Motivation, Signaling and Peer Effects: Evidence from Rooftop Solar and Household Green Power Purchases

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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 (purchasing green power). Exploiting spatial variation in the feasibility of installing solar panels and sharp changes in incentives over time, I find that panels increase purchases of green electricity by neighbors, and this crowding-in effect is smaller during high-subsidy periods. The results support the hypothesis that signals drive peer responses to visible public good contributions, and that economic incentives blur those signals.

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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 a considerable volume of research. Insights into the motivation behind prosocial activity, for example, will lead to better predictions of the impact of tax rebates and direct subsidies on public goods.

From a theoretical standpoint, high rates of prosocial behavior challenge traditional models of behavior, 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 economic incentives can 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 is therefore compromised by other rewards. 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, economic incentives are more likely to reduce 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; Meer, 2011; Jack and Recalde, 2015; Smith et al., 2015; Archambault et al., 2016; Kessler, 2017). Less is known, however, about the role of motivation and signaling in generating these peer effects. Signaling one's prosocial type may encourage peer contributions for example by establishing norms for prosocial behavior or by creating peer pressure. If economic incentives compromise the prosocial signal of a contribution then they may also reduce peer contributions by lowering peer pressure. Such an effect would also be consistent with new evidence that donors exploit excuses such as uncertainty and moral wiggle room to lower their contributions (Dana et al., 2007; Exley, 2015a,b).

I test whether visible and subsidized prosocial behavior crowds in unobserved, unsubsidized contributions from neighbors. The visible action is the installation of solar panels. The private or unobserved action is electing to pay a premium for green power - a voluntary program that increases the volume of renewable energy at the wholesale level. Critically, the installation of solar panels is not only visible but is also heavily subsidized while electing to buy green power is neither subsidized nor visible. 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.

I study the effects of rooftop solar installation on voluntary purchases of accredited green power in the state of Victoria, Australia over the period 2009 to 2016. The primary data contain the full customer inventory for a single electricity retailer in the state. I match each new contract to the number of solar panels installed in that postcode 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. The identification strategy exploits differences in the visibility of solar panel adoption and green power contracting, and an instrument to overcome the problem of correlated, time-varying unobservables. The instrument combines plausibly exogenous 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. 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 metal to tile roof ratios.

Despite a strong negative correlation between solar panel installation and green power purchases over time, I find that, on average, 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 an impure public good is crowded in by a visible peer contribution.

The second empirical objective is to test whether economic incentives interact with peer effects. To do so, I test whether an additional solar panel has a smaller impact on green power purchases in a high subsidy period relative to that same 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] These results survive robustness checks that include adding controls, using differences in roof type as an instrument, redefining the event window and dropping early observations from the sample. I also undertake a placebo exercise to demonstrate that the event study effects are not spurious.

1.1 Related Literature

The primary contribution of this paper is to study whether economic incentives attenuate peer effects in public goods settings. In doing so, it connects two related but separate branches of literature on prosocial behavior. The first branch focuses on motivation. To date, the primary concern of this 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 (Bénabou and Tirole, 2006; Ariely et al., 2009; Lacetera et al., 2012). 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 add to this literature by demonstrating 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 impure public goods and in particular the effects of government incentives for environmentally friendly technologies (for a recent study of impure public good contributions see Kesternich et al., 2016). Outside of char-

[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.

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

itable 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. (2018) show that diffusion of dry landcaping for water conservation is stronger when there are financial incentives to reduce water consumption. The effect of neighborhood solar on green power purchases is unlikely to be influenced by learning about private benefits, and hence 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).

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). Several 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 one studies the role of observability (Delmas and Lessem, 2014). This paper focuses on how visible environmental actions, and in particular those that are heavily subsidized, affect the behavior of peers.

Many papers also 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.

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 3 shows aggregate, state-level, trends in rooftop solar using data from the Clean Energy Regulator.[3] 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 3 reports the subsidies available over the study period. Explicit incentives to install solar were provided by both federal and state governments.[4] The federal government used two different mechanisms to subsidize rooftop solar. Initially, they provided 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. 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.[5] Households are typically guaranteed 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

[3]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 progams.

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

[5]These feed-in tariffs are referred to locally as *net* feed-in tariffs because they pay households for electricity produced, net of the household's own simultaneous consumption.

to 8c/kWh and then 6c/kWh in 2013 and 2014 respectively.

Figure 6 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.[6] 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 the number of customers electing to purchase green power. Figure 3 plots aggregate trends in green power purchases over the sample period using data from the National Green Power Accreditation Program.[7] Customers can elect to purchase a green power product in a relatively mature retail market for electricity. In this sector, competitive retailers compete for customers by offering a variety of plans, including the option of purchasing an accredited green power product. 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.[8] Most retailers carry an accredited green power product.

Figure 3 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

[6]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 Photovolatic Institute along with changes in subsidies. See Appendix B for further details on this calculation.

[7]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.

[8]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.

be spurious or driven by some other time varying factor. Figure 3 also shows that during the period where 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.

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.[9]

3 Data

To identify the causal relationship between solar panels and green power purchases I use customer-level data on plan choice. The data contain the full inventory of customers for a small-medium size electricity retailer in the state of Victoria over the period 2006-2016. For approximately 300,000 the data include plan choice, contract start and end 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.[10] The distribution of customers over the state at the postcode level is shown in Appendix Figure A1. The sample is drawn from across the state with more customers in the more densley-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[11] and postcode-quarter

[9] See for example the following articles published in national media outlets over 2010-2012: The Australian December 1 2010, The Australian May 5 2011, ABC Dec 1 2010, ABC 16 Nov 2012

[10] 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.

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

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) v9 2017. 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.[12] The instrument also uses a global price index for solar modules from Bloomberg New Energy Finance.

Table 1 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 though observations of green power purchases prior to 2009 provide evidence for identification via pre-trends. 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. Figures 1 and 2 show the distribution of green power and solar panels in the sample across the state while Appendix Figures A3 and A4 show 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 4 shows similar trends to the aggregate trends in Figure 3 but for the share of new contracts that are green power and for the retailer sample used in this paper. 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

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

the number of consumers willing to purchase green power. However other time-varying factors, such as the cost of purchasing electricity and the cost of installing solar panels, may be driving this correlation.[13] 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 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 5 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. Before 2009, there is no difference in the number of solar installations, by the end of the sample they have more solar installations. Before 2009, 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.

I then use sharp changes in subsidies to identify whether economic incentives impact the magnitude of any peer effect. More detail on the empirical strategy is provided in the next section.

4 Empirical Strategy

The empirical analysis proceeds in two stages. In the first stage, I outline the strategy to uncover the average effect of solar panel installation on purchases of green power. If

[13] Appendix Figure A2 shows substantial increases in average electricity prices over the same period, and in particular for households opting to purchase green power. Appendix Figure A2 also shows that over the period of rising electricity prices, the cost of solar panel modules was also falling dramatically.

this effect is negative it indicates that solar panels crowd out purchases of green power. If it is positive then it indicates that solar panels crowd in purchases of green power - a result that would be consistent with the literature on peer effects in charitable giving. In the second stage, I focus on identifying whether there is evidence that higher incentives for solar panel installation impact the size of these peer effects.

4.1 Do Solar Panels Affect Neighbors' Purchases of Green Power?

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 to pay higher prices for greener electricity.[14] 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 commencing 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.

An immediate 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 that are correlated with both solar installation and green power purchases. To address this identification problem, I exploit variation across neighborhoods in how feasible it is

[14] I do not look at the direct crowding of a consumer switching from buying green power to solar panel installation. In theory it is feasible for solar households to install solar and purchase green power for electricity they source from the grid. In practice this is extremely rare. Including customers who install solar panels does not significantly alter the average effect of solar panel installation on green power purchases, even though households that install solar do reduce their purchases of green power.

to install solar panels based on the average type of roofing in the postcode. In Australia, approximately 75% of houses have roofs made of metal sheeting, while 20% have roofs of tile (either concrete or terracotta), the remainder being materials such as concrete and fibre cement. On average, the costs of installing metal and tiled roofs do not differ substantially.[15] While metal roofing has greater fire safety and is a more versatile roofing material than tile it is considered noisier and less durable. Both roofing materials are utilized in old and new houses yet metal roofing reduces the cost of solar panel installation.

To estimate the effect of solar panels on green power purchases, 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 yet it is also plausible that shocks to environmental preferences that cause additional green power sign ups are not correlated with average neighborhood roofing materials.

I use roof suitability to develop an instrument for the change over time in the number of solar installations in a postcode. To construct the 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 scale, I multiply this ratio by a time invariant measure of the number of dwellings. 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 $\frac{Metal_i}{Tile_i}$ is a time-invariant measure of the ratio of metal to tile roofs in postcode i,

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

$Roofs_i$ is the number of roofs in postcode i and $Module\ Price_t$ is the global solar panel module price index at time t. Figure 7 shows the variation in the instrument across the state, while Appendix Figure A5 shows variation within the capital city of Melbourne.

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. This would appear to be a plausible assumption.[16] Identification also relies on shocks to environmental preferences being orthogonal to the ratio of metal to tile roofing. 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 2 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 more in postcodes with more metal roofs. This is consistent with a crowd in effect and also evident in the trend in Figure 5. 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.

One concern with these trends is that there is limited pre-period data available for testing pre-trends. As further supporting evidence therefore, Figure A6 plots the differ-

[16] 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.

ence 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 A2 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.

The next section outlines the strategy to identify whether incentives to install rooftop solar moderate the effect that these panels have on green power purchases.

4.2 Do Incentives Attenuate Peer Effects?

The second empirical objective is to identify whether economic incentives, or extrinsic motivations, attenuate the peer effect from solar panel installation to green power purchasing. To do so, I exploit sharp changes in solar subsidies over time. I wish to estimate the following equation at the postcode level:

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

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 period immediately before a subsidy increase is period $\tau = -1$ and the period immediately after a subsidy increase is period $\tau = 1$. Coefficients θ_τ therefore measure the effect of an additional solar panel on purchases of green power in relatively low ($\tau < 0$) and relatively high ($\tau > 0$) subsidy periods during the event window W. Because multiple subsidy changes may occur within a given event window, each event is coded independently. Hence a given time period may be both two periods before a subsidy decrease, and one period after a subsidy decrease.

To estimate the impact of subsidies, I compare θ_τ coefficients in periods immediately before and immediately after a subsidy change.[17] 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. This assumption is plausible as it is difficult to argue that some other factor would cause the same pattern of changes in green power purchases at exactly the same points in time as subsidy changes.[18] 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 above where for each event interaction ($Solar\ Rooftops_{i\tau} \times Event\ Period_\tau$) I construct an instrument ($Z_{i\tau} \times Event\ Period_\tau$). Section 5.2.1 also reports the results of a range of other robustness checks.

5 Results

This section presents estimates of the average effect of solar panels on neighbors' green power purchases and then tests whether economic incentives alter the magnitude of these peer effects.

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

[18] 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.

5.1 Solar Panels and Peer Green Power Purchases

Table 4 shows estimates of the average effect of neighborhood level solar panel installation on green power purchases. All standard errors are clustered at the postcode level and the regression is weighted by number of customers. Using a straight fixed effects model (Column 1) 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. The effect does not change when controlling for median income, age and rental rates (Column 2), three time-varying variables that we would expect to be correlated with gentrification.[19]

Employing the roof ratio instrument does very little to change the magnitude of the estimated effects. In columns (3) and (4) I find that an additional 1000 solar panels increases the fraction of new contracts that opt in to green power by 0.03, which is not statistically or economically different from the estimates in columns (1) and (2). Table 4 also reports F statistics for the first stage regressions, demonstrating that the instruments are strong.

5.1.1 Average Effects Robustness

The average effect results are robust across a range of specifications. I first demonstrate that the crowd in effect is not unique to the effect of cumulative solar rooftops. Table 5 shows results where the measure of exposure to solar panels is panels per rooftop (columns (1) and (2)) and where the measure of exposure to solar panels is panels per area (km^2). Once again, I find a significant crowd in effect that does not differ across fixed effect or instrumental variables specifications, and does not change significantly with the inclusion of time-varying controls.

The main threat to identification comes from the possibility of non-parallel trends, or shocks to green-power purchases in postcodes with high metal to tile roof ratios. To

[19]The results are also robust to including other demographic controls. I do not control for either house prices or electricity prices as these are both outcomes of solar panel installation (several subsidies to solar panels are recovered via electricity rates).

account for regional shocks in green power purchasing, for example those arising from gentrification, Table 6 reports results employing year by region fixed effects, where region is the Statistical Area Level 3 (SA3) identifier from the Australian Bureau of Statistics Statistical Geography for the census. An SA3 consists of between 30,000 and 130,000 people and aligns closely to municipal boundaries. The results are robust to the inclusion of these fixed effects and therefore to flexible time trends at the municipal level.

It is also possible that the effect of solar rooftops is nonlinear, and in particular that the effect declines as the number of panels increases. Table 7 shows that there is some curvature in the effect, though the average effect of a solar panel is approximately unchanged from the linear specification.

5.2 Solar Panel Subsidies and Peer Green Power Purchases

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 8 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. In all columns I find that the effect of a solar panel in a low subsidy ($\tau < 0$) period is positive and significant. The effect of a solar panel in a high subsidy ($\tau > 0$) period 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 how strong the prosocial signal is.

5.2.1 Event Study Robustness

The event study analysis is also robust to a range of checks. In Figure 10 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 3). Figure 11 demonstrates that this single increase in subsidies during the sample is not driving the results. 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 12 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.

Finally, Figure 13 displays the results of a placebo exercise reassigning subsidy change dates to random dates throughout the sample period and replicating 1000 times. There is no evidence of a reduction in the magnitude of the estimated peer effect during 'high' subsidy periods, indeed the average effect is positive for all event periods, which is consistent with the results reported in Table 4.

6 Policy Implications

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 purhases of green power among those households not going solar. On the other hand, subsidies to the installers of panels reduce green power purchases. If solar installers are marginal to the subsidies, i.e. the solar subsidies *caused* the installation of panels, then they may not have crowded out green power purchases, and may have, on net, crowded in purchases. On the other hand, if solar installers are inframarginal, such that they would have installed solar panels in the absence of the subsidies, then the subsidies on net have a negative impact on public good contributions. Boomhower and Davis (2014) suggest that a non-negligible number of environmental 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. 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 of the contribution, they may in turn lower peer contributions.

7 Conclusion

This paper delivers two main results. First, that solar panel installation crowds in public good contributions via greater green power plan uptake. Second, that the magnitude of this peer effect is lower when solar installers receive higher subsidies. That is, a solar panel during a high subsidy period generates less of a prosocial spillover than that same solar panel during a low subsidy period.

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 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 how visible and how subsidized two related prosocial actions are to demonstrate that extrinsic incentives also affect the behavior of the individuals receiving those signals.

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8 Figures

Figure 1: Map of Green Power in the Sample

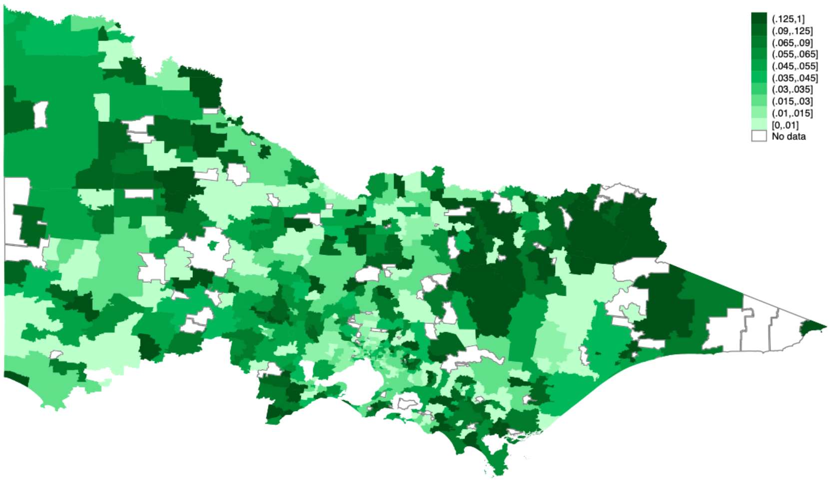


Figure shows average number of the share of new contracts that opt in to green power in the sample at the postcode level.

Figure 2: Map of Solar Rooftops in the Sample

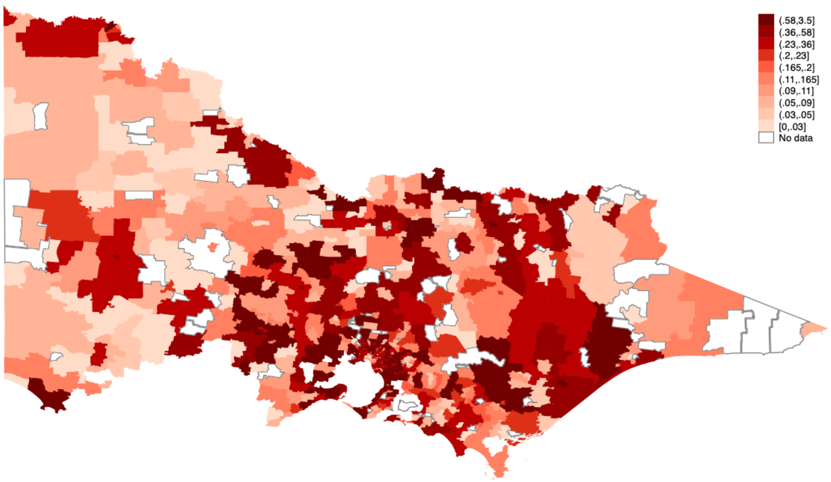


Figure shows average number of solar rooftops in the sample at the postcode level.

Figure 3: Aggregate Trends in Solar Installation and Green Power Purchases

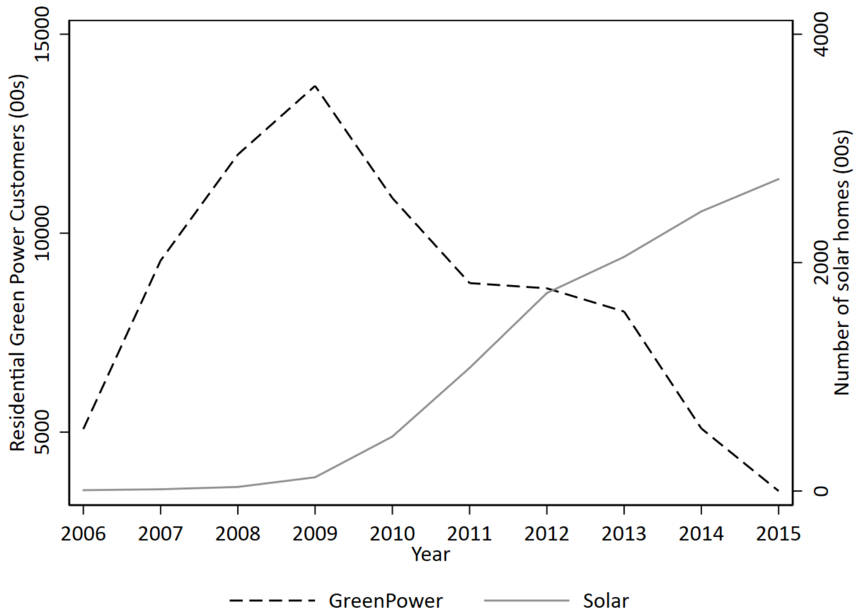


Figure plots the number of solar panel installations and residential green power customers for the state. Green power data are sourced from quarterly reports to the National Green Power Accreditation Program. Solar installation data are sourced from the Clean Energy Regulator.

Figure 4: Retailer Sample Trends in Solar Installation and Green Power Purchases

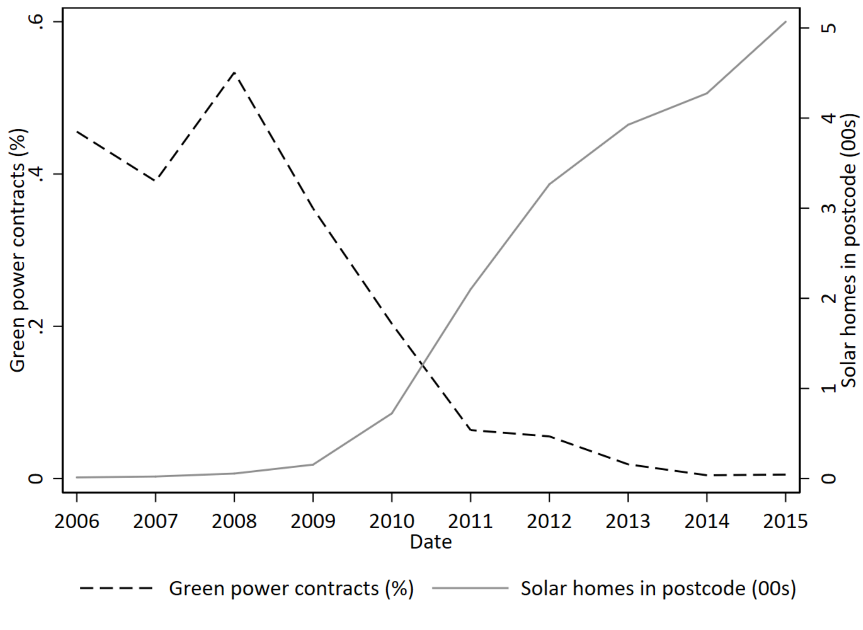


Figure plots the percentage of new contracts in a postcode in which customers opt in to green power and the number of solar panel installations in those postcodes.

Figure 5: Variation Within and Across Time in Solar Installation and Green Power Purchases

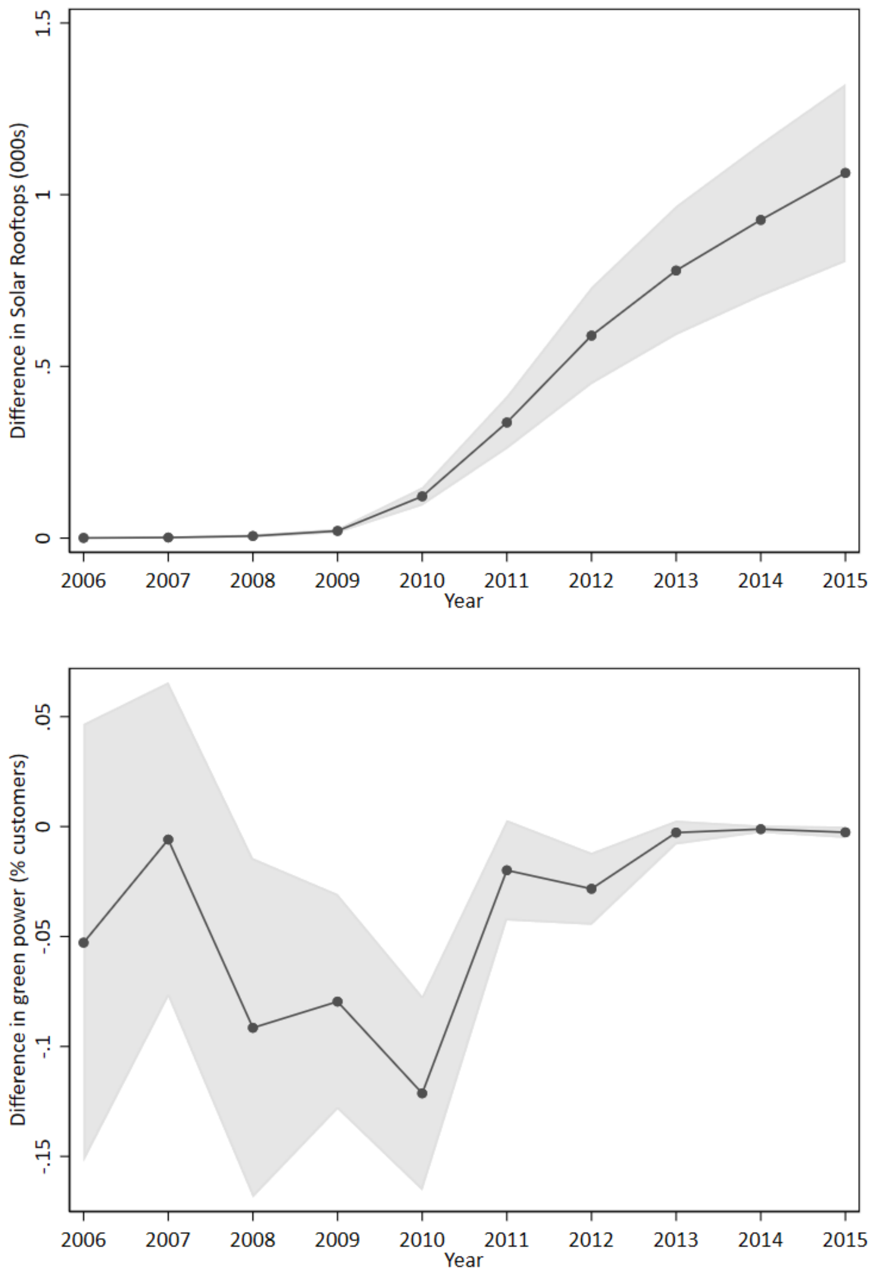


Figure shows the difference in the percentage of green power customers and solar installations between postcodes with above and below median numer of houses with metal roofs.

Figure 6: Net Present Value of Solar Installation

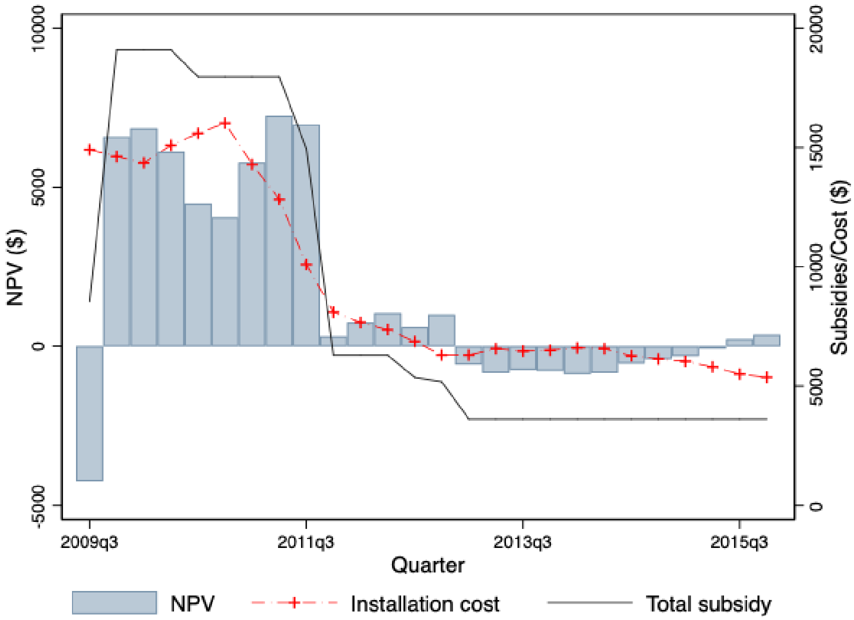


Figure shows back of the envelope caluclations of the net present value of solar panel installation following Wood and Blowers (2015). See Appendix B for details on the calculations.

Figure 7: Map of Relative Roof Instrument in the Sample

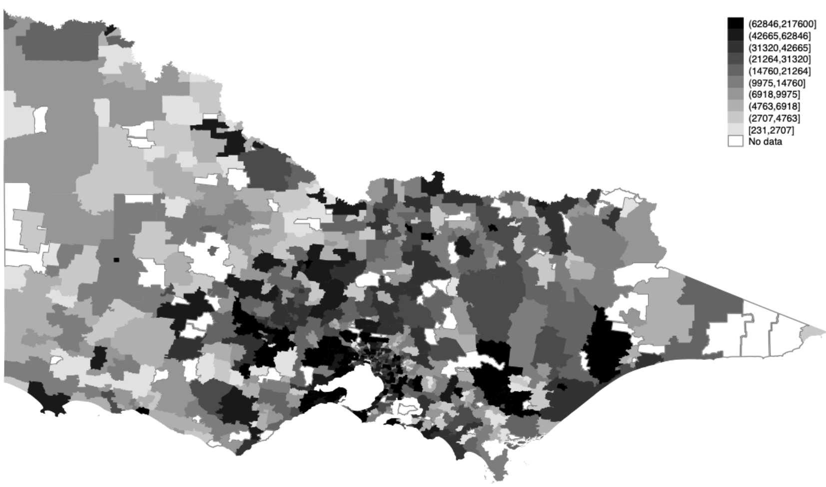


Figure shows mean relative roof instrument in the sample at the postcode level.

Figure 8: Incentives and Peer Effects

(a) Fixed Effect Estimates

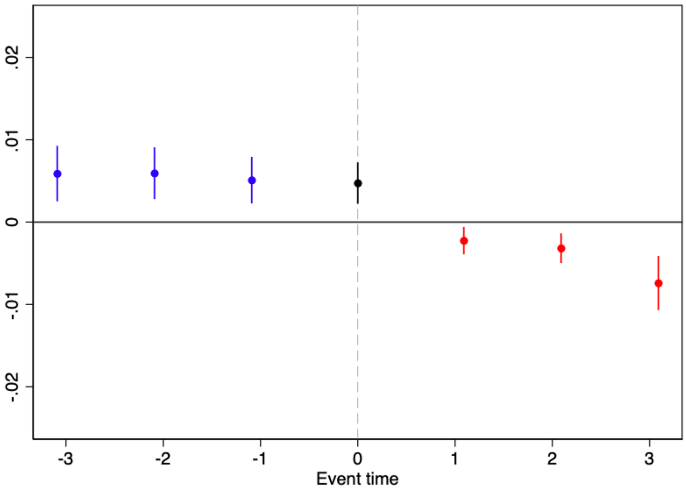
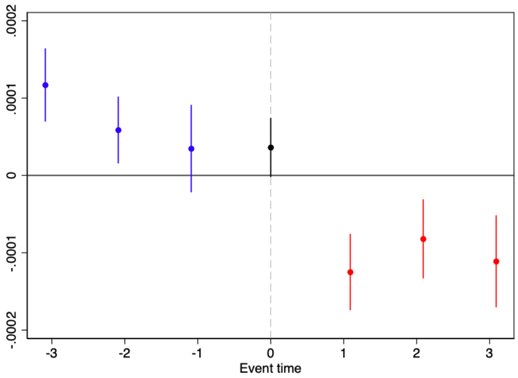


Figure plots coefficients and 95% confidence intervals for θ_τ where τ denotes event time. Coefficients are the effect of a solar panel on the likelihood an individual signs a green power contract during an event period. Events are changes in incentives to install rooftop solar with $\tau > 0$ being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

Figure 9: Instrumental Variables Estimates - Incentives and Peer Effects

(a) Reduced Form



(b) Instrumental Variables Estimates

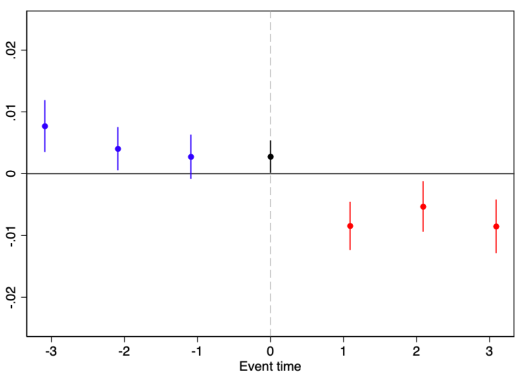


Figure plots coefficients and 95% confidence intervals for θ_τ where τ denotes event time. Coefficients are the effect of a solar panel on the likelihood an individual signs a green power contract during an event period. Events are changes in incentives to install rooftop solar with $\tau > 0$ being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

Figure 10: Instrumental Variables Estimates with Controls - Incentives and Peer Effects

(a) Reduced Form

(b) Instrumental Variables Estimates

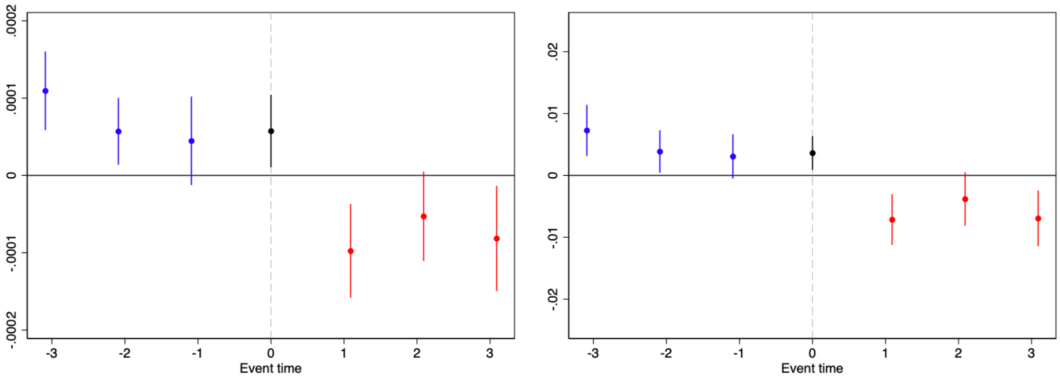


Figure plots coefficients and 95% confidence intervals for θ_τ where τ denotes event time. Coefficients are the effect of a solar panel on the likelihood an individual signs a green power contract during an event period. Events are changes in incentives to install rooftop solar with $\tau > 0$ being 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 number of dwellings with metal roofs and a 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. Specification includes controls. Standard errors are clustered at the postcode level.

Figure 11: Restricted Sample - Incentives and Peer Effects

(a) Fixed Effect Estimates

(b) Instrumental Variables Estimates

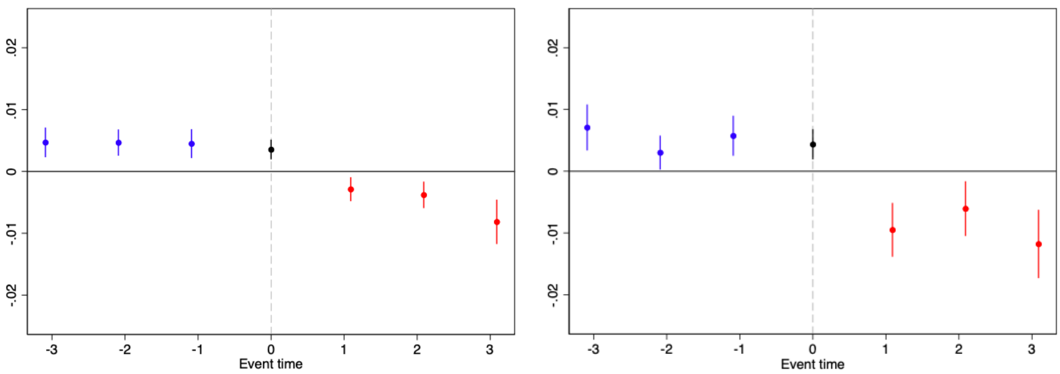


Figure plots coefficients and 95% confidence intervals for θ_τ where τ denotes event time. Coefficients are the effect of a solar panel on the likelihood an individual signs a green power contract during an event period. Events are changes in incentives to install rooftop solar with $\tau > 0$ being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

Figure 12: Alternative Event Windows - Incentives and Peer Effects

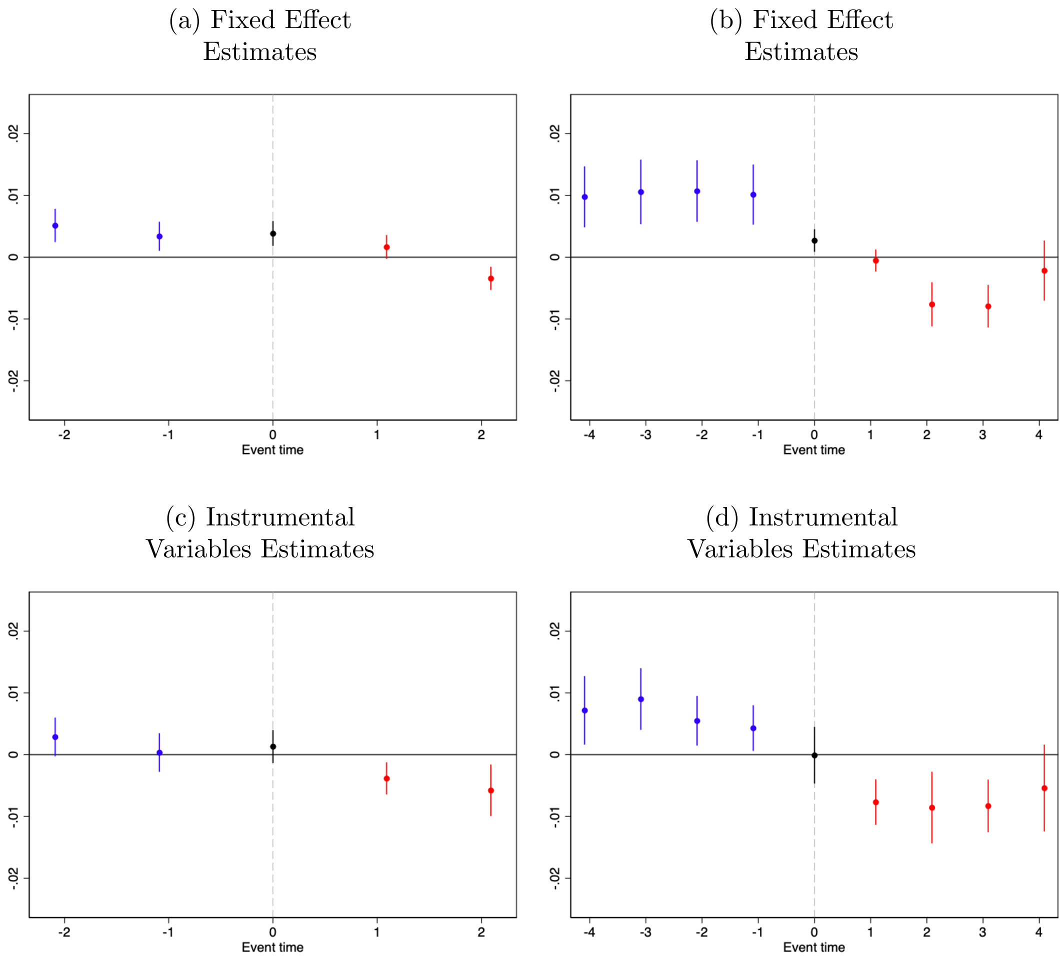


Figure plots coefficients and 95% confidence intervals for θ_τ where τ denotes event time. Coefficients are the effect of a solar panel on the likelihood an individual signs a green power contract during an event period. Events are changes in incentives to install rooftop solar with $\tau > 0$ being a high subsidy period and $\tau < 0$ being a low subsidy period. Panels (a) and (c) restricts 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 instrumnetal variables estimates. Instrument is an interaction between roof ratio and a global solar module price index. Standard errors are clustered at the postcode level.

Figure 13: Placebo Test - Incentives and Peer Effects

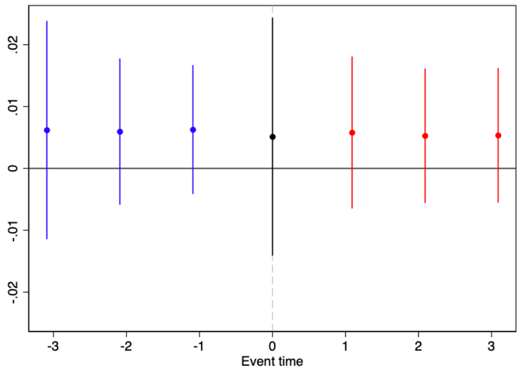


Figure plots coefficients and 95% confidence intervals for the estimate of θ_τ from a placebo exericse re-assigning subsidy changes to random dates throughout the sample with 1000 replications. Coefficients are from a fixed effects model and measure the effect of a solar panel on the likelihood an individual 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.

9 Tables

Table 1: Summary Statistics

	(1)
Green power (%)	0.0233
	(0.0821)
Solar panels (000s)	0.908
	(0.960)
Median income (AUD 000s)	0.617
	(0.155)
Median rental payment (AUD 000s)	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)
Observations	11545
Postcodes	605

Notes: Table reports mean and standard deviations in parentheses weighted by number of customers. Share of new contracts that are green plan is from retailer inventory data. Solar panels are from the Australian Photovoltaic Institute. All other variables are from interpolations of the 2006, 2011 and 2016 Australian census at the postcode level.

Table 2: Pre-trends in green power purchasing by roof suitability

	(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	2.142	-0.973***	-0.366**	
	(1.574)	(0.196)	(0.150)	
Above Median × Quarter	-0.011	0.004***	0.002**	
	(0.008)	(0.001)	(0.001)	
Pre 2009 × Quarter				0.015*
				(0.008)
Post 2009 × Quarter				-0.012***
				(0.001)
Below Median × Pre 2009				-5.136***
				(1.563)
Below Median × Post 2009				0.000
				(.)
Above Median × Pre 2009				-2.995***
				(0.505)
Above Median × Post 2009				-0.834***
				(0.200)
Above Median × Pre 2009 × Quarter				-0.011
				(0.008)
Above Median × Post 2009 × Quarter				0.004***
				(0.001)
Observations	3182	11545	15556	15556

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. Above Median is above median value of the roof ratio instrument in equation 2. Standard errors clustered at postcode level. Regression is weighted by number of customers.

Table 3: 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

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

Table 4: Average Effect of Solar Rooftops on Green Power Purchases

VARIABLES	(1) FE	(2) FE	(3) IV	(4) IV
Solar panels (000s)	0.023***	0.021***	0.029***	0.029***
	(0.006)	(0.006)	(0.007)	(0.007)
Median income (AUD 000s)		-0.051		-0.020
		(0.056)		(0.059)
Median age		-0.001		-0.000
		(0.001)		(0.001)
Median rental payment (AUD 000s)		0.093		0.083
		(0.062)		(0.061)
Observations	11,545	11,545	11,545	11,545
R^2	0.419	0.420	0.418	0.419
Number of postcode	605	605	605	605
Postcode FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Mean dep var	.023	.023	.023	.023
CDW F-test			27.45	26.69

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. 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.

Table 5: Average Effect of Solar Rooftops on Green Power Purchases: Independent Variable Robustness

VARIABLES	(1) IV	(2) IV	(3) IV	(4) IV
Solar panels per dwelling	2.271***	2.186***		
	(0.733)	(0.742)		
Solar panels per area (1000 panels/ km^2)			2.877**	3.375**
			(1.364)	(1.378)
Median income (AUD 000s)		0.154		-0.334*
		(0.113)		(0.182)
Median age		-0.009		0.006
		(0.006)		(0.005)
Median rental payment (AUD 000s)		-0.047		0.035
		(0.090)		(0.108)
Observations	11,545	11,545	11,545	11,545
R^2	0.301	0.319	0.387	0.387
Number of postcode	605	605	605	605
Postcode FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Mean dep var	.023	.023	.023	.023
CDW F-test	12.16	11.79	9.845	14.39

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. Standard errors are clustered at the postcode level. Columns (1) and (2) regression is weighted by number of customers, Columns (3) and (4) regression is weighted by inverse area of postcode. All columns (1) and (2) present IV estimates.

Table 6: Average Effect of Solar Rooftops on Green Power Purchases: Region by Year Fixed Effects

VARIABLES	(1) FE	(2) FE	(3) IV	(4) IV
Solar panels (000s)	0.018***	0.019***	0.033***	0.034***
	(0.004)	(0.005)	(0.007)	(0.007)
Median income (AUD 000s)		0.054		0.080*
		(0.041)		(0.044)
Median age		0.000		0.001
		(0.001)		(0.001)
Median rental payment (AUD 000s)		-0.016		-0.018
		(0.039)		(0.039)
Observations	11,545	11,545	11,545	11,545
R^2	0.071	0.071	0.069	0.069
Number of postcode	605	605	605	605
Postcode FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
SA3-year FE	Yes	Yes	Yes	Yes
Mean dep var	.023	.023	.023	.023
CDW F-test			94.03	87.20

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. Standard errors are clustered at the postcode level. Regression is weighted by number of customers. All columns (1) and (2) present IV estimates.

Table 7: Average Effect of Solar Rooftops on Green Power Purchases Nonlinear Effects

VARIABLES	(1) FE	(2) FE	(3) IV	(4) IV
Solar panels (000s)	0.079***	0.077***	0.101***	0.100***
	(0.013)	(0.013)	(0.022)	(0.022)
Solar panels (000s)^2	-0.011***	-0.011***	-0.016***	-0.016***
	(0.002)	(0.002)	(0.005)	(0.005)
Median income (AUD 000s)		-0.043		-0.054
		(0.056)		(0.060)
Median age		-0.001		-0.001
		(0.001)		(0.002)
Median rental payment (AUD 000s)		0.066		0.059
		(0.061)		(0.060)
Observations	11,545	11,545	11,545	11,545
R^2	0.429	0.429	0.427	0.427
Number of postcode	605	605	605	605
Postcode FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Mean dep var	.023	.023	.023	.023

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. Standard errors are clustered at the postcode level. Regression is weighted by number of customers. All columns (1) and (2) present IV estimates.

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

VARIABLES	(1) FE	(2) FE	(3) IV	(4) IV
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	0.003*
	(0.001)	(0.001)	(0.002)	(0.002)
Event period	0.005***	0.006***	0.003**	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Event period +1	-0.002***	-0.001	-0.008***	-0.007***
	(0.001)	(0.001)	(0.002)	(0.002)
Event period +2	-0.003***	-0.001	-0.005**	-0.004*
	(0.001)	(0.001)	(0.002)	(0.002)
Event period +3	-0.007***	-0.005***	-0.009***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Median income (AUD 000s)		-0.147***		-0.135**
		(0.056)		(0.056)
Median age		-0.002		-0.001
		(0.001)		(0.001)
Median rental payment (AUD 000s)		0.125*		0.120*
		(0.065)		(0.064)
Observations	11,545	11,545	11,545	11,545
R^2	0.412	0.414	0.411	0.414
Number of postcode	605	605	605	605
Postcode FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes

Notes: Dependent variable is share of new contracts in postcode opting to purchase green power. 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. First stage F statistics for endogenous variables are provided in the Appendix. Instruments are strong.

Appendix A: Supplemental Figures and Tables

Figure A1: Map of Customer Inventory

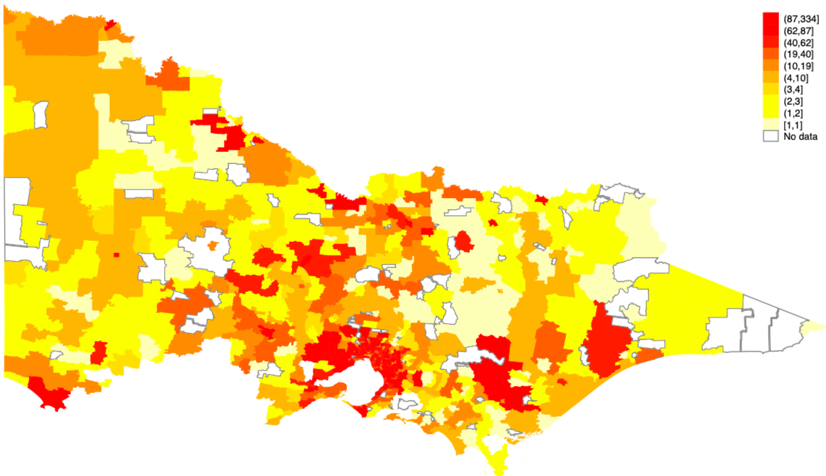


Figure maps the customer inventory over the state at the postcode level.

Figure A2: Electricity and Solar Prices

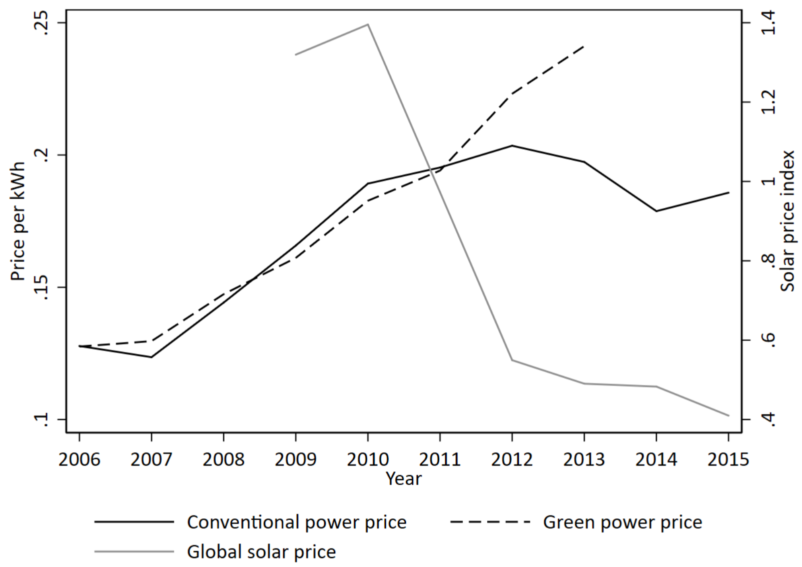


Figure shows average electricity prices over the sample period (excluding green power customers) and electricity prices for green power customers in the retailer sample, and the global solar panel module price index from Bloomberg.

Figure A3: Map of Green Power in the Sample - Melbourne

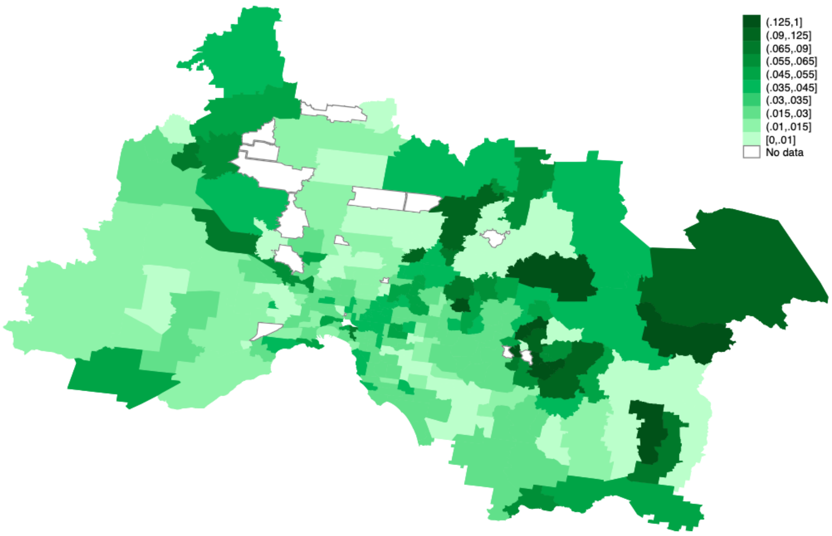


Figure shows average number of the share of new contracts that opt in to green power in the sample at the postcode level, restricted to capital city Melbourne.

Figure A4: Map of Solar Rooftops in the Sample - Melbourne

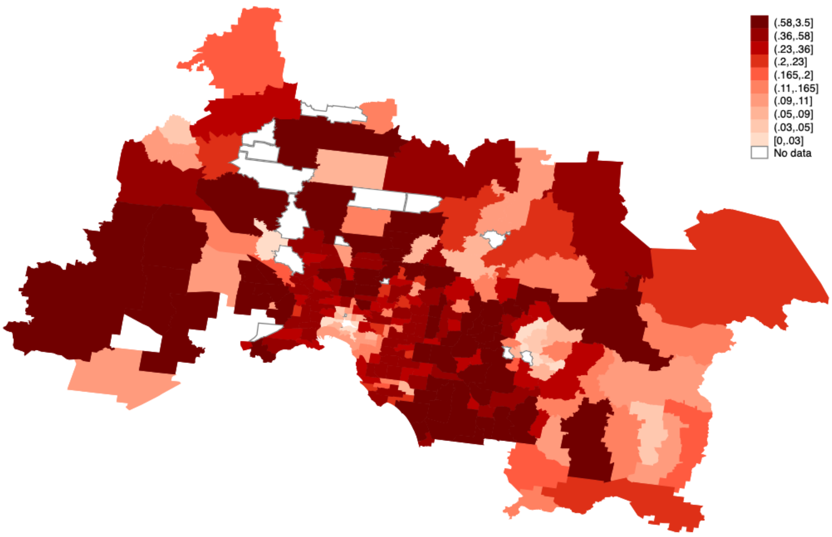


Figure shows average number of solar rooftops in the sample at the postcode level, restricted to capital city Melbourne.

Figure A5: Map of Roof Ratio Instrument in the Sample - Melbourne

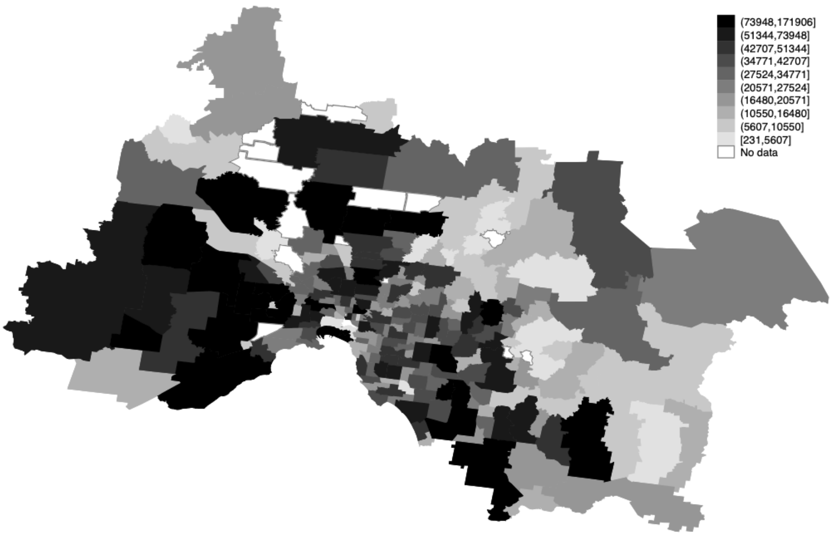


Figure shows mean relative roof instrument in the sample at the postcode level, restricted to capital city Melbourne.

Figure A6: Trends in Dwelling Prices by Roof Ratio

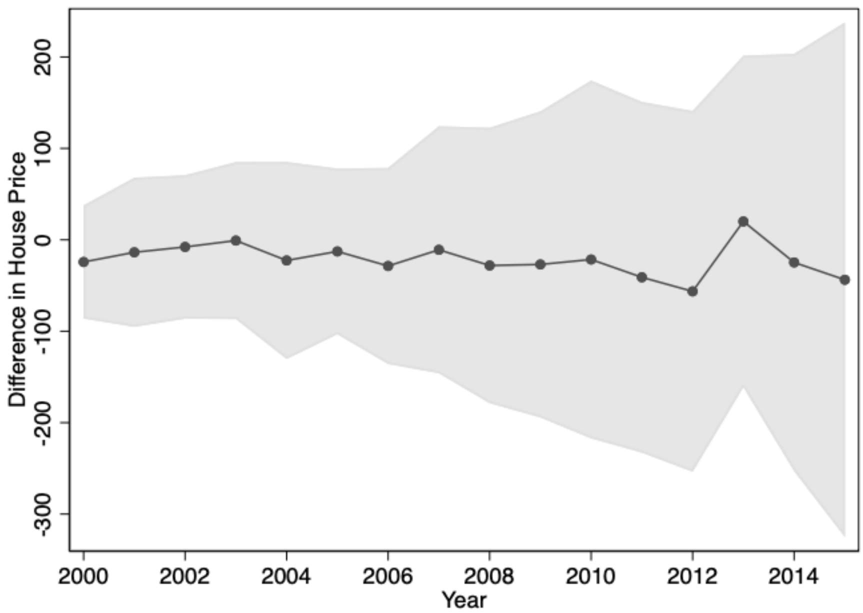


Figure plots the difference in house prices across postcodes with above versus below median roof ratio instrument.

Table A1: Summary Statistics 2006-2016

	(1)
Green power (%)	0.0729
	(0.181)
Solar panels (000s)	0.790
	(0.945)
Median income (AUD 000s)	0.602
	(0.154)
Median rental payment (AUD 000s)	0.272
	(0.0712)
Proportion bachelor's degree	0.191
	(0.112)
Median house size	2.937
	(0.335)
Proportion employed full time	0.374
	(0.0620)
Median age	37.32
	(4.884)
Observations	15602

Notes: Table reports mean over postcodes with standard deviations in parentheses for postcodes from 2006-2016. Proportion green plan and electricity price are from retailer inventory and invoice data. Solar panels are from 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 Dwelling Prices 2000-2015

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

Notes: Dependent variable is average house price at the quarter-year and postcode level. Sample restricted to observations with above 5 sales. Regression weighted by number of dwellings.

Table A3: Average effects using customer level data

VARIABLES	(1) FE	(2) FE	(3) IV	(4) IV
Solar panels (000s)	0.016**	0.022***	0.018*	0.029***
	(0.006)	(0.006)	(0.010)	(0.007)
Median income (AUD 000s)		0.117*		0.142**
		(0.060)		(0.061)
Median age		0.006***		0.006***
		(0.002)		(0.002)
Median rental payment (AUD 000s)		0.132**		0.121**
		(0.060)		(0.059)
Observations	289,074	289,074	289,074	289,074
R^2	0.144	0.149	0.144	0.149
Postcode FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Mean dep var	.023	.023	.023	.023
CDW F-test			28.35	26.32

Notes: Dependent variable is whether a new customer-contract opts in to green power. Table reports estimates using customer level data.

Table A4: F statistics for first stage in Table 8

	FullFstats	
	F stats for column (3)	F stats for column (4)
Event period -3	63.55713	52.83956
Event period -2	40.93745	40.09236
Event period -1	104.542	115.9753
Event period	69.85873	74.48544
Event period 1	60.72712	76.03232
Event period 2	66.20934	56.97484
Event period 3	49.90964	39.6985

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

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 Photovolatic 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 maintenace 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.

$$\begin{aligned}
ExpectedRevenue_{2015} &= \sum_{j=0}^{14} \frac{Revenue_{2015+j}}{(1.05)^j} \\
&= \sum_{j=0}^{14} \frac{FIT_{2015+j} \times kWh}{(1.05)^j} \\
&= \sum_{j=0}^{14} \frac{FIT_{2015}(1.035)^j \times kWh}{(1.05)^j} \\
&= FIT_{2015} \times kWh \times \sum_{j=0}^{14} \left(\frac{1.035}{1.05}\right)^j \\
&\approx FIT_{2015} \times kWh \times 13.6 \\
kWh &\approx \frac{ExpectedRevenue_{2015}}{FIT_{2015} \times 13.6}
\end{aligned}$$

(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.