Solar Photovoltaic Systems Capitalization in Western Australian Property Market

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03 March 2015
Working Paper 1503
School of Agricultural and Resource Economics
http://www.are.uwa.edu.au

THE UNIVERSITY OF WESTERN AUSTRALIA

Citation: Ma, C., M. Polyakov & R. Pandit,(2015). *Solar Photovoltaic Systems Capitalization in Western Australian Property Market*, Working Paper 1503, School of Agricultural and Resource Economics, University of Western Australia, Crawley, Australia.

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Abstract

Using a large sample of property sales data and high-resolution aerial maps, this study provides the first empirical estimate of the price premium of properties with photovoltaic (PV) panels in Australia. We use three model specifications to control for spatial heterogeneity and correlation as well as price dynamics over time. Results from hedonic models, repeated sales models and hybrid models have all shown strong evidence that PV panels contribute a 2.34 to 4.12 percent premium to properties prices. This suggests that PV investments are, on average, over-capitalized into property prices during our sample period, which we argue is largely a reflection of changing policy parameters regarding feed-in tariffs. Greater premium is found in localities with a larger share of votes for the Green Party and Australian Labor Party in 2008 State Election and votes for no daylight saving in 2009 State Referendum, registered Prius hybrid vehicles and college graduates and postgraduates. The results have significant implications for property owners, builders, financial institutions, PV retailers, and policy makers.

Keywords: Hedonic, Repeated Sales, Solar Panels, Photovoltaic

JEL Classification: O18, Q42, R21

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1. Introduction

Australia has the greatest potential of any country for the development of a solar PV industry with the highest average solar radiation of any continent in the world (IEA, 2010). Judging from the efficiency perspective, PV panels are neither the most efficient way of producing electricity nor cost-effective to mitigate carbon emissions (GI, 2011). However, support for PV panels is often justified on the grounds of other public benefits including environmental benefits, energy security, technology spillover, scale economy and green jobs creation (Borenstein, 2012). Since January 2000, the Australian government has adopted a number of programs to subsidize the uptake of rooftop PV panels which has created strong demand in the residential sector. The Photovoltaic Rebate Program (PVRP) faced immediate problems with oversubscription after its introduction in January 2000. The government reduced the rebate rate in October 2000 but over-subscription had again become a problem by early 2003. To address this problem additional measures were introduced later that include a cap on total monthly approvals and further reductions in the rebate rate. In late 2007, the program changed its name to the Solar Homes and Communities Plan (SHCP) and doubled the rebate rate from $4/w to $8/w following the new Labor Government's election victory. By May 2008, oversubscription has again triggered more changes in the plan – among others, a means test which limited eligibility to households with an annual taxable income of less than $100,000. The means test did not result in a downturn in demand as predicted. Facing a substantial overrun in the costs of the SHCP, the government had to close the program on 9 June 2009 and replaced it with a new Solar Credit program which has been phased out in January 2013 ahead of schedule.

In addition to the federal programs, all states have introduced PV feed-in tariffs in the late 2000s which compensate households for electricity generated from PV panels on a gross or net (of household consumption) basis. The feed-in tariff typically consists of a government's contribution (major part) and a utility retailer's contribution (minor part). In the last couple of years, all states except Northern Territory have chosen to either substantially reduce the government contribution to the feed-in-tariffs (South Australia, Tasmania and Australian Capital Territory) or completely discontinue the government contribution (Western Australia, Queensland and New South Wales). The introduction of a carbon tax in 2012 creates an even stronger economic incentive to adopt panels with higher expected electricity price and thus higher savings on energy bills. The Western Australia has observed the largest increase in electricity price among all Australian states and territories – a whopping 69% since 2009. On the other hand, PV installation cost has dropped substantially over the last few years. Typical turnkey system prices have plummeted from roughly $9 per peak watt in 2009 to merely $2.13 per peak watt by mid 2013. These economic incentives plus the falling cost of PV installations have contributed to the sharp rise of PV capacity in late 2000s and early 2010s (Fig. 1) reaching an average rooftop PV penetration of roughly 10% in Australian residential sector by the end of 2012. Despite reduced direct support from the federal and state governments in the last couple of years, demand for PV panels has continued and become even stronger (Fig. 2). Australia has now over a million roofs with PV systems. In Western Australia alone, the total number has reached over 140,000 – a tenfold increase from less than 14,000 in 2008. On average, 2,900 new PV panels are being installed every month (2011-2013).

Private decision making about the adoption of PV panels often involves a comparison between the installation and maintenance costs on the one side and saved electricity bills, revenues from feed-in tariff and possibly “warm glow” utility on the other (Andreoni, 1989 & 1990). From a policy maker’s perspective, optimal PV supporting program design typically also involves the comparison between the social cost of public funds and the aforementioned public benefits (Gillingham and Sweeney, 2008; Borenstein, 2008; Wand and Leuthold, 2011). Less appreciated in the discussion of the PV economics is the fact that PV panels may add values to the property. Like any other property attributes, a PV panel may be thought of as a quality improvement in the property and capitalized into property prices (Dastrup et al., 2012; Hoen et al., 2013). If consumers capitalize PV panels into property value, then the high installation cost may not be viewed as a major barrier to adoption and the demand may be higher than would otherwise be.

The study contributes to the literature on the capitalization of energy-related green features of property market. Research on this market has shown considerable consumers willing to rent or buy properties with desirable energy features at a premium (Laquatra 1986; Dinan and Miranowski 1989; Eichholtz et al, 2010; Fuerst and McAllister, 2011; Brounen and Kok, 2011; Dastrup et al, 2012; Hoen et al, 2013; Eichholtz et al, 2013; Kahn and Kok, 2013). Most studies in this area look at the capitalization of energy efficiency features of properties. For instance, Eichholtz et al (2010) investigate the Energy Star and LEED status for commercial buildings in the U.S. and estimate substantial premium to rental and selling price respectively. They (2013) also show that the return to green buildings relative to those of comparable high quality property investments are not significantly affected by increasing supply of green buildings and recent volatility in property market. Similarly, Brounen and Kok (2010) examine the capitalization of residential energy efficiency certification into Dutch home prices and find consumers capitalize the certification information into the price of their prospective homes. Relatively little research exists estimating the marginal impact of PV panels on property values. The only two existing studies (Dastrup et al., 2012; Hoen et al., 2013) have examined the solar home price premium in the Californian property market. Hoen et al. (2013) estimate a premium of 3.6% of property values using sales data up to 2009 for 31 out of 58 counties in California. Dastrup et al. (2012) find a 3.6% - 7% premium using sales data up to 2010 for San Diego and Sacramento counties.

Despite rapid penetration of rooftop PV panels in Australian residential sector, estimate of marginal contribution of this green feature to property values is nonexistent. Using a large sample of property sales data and high-resolution aerial photographs, this study provides the first systematic estimate of the price premium of properties with PV panels relative to properties without PV panels in Australia. Results from hedonic models, repeated sales models and hybrid models have shown strong evidence that PV panels contribute a 2.3 to 4.4 percent premium to properties prices. Our models also capture a dynamic premium effect that the market has only started to capitalize this green feature in the last couple of years. We also find consumers in greener communities tend to value PV panels more. Greater premium is found in localities with a larger share of votes for the Green Party and Australian Labor

Party in 2008 State Election, votes against daylight saving in 2009 State Referendum, registered Prius hybrid vehicles, and university graduates and postgraduates. For the sample period we study, we find that home owners, on average, are overcompensated for PV investment upon sale of the property. Results of this study on the ability, dynamics and heterogeneity of the market to capitalize PV panels have great significance to a number of stakeholders including property owners, builders, financial institutions, PV retailers, and policy makers.

The next section of this paper briefly reviews the related literature on the capitalization of PV panels in the property market. Section 3 presents various empirical models to be estimated. Section 4 describes the data and provides descriptive statistics. Section 5 presents and discusses the empirical results and the last section concludes the paper.

2. PV Panels Premium, Premium Dynamics and Premium Heterogeneity

Australian consumers who have installed PV panels have certainly taken into account the capitalization potential of PV panels. In a survey we conducted in 2012 (Ma and Burton, 2012), we ask owners of properties with PV installed to rate the most significant factors in their decisions to adopt PV panels. "Increasing your property's value" is rated the second most important factor only after "Saving money from reduced electricity bill"[1]. Consumers' expectation of the capitalization effect has also been picked up by the market. Real estate agencies has started to include eco-friendly features including PV panels in their property advertisements as other standard indoor and outdoor features[2]. However, there has been no systematic analysis about whether and to what extent this expectation has been realized in the market.

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[1] The six identified factors in order are saving money from reduced electricity bill, increasing your property's value, reduction of greenhouse gas emission, interest in the new technology, a statement about myself (eg. being environmentally friendly) and increasing the reliability of your electricity supply. The survey was conducted in two states of Western Australia and New South Wales. Results of the survey will be summarized in a separate paper.

[2] Other eco-friendly features include solar water heater, water tank, grey water system and energy efficiency rating. Eco-friendly features are now listed as one of the default search options like regular indoor or outdoor features in Australia's top residential property website realestate.com.au.

Because it is relatively easy to have PV panels installed at any time, consumers effectively have the option to "make" or "buy" in the sense that consumers can either buy a property without PV and pay a retailer to install or to buy a property with PV installed already. As Dastrup et al. (2012) argue, this "make" versus "buy" option should impose cross-constraints on the size of capitalization effect. A very high premium would dampen the demand for the "buy" option – i.e. properties with PV installed already as compared to the "make" option. On the other hand, a very low premium will push up the demand for PV properties. However, the premium under a "buy" option is not necessarily equal to the installation cost (plus transaction cost) under a "make" option. Firstly, consumers in the property market may not have the complete information about PV costs. After all, they are home buyers, not PV buyers and PV system is simply an add-on feature of the property they intend to buy. The impact of incomplete information on the realized premium in the market is uncertain. Secondly, at any point in time there are never two identical properties with and without PV panels. A property bundles a ranges of diverse features such that properties are only close substitutes at the margin (Rosen, 2002). Lastly, Western Australia has introduced a short-lived feed-in tariff during the period of August 2010 to August 2011. During this period, PV property owners can apply to sign up to the government's feed-in tariff scheme. The scheme provides a fix-term contract that allows customers to receive a net tariff of 40 cents or 20 cents per unit of electricity that their PV systems feed back into the grid over a ten-year period. Such contract will be carried over the new owner upon sale of the property. However, this scheme has been suspended and no longer available to new PV installations. This changing policy makes the option to "buy" a PV property that carries such a contract a superior product to the option to "make" a new installation. If there are a sufficient proportion of such properties, people might expect to see an over-capitalization effect in the sense that the premium that a PV system adds to the property value is higher than installation costs.

The premium is also expected to exhibit temporal dynamics in the mid run; however, the pattern of the dynamics is unclear. Different forces are at play. On the one hand, rising property prices combined with the cross-constraint imposed by the declining cost of PV panels would push the percentage premium down. On the other hand, the role of information spread and the relation between consumer awareness and perceived utility of purchase is well established in the literature of the diffusion of new products and technologies (Mahajan et al., 1990; Shurmer and Swann, 1995; Berndt et al., 2003). People are more likely to buy as they become increasingly more aware about a new product or technology. Due to information spread, a clustering pattern is often observed in the market of new products and technologies. For instance, Goolsbee and Klenow (2002) show that people in the U.S. are more likely to buy a computer if more people in their local area have already adopted the technology. Similar conclusions are also found by Jager (2006) and Bollinger and Gillingham (2012) among adopters of PV panels in the Netherlands and the U.S. It is likely that the consumer market does not appreciate the PV investment at very early stage of diffusion; however, the premium becomes more salient as people are more aware of the technology. In addition, rising electricity tariff (e.g. as a result of carbon tax), be it real or expected, will push the premium further up.

We would also expect to see heterogeneous capitalization effect across different market segments. Due to the cross-constraint imposed by the "make" or "buy" option, the absolute marginal contribution of a PV panel to a property should be constrained to the ballpark value of the installation cost. This then translates to a higher percentage premium in low end market and a lower percentage premium in high end market of residential properties. Valuations of property or else generally vary among individuals. People with different environmental ideology, lifestyles, education level and tastes may value eco-friendly features differently and have different bid and offer functions (Rosen, 2002). Like-minded people often cluster around thus models with spatial features can be applied to capture the diversity on peoples' preference and tastes (Kahn, 2007; Cragg et al., 2013).

3. Empirical Specification

In this paper, we use three types of models - hedonic, repeated sales and hybrid - to evaluate the premium that PV panels contribute to property prices. We now introduce our empirical specifications.

3.1 Hedonic Models

The hedonic approach decomposes property price into the implicit prices of the property characteristics while controlling for price trends across time and space. Our baseline specification is:

$$Log(Price_{it}) = \alpha PV_{it} + \boldsymbol{\beta} \boldsymbol{x}_{it} + \boldsymbol{\gamma} \boldsymbol{y}_i + \boldsymbol{\delta} \boldsymbol{z}_t + \varepsilon_{it} \quad (1)$$

where $Price_{it}$ is the recorded sale price for property *i* in time *t*, PV_{it} is a binary variable taking the value of one for properties with PV installed and zero otherwise, $\mathbf{x}_{it}$ is the the vector of structural variables $\boldsymbol{y}_i$ is the vector of locational characteristics of properties, $\boldsymbol{z}_t$ is the vector of temporal (year-quarter) fixed effects to control for market price trends, α, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, and $\boldsymbol{\delta}$ are model parameters to be estimated, and ε_{it} is the error term. Variables that describe structural characteristics of the properties are listed in Table 1.

We use coefficient α to calculate the marginal contribution of PV panels as a percentage of the property price. In a semi-log model, percentage contribution *p* is calculated $p = \exp(\alpha) - 1$ (Halvorsen and Palmquist 1980). Note that in Eq. (1) we assume a constant PV premium across the whole market. This, however, can be relaxed to capture temporal dynamics through an introduction of an interaction term with time. The error term ε_{it} comprises a random component and possibly a specification error component. For valid inference, we need to assume that the specification error component is uncorrelated with other variables included in the model.

Property sales data often exhibit spatial dependencies due to spatially correlated omitted variables, measurement error, or influence of observed prices of sold neighboring properties. The adoption of PV panels is often not independent due to information spread or neighboring effect (Jager, 2006; Bollinger and Gillingham, 2012). As a result, a clustering pattern is often found in small localities. The presence of spatial dependencies can cause bias, inconsistency or inefficiency in coefficients estimates when the ordinary least squares (OLS) method is used (Anselin 1988). Therefore we test residuals of the OLS for the presence and type of spatial dependencies and estimate appropriate model.

3.2 Repeated Sales (RS) Models

RS models measure the average PV capitalization as the average difference in the price appreciation in consecutive sales between properties where PV panels were installed between sales and other properties with no PV panels installation in the same period. Depending on the assumption about the variability of implicit prices and spatial heterogeneity across consecutive sales, we have static and dynamic RS models. A static RS model assumes constant implicit prices and spatial heterogeneity across the two sales:

$$Log\left(Price_{i(t+\Delta t)}\right) = \alpha PV_{i(t+\Delta t)} + \boldsymbol{\beta x}_{i(t+\Delta t)} + \boldsymbol{\gamma y}_i + \boldsymbol{\delta z}_{t+\Delta t} + \varepsilon_{i(t+\Delta t)} \quad (2a)$$

$$Log(Price_{it}) = \alpha PV_{it} + \boldsymbol{\beta x}_{it} + \boldsymbol{\gamma y}_i + \boldsymbol{\delta z}_t + \varepsilon_{it} \quad (2b)$$

where $Price_{it}$ and $Price_{i(t+\Delta t)}$ are property prices of consecutive sales at time t and $t + \Delta t$. A RS model is derived by differencing Eq. (2b) from Eq. (2a) so that variables that do not change between consecutive sales (i.e. $\boldsymbol{x}_{i(t+\Delta t)} = \boldsymbol{x}_{it} = \boldsymbol{x}_i$) drop out of the equation. If the specification error component in hedonic models is invariant over time and correlated with other variables included in the model, then a RS model has the advantage over a hedonic model as the error drops out in differencing[3]. The baseline RS specification then becomes:

$$Log\left(\frac{Price_{i(t+\Delta t)}}{Price_{it}}\right) = \alpha \Delta PV_{i(t+\Delta t)} + \boldsymbol{\delta \tilde{z}}_{t+\Delta t} + \tilde{\varepsilon}_{i(t+\Delta t)} \quad (3)$$

where $\Delta PV_{i(t+\Delta t)}$ indicates the installation of PV panels between the two sales and the vector variable $\boldsymbol{\tilde{z}}_{t+\Delta t}$ is equal to $\boldsymbol{z}_{t+\Delta t} - \boldsymbol{z}_t$. The model can be estimated by simple OLS; however, it is possible that the error term is dependent on the time span between consecutive sales (i.e. Δt). A standard 3-stage GLS can be used in the presence of such heteroscedasticity.

[3] It is possible that there are other structural changes that we do not observe in our data but meanwhile contributing to the increase of property prices between consecutive sales. However, as long as these changes are not correlated with PV installations, the RS estimates are unbiased. This is the assumption we need to make.

Similarly, the temporal dynamics of PV capitalization can be captured through the introduction of a PV interaction term with time.

The assumption of constant implicit prices may be valid for repeated sales occurring within relatively short periods of time. However for the property market, the time span between two sales can sometimes be very long such that implicit prices may vary over time according to changing tastes and the relative scarcity of property characteristics (Case and Quigley, 1991). Our repeated sales sample shows an average gap of 8 years between consecutive sales with the largest span reaching 23 years. In such cases, a dynamic RS model allowing varying implicit prices may be appropriate.

$$Log\left(Price_{i(t+\Delta t)}\right) = \alpha PV_{i(t+\Delta t)} + \boldsymbol{\beta}_{t+\Delta t}\boldsymbol{x}_{i(t+\Delta t)} + \boldsymbol{\gamma}_{t+\Delta t}\boldsymbol{y}_i + \boldsymbol{\delta z}_{t+\Delta t} + \varepsilon_{i(t+\Delta t)} \quad \text{(4a)}$$

$$Log(Price_{it}) = \alpha PV_{it} + \boldsymbol{\beta}_t\boldsymbol{x}_{it} + \boldsymbol{\gamma}_t\boldsymbol{v}_i + \boldsymbol{\delta z}_t + \varepsilon_{it} \quad \text{(4b)}$$

In the simplest specification, we allow linear dynamics where $\boldsymbol{\beta}_{t+\Delta t} - \boldsymbol{\beta}_t = \widetilde{\boldsymbol{\beta}}(\Delta \boldsymbol{t})$ and $\boldsymbol{\gamma}_{t+\Delta t} - \boldsymbol{\gamma}_t = \widetilde{\boldsymbol{\gamma}}(\Delta t)$, and we have a dynamic RS specification:

$$Log\left(\frac{Price_{i(t+\Delta t)}}{Price_{it}}\right) = \alpha \Delta PV_{i(t+\Delta t)} + \widetilde{\boldsymbol{\beta}}(\Delta t)\boldsymbol{x}_i + \widetilde{\boldsymbol{\gamma}}(\Delta t)\boldsymbol{y}_i + \boldsymbol{\delta}\tilde{\boldsymbol{z}}_{t+\Delta t} + \tilde{\varepsilon}_{i(t+\Delta t)} \quad \text{(5)}$$

3.3 Hybrid Models

The last model we employ is the hybrid model initially introduced by Case and Quigley (1991) and we follow Fogarty and Jones (2011)'s modified approach. As the possible specification error component is unidentified in the hedonic model, the hybrid model uses repeated sales information to identify this specification error and this additional information allows more efficient estimation. The hybrid model can be specified as follows. Let $i \in \{1, \ldots, I\}$ be the subset of properties that sell only once during the sample period and $j \in \{1, \ldots, J\}$ be the subset of properties that have repeated sales. By decomposing the error term ε_{it} in Eq. (1) into a random term e_{it} and a specification error term φ_i, Eq. (1) can be modified with the first sale, second sale and single sale hedonic models identified separately:

$$Log(Price_{it}) = \alpha PV_{it} + \boldsymbol{\beta X}_{it} + \boldsymbol{\gamma Y}_i + \boldsymbol{\delta Z}_t + \varphi_i + e_{it} \quad (6a)$$

$$Log\left(Price_{jt}\right) = \alpha PV_{jt} + \boldsymbol{\beta X}_{jt} + \boldsymbol{\gamma Y}_j + \boldsymbol{\delta Z}_t + \varphi_j + e_{jt} \quad (6b)$$

$$Log\left(Price_{j(t+\Delta t)}\right) = \alpha PV_{j(t+\Delta t)} + \boldsymbol{\beta X}_{j(t+\Delta t)} + \boldsymbol{\gamma Y}_j + \boldsymbol{\delta Z}_{(t+\Delta t)} + \varphi_j + e_{j(t+\Delta t)} \quad (6c)$$

Assuming constant implicit prices, we can derive the hybrid model by differencing Eq. (6b) from Eq. (6c) and replacing Eq (6c) with the repeated sales equation:

$$Log\left(\frac{Price_{j(t+\Delta t)}}{Price_{jt}}\right) = \alpha PV_{j(t+\Delta t)} + \boldsymbol{\delta \widetilde{Z}}_{(t+\Delta t)} + e_{j(t+\Delta t)} - e_{jt} \quad (6d)$$

Following Case and Quigley (1991) and Fogarty and Jones (2011), the system of three equations formed by (6a), (6b), and (6d) can be estimated as a single stacked model. As the error structure is apparently non-spherical, we follow Fogarty and Jones (2011) to estimate the covariance matrix associated with the hybrid model and use GLS to estimate the model.

4. Data

4.1 Study Area

Our choice of study area follows previous hedonic studies that examine the impact of urban wetlands (Tapsuwan et al., 2009) and tree cover (Pandit et al. 2012; Pandit et al., 2013) on property values in the same region. However, we extend the coverage to approximately 453.75 sq. km going 27.5 km north-south and 16.5 km east-west around the city of Perth in Western Australia (Fig. 3). The study area expands across 125 state suburbs in the central part of Perth metropolitan area.

We acquired property sale records of the Perth Metropolitan area for the period of 2009 – 2012 from Landgate, a state government agency that maintains property data in Western Australia. For the purpose of this research, we restrict our analysis to sale records falling within the predefined study area (Fig. 3) and focus on detached and semi-detached single family houses. This gives us a sample of 26,507 sales. Details on property sales data, cadastral information, PV property identification and locality characteristics are presented in the Appendix. Table 1 provides definitions of variables and Table 2 presents summary statistics of the variables. As shown in Figure 4 and Table 2, the distribution of all property prices is highly skewed with long tail to the right; however, the distribution of PV property prices is much less skewed. We have no PV property observations at the high end of the sample market. On the other hand, the lowest property price in our sample is merely $37,000 for a 3-bedroom property on a 700-square-meters land, which is likely an error. To account for the right-skewed tail where we have no PV observations and possible errors at the lower end, we truncate the bottom and top 1% distribution off the sample and use this truncated sample to estimate all models. This gives us a dataset of 25,985 property sales records characterized by 15,169 properties with repeated sales information, 413 of which have PV panels installed at the time of sale and 258 have PV panels installed between the two recent sales. Table 2 shows patterns that are consistent with those observed in Dastrup et al. (2012). Properties sold with PV installed are larger than those with no PVs, have more bedrooms, bathrooms, other rooms, carports and garages. They are also slightly newer and more likely to have a pool.

5. Estimation Results on PV Capitalization

5.1 Hedonic Estimation Results

Table 3 presents estimation results from hedonic regressions. The dependent variable in the hedonic model is the CPI-adjusted sales price of a property. We used the Box-Cox test to determine the appropriate functional form for the hedonic price function, which resulted in a function with a natural log transformed dependent variable. We also used natural log transformed driving times to major amenities (CBD, ocean, and rivers). We used 25-nearest neighbors based spatial weight matrix to test for the presence of the spatial dependencies on OLS model results (Table 4). Moran I statistic indicates a clustering pattern in the OLS residuals. The LM and RLM tests (Anselin et al. 1996) indicate the presence of spatial error and spatial lag dependencies, although spatial error dependency is much more prominent.

Therefore, we estimated a spatial error model (SEM). It had been shown (Kuminoff et al. 2010) that spatial dependencies could be controlled using spatial fixed effect models (SFEM). Therefore we also estimate a SFEM that uses Statistical Areas Level 1 (SA1s) as fixed effects to control for unobserved neighborhood and location amenities and spatial dependencies in the data. The SA1s are the second smallest statistical units under the new Australian Statistical Geography Standard (ASGS) and have an average population of 400 persons. Results from both SEM and SFEM are presented in Table 3. The SEM shows substantial improvement of fit over OLS model with highly and statistically significant spatial error coefficient. The SFEM provides the best model fit across all hedonic specifications. The Moran I statistic indicates clustering pattern in residuals of SFEM only at 10% level while LM and RLM tests do not indicate the presence of any spatial dependencies (Table 4).

The PV capitalization effect ("PV Premium Average") has the expected sign but is not statistically significant in our baseline model. This effect becomes statistically significant once we control for spatial dependence in SEM and SFEM. The magnitudes of effects are consistent between SEM and SFEM and indicate PV premium of 2.49 to 3.01 per cent on average. For each hedonic model, we also test for possible temporal dynamics in capitalization effect through an interaction term between the PV indicator and a time period dummy. Due to limited observations of PV properties, we have chosen to create two dummy variables indicating properties with PV sold during the periods of either 2009–2010 or 2011–2012. The results indicate no significant capitalization effect for 2009–2010 period but a highly significant effect for 2011–2012. A similar but more significant pattern is also observed in SEM and SFEM with a 2.80 to 3.25 percent premium for the properties sold with PV during 2011–2012. However, the market has only started to capitalize this effect in the last couple of years.

5.2 Repeated Sales and Hybrid Estimation Results

Table 5 provides estimation results from repeated sales regressions and hybrid regressions. Our Static RS models assume constant implicit prices over time thus all structural and locational variables drop out. We test for the possibility that the error term is dependent on the time span between consecutive sales (i.e. Δt) and the Breusch-Pagan and Cook-Weisberg tests have found significant heterscedasiticity in the error term. To address this issue, we estimate a 3-stage GLS where observations in the final stage are weighted based on the fitting of first-stage residuals on linear and quadratic terms of time between the two sales (DeltaT).

The dynamic RS models assume that implicit prices of structural variables change linearly with the time span between the two sales. Tests for spatial dependencies presented in Table 4 indicate that clustering residuals patterns in dependencies as well as presence of spatial error dependencies. Robust LM test does not confirm spatial lag dependency in the presence of spatial error. To control for spatial dependencies we estimate SEM and SFEM for the dynamic RS model (Table 5). Moran I of the residuals of the SFEM indicate dispersed patterns of spatial autocorrelation. RLM test indicates presence of spatial error dependence. It seems that fixed effects overcorrected spatial autocorrelation in our dynamic RS model. Furthermore, based on AIC, SEM is superior to SFEM for the dynamic repeated sales model.

The last model (Hybrid GLS) follows Case and Quigley (1991) and Fogarty and Jones (2011) to employ all information available in the sample to identify possible specification error and to make estimation more efficient. As this is estimating a stacked equation system and observations are also stacked resulting an augmented 41154 total observations and 671 PV property observations.

Results from repeated sales and hybrid models show strong evidence of a PV capitalization effect. The PV indicator is also interacted with a period dummy indicating the first two years or the last two years of our sample period. We find results similar to those of hedonic estimations that PV capitalization is insignificant in 2009 and 2010 but very significant in the last two years. Dynamic SEMs provide the best model fit among all RS models and estimate a 3.26 to 4.12 percent PV premium depending on the specifications. We also find that PV premiums in hybrid estimations are slightly greater than hedonic estimates and smaller than repeated sales estimates.

5.3 Heterogeneous Capitalization

People with different environmental ideology, lifestyles, education level and tastes may value eco-friendly features differently and have different bid and offer functions (Rosen, 2002). If we believe that like minded people often cluster around, then neighborhood characteristics can be used to capture heterogeneous "bid and offer" in terms of PV capitalization. The Green Party and the Australian Labor Party are often viewed as greener than the Liberals and the Nationals in Australia. Political ideology has been proposed as a proxy of environmental ideology (Kahn, 2007; Cragg et al., 2013) which may affect people's "bid and offer" functions. Kotchen (2006) argues that environmentalists are more likely to be willing to purchase private goods that help to supply public goods. This is also confirmed in our recent survey conducted in Western Australia that people who vote for the Green Party are more likely to subscribe into green electricity program at a premium (Ma and Michael, 2013). In this paper, we use a locality's share of votes for the Green Party and Australian Labor Party in 2008 State Election as proxies of their environmental ideology. Alternatively, we use a locality's share of votes for "NO Daylight Saving" in 2009 State Referendum as another proxy. The case against the introduction of Daylight Saving in Western Australia is partly justified on the environmental ground of increased electricity consumption due to air conditioning in early evenings and delayed natural cooling. We also use the share of registered Prius hybrid vehicles to indicate a locality's willingness to accept and adopt environmental friendly new technologies. The share of bachelor and postgraduate degrees reported in 2011 Australian Census is used to represent the neighborhood education level.

The heterogeneous capitalization effect can be measured through an introduction of interaction terms between the PV indicator and these neighborhood characteristics. Table 6 provides results from hedonic regressions with these interaction terms. The hedonic SA1 model in Table 3 is reproduced here as the baseline. As expected, the PV capitalization effect is positively associated with the share of votes for the Green Party and Australian Labour Party, the share of votes for no daylight saving, and the share of registered Prius hybrid vehicles although the coefficients are not statistically different from zero. These results are consistent with the theoretical work of Kotchen (2006) and empirical work of Kahn (2007) and Cragg et al. (2013). The association with the share of bachelor and higher degrees, however, is negligible and insignificant.

Although not reported here, we have also examined the heterogeneous capitalization effect (percentage premium) across different market segments. We expect that the absolute marginal contribution of a PV panel to a property should be constrained to the ballpark value of the installation cost, which translates to a higher percentage premium in low end market and a lower percentage premium in high end market. We estimate all our models two split samples: a low-end market with property prices lower than the median price and a high-end market with property prices higher than the median price. We observe a greater and highly significant capitalization effect in the low-end market but a smaller and generally insignificant capitalization effect in the high-end market[4].

5.4 To Buy or To Make

Our results (Table 3 and Table 5) show a PV premium of 2.31-3.21% for the entire sample period (2009-2012) and 2.76-4.04% for 2011-2012. Based on these percentage premium ranges, added value of PV to a medium-priced ($695,000) property can be calculated. The value ranges are then compared with market average turnkey prices for PV systems with typical sizes in Table 7. Medium sizes of installed residential PV systems for each year of our sample period are calculated using data provided by Clean Energy Regulator which keeps records of all installed PV systems since 2001. We calculate the average turnkey prices for medium-sized systems. Unit prices ($/Wp) for each year of our sample period are taken from *PV in Australia 2010-2012* (APVA, 2010-2012) for the whole country. Prices for 2013 are mean prices for Western Australia only, calculated using data from the Solar Choice installer network database, which contains current pricing and product details from over 125 solar installation companies across Australia. Prices do not include meter installation charges, extra

[4] Results are not reported here but are available upon request.

charges for difficult installations or recurring charges after installation such as battery replacement or operation and maintenance. PV installers will get a subsidy in the form of Small-scale Technology Certificate (STC) under the Australian Solar Credit Scheme. These certificates are normally claimed at the time of installation through a discounted installation price. Prices quoted in Table 7 are after subsidy – that is the STC discounted prices.

Using a lower-end estimate of 3.6% premium, Dastrup et al. (2012) find that property owners in California on average fully recover the costs of installing PV panels upon sale of the property. Consistent results are also found in Hoen et al (2013) showing a near full return on residential PV investment. In this study, we provide a range of capitalization estimates using different model specifications. Even the lower-end estimates seem to suggest that property owners in Western Australia are overcompensated for their PV investment upon sale of the property. Here we provide several explanations for this strong over-capitalization effect.

Firstly, as we pointed our earlier, consumers may not have the complete information of PV cost reduction. After all, the substantial cost reduction in Australia only happened in the last few years from a typical price of $9/wp in 2009 to $2.13/wp in 2013. For the most period of 1997-2008, typical turnkey cost of PV systems has stayed quite stably within the range of $10-14/wp. Home buyers may still hold the impression that PV systems are quite expensive resulting in an over-capitalization. The effect may be enhanced by frequent media exposure of reduced federal and state government subsidies for that the benefit of reduced PV cost may be offset by reduced subsidies.

A second explanation relates to the fact that quoted system prices normally do not include charges of grid connection and meter upgrade. Other transaction costs such as searching for best deals, checking eligible financial incentives and negotiating tariff contracts with utility companies are also not included. However, the difference between actual installation cost and quoted turnkey prices is probably not wide enough to fully account for this substantial over-capitalization (especially for 2011 and 2012).

A more important reason has to do with the changing policy parameters. Western Australia introduced a feed-in tariff scheme from August 1st 2010 which allows subscribed customers to receive a net tariff of 40 cents per unit of electricity that their PV systems feed back into the grid over a ten-year period. New applicants after June 30th 2011 will only get a ten-year contract at 20 cents per unit. In addition to this government feed-in tariff scheme, utility companies also pay 7-8 cents per unit under the Renewable Energy Buyback Scheme (REBS). The government feed-in tariff scheme was short-lived and suspended on August 1st 2011 due to high demand and short budget. Installations after this date will only receive the utility incentive under REBS. About half of all existing residential PV systems in WA have been signed up to the government scheme during August 2010 to July 2011. Such feed-in tariff contracts will be carried over to new owners upon sale of the properties. This changing policy makes old PV systems that carry such contracts more valuable than a new installation. As such, we might expect to see an over-capitalization effect in the sense that the premium that an old PV system adds to the property value is higher than installation costs. For a typical Australian household with a daily electricity consumption of 18 kilowatt hours (kWh), a 1.5 kW system will produce just enough power in summer to meet the household's demand at 1pm when the sun is at its peak. The average household uses more than the PV system can produce during the rest of the day. In winter, a PV system almost never fully meets an average household's demand. However, as shown in Table 7, we have observed a trend of increasing size of installed PV systems over the years. A 3kW system typically feeds 6 kWh in summer and 4 kWh in winter back into the grid every day[5]. Assuming a 5 percent discount rate, a ten-year contract for a 3kW PV system is worth roughly $6,000 at 40 cents per kWh or $3,000 at 20 cents per kWh. This seems to be the largest contributor to the over-capitalization effect.

6. Conclusion

Despite the fact that federal and state governments have substantially reduced direct financial subsidies to residential PV installations, Australia has witnessed the strongest growth in PV

[5] http://www.solarchoice.net.au/blog/home-energy-consumption-versus-solar-pv-generation/

installations during the last couple of years. Discussions about the private and public benefits of PV installations often ignore the fact that PV installations may add value to properties. This is clearly evidenced by homebuyers explicitly looking for such eco-friendly features and real estate agents using such information in property advertisements. Based on a comprehensive set of property sales records (25,985 with 413 with PV installed at the time of sale) and controlling for other variables that influence property prices, we estimated a number of hedonic, repeated sales and hybrid models to provide the first systematic analysis of PV capitalization effect in Australian residential property market.

We find strong evidence that properties in Western Australia with PV installed at the time of sale have sold for a premium of 2.34 to 4.12 percent over comparable properties without PV panels. This corresponds to a capitalization of $16,055 to $24,047 for a median-priced property. Comparing the estimates with typical market turnkey prices for median-sized installations in 2009-2012 implies a minimum of full return on property owners' PV investment. We provide a number of explanations for the substantial over-capitalization including possible searching and transaction cost not included in quoted turnkey prices as well as consumers' lack of complete cost information due to drastically declining cost occurring in a relatively short period of time. However, the most important reason relates to changing policy parameters. In particular, old PV systems that carry a government feed-in tariff contract are considered superior to new installations, which provides a justification for the over-capitalization effect that we observe in the market. We attempt to identify spatial heterogeneity in PV capitalization. While we find moderate evidence that greener communities tend to value PV installations more, the effect is not significant though. The current sample is limited to the period of 2009-2012 in our predefined area. It would be interesting to see how the premium dynamics and heterogeneity change over time and across localities using more recent sales from a larger geographic area.

We found that models without control for spatial dependencies fail to identify effect of PV panels on property prices. We control for spatial correlation in error terms using Spatial Error Models and Spatial Fixed Effect Models. The estimates of the models parameters are consistent between SEM and SFEM. SFEM provides better fit in cross-sectional hedonic model, while in dynamic repeated sales model it is inferior to SEM and do not fully control for spatial dependencies. More investigation is needed into selection of spatial weight matrices and spatial fixed effects.

Our results have great significance to a number of stakeholders in the residential property market. The magnitude of the premium suggests that PV installations are a sensible investment option for potential property sellers and developers as they can at least fully recover the investment upon sale. The significant premium also suggests that home buyers do value PV properties more than comparable properties without PV. For marketing purpose, real estate agents should treat PV installation as standard structural property attributes and disclose relevant information. The premium and associated spatial heterogeneity may also be used by PV retailers as a market campaign strategy as well as locating the most promising market area. More importantly, our research has significant implications for informed demand modeling and policy making. The frequent stop-start nature of a number of federal and state PV support programs has suggested persistent underestimate of consumer demand for PV installations. In fact, the demand has been even stronger in the past two years when the federal and state governments have substantially reduced financial support for PV installations. If homeowners anticipate a fair appreciation of property value as a result of PV installation, the initial cost of installation may not pose a significant barrier to adoption. PV demand modeling and policy making need to consider this capitalization effect in the future.

Appendix: Data Description

Property Sales and Cadastral Data

The state government agency – Landgate – maintains and distributes the most authoritative property data for Perth Metro area. We are able to aquire the complete set of property sale records for the state during the period of 2009 – 2012. For the purpose of this research, we restrict our analysis to the predefined study area and focus on detached and semi-detached houses. This gives us a final sample of 26,507 sale observations. The data contains most recent sale price and structural characteristics. It also has information on previous sales if the property has been transacted multiple times. We also retrieve the most recent update of cadastral map from Landgate's Shared Land Information Platform (SLIP) which allows delineation of property boundaries, spatially referencing the sample properties and matching identified PV panels.

PV Identification

The most authoritative identification information should come from utility companies as PV adopters need to apply to upgrade metres to connect to the grid. However, such information is often kept confidential. Alternatively, the Department of Climate Change and Energy Efficiency (DCCEE) keeps address information for those who have applied various kinds of solar subsidies through the department; however, this information would not be disclosed for similar privacy reasons. Our identification information comes from two sources. REA Group Limited is a leading digital advertising business specializing in property. The Group operates Australia's top residential property website realestate.com.au which is home for lists of rental and sale property and other listings by real estate agents. The site has information about property characteristics including eco-friendly features like solar panels for properties currently for sale and sold properties. Using this website, we are able to identify 358 properties with solar panels at the time of property sale for the entire Western Australia. This list is however not exhaustive as it is not compulsory for agents to disclose information about eco-friendly features. Our second source is the analysis using high-resolution aerial maps provided by NearMap (www.nearmap.com). We visually identify PV properties within the boundary of predefined study area as of the end of 2012. Identified PV property locations are then matched with our sales record. The high-resolution aerial photos are monthly updated which allows us to date the PV installation and to identify properties that had PV at the time of sale. This gives us 420 properties with PV panels installed for the full sample and 413 properties with PV panels installed for the 1-99% truncated sample.

Locality Characteristics

We gathered data for several aspects of locality characteristics. Boundary maps corresponding to the new Australian Statistical Geography Standard (ASGS) are available from the Australian Bureau of Statistics. We created location dummies at Statistical Areas Level 1 (SA1s) which has an average population of 400 and are the smallest region for which a wide range of Census data are available. Data for political ideology (party votes in 2008 state election) and daylight saving referendum (2009) by electoral district are both obtained from the Western Australian Electoral Commission. Latest data on education attainment by SA1s is available from Australian 2011 Census. Prius penetration by postcode is calculated from annual Moto Vehicle Census.

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Figure 1 – PV Capacity Monthly Growth (Megawatts)

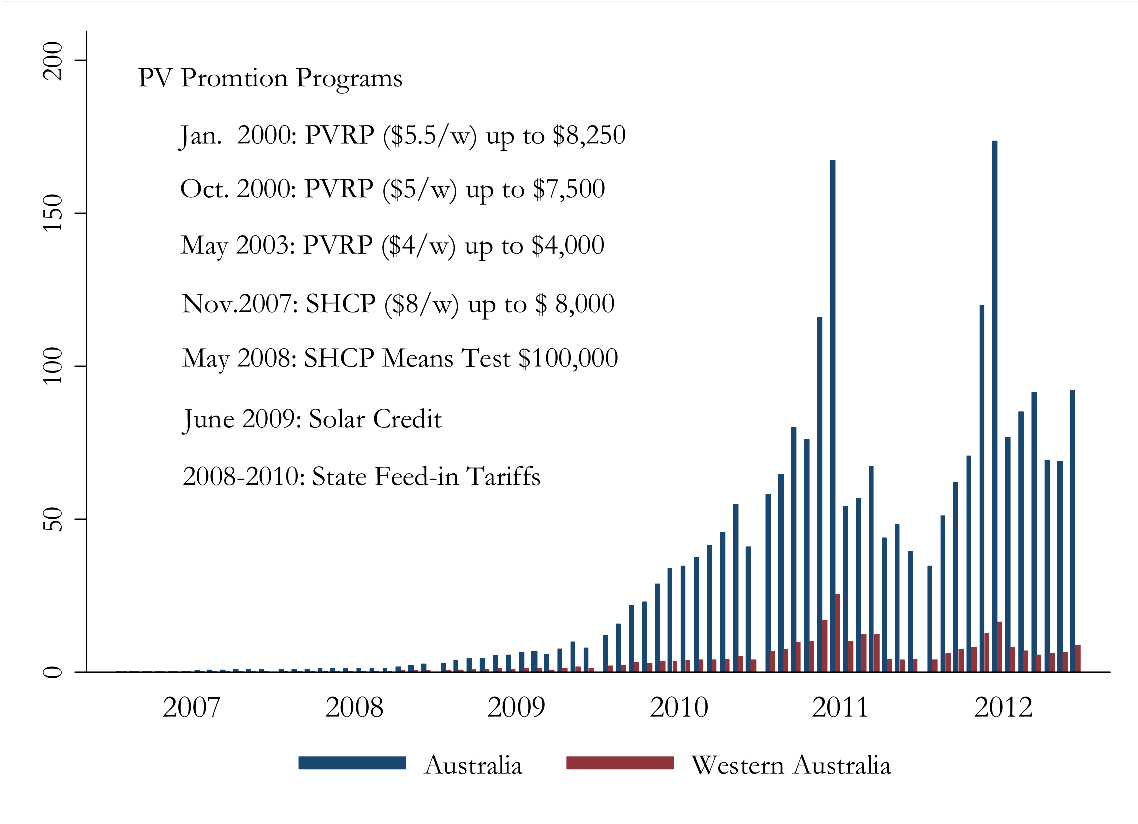

Figure 2 – Kernel Distribution of PV Penetration (%) at SA1s in WA in 2012

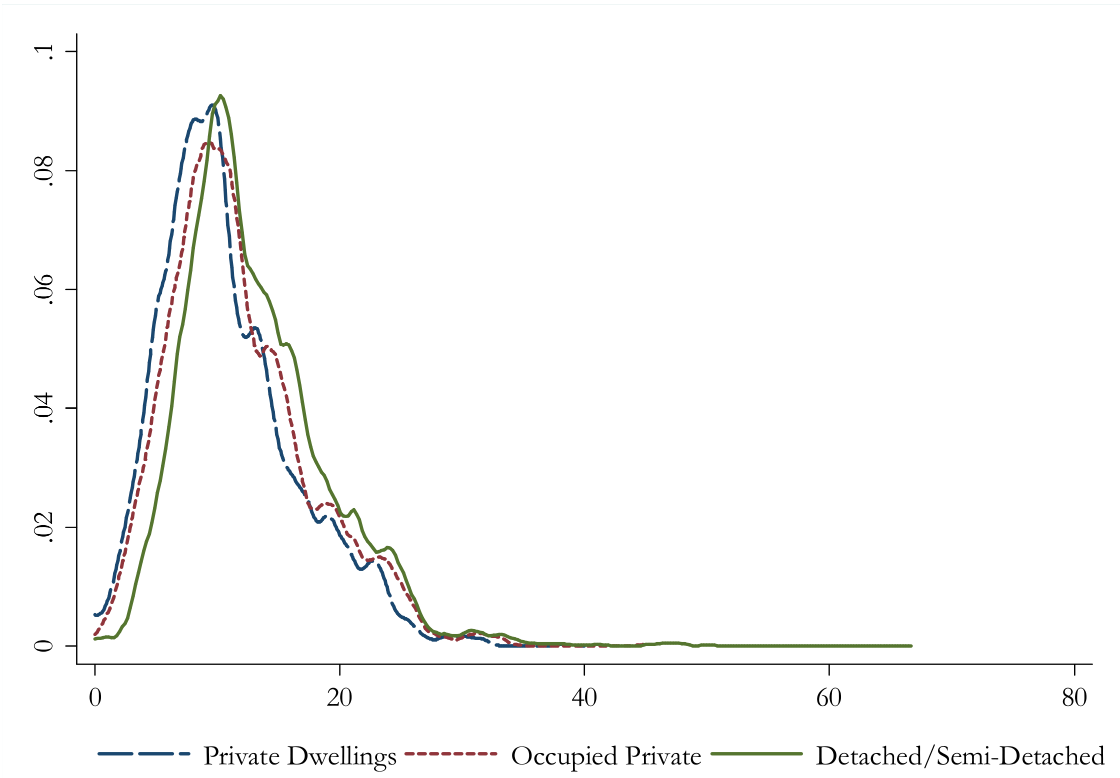

Figure 3 – Study Area with Property Locations

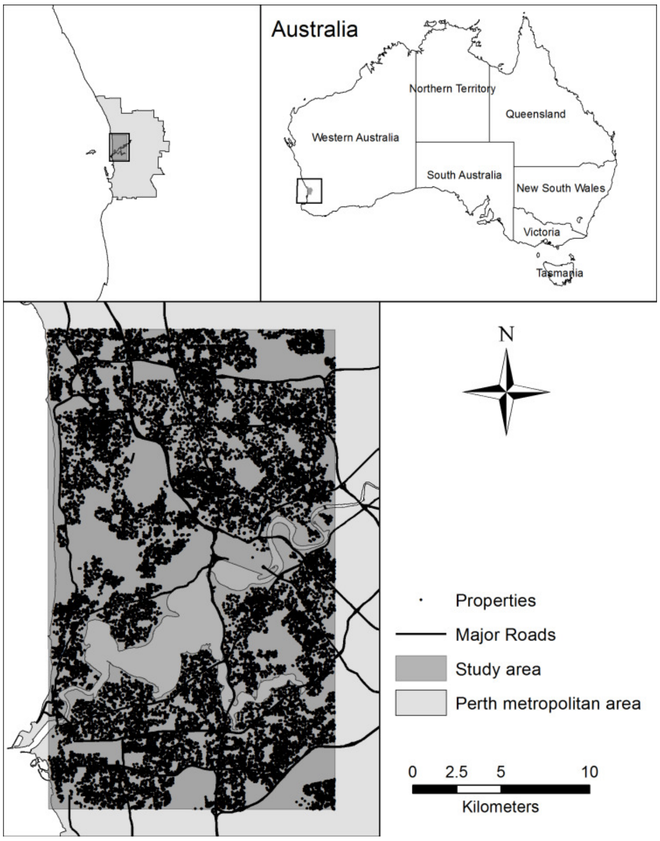

Figure 4 – Distribution of Property Prices ($1,000)

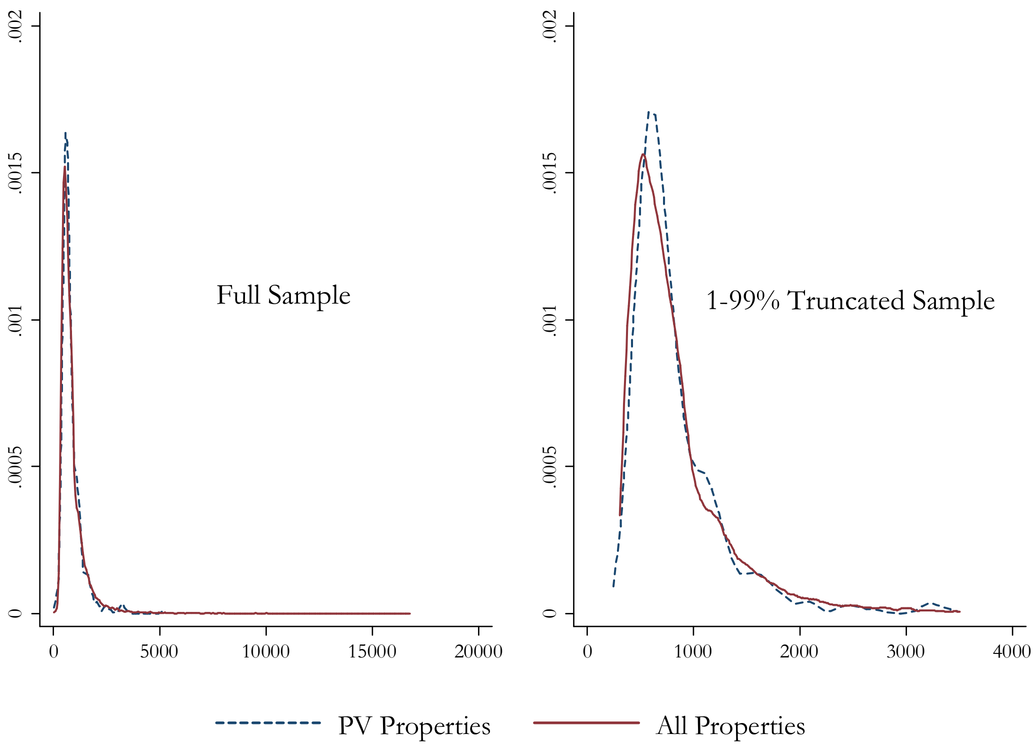

Table 1 – Variables Definition

Variables	Definition
Sale Price 1	Property sale price for the latest sale in Australian dollars
Sale Price 2	Property sale price for previous sale in Australian dollars
DeltaT	Years between Sale 1 and Sale 2
PV Dummy	1 for properties with PV panels installed
Bed	Number of bedrooms
Baths	Number of bathrooms
Other Rooms	Number of other rooms
Brickwalls	1 for properties with brick walls
Tileroof	1 for properties with tile roof
Carport	Number of car ports
Garage	Number of garages
Pool	1 for properties with a swimming pool
Tennis Court	1 for properties with a tennis court
House Age	Age of property in years
Log Land Area	Log of reported land area in squared metres
Log Distance to River	Log of driving distance to the Swan River in kilometres
Log Distance to CBD	Log of driving distance to the CBD in kilometres
Log Distance to Ocean	Log of driving distance to the ocean in kilometres
Green Share	% of votes for the Green Party in 2008 State Election
ALP Share	% of votes for the Australian Labor Party in 2008 State Election
Daylight Saving	% of people voting "NO" in 2009 State Daylight Saving Referendum
Prius Share	% of registered Prius in total registered vehicles
Bachelor & Above	% of people with a bachelor or postgraduate degree

Table 2 – Summary Statistics

Variables	Full Sample		Truncated Sample (1-99%)	
	Sales with no PV	Sales with PV	Sales with no PV	Sales with PV
	Mean/Min/Max/Std. Dev.			
Sale Price 1 ($1,000)	865/37/16750/658	828/104/5188/498	829/305/3500/468	827/325/3400/447
Sale Price 2 ($1,000)	447/0.005/13875/462	449/0.005/2900/397	430/0.005/4380/379	446/0.005/2900/381
DeltaT	8.3/0.008/60.99/5.47	8.35/0.61/23.61/5.17	8.29/0.008/60.99/5.46	8.32/0.61/23.61/5.17
Bed	3.19/1/7/0.85	3.36/1/6/0.82	3.18/1/7/0.85	3.35/1/6/0.82
Baths	1.55/1/14/0.67	1.67/1/5/0.62	1.54/1/14/0.64	1.67/1/4/0.6
Other Rooms	3.84/2/28/1.48	4.28/2/8/1.43	3.83/2/28/1.47	4.27/2/8/1.42
Brickwalls	0.86/0/1/0.35	0.87/0/1/0.33	0.86/0/1/0.34	0.87/0/1/0.33
Tileroof	0.81/0/1/0.39	0.81/0/1/0.39	0.81/0/1/0.39	0.81/0/1/0.39
Carport	0.53/0/7/0.76	0.59/0/5/0.85	0.54/0/7/0.76	0.59/0/5/0.86
Garage	0.89/0/8/0.9	0.94/0/4/0.97	0.88/0/7/0.89	0.94/0/4/0.96
Pool	0.22/0/1/0.42	0.28/0/1/0.45	0.22/0/1/0.41	0.28/0/1/0.45
Tennis Court	0.0009/0/1/0.03	0/0/0/0	0.0006/0/1/0.03	0/0/0/0
House Age	37.79/0/139/25.26	34.03/0/112/25.1	37.89/0/139/25.26	34.05/0/112/25.23
Log Land Area	6.41/4.66/9.68/0.39	6.42/5.30/7.69/0.36	6.41/4.66/9.68/0.39	6.42/5.30/7.69/0.36
Log Distance to River	1.35/-2.3/2.69/0.93	1.39/-1.83/2.63/0.86	1.35/-2.30/2.69/0.92	1.39/-1.83/2.63/0.85
Log Distance to CBD	2.33/0.72/3.03/0.35	2.40/1.47/297/0.33	2.32/0.72/3.03/0.35	2.40/1.47/2.97/0.33
Log Distance to Ocean	2.02/-2.1/2.97/0.79	2.04/-1.45/2.94/0.77	2.03/-2.10/2.97/0.78	2.04/-1.45/2.94/0.77
Green Share	13.2/8.05/26/4.42			
ALP Share	32.82/15.33/48.19/10.13			
Daylight Saving	48.64/40.04/57.61/3.01			
Prius Share	0.11/0.02/0.33/0.05			
Bachelor & Above	21.25/1.09/54.72/8.04			

Table 3 - Hedonic Models

Dependent Variable: Log (Sale Price 1)	**Baseline**		**SEM**		**SFEM**	
PV Variables						
PV Premium Average	**0.0162**		**0.0297****		**0.0246****	
	(1.45)		**(3.70)**		**(3.06)**	
PV Premium 2011-2012		**0.0092**		**0.0200**		**0.0121**
		(0.36)		**(1.10)**		**(0.66)**
PV Premium 2011-2012		**0.0179**		**0.0320****		**0.0276****
		(1.44)		**(3.58)**		**(3.08)**
Structural Variables						
Beds	0.0391**	0.0391**	0.0318**	0.0318**	0.0312**	0.0312**
	(16.64)	(16.64)	(18.42)	(18.43)	(17.83)	(17.83)
Baths	0.1228**	0.1228**	0.0816**	0.0816**	0.0780**	0.0780**
	(36.25)	(36.24)	(32.86)	(32.86)	(30.95)	(30.95)
Other Rooms	0.0333**	0.0333**	0.0162**	0.0162**	0.0154**	0.0154**
	(23.26)	(23.26)	(14.45)	(14.45)	(13.53)	(13.53)
Brickwalls	0.1001**	0.1001**	0.0078	0.0078	0.0041	0.0041
	(20.91)	(20.91)	(1.91)	(1.91)	(0.98)	(0.98)
Tileroof	-0.0445**	-0.0445**	-0.0304**	-0.0304**	-0.0293**	-0.0294**
	(-11.05)	(-11.05)	(-10.03)	(-10.03)	(-9.57)	(-9.57)
Carport	0.0176**	0.0176**	0.0061**	0.0061**	0.0056**	0.0056**
	(7.18)	(7.18)	(3.39)	(3.39)	(3.06)	(3.06)
Garage	0.0683**	0.0683**	0.0415**	0.0415**	0.0406**	0.0406**
	(30.09)	(30.09)	(24.27)	(24.27)	(23.45)	(23.45)
Pool	0.0967**	0.0967**	0.0679**	0.0679**	0.0694**	0.0694**
	(26.39)	(26.38)	(25.19)	(25.18)	(25.54)	(25.54)
Tennis Court	0.2786**	0.2787**	0.1254**	0.1254**	0.1084**	0.1085**
	(4.82)	(4.82)	(3.01)	(3.00)	(2.56)	(2.56)
House Age	-0.0048**	-0.0048**	-0.0069**	-0.0069**	-0.0069**	-0.0069**
	(-18.72)	(-18.72)	(-34.45)	(-34.46)	(-33.83)	(-33.83)
House Age Squared	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**
	(21.47)	(21.47)	(30.65)	(30.65)	(29.70)	(29.70)
Log Land Area	0.3778**	0.3778**	0.3522**	0.3522**	0.3537**	0.3538**
	(78.59)	(78.59)	(88.25)	(88.25)	(85.82)	(85.82)
Other Variables						
Log Distance to River	-0.1781**	-0.1781**	-0.1909**	-0.1909**		
	(-108.61)	(-108.61)	(-39.32)	(-39.32)		
Log Distance to CBD	-0.6292**	-0.6292**	-0.4078**	-0.4079**		
	(-120.95)	(-120.95)	(-23.20)	(-23.20)		
Log Distance to Ocean	-0.3646**	-0.3646**	-0.3183**	-0.3183**		
	(-176.38)	(-176.38)	(-44.80)	(-44.81)		
SA1 Dummies					YES	YES
Year.Quarter Dummies	YES	YES	YES	YES	YES	YES

Spatial Error			0.8816**	0.8816**		
			(204.80)	(204.95)		
R-squared	0.7717	0.7717			0.8944	0.8944
AIC	-4173.8	-4171.9	-18996	-18994	-21040.7	-21039.3
N of Obs	25985					
N of PV Properties	413					

** and * refer to significance level at 1% and 5%.

Table 4 – Test for Spatial Dependencies

Test	OLS		SFEM		OLS repeated		SFEM repeated	
	Test value	**P-value**	**Test value**	**P-value**	**Test value**	**P-value**	**Test value**	**P-value**
Spatial correlation in OLS residuals								
Moran's I statistics standard deviate	249.84	< 2.2e-16	1.51	0.066	11.09	< 2.2e-16	-15.05	1.000
Spatial error dependence								
Lagrange multiplier test	62335.57	< 2.2e-16	2.21	0.138	122.10	< 2.2e-16	226.70	< 2.2e-16
Robust Lagrange multiplier test	62100.59	< 2.2e-16	2.21	0.137	105.64	< 2.2e-16	160.71	< 2.2e-16
Spatial lag dependence								
Lagrange multiplier test	299.29	< 2.2e-16	0.00	0.952	16.56	4.72E-05	66.10	4.44E-16
Robust Lagrange multiplier test	64.32	1.11E-15	0.01	0.915	0.10	0.7572	0.12	0.731
Spatial lag and error dependance (SARMA)								
Lagrange multiplier test	62399.88	< 2.2e-16	2.22	0.330	122.20	< 2.2e-16	226.81	< 2.2e-16

Table 5 – Repeated Sales and Hybrid Models

Dependent Variable: Log (Sale Price 1 / Sale Price 2)	Static OLS		Static GLS		Dynamic OLS		Dynamic SEM		Dynamic SFEM		Hybrid GLS†	
PV Variables												
PV Premium Average	**0.0248 (1.90)**		**0.0282* (2.24)**		**0.0346** (2.82)**		**0.0321** (2.64)**		**0.0282* (2.27)**		**0.0231** (2.82)**	
PV Premium 2009-2010		**-0.0152 (-0.52)**		**-0.0141 (-0.51)**		**-0.0041 (-0.15)**		**-0.0018 (-0.07)**		**-0.0061 (-0.22)**		**0.0013 (0.07)**
PV Premium 2011-2012		**0.0345** (2.37)**		**0.039** (2.76)**		**0.0442** (3.23)**		**0.0404** (2.98)**		**0.0368** (2.64)**		**0.0285** (3.11)**
Structural Variables											YES	YES
Structural Var.s *DeltaT					YES	YES	YES	YES	YES	YES		
Other Variables												
SA1 Dummies											YES	YES
Year.Quarter Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
(Log Distance to River, CBD & Ocean)*DeltaT					YES	YES	YES	YES				
SA1 Dummies*DeltaT									YES	YES		
Spatial Error							0.2599** (10.53)	0.2593** (9.99)				
R-squared	0.8558	0.8558	0.8463	0.8464	0.8728	0.8728			0.8938	0.8938	0.9987	0.9987
AIC	-4808.6	-4811.0	-5926.0	-5932.5	-6684.3	-6682.8	-6781.9	-6779.8	-6334.1	-6338.1	165554	165764
N of Obs.	15169										41154†	
N of PV Properties	258										671	

†Hybrid GLS is a stacked regression model in which the number of observation is the sum of those of a hedonic model and a repeated sales model. The dependent variable is also that of a hedonic model (i.e. Log (Sale Price 1)) and a repeated sales model (i.e. Log (Sale Price 1 / Sale Price 2).

Table 6 – Hedonic Models with PV interacted with Neighbourhood Characteristics

Dependent Variable: Log (Sale Price)	Baseline	Green Share	ALP Share	Daylight Saving No	Prius Share	Bachelor & Above
PV Variables						
PV Dummy	0.0246** (3.06)	0.0116 (0.50)	-0.0446 (-1.47)	-0.0757 (-0.58)	0.0226 (1.16)	0.0294 (1.26)
Neighborhood Var.s * PV Dummy		0.0009 (0.60)	0.0020* (2.37)	0.0021 (0.77)	0.0189 (0.11)	-0.0002 (-0.22)
Joint F for PV Terms		4.86**	7.49**	4.98**	4.69**	4.70**
Other Variables						
Structural Var.s	YES					
Year.Quarter Dummies	YES					
SA1 Dummies	YES					
R-squared	0.8944	0.8944	0.8944	0.8944	0.8944	0.8944
AIC	-21040.7	-21039.0	-21044.6	-21039.3	-21038.7	-21038.7
N of Obs.	25985					
N of PV Properties	413					

Table 7 – To Buy or To Make

	Average Unit Price	Median Size (kw)	Average Price for Median-sized Systems	PV capitalization
Jan.-July 2013	$2.13/watt	3.07	$6,539	$17048 - $30492 for 2011-20112
2012	$3/watt	2.66	$7,980	
2011	$3.9/watt	2.65	$10,335	
2010	$6/watt	2.21	$13,260	$16055 - $24047 for 2009-2012
2009	$9/watt	1.19	$10,710	