure the effect of a solar panel on the likelihood an individual signs a green power contract during a placebo event period. Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high-subsidy period and $\tau < 0$ being a low-subsidy period. Regressions weighted by number of customers. Standard errors clustered by postcode.

Figure 12: Placebo Tests: Concession, Manual Payment and Green-Power Price

(a) Manual Payment Instrumental Variables



(b) Concession Instrumental Variables



(c) Price of Green Power Plans

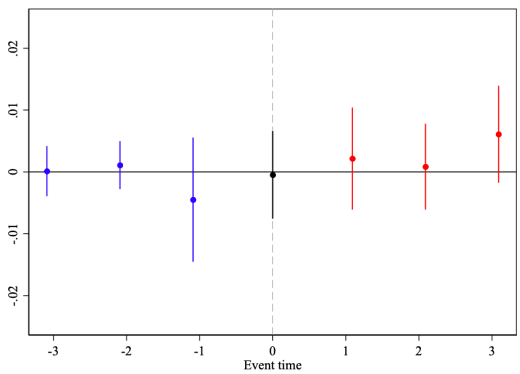


Figure plots coefficients and 95% confidence intervals for the estimate of θ_τ from a placebo exercise where the dependent variable is the share of new contracts that select manual payment (panel (a)), the share of contracts that are entitled to a concession subsidy (panel (b)) and the price of green power plans (panel (c)). Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high-subsidy period and $\tau < 0$ being a low-subsidy period. Instrument is an interaction between scaled roof ratio and a global solar module price index. Regressions weighted by number of customers. Standard errors are clustered at the postcode level.

Tables

Table 1: Changes to Solar-Support Policies During Sample Period

Date	Policy	Government
2007	$8000 rebate	Federal
January 2008	Feed-in tariff 1:1 with retail rate	State
June 2009	Renewable Energy Credits value up to $5600*	Federal
November 2009	Feed-in tariff 60c/kWh	State
July 2011	Renewable Energy Credits value up to $3733*	Federal
December 2011	Feed-in tariff 25c/kWh	State
July 2012	Renewable Energy Credits value up to $2800*	Federal
January 2013	Renewable Energy Credits value up to $1866*	Federal
	Feed-in tariff 8c/kWh	State
January 2014	Feed-in tariff 6c/kWh	State

* value of credits for a 3kW system in Melbourne and assuming a credit is worth $35.

Table 2: Summary Statistics

	(1)
Share Green	0.0233
	(0.0821)
Solar Panels (000s)	0.908
	(0.960)
Electricity Tariff (per kWh)	0.234
	(0.0264)
Median Mortgage Payment (000/month)	1.788
	(0.421)
Median Income (000/week)	0.617
	(0.155)
Median Rental Payment (000/week)	0.281
	(0.0692)
Proportion Bachelor's Degree	0.198
	(0.114)
Median House Size	2.932
	(0.346)
Proportion Employed Full Time	0.373
	(0.0628)
Median Age	37.32
	(4.924)
Proportion Separate Dwellings	0.739
	(0.212)
Proportion Rental Properties	0.290
	(0.116)
Proportion Roof Metal	0.718
	(0.0647)
Proportion Roof Tile	0.256
	(0.0676)
Observations	11545

Notes: Table reports mean and standard deviations in parentheses weighted by number of customers. Share of new contracts that are green plan and average electricity tariffs are from retailer inventory data. Solar panels are from the Clean Energy Regulator via the Australian Photovoltaic Institute. Roof materials are from GeoScience Australia. All other variables are from interpolations of the 2006, 2011 and 2016 Australian census at the postcode level.

Table 3: Pre-trends in Green-Power Purchasing by Roof Suitability

VARIABLES	(1) Pre 2009	(2) Post 2009	(3) Pre + Post 2009	(4) Pre + Post 2009
Quarter	0.015*	-0.010***	-0.015***	
	(0.008)	(0.001)	(0.001)	
Above Median Scaled Roof Ratio	2.142	-0.973***	-0.366**	
	(1.574)	(0.196)	(0.150)	
× Quarter	-0.011	0.004***	0.002**	
	(0.008)	(0.001)	(0.001)	
× Pre 2009				-2.995***
				(0.505)
× Post 2009				-0.834***
				(0.200)
× Pre 2009 × Quarter				-0.011
				(0.008)
× Post 2009 × Quarter				0.004***
				(0.001)
Pre 2009 × Quarter				0.015*
				(0.008)
Post 2009 × Quarter				-0.012***
				(0.001)
Below Median Scaled Roof Ratio × Pre 2009				-5.136***
				(1.563)
Observations	3182	11545	15556	15556

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. Significance of coefficients: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Above Median Scaled Roof Ratio is above median of the time invariant component of the instrument in equation 2. Standard errors clustered at postcode level. Regression is weighted by number of customers.

Table 4: Average Effect Solar Rooftops on Green Power Purchases: Fixed Effects

VARIABLES	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE
Solar Panels (000s)	0.023***	0.021***	0.079***			0.019***
	(0.006)	(0.006)	(0.013)			(0.006)
Median Income (000/week)		-0.048				
		(0.057)				
Median Mortgage Payment (000/month)		-0.054*				
		(0.029)				
Proportion Bachelor's Degree		0.155				
		(0.325)				
Proportion Employed Full Time		0.131				
		(0.324)				
Solar Panels (000s) ^{2}			-0.011***			
			(0.002)			
Solar Panels per Dwelling				0.207*		
				(0.113)		
Solar Panels (000s) per km^2					0.666***	
					(0.155)	
Solar Panels (Rest of Municipality, 000s)						0.004**
						(0.002)
Observations	11,545	11,545	11,545	11,545	11,545	11,545
R^2	0.419	0.420	0.429	0.412	0.416	0.420
Number of postcode	605	605	605	605	605	605
Postcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep var	0.023	0.023	0.023	0.023	0.023	0.023

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. Significance of coefficients: $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors are clustered at the postcode level. Regression is weighted by number of customers. All columns are fixed effect estimates.

Table 5: Average Effect of Solar Rooftops on Green Power Purchases: Instrumental Variables

VARIABLES	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV
Solar Panels (000s)	0.029***	0.028***	0.033***	0.029***	0.019***	0.017**
	(0.007)	(0.008)	(0.007)	(0.007)	(0.006)	(0.007)
Median Income (000/week)		-0.032				
		(0.059)				
Median Mortgage Payment (000/month)		-0.045				
		(0.030)				
Proportion Bachelor's Degree		0.009				
		(0.360)				
Proportion Employed Full Time		0.282				
		(0.336)				
Observations	11,545	11,545	11,545	11,545	11,545	11,545
R^2	0.418	0.419	0.069	0.418	0.430	0.437
Number of postcode	605	605	605	605	605	605
Postcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
SA3-Year FE	No	No	Yes	No	No	No
Distance-Year Control	No	No	No	Yes	No	No
Above Median Roof Index-Year FE	No	No	No	No	Yes	No
Quintile Roof Index-Year FE	No	No	No	No	No	Yes
Mean dep var	0.023	0.023	0.023	0.023	0.023	0.023
CDW F-test	27.45	29.31	94.03	27.45	23.63	13.27

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. Significance of coefficients: $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors are clustered at the postcode level. Regression is weighted by number of customers. All columns are instrumental variable estimates. Instrument is an interaction between scaled roof ratio and global solar module price index. See Appendix Table A4 for first stage estimates.

Table 6: Average Effect of Solar Rooftops on Green Power Purchases: Inner, Middle and Outer Melbourne

VARIABLES	(1) All Suburbs	(2) Inner Suburbs	(3) Middle Suburbs	(4) Outer Suburbs
Solar Panels (000s)	0.017***	0.639	0.037***	0.002
	(0.005)	(0.414)	(0.014)	(0.004)
Observations	5,652	537	2,751	2,364
R^2	0.469	0.663	0.514	0.437
Number of postcode	237	21	103	113
Postcode FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Mean dep var	0.022	0.028	0.021	0.021
CDW F-test	41.20	5.116	17.68	27.17

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. Significance of coefficients: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. Standard errors are clustered at the postcode level. Regression is weighted by number of customers. All columns are instrumental variable estimates. Instrument is an interaction between scaled roof ratio and global solar module price index. Column (1) restricts the sample to the capital city of Melbourne as defined by the Australian census. Inner suburbs are within 5km of Melbourne General Post Office, middle suburbs are between 5 and 20 km and outer suburbs are those greater than 20 km but still within Melbourne.

Table 7: Average Effect of Solar Rooftops on Green Power Purchases: Accounting for Marketing Effects

VARIABLES	(1) FE	(2) IV	(3) FE	(4) IV
Solar Panels (000s)	0.023***	0.029***	0.023***	0.029***
	(0.006)	(0.007)	(0.006)	(0.007)
Sales Driven Acquisition			0.058***	0.058***
			(0.007)	(0.007)
Customer Driven Acquisition			0.038***	0.038***
			(0.008)	(0.008)
Observations	11,498	11,498	11,498	11,498
R^2	0.420	0.419	0.422	0.422
Number of postcode	604	604	604	604
Postcode FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Mean dep var	0.023	0.023	0.023	0.023

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. Significance of coefficients: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. *Sales Driven Acquisition* is the share of new contracts in a postcode that were acquired by direct marketing efforts. *Customer Driven Acquisition* is the share of new contracts in a postcode that were acquired by indirect marketing. Standard errors are clustered at the postcode level. Regression is weighted by number of customers. Columns (1) and (3) are fixed effect estimates, Columns (2) and (4) are instrumental variable estimates. Instrument is an interaction between scaled roof ratio and global solar module price index.

Table 8: Impact of Incentives on the Magnitude of Peer Effects

VARIABLES	(1) FE	(2) FE	(3) IV	(4) IV
Solar Panels (000s) ×				
Event Period -3	0.006***	0.005***	0.008***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Event Period -2	0.006***	0.006***	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
Event Period -1	0.005***	0.005***	0.003	0.004*
	(0.001)	(0.001)	(0.002)	(0.002)
Event Period	0.005***	0.006***	0.003**	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Event Period +1	-0.002***	0.000	-0.008***	-0.006**
	(0.001)	(0.001)	(0.002)	(0.002)
Event Period +2	-0.003***	-0.000	-0.005**	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)
Event Period +3	-0.007***	-0.004*	-0.009***	-0.005*
	(0.002)	(0.002)	(0.002)	(0.003)
Median Income (000/week)		-0.096*		-0.091
		(0.057)		(0.057)
Median Mortgage Payment (000/month)		-0.080***		-0.078***
		(0.028)		(0.028)
Proportion Bachelor's Degree		0.575**		0.540*
		(0.291)		(0.291)
Proportion Employed Full Time		-0.304		-0.269
		(0.326)		(0.322)
Observations	11,545	11,545	11,545	11,545
R^2	0.412	0.416	0.411	0.415
Number of postcode	605	605	605	605
Postcode FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Mean dep var	0.023	0.023	0.023	0.023

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high-subsidy period and $\tau < 0$ being a low-subsidy period. Significance of coefficients: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. Standard errors are clustered at the postcode level. Regression is weighted by number of customers. Columns (1) and (2) are fixed effect estimates, Columns (3) and (4) are instrumental variable estimates. Instrument is an interaction between scaled roof ratio and global solar module price index. First stage F statistics for endogenous variables are provided in the Appendix. Instruments are strong.

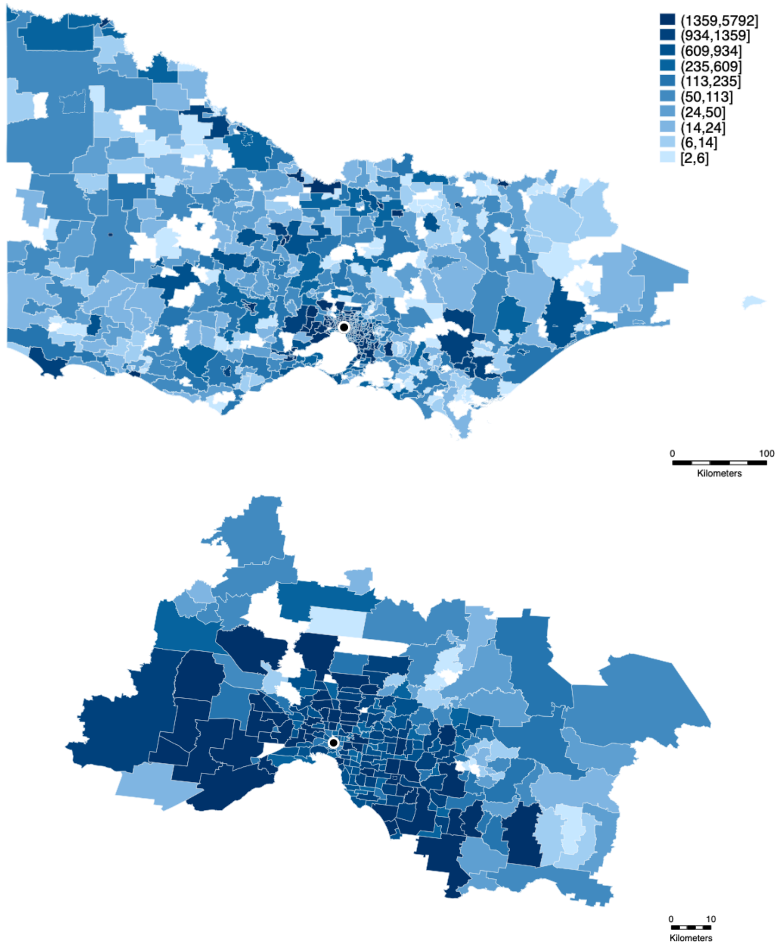
Table 9: Impact of Incentives on the Magnitude of Peer Effects: Customer Level Data Including Solar Households

VARIABLES	(1) FE	(2) FE
Adopted Solar		-0.006***
		(0.001)
Peer Solar Panels (000s) ×		
Event period -3	0.005***	0.005***
	(0.001)	(0.002)
Event period -2	0.005***	0.005***
	(0.001)	(0.001)
Event period -1	0.004***	0.004***
	(0.001)	(0.001)
Event period	0.004***	0.004***
	(0.001)	(0.001)
Event period +1	-0.002***	-0.002***
	(0.001)	(0.001)
Event period +2	-0.004***	-0.004***
	(0.001)	(0.001)
Event period +3	-0.007***	-0.007***
	(0.002)	(0.002)
Observations	307,100	307,100
R^2	0.115	0.115
Number of postcode	605	605
Postcode FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Mean dep var	0.022	0.022

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. Data is at the customer level. *Adopted Solar* is an indicator variable for the customer had rooftop solar panels in that quarter. *Peer Solar Panels (000s)* is the number of solar panels in a customer's postcode at that quarter. Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high-subsidy period and $\tau < 0$ being a low-subsidy period. Significance of coefficients: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. Both columns are fixed effects estimates. Standard errors are clustered at the postcode level.

Appendix A: Supplemental Figures and Tables

Figure A1: Map of Customer Inventory



Top panel maps the number of customers in the sample over the state at the postcode level. Bottom panel maps the number of customers in the sample within the capital city of Melbourne. Colors represent deciles of the full sample. Black and white point indicated on the maps is the Melbourne General Post Office.

Figure A2: Bloomberg Global Solar Module Price Index

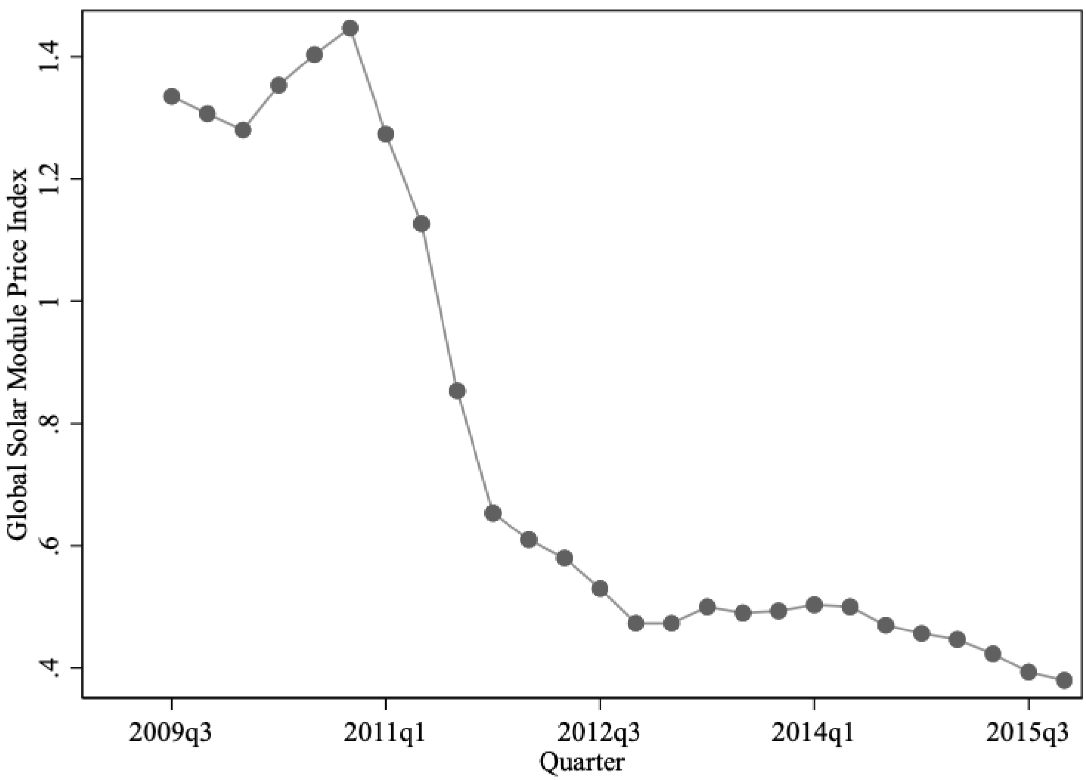
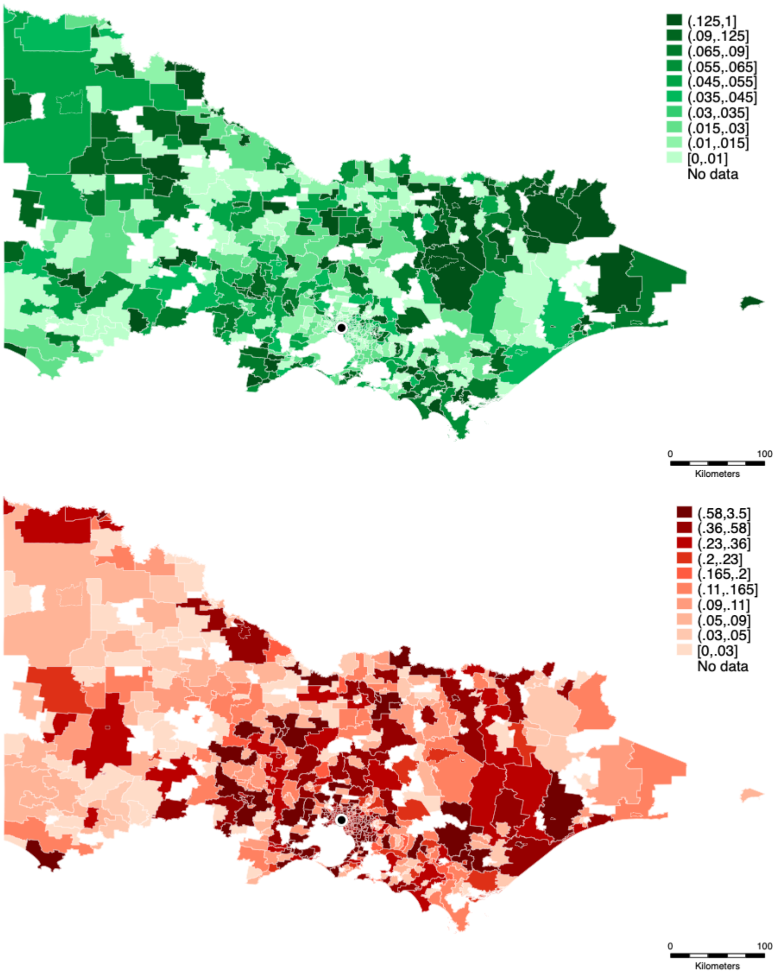


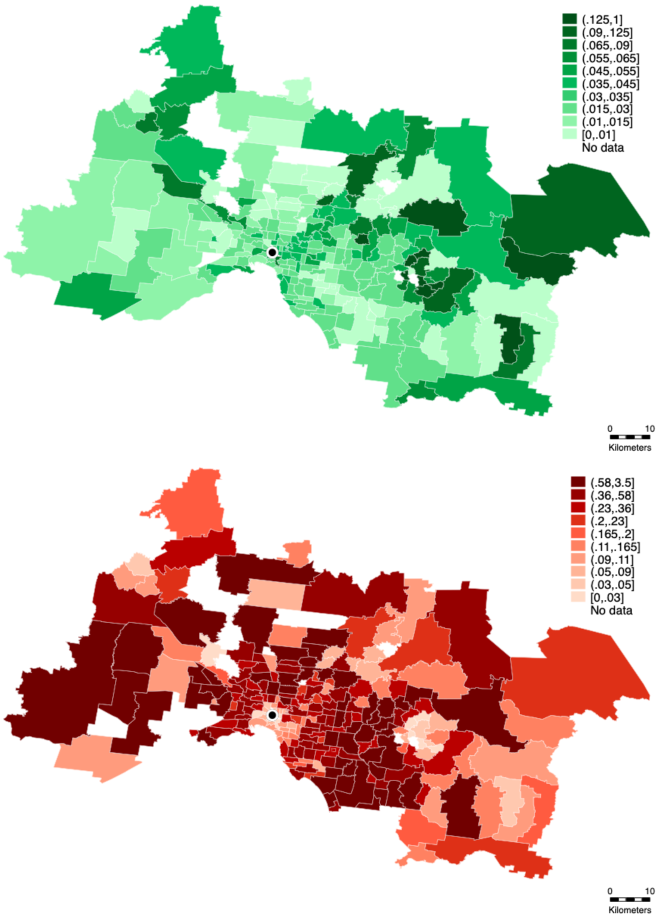
Figure plots Bloomberg's Global Solar Module Price Index by quarter from the third quarter of 2009 to 2016.

Figure A3: Map of Green Power and Solar Rooftops in the Sample



Top map shows the share of new contracts that opt in to green power in the sample at the postcode level. Bottom map shows the average number of solar rooftops in the sample at the postcode level (000s). In each map, colors represent deciles of the full sample. The black and white point on each map represents the Melbourne General Post Office.

Figure A4: Map of Green Power and Solar Rooftops in the Sample: Melbourne



Top map shows share of new contracts that opt in to green power in the sample at the postcode level, restricted to capital city Melbourne. Bottom map shows average number of solar rooftops in the sample at the postcode level (000s), restricted to capital city Melbourne. Colors represent deciles of the full sample distribution. The black and white point on each map represents the Melbourne General Post Office.

Figure A5: Mixed Roofing in Inner and Outer Australian Suburbs

Images of mixed roofing in inner and outer city suburbs. Terraced housing image by Sardaka (talk) 06:51, 3 June 2013 (UTC) - Own work, CC BY 3.0, https://commons.wikimedia.org/w/index.php?curid=26464838. Suburban image from One Step Off the Grid https://onestepoffthegrid.com.au/wa-trials-tesla-battery-suburban-grid-top-solar-postcode-mandurah/

Figure A6: Map of Scaled Roof Ratio

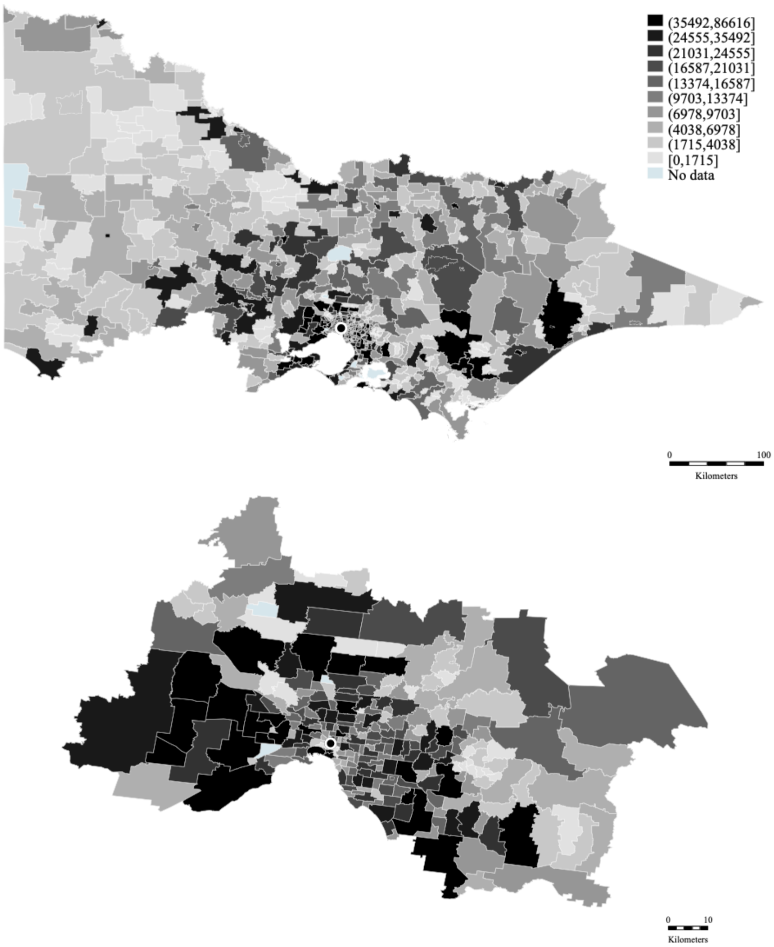


Figure shows the time invariant component of the instrument ($\frac{Metal}{Tile} * Roofs$) at the postcode level for the state and for the capital city of Melbourne. In both maps the Melbourne General Post Office is marked with a black and white point. Shading represents deciles of the distribution within the state.

Figure A7: Trends in Dwelling Prices by Roof Ratio

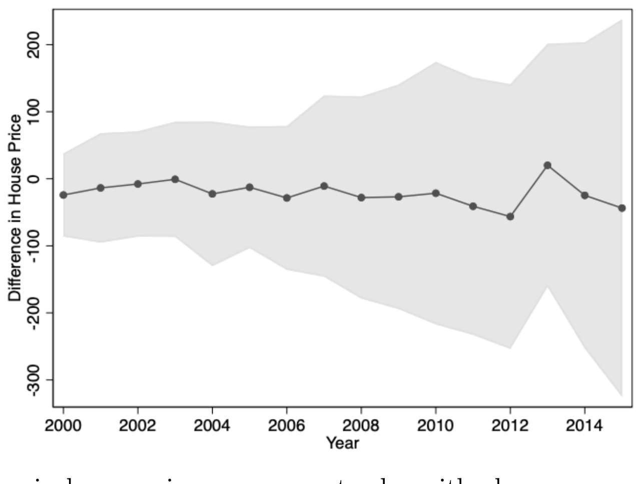
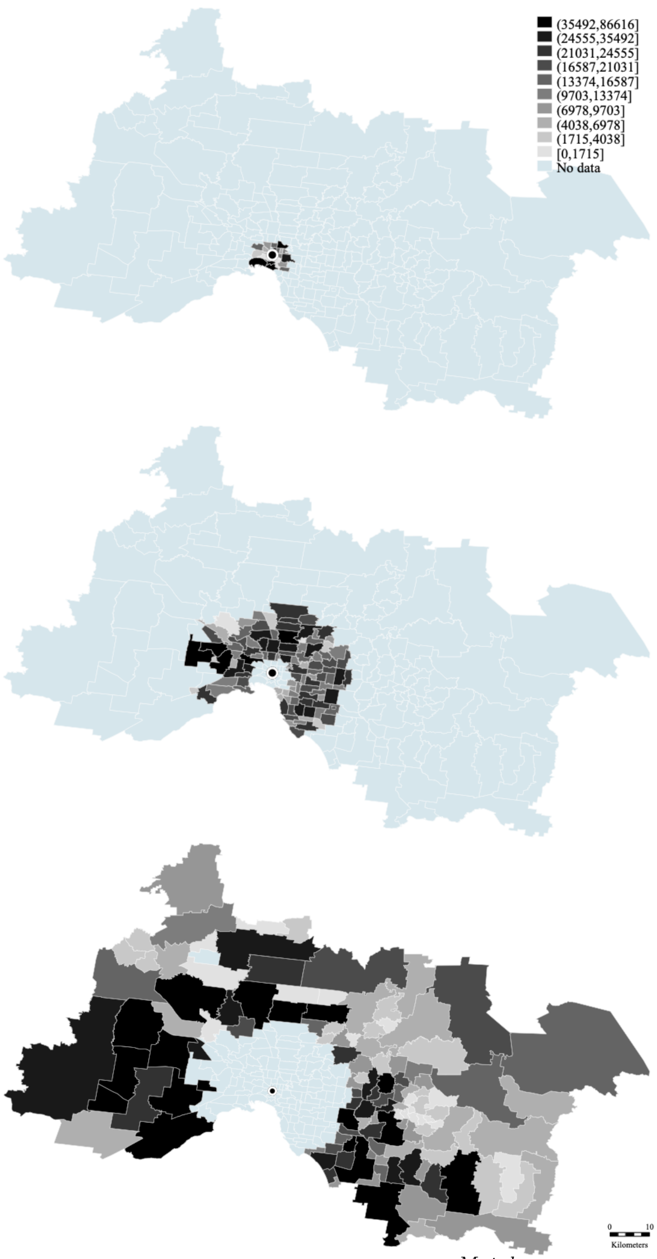


Figure plots the difference in house prices across postcodes with above versus below median roof ratio instrument.

Figure A8: Map of Scaled Roof Ratio with Suburb Sample Restrictions



Maps show the time invariant component of the instrument ($\frac{Metal}{Tile} * Roofs$) at the postcode level for inner, middle and outer suburbs of Melbourne. Inner city are suburbs within 5km of Melbourne General Post Office, middle suburbs are between 5 and 20 km and outer suburbs are those greater than 20 km but still within Melbourne. In all maps the Melbourne General Post Office is marked with a black and white point. Grey shading represents deciles of the distribution within the state. Light blue shading indicates not included in the sample.

Figure A9: Trends in Sales Channels

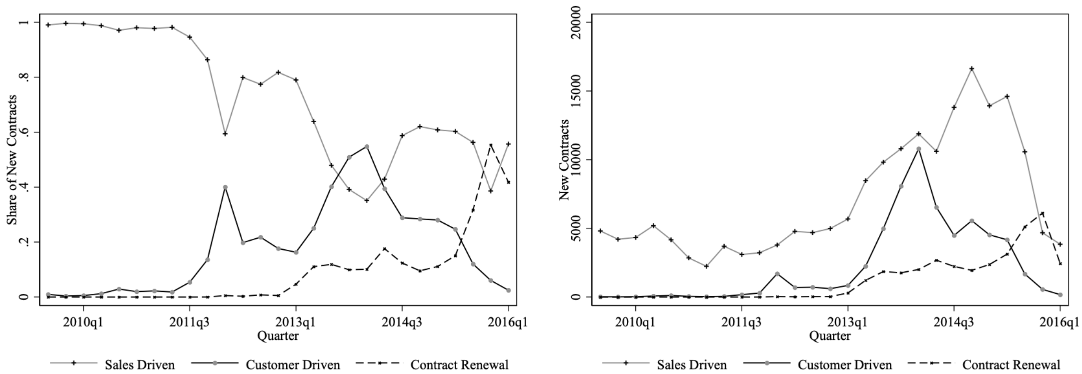


Figure plots the share of customers by sales channel (left) and the aggregate number of customers by sales channel (right). *Sales Driven Acquisition* is the share of new contracts in a postcode that were acquired by direct marketing efforts. *Customer Driven Acquisition* is the share of new contracts in a postcode that were acquired by indirect marketing.

Figure A10: Share of Observations by Event Period

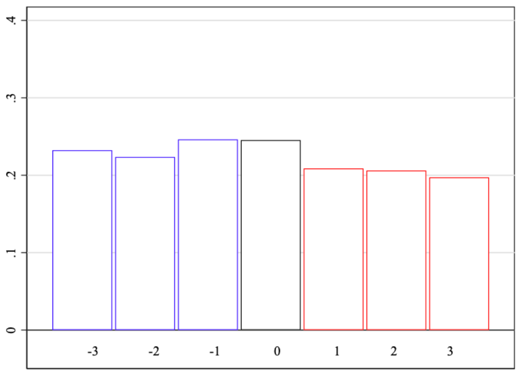
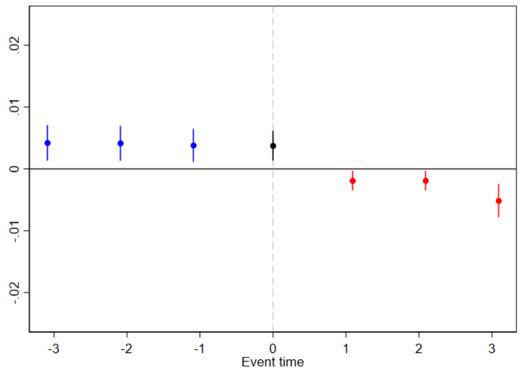


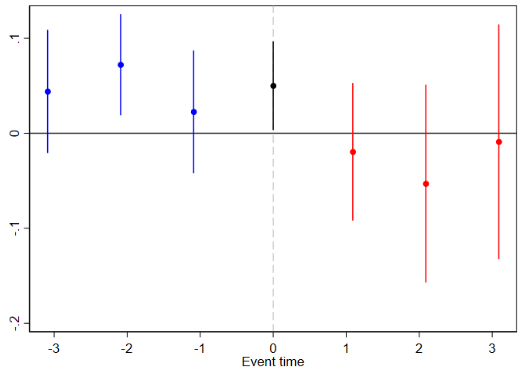
Figure shows the share of observations in each Event Period. Event Period is quarter relative to the quarter of an Event where an Event is a change in a solar subsidy. Shares do not add to 1 as each observation can be in more than one Event Period.

Figure A11: Restricted Suburb Sample: Incentives and Peer Effects

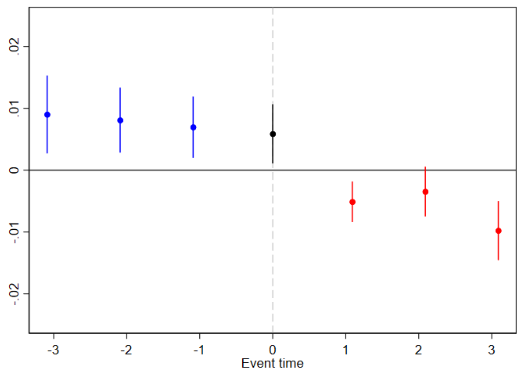
(a) All Suburbs



(b) Inner Suburbs



(c) Middle Suburbs



(d) Outer Suburbs

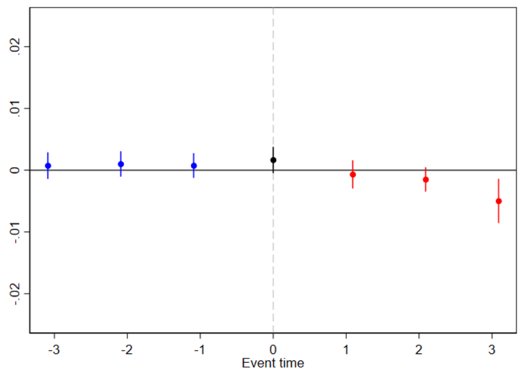


Figure plots coefficients and 95% confidence intervals for θ_τ where τ denotes event time. Coefficients are the effect of a solar panel on the likelihood an individual signs a green power contract during an event period. Regressions are weighted by number of customers. Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high-subsidy period and $\tau < 0$ being a low-subsidy period. All suburbs are all suburbs in the capital city of Melbourne. Inner city are suburbs within 5km of Melbourne General Post Office, middle suburbs are between 5 and 20 km and outer suburbs are those greater than 20 km but still within Melbourne. Standard errors are clustered at the postcode level.

Table A1: Summary Statistics 2006-2016

	(1)
Share Green	0.0729
	(0.181)
Solar Panels (000s)	0.791
	(0.945)
Electricity Tariff (per kWh)	0.223
	(0.0393)
Median Mortgage Payment (000/month)	1.739
	(0.428)
Median Income (000/week)	0.602
	(0.154)
Median Rental Payment (000/week)	0.272
	(0.0712)
Proportion Bachelor's Degree	0.191
	(0.112)
Median House Size	2.936
	(0.335)
Proportion Employed Full Time	0.374
	(0.0620)
Median Age	37.32
	(4.882)
Proportion Separate Dwellings (000s)	0.747
	(0.206)
Proportion Rental Properties	0.283
	(0.115)
Proportion Roof Metal	0.718
	(0.0647)
Proportion Roof Tile	0.256
	(0.0675)
Observations	15556

Notes: Table reports mean over postcodes with standard deviations in parentheses for postcodes from 2006-2016. Share green and electricity price are from retailer inventory and invoice data. Solar panels are from the Clean Energy Regulator via the Australian Photovoltaic Institute. All other variables are from interpolations of the 2006, 2011 and 2016 Australian census at the postcode level.

Table A2: Trends in Contract Characteristics

	(1) Manual Payment	(2) Not Concession
Pre 2009 × Quarter	0.002	-0.012**
	(0.002)	(0.005)
Post 2009 × Quarter	0.004***	0.000
	(0.000)	(0.001)
Below Median Scaled Roof Ratio × Pre 2009	0.287	2.395***
	(0.399)	(0.885)
Above Median Scaled Roof Ratio × Pre 2009	0.179	2.067***
	(0.174)	(0.368)
Above Median Scaled Roof Ratio × Post 2009	-0.006	-0.106
	(0.100)	(0.168)
Above Median Scaled Roof Ratio × Pre 2009 × Quarter	0.001	0.002
	(0.002)	(0.005)
Above Median Scaled Roof Ratio × Post 2009 × Quarter	0.000	0.000
	(0.000)	(0.001)
Observations	15556	15556

Notes: Dependent variable in column (1) is the share of new contracts that elect manual bill payment. Dependent variable in column (2) is the share of new contracts that are not eligible for a low income concession subsidy. Above Median Scaled Roof Ratio is above median of the time invariant component of the instrument in equation 2. Significance of coefficients: $^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$. Regression weighted by number of customers. Standard errors are clustered at the postcode level.

Table A3: Trends in Dwelling Prices 2000-2015

	(1)
	Pre + Post 2009
Pre 2009 × Quarter	6.447***
	(0.989)
Post 2009 × Quarter	5.490***
	(1.472)
Below Median Scaled Roof Ratio × Pre 2009	-195.251
	(139.261)
Above Median Scaled Roof Ratio × Pre 2009	-241.879
	(236.974)
Above Median Scaled Roof Ratio × Post 2009	-80.370
	(249.462)
Above Median Scaled Roof Ratio × Pre 2009 × Quarter	0.397
	(1.044)
Above Median Scaled Roof Ratio × Post 2009 × Quarter	0.547
	(1.553)
Observations	26069

Notes: Dependent variable is average house price at the quarter-year and postcode level. Above Median Scaled Roof Ratio is above median of the time invariant component of the instrument in equation 2. Significance of coefficients: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. Sample restricted to observations with above 5 sales. Regression weighted by number of dwellings. Standard errors clustered at the postcode level.

Table A4: First Stage for Table 5

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Relative Roof Instrument	0.021***	0.019***	0.016***	0.019***	0.019***	0.017***
	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)	(0.005)
Median Income (000/week)		-1.398**	-0.465	-1.398**	-1.404**	-1.375**
		(0.587)	(0.415)	(0.587)	(0.582)	(0.563)
Median Mortgage Payment (000/month)		-0.621***	-0.199	-0.621***	-0.628***	-0.626***
		(0.215)	(0.149)	(0.215)	(0.214)	(0.214)
Proportion Bachelor's Degree		13.226**	8.881**	13.226**	12.811*	13.397**
		(6.313)	(4.166)	(6.313)	(6.582)	(6.516)
Proportion Employed Full Time		-14.749***	-6.011**	-14.749***	-14.829***	-15.745***
		(4.246)	(2.877)	(4.246)	(4.190)	(4.185)
Observations	11,545	11,545	11,545	11,545	11,545	11,545
R^2	0.753	0.790	0.579	0.790	0.540	0.789
Number of postcode	605	605	605	605	605	605
Postcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
SA3-Year FE	No	No	Yes	No	No	No
Distance-Year Control	No	No	No	Yes	No	No
Above Median Roof Index-Year FE	No	No	No	No	Yes	No
Quintile Roof Index-Year FE	No	No	No	No	No	Yes
Mean dep var	0.908	0.908	0.908	0.908	0.908	0.908

Notes: Significance of coefficients: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Table reports first stage results for instrumental variables regressions in Table 5. Order of columns follows order of columns in Table5.

Table A5: Average Effects Using Customer Level Data

VARIABLES	(1) FE	(2) FE	(3) IV	(4) IV
Peer Solar Rooftops (000s)	0.021***	0.019***	0.028***	0.027***
	(0.006)	(0.006)	(0.007)	(0.007)
Median Income (AUD 000s)		-0.044		-0.028
		(0.054)		(0.056)
Median Mortgage Payment (AUD 000s)		-0.058**		-0.048*
		(0.028)		(0.029)
Proportion Bachelor's Degree		0.235		0.081
		(0.315)		(0.351)
Proportion Employed Full Time		0.157		0.313
		(0.307)		(0.321)
Observations	289,072	289,072	289,072	289,072
R^2	0.117	0.118	0.117	0.117
Number of postcode	605	605	605	605
Postcode FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Mean dep var	0.023	0.023	0.023	0.023
CDW F-test			27.21	29.08

Notes: Dependent variable is whether a new customer-contract opts in to green power. Table reports estimates using customer level data. *Peer Solar Rooftops* are solar rooftops of other households in a postcode. Significance of coefficients: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. Table reports estimates using customer level data. Standard errors are clustered at the postcode level.

Table A6: Number of Observations by Number of Event Periods

Event Periods	Observations	Cumulative %
0	2393	20.73
1	3088	26.75
2	3678	31.86
3	1983	17.18
4	403	3.49
Total	11545	100.00

Notes: Table shows number of observations by number of Event Periods. An Event Period is a change in solar subsidy. "0" Event Periods indicates the observation is outside the Event Window. "1" Event Period indicates the observation is within an Event Window for one Event. "2" Event Periods indicates the observation is within an Event Window for two Events and so on.

Table A7: F Statistics for First Stage in Table 8

	F statistics for column (3)	F statistics for column (4)
Event period -3	63.55711	59.95739
Event period -2	40.93745	40.62569
Event period -1	104.542	124.9818
Event period	69.85871	68.34027
Event period 1	60.72711	69.67813
Event period 2	66.20934	57.39216
Event period 3	49.90966	38.8095

Notes: Instrument strength is judged using the F statistic for multiple endogenous variables outlined in Sanderson and Windmeijer (2016).

Table A8: Restricted Sample
(Figure 9)

VARIABLES	(1) FE	(2) IV	(3) FE	(4) IV
Solar Panels (000s) ×				
Event Period -3	0.005***	0.007***	0.001	0.002*
	(0.001)	(0.002)	(0.001)	(0.001)
Event Period -2	0.005***	0.003**	0.001	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Event Period -1	0.004***	0.006***	0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.001)
Event Period	0.004***	0.004***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Event Period +1	-0.003***	-0.009***	-0.003***	-0.004***
	(0.001)	(0.002)	(0.001)	(0.001)
Event Period +2	-0.004***	-0.006***	-0.004***	-0.007***
	(0.001)	(0.002)	(0.001)	(0.002)
Event Period +3	-0.008***	-0.012***	-0.006***	-0.009***
	(0.002)	(0.003)	(0.002)	(0.003)
Observations	10,763	10,763	9,218	9,218
R^2	0.348	0.348	0.365	0.365
Number of postcode	601	601	597	597
Postcode FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Mean dep var	0.017	0.017	0.011	0.011

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high-subsidy period and $\tau < 0$ being a low-subsidy period. Significance of coefficients: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Standard errors are clustered at the postcode level. Regression is weighted by number of customers. Columns (1) and (2) sample is restricted to post 2010. Columns (3) and (4) sample is restricted to post 2011.

Table A9: Alternative Event Window Half Year
(First Column of Figure 10)

VARIABLES	(1) FE	(2) IV
Solar Panels (000s) ×		
Event Period -2	0.005***	0.003*
	(0.001)	(0.002)
Event Period -1	0.003***	0.000
	(0.001)	(0.002)
Event Period	0.004***	0.001
	(0.001)	(0.001)
Event Period +1	0.002*	-0.004***
	(0.001)	(0.001)
Event Period +2	-0.003***	-0.006***
	(0.001)	(0.002)
Observations	11,545	11,545
R^2	0.411	0.411
Number of postcode	605	605
Postcode FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Mean dep var	0.023	0.023

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high-subsidy period and $\tau < 0$ being a low-subsidy period. Significance of coefficients: $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors are clustered at the postcode level. Regression is weighted by number of customers.

Table A10: Alternative Event Window Year (Second Column of Figure 10)

VARIABLES	(1) FE	(2) IV
Solar Panels (000s) ×		
Event Period -4	0.006***	0.007**
	(0.002)	(0.003)
Event Period -3	0.007***	0.009***
	(0.002)	(0.003)
Event Period -2	0.007***	0.005***
	(0.002)	(0.002)
Event Period -1	0.006***	0.004**
	(0.002)	(0.002)
Event Period	0.002**	-0.000
	(0.001)	(0.002)
Event Period +1	-0.002**	-0.008***
	(0.001)	(0.002)
Event Period +2	-0.006***	-0.009***
	(0.002)	(0.003)
Event Period +3	-0.007***	-0.008***
	(0.002)	(0.002)
Event Period +4	-0.005**	-0.005
	(0.002)	(0.004)
Observations	11,545	11,545
R^2	0.413	0.412
Number of postcode	605	605
Postcode FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Mean dep var	.023	.023

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high-subsidy period and $\tau < 0$ being a low-subsidy period. Significance of coefficients: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. Standard errors are clustered at the postcode level. Regression is weighted by number of customers.

Table A11: Solar Adoption and Green Power Purchasing

VARIABLES	(1)
Pre Solar Adoption	-0.047***
	(0.003)
Always Solar	-0.067***
	(0.002)
Post Solar Adoption	-0.062***
	(0.002)
Constant	0.069***
	(0.002)
Observations	346,429
R^2	0.003

Notes: Dependent variable is an indicator for whether a new contract included green power. Significance of coefficients: $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. Table reports results of a linear probability model. *Pre solar adoption* is an indicator variable for the customer will install solar panels in the future. *Post solar adoption* is an indicator variable for the customer has installed solar panels. *Always solar* is an indicator variable for the customer is only observed with solar panels. Standard errors clustered at postcode level.

Table A12: Impact of Incentives on the Magnitude of Peer Effects: Customer Level Data

VARIABLES	(1)
Solar Panels (000s) ×	
Event period -3	0.005***
	(0.002)
Event period -2	0.005***
	(0.001)
Event period -1	0.005***
	(0.001)
Event period	0.004***
	(0.001)
Event period +1	-0.002***
	(0.001)
Event period +2	-0.003***
	(0.001)
Event period +3	-0.007***
	(0.002)
Observations	289,072
Number of postcode	605
R^2	0.116
Postcode FE	Yes
Year-Quarter FE	Yes
Mean dep var	0.023

Notes: Dependent variable is an indicator for whether a new contract included green power. Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high-subsidy period and $\tau < 0$ being a low-subsidy period. Significance of coefficients: $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. Table reports results of a linear probability model. Standard errors clustered at postcode level.

Table A13: Average Effects Using Customer Level Data Including Solar Households

VARIABLES	(1) FE	(2) FE	(3) IV	(4) IV
Peer Solar Rooftops (000s)	0.021***	0.019***	0.027***	0.026***
	(0.006)	(0.006)	(0.007)	(0.007)
Adopted Solar	-0.007***	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Median Income (AUD 000s)		-0.042		-0.026
		(0.052)		(0.054)
Median Mortgage Payment (AUD 000s)		-0.055**		-0.046
		(0.028)		(0.028)
Proportion Bachelor's Degree		0.216		0.067
		(0.309)		(0.345)
Proportion Employed Full Time		0.149		0.299
		(0.299)		(0.313)
Observations	307,100	307,100	307,100	307,100
R^2	0.117	0.117	0.116	0.117
Number of postcode	605	605	605	605
Postcode FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Mean dep var	0.022	0.022	0.022	0.022
CDW F-test			26.93	28.93

Notes: Dependent variable is an indicator for whether a new contract included green power. Table reports estimates using customer level data. *Peer Solar Rooftops* are solar rooftops of other households in a postcode. Significance of coefficients: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Results are from a linear probability model. Standard errors clustered at postcode level.

Appendix B: NPV calculations

For a back of the envelope calculation of the net present value of solar panel installation, I take the estimates of Wood and Blowers (2015) for a 3kW system installed in 2015 and a 5% discount rate in Melbourne and adjust it for an estimate of the change in the cost of installation and subsidies over time. The net present value of a solar panel installation includes the cost of installation and maintenance and the benefits from reduced electricity bill expenditure, revenue from feed-in tariffs and any lump sum subsidies. I outline my approach to calculating each of these components below.

1. Cost of installation

   The cost of a solar panel includes the cost of the module, inverter and the cost of installation itself. To construct an estimate of the cost of installation over time, I take monthly installation cost data reported to the Clean Energy Regulator over 2012-2016 and sourced from the Australian Photovoltaic Institute. I regress this data on the global solar panel module price index from Bloomberg to predict installation cost for 2009-2011. I use this predicted value for all dates in the sample period.

2. Expected lifetime maintenance costs

   I assume that there are no changes in the expected costs of maintenance for a solar panel installed between 2009 and 2016. These costs include the cost of cleaning panels, repairs and inverter replacement cost after 10 years.

3. Expected reduction in electricity bill

   The expected reduction in a household's electricity bill depends on many household specific factors. The Grattan Institute reports expected bill savings from a simulation of average household electricity consumption and average solar PV output multiplied by expected electricity tariffs where electricity tariffs are assumed to increase at a rate of 1% per annum in real terms. I assume no change to the expected reduction in future electricity bills for a solar panel installed between 2009 and 2016.

4. Subsidy payments

   Subsidy payments include those from selling electricity (feed-in tariff revenue) and lump sum payments at the time of installation.

   (a) Feed-in tariff revenue

   Feed-in tariff revenue depends on how much solar output is sold to the grid (a function of household consumption). The Grattan Institute reports expected revenue for a panel installed in 2015 assuming no changes in production or consumption over time, a 3.5% annual increase in the feed-in tariff and a discount rate of 5%. I use the Grattan calculation to derive an estimate of the volume of electricity sold and then apply the appropriate feed-in tariff for the date of installation. Once feed-in tariffs expire I assume a household receives the minimum feed-in tariff as given by Grattan.

   (b) Lump sum payments

   Lump sum payments over the sample period are received in the form of revenue from selling Smallscale Renewable Energy Certificates (SRES). Over the period of study, subsidies were reduced by lowering the number of certificates a given system was eligible to sell. Following Wood and Blowers (2015), I assume that the price of certificates in fixed at $35 over the sample period, and adjust the lump sum payment for the volume of certificates created by installation date.