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Capitalisation of residential solar photovoltaic systems in Western Australia*

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Due to government financial incentives and falling prices of photovoltaic (PV) systems, solar power has become the fastest growing renewable energy source in Australia. As financial incentives are being reduced or phased out, there is a possibility that adoption of this technology will slow down, thus creating a need for improved policy instruments targeted at adoption of residential PV systems. One of the factors affecting adoption of solar technology in the residential sector is its capitalisation in property values. Yet, the awareness of the capitalisation of PV investments in the Australian property market is limited. Our data indicate that homeowners who anticipate selling their properties in the near future are reluctant to adopt PV systems. This paper presents the first empirical estimate of the property price premiums associated with residential solar PV systems in Australia using residential property sales data from the Perth metropolitan area of Western Australia. An estimated 2.3–3.2 per cent property price premium associated with the PV systems suggests that homeowners fully recover the costs of PV investments upon the sale of their properties. Effective government policy could use this information to encourage adoption of residential PV systems by homeowners.

Key words: Australia, hedonic, photovoltaic, repeated sales, solar panels.

1. Introduction

Globally, the market for solar photovoltaic (PV) systems is evolving rapidly with 89.3 gigawatt (GW) of cumulative PV installations by the end of 2012 (IEA 2013). While PV technology is neither the most efficient way of producing electricity nor the most cost-effective in mitigating carbon emissions (Enkvist *et al*. 2010), its support is often justified on the grounds of other public benefits, including environmental benefits, energy security, technology spillover, scale economy and the creation of green jobs (Borenstein 2012).

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Since the late 2000s, Australia has experienced a sharp rise in PV capacity, by the end of 2012 becoming top 7th global PV market (IEA 2013). By 2013, Australia had over a million roofs with PV systems. In Western Australia alone, the total number has reached over 140,000 – a tenfold increase since 2008 (CER 2013). This development is the result of a combination of natural, economic and policy factors. First, being the continent with the highest average solar radiation, Australia has a high natural potential for producing solar energy. Second, in recent decades Australia has experienced a significant growth in electricity prices. The largest growth has occurred in Western Australia. For example, from January 2009 to December 2012 electricity prices increased by 75 per cent (ABS 2013). Furthermore, the short-lived carbon tax (1 July 2012 to 30 June 2014) has created an expectations of further increase of electricity prices and strengthened the incentive to adopt PV systems to save on energy bills. Third, the PV installation cost has substantially declined over the last few years. The typical turnkey price of a PV system plummeted from roughly \$9000 per kilowatt (kW) in 2009 to a mere \$2130 per kW by mid-2013 (Watt and Passey 2013). Finally, a number of PV supporting programs have been adopted by the federal and state/territorial governments. Since January 2000, the federal government has subsidised the uptake of rooftop PV systems in the residential sector through the Photovoltaic Rebate Program (PVRP), the Solar Homes and Communities Plan (SHCP) and the Solar Credit (SC) programs. In addition, all states introduced PV feed-in tariffs (FITs) in the late 2000s to compensate households for electricity generated by PV systems and supplied to the grid. The FIT typically consists of two parts: government's contribution (a major part) and utility retailer's contribution (a minor part). However, by September 2013 all states and territories except Tasmania had chosen to either substantially reduce the government's contribution to the FITs (Northern Territory) or completely discontinue this contribution (South Australia, Australian Capital Territory, Victoria, Queensland and New South Wales). The Western Australian government announced on 8 August 2013 that it would be reducing the FIT rate (Simpson and Clifton 2015), but following public outrage the decision was repealed (Barnett 2013).

Despite a substantial regulatory and public interest in utilising Australia's abundant solar resource, there are gaps in understanding of why households decide to install solar PV systems. For a homeowner, the decision to adopt a PV system involves comparison of its costs and benefits. The costs include cost of time required to research, installation cost and maintenance cost. The benefits include lowering electricity bills, revenues from exporting excess electricity to the grid and, if a homeowner is environmentally conscientious, the 'warm glow' for reducing greenhouse gas emissions (Andreoni 1990). When a house is sold during the lifetime of a PV system, the owner could be expected to capture the remaining future stream of benefits from the PV system capitalised into the house price (Dastrup *et al*. 2012). If a homeowner is not certain how long he or she will stay in the house, ignoring the capitalisation effect may be a barrier to adoption. Designing effective policy instruments to encourage adoption of residential PV system requires information about the extent to which PV systems are capitalised in the property market. This issue has not been widely subjected to empirical investigation and is addressed in this paper.

The literature on the capitalisation of energy-related green features in property markets demonstrates a considerable willingness of consumers to pay a premium price for properties with desirable energy features such as energy efficiency (Laquatra 1986; Dinan and Miranowski 1989; Eichholtz *et al*. 2010; Brounen and Kok 2011; Dastrup *et al*. 2012; Hoen *et al*. 2013; Kahn and Kok 2013). For instance, Eichholtz *et al*. (2010) investigated the Energy Star and Leadership in Energy and Environmental Design (LEED) status of commercial buildings in the United States and estimated a substantial premium to the rental and the selling prices respectively. Commercial buildings with a LEED and/or Energy Star label attract about three to six per cent higher rent, and the selling price premium can be as much as 16 per cent. They also show that the return on property investments of green buildings relative to those of comparable quality is quite robust and has not been significantly affected by the increasing supply of green buildings and recent volatility in the property market. Similarly, Brounen and Kok (2011) found that residential energy efficiency certification is capitalised into Dutch residential home prices. However, relatively little empirical research exists on the capitalisation of PV systems into property values, with none outside the United States. The only two existing US studies, Dastrup *et al*. (2012) and Hoen *et al*. (2013), have both examined the Californian property market and found significant premiums for homes with PV systems.

Despite rapid penetration of rooftop PV systems in the Australian residential sector, there have been no studies on the capitalisation of PV systems in property values. This study aimed to fill this gap in the empirical literature. Using high-resolution aerial photographs and a large sample of property sales data from Perth, Western Australia, it provides the first systematic estimate of property price premiums associated with PV systems in Australia. Estimates from several models (hedonic, repeated sales and hybrid) consistently provide the evidence that PV systems add premiums to property prices at a range of 2.3–3.2 per cent. Comparison of these premiums with the costs and present values of benefits generated by PV systems under different incentive schemes suggests that home owners are able to fully recover costs of investments in PV systems upon the sale of their properties.

The next section of this paper briefly reviews the related literature on the capitalisation of PV systems in the property market. Section 3 presents three empirical models (hedonic, repeated sales and hybrid) that were used to estimate PV premiums capitalised in property prices. Section 4 describes the data and provides the descriptive statistics of the variables used in the models.

Section 5 presents and discusses the empirical results, and Section 6 concludes the paper.

2. Solar photovoltaic premiums

Australian consumers who have installed PV systems have certainly taken into account their capitalisation potential. In a survey of 497 PV system adopters in Western Australia and New South Wales, Ma and Burton (2013) found that an 'increase in property value' was rated as the second most important factor, only after 'saving money from reduced electricity bills'[1] for adopting PV systems. Consumers' expectations of the capitalisation effect of PV systems have also been picked up by the property market as real estate agencies have started to include the presence of PV systems as one of the eco-friendly features in their property advertisements[2] . However, there has been no systematic analysis about whether and to what extent these expectations have been realised in the market.

It is relatively easy to have PV systems installed at any time; therefore, a homebuyer who wants to live in a home with a PV system can effectively choose between the option to 'install' or to 'buy'. Buying a home without a PV system and paying a retailer to install a PV system represents an 'install' option, while buying a PV system-installed home represents a 'buy option'. The choice between the two options should impose cross-constraints on the size of the capitalisation effect (Dastrup *et al.* 2012). However, the premium under a 'buy' option is not necessarily equal to the installation cost under an 'install' option. Firstly, consumers in the property market may not have complete information on PV system costs. The impact of incomplete information on the realised premium is, thus, uncertain. Secondly, at any point in time there are never two identical properties with and without a PV system. A property bundles a range of diverse features such that properties are only close substitutes at the margin (Rosen 2002). Lastly, Western Australia previously introduced a short-lived FIT scheme (from August 2010 to July 2011), which has been suspended and is no longer available for new PV installations. When the scheme was available, PV property owners could sign up to the government's FIT contract which allows customers to receive a net tariff of 40 cents or 20 cents per unit of electricity over a 10-year period. The contract can be carried over to the new owner upon sale of the property. The change in FIT policy makes an old PV system which carries such a contract superior to a new installation.

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[1] Ma and Burton (2013) identified six factors in order as: saving money from reduced electricity bill, increasing your property's value, reduction of greenhouse gas emissions, interest in the new technology, a statement about myself (e.g. being environmentally friendly) and increasing the reliability of your electricity supply.

[2] Eco-friendly features, such as water heater, water tank, grey water system and energy efficiency rating, are now listed as search options in Australia's top residential property website realestate.com.au.

3. Empirical specification

3.1 Hedonic model

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

$$\mathrm{Log}(\mathrm{Price}_i) = \alpha \mathrm{PV}_i + \boldsymbol{\beta} \boldsymbol{x}_i + \gamma \boldsymbol{y}_i + \boldsymbol{\delta} \boldsymbol{z}_t + \varepsilon_i \tag{1}$$

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

The coefficient α is used to calculate the PV premium as a percentage of the property price. In a semi-log model, the percentage contribution, p, is calculated as $p = \exp(\alpha) - 1$ (Halvorsen and Palmquist 1980). In Eqn (1), a constant PV premium across the whole market is assumed, which can be relaxed to capture temporal dynamics through an interaction term with time. The error term ε_i consists of a random component and possibly a specification error component.

Property sales data often exhibit spatial dependencies due to spatially correlated omitted variables, measurement errors, or the influence of observed prices of neighbouring properties that have been sold. The presence of spatial dependencies can cause bias, inconsistency or inefficiency in coefficient estimates when the ordinary least squares (OLS) method is used (Anselin 1988). Therefore, residuals of the OLS model need to be tested for the presence and type of spatial dependencies in the data to select the appropriate model.

3.2 Repeated sales model

A repeated sales (RS) model measures the average PV capitalisation as the average difference between the price appreciations of properties with PV system installed between consecutive sales and properties with no PV system installed in the same period. A static RS model assumes constant implicit prices and spatial heterogeneity across the two sales:

$$\mathrm{Log}(\mathrm{Price}_{i(t+\Delta t)}) = \alpha \mathrm{PV}_{i(t+\Delta t)} + \beta x_{i(t+\Delta t)} + \gamma y_i + \delta z_{(t+\Delta t)} + \varepsilon_{i(t+\Delta t)} \tag{2a}$$

$$\mathrm{Log}(\mathrm{Price}_{it}) = \alpha \mathrm{PV}_{it} + \beta x_{it} + \gamma y_i + \delta z_t + \varepsilon_{it} \tag{2b}$$

Table 1 Summary statistics (truncated sample)

Variables	Definition	Sales without PV system (n = 25,557)				Sales with PV system (n = 413)			
		Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
Price 1	Property price for the latest sale ($1000)	828	466	305	3500	827	447	325	3400
Price 2	Property price for previous sale ($1000)	451†	340†	60†	2350†	457‡	318‡	80‡	1900‡
Delta T	Time between consecutive sales (years)	8.29†	5.46†	0.008†	60.99†	8.32‡	5.17‡	0.61‡	23.61‡
Bed room	Number of bedrooms	3.18	0.85	1	7	3.35	0.82	1	6
Bath room	Number of bathrooms	1.54	0.64	1	14	1.67	0.60	1	4
Other room	Number of other rooms	3.83	1.47	2	28	4.27	1.42	2	8
Brick wall	1 for properties with brick walls	0.86	0.34	0	1	0.87	0.33	0	1
Tile roof	1 for properties with tile roof	0.81	0.39	0	1	0.81	0.39	0	1
Carport	Number of car ports	0.54	0.76	0	7	0.59	0.86	0	5
Garage	Number of garages	0.88	0.89	0	7	0.94	0.96	0	4
Pool	1 for properties with a swimming pool	0.22	0.41	0	1	0.28	0.45	0	1
House age	Age of property (years)	37.90	25.27	0	139	34.05	25.23	0	112
Log land area	Log of reported land area (m^3)	6.41	0.39	4.66	9.68	6.42	0.36	5.3	7.69
Log driving time to river	Log of driving time to the Swan River (min)	1.35	0.92	−2.30	2.69	1.39	0.85	−1.83	2.63
Log Driving time to CBD	Log of driving time to the Perth CBD (min)	2.32	0.35	0.72	3.03	2.40	0.33	1.47	2.97
Log driving time to ocean	Log of driving time to the Indian ocean (min)	2.03	0.78	-2.10	2.97	2.04	0.77	−1.45	2.94

Note †n = 14,906; ‡n = 258.

where Price_{it} and $\text{Price}_{i(t+\Delta t)}$ are the property prices of consecutive sales at time t and $t + \Delta t$. An RS model is derived by subtracting Eqn (2b) from Eqn (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 the hedonic model is time invariant and correlated with other model variables, then a RS model has an advantage over the hedonic model as the error drops out in subtracting. A static RS specification then becomes:

$$\text{Log}\left(\frac{\text{Price}_{i(t+\Delta t)}}{\text{Price}_{it}}\right) = \alpha\Delta\text{PV}_{i(t+\Delta t)} + \delta\tilde{z}_{(t+\Delta t)} + \tilde{\varepsilon}_{i(t+\Delta t)} \tag{3}$$

where $\Delta\text{PV}_{i(t+\Delta t)}$ indicates the installation of PV systems between the two sales and the vector $\tilde{\boldsymbol{z}}_{t+\Delta t}$ is equal to $\boldsymbol{z}_{t+\Delta t} - \boldsymbol{z}_t$. The model can be estimated using 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 generalised least squares (GLS) model can be used in the presence of heteroscedastic OLS errors.

The assumption of constant implicit prices may be valid for repeated sales that occur within a short period 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 due to changes in tastes and the relative scarcity of property characteristics (Case and Quigley 1991). The average time span between the consecutive sales in our sample is 8 years with the largest span reaching 23 years. In such cases, a dynamic RS model allowing varying implicit prices would be appropriate as specified below.

$$\text{Log}(\text{Price}_{i(t+\Delta t)}) = \alpha\text{PV}_{i(t+\Delta t)} + \beta_{(t+\Delta t)}x_{i(t+\Delta t)} + \gamma_{(t+\Delta t)}y_i + \delta z_{(t+\Delta t)} + \varepsilon_{i(t+\Delta t)} \tag{4a}$$

$$\text{Log}(\text{Price}_{it}) = \alpha\text{PV}_{it} + \beta_t x_{it} + \gamma_t v_i + \delta z_t + \varepsilon_{it} \tag{4b}$$

The simplest specification that allows linear dynamics of the implicit prices, where $\boldsymbol{\beta}_{(t+\Delta t)} - \boldsymbol{\beta}_t = \tilde{\boldsymbol{\beta}}(\Delta \boldsymbol{t})$ and $\gamma_{(t+\Delta t)} - \gamma_t = \tilde{\gamma}(\Delta t)$, gives the following dynamic RS specification:

$$\text{Log}\left(\frac{\text{Price}_{i(t+\Delta t)}}{\text{Price}_{it}}\right) = \alpha\Delta\text{PV}_{i(t+\Delta t)} + \tilde{\beta}(\Delta t)x_i + \tilde{\gamma}(\Delta t)y_i + \delta\tilde{z}_{(t+\Delta t)} + \tilde{\varepsilon}_{i(t+\Delta t)} \tag{5}$$

3.3 Hybrid Model

Both the hedonic model and the repeated sales model have their advantages and disadvantages. The hedonic model requires detailed information about property characteristics, while the repeated sales model requires information on two consecutive sales of the same property, which limits the number of observations. A hybrid model developed by Case and Quigley (1991) and extended by Fogarty and Jones (2011) combines the desirable aspects of the hedonic and repeat sales models. As the possible specification error of the component is unidentified in the hedonic model, the hybrid model uses repeated sales information to identify this specification error and allows more efficient estimation. The hybrid model can be specified as follows. Let $i \in \{1, \ldots, I\}$ be the subset of properties that were sold only once during the sample period and $j \in \{1, \ldots, J\}$ be the subset of properties that had repeated sales. By breaking down the total error ε_{it} in Eqn (1) into a random term e_{it} and a specification error term φ_i, Eqn (1) can be modified for the first sale, second sale and single sale hedonic models separately:

$$\mathrm{Log}(\mathrm{Price}_{it}) = \alpha \mathrm{PV}_{it} + \beta X_{it} + \gamma Y_i + \delta Z_t + \varphi_i + e_{it} \tag{6a}$$

$$\mathrm{Log}(\mathrm{Price}_{jt}) = \alpha \mathrm{PV}_{jt} + \beta X_{jt} + \gamma Y_j + \delta Z_t + \varphi_j + e_{jt} \tag{6b}$$

$$\mathrm{Log}(\mathrm{Price}_{j(t+\Delta t)}) = \alpha \mathrm{PV}_{j(t+\Delta t)} + \beta X_{j(t+\Delta t)} + \gamma Y_j + \delta Z_{(t+\Delta t)} + \varphi_j + e_{j(t+\Delta t)} \tag{6c}$$

Assuming constant implicit prices, the hybrid model can be derived by subtracting Eqn (6b) from Eqn (6c) and replacing Eqn (6c) with the repeated sales equation:

$$\mathrm{Log}\left(\frac{\mathrm{Price}_{j(t+\Delta t)}}{\mathrm{Price}_{jt}}\right) = \alpha \mathrm{PV}_{j(t+\Delta t)} + \delta \tilde{Z}_{(t+\Delta t)} + e_{j(t+\Delta t)} - e_{jt} \tag{6d}$$

The system of the three equations formed by (6a), (6b) and (6d) can be estimated as a single stacked model. Because of the apparent nonspherical error structure, the covariance matrix associated with the hybrid model was estimated first, and then, the final model was estimated using GLS.

4. Study area and data

The choice of the study area was guided by previous hedonic studies of property values in the same region (Pandit *et al.* 2013, 2014), but the coverage was extended to approximately 453.75 sq. km around the city of Perth in Western Australia (Figure 1). The study area expands across 125 suburbs in the central part of Perth metropolitan area.

Property sales data for the period of 2009–2012 were acquired from Landgate, a statutory authority that maintains the official register of Western Australia's land ownership and survey data. Our analysis focuses on single family houses within the predefined study area (Figure 1). The data contain

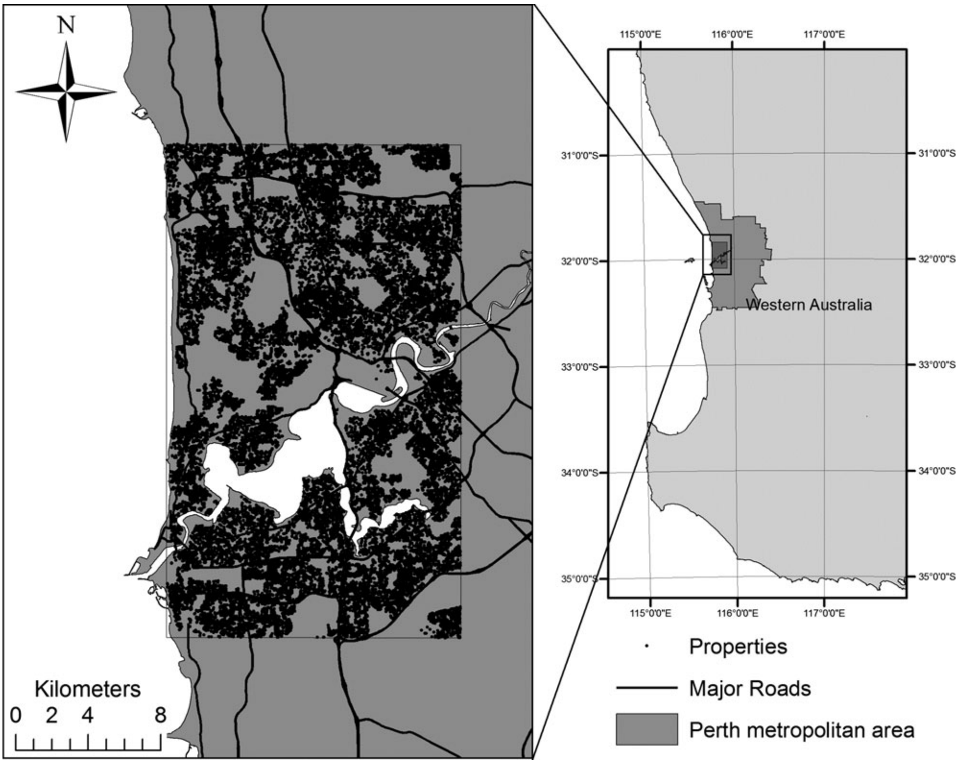

Figure 1 Study area with property locations.

the most recent sale price and structural characteristics. It also has information on previous sales if the property had been transacted multiple times. The most recent update of the cadastral map, which allows delineating property boundaries, spatially referencing sample properties and matching identified PV systems, was retrieved from Landgate's Shared Land Information Platform. To capture the influence of locational characteristics, the travel time from each property to the Perth Business District (Perth Council House), the Indian Ocean and the Swan River was calculated following the designated road speed on motorways using Network Analyst for ArcGIS 10.0 (ESRI, Redlands, CA, USA). Table 1 presents variable descriptions and summary statistics.

To identify the presence of PV systems on the properties sold within the study area, we used high-resolution aerial photographs provided through Web Map Service (WMS) by NearMap (www.nearmap.com), which are updated on a monthly basis. First, the latest aerial photographs dated early 2013 were overlaid with the cadastral map of the study area, and properties with PV system were visually identified and recorded. There are 25,268 such properties within the study area. According to the 2011 Census, there are about 212,000 houses, duplexes and villas in the study area. This implies a penetration rate of approximately 12 per cent, which is consistent with the

Table 2 Proportion of properties with PV in study area

Year	Proportion of dwellings with PV systems in study area	
	Among all detached and semi-detached houses† (%)	Among sold houses (%)
2009	N/D	0.2
2010	4.1	0.9
2011	9.8	2.0
2012	13.8	3.3

Note †Sources: (ABS 2011; CER 2015).

penetration rate in Western Australia by late 2012. Second, properties with PV systems were matched with property sales data, and the presence of a PV system prior to the latest sale was verified using an aerial photograph with the date closest to the date of sale of the property. The sizes of PV systems (number of panels) were also recorded, providing the ability to test whether the size has a nonconstant return to scale[3] effect. There are 413 properties with a PV system installed prior to the latest sale out of 25,970 sold properties (Table 1). This indicates that the average proportion of houses sold with PV systems is substantially lower than PV penetration in the residential sector, which is consistent with the previous literature (Dastrup *et al*. 2012; Hoen *et al*. 2013). Because of the sharp increase in residential PV adoption during the study period, we compared the proportion of houses sold with PV system in our sample with the proportion of PV properties in the study area by year (Table 2). They show similar trends; however, the proportion of houses sold with PV systems is four to five times lower than the PV penetration rate in residential sector in respective years. This indicates that homeowners who anticipate selling their properties in the near future are much less likely to adopt PV systems.

As shown in Table 1 and Figure 2, the distribution of property prices is right-skewed for properties both with and without PV systems; however, the distribution of property prices for PV-installed properties is much less skewed. There are no PV property observations in the sample at the high end of the property market. On the other hand, the lowest property price in our sample is merely $37,000 for a 3-bedroom property on 700 square metres of land, which is likely to be an outlier. To account for possible outliers, the bottom and top 1 per cent of the sample's distribution were truncated[4] .

[3] The number of panels was initially included in all models as an indicator of the size of the PV system; however, the variable was not significant. It did not add any useful information in addition to the absence/presence of the PV system. The possible reasons are measurement error and variability on the capacity of PV panels. This variable was removed from the models presented in the paper.

[4] To further account for skewness, we also estimated all models with the bottom and top 5 per cent of the sample's distribution truncated. The two truncated samples produce consistent estimates on the PV premium. We have chosen to report results from the 1–99 per cent truncated sample. The results from the 5–95 per cent truncated sample are also available from the authors upon request.

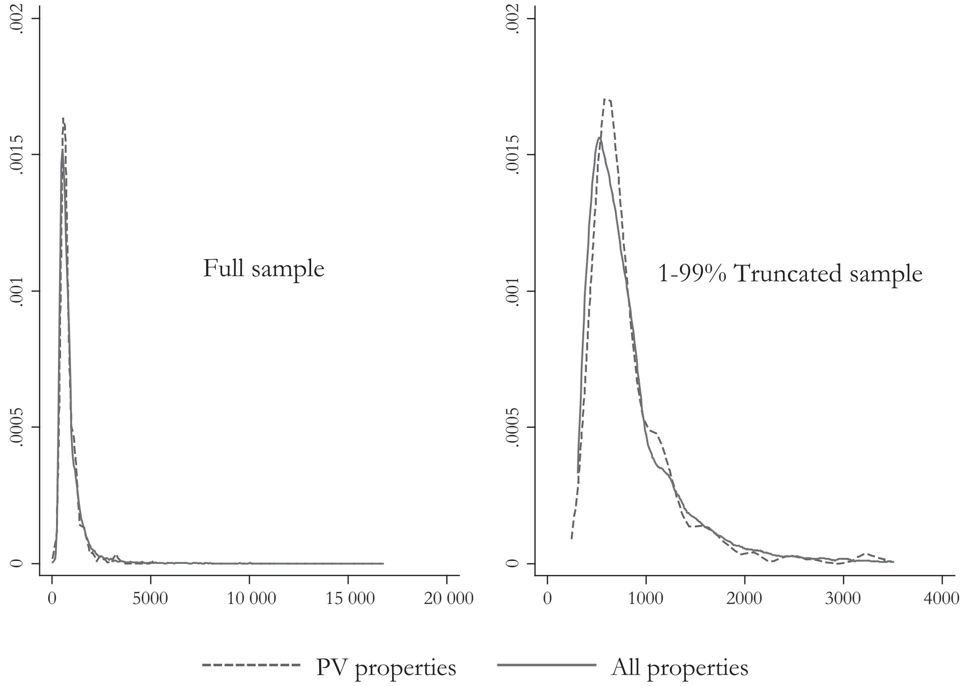

Figure 2 Distribution of property prices ($1000).

Fifteen property observations with tennis courts were also dropped as none of this subset of properties had PV systems installed. This gives a data set of 25,970 property sales, including 413 with PV systems. The data set also contains 15,164 properties with repeated sales information. Table 1 also shows that PV-installed properties are larger than those with no PV. They have more bedrooms, bathrooms, other rooms, carports and garages. Furthermore, they are slightly newer and more likely to have a pool.

5. Results and discussion

5.1 Hedonic model results

The dependent variable in the hedonic model is the CPI-adjusted latest sale price of the properties. To determine the appropriate functional form for the hedonic price function, a Box–Cox test was used that resulted in a function with a natural log-transformed dependent variable. Explanatory variables representing driving times to major amenities (CBD, ocean and river), as well as land area, were also log-transformed. To test for the presence of the spatial dependencies in the residuals of the OLS model, a 25-nearest-neighbours-based spatial weight matrix was used. As evidenced by Moran's I statistic, the result indicates a clustering pattern in the OLS residuals (Table 3). Following the results of LM and RLM tests (Anselin *et al.* 1996) that indicate the

Table 3 Test for spatial dependencies

Test	OLS		SFEM		OLS repeated		SFEM repeated	
	Test statistic	*P*-value	Test statistic	*P*-value	Test statistic	*P*-value	Test statistic	*P*-value
Spatial correlation in OLS residuals								
Moran's I statistics standard deviate	249.84	<2.2e-16	1.41	0.080	11.09	<2.2e-16	−8.41	1.000
Spatial error dependence								
Lagrange multiplier test	62335.57	<2.2e-16	1.91	0.167	120.74	<2.2e-16	71.06	<2.2e-16
Robust lagrange multiplier test	62100.59	<2.2e-16	1.91	0.167	105.06	<2.2e-16	57.32	<3.71e-14
Spatial lag dependence								
Lagrange multiplier test	299.29	<2.2e-16	0.00	0.948	15.75	7.24E-05	13.75	2.09E-04
Robust Lagrange multiplier test	64.32	1.11E-15	0.01	0.983	0.06	0.7572	0.01	0.927
Spatial lag and error dependence (SARMA)								
Lagrange multiplier test	62,399.88	<2.2e-16	21.91	0.385	120.81	<2.2e-16	71.06	<3.33e-16

Table 4 Hedonic model results (Dependent variable: Log (Price 1))

Variables	SEM	SFEM
PV variables		
PV premium	0.0297** (3.71)	0.0247** (3.07)
Structural variables		
Bed room	0.0318** (18.43)	0.0312** (17.84)
Bath room	0.0818** (32.91)	0.0782** (31.02)
Other room	0.0161** (14.41)	0.0154** (13.49)
Brick wall	0.0078 (1.91)	0.0040 (0.98)
Tile roof	−0.0303** (−9.98)	−0.0291** (−9.48)
Carport	0.0062** (3.41)	0.0057** (3.11)
Garage	0.0415** (24.25)	0.0405** (23.42)
Pool	0.0678** (25.16)	0.0694** (25.53)
House age	−0.0069** (−34.41)	−0.0069** (−33.77)
House age squared	0.0001** (30.62)	0.0001** (29.67)
Log land area	0.3520** (88.18)	0.3534** (85.77)
Other variables		
Log driving time to River	−0.1907** (−39.25)	-
Log driving time to CBD	−0.4071** (−23.16)	-
Log driving time to ocean	−0.3180** (−44.77)	-
SA1 dummies	-	YES
Year.Quarter dummies	YES	YES
Spatial error	0.8816** (204.90)	NA
R-squared	NA	0.8942
AIC	−19,005	−21,061
N of Obs.	25,970	25,970
N of PV properties	413	413

Note ** and * refer to significance level at 1 per cent and 5 per cent. Figure in the parenthesis indicates *t*-statistic.

presence of a much more prominent spatial error dependency, a spatial error model (SEM) was estimated (Table 4). Alternatively, following Zhang *et al.* (2015), a spatial fixed-effect model (SFEM) that uses Statistical Areas Level 1 (SA1s[5]) as a fixed effect was estimated to control for unobserved neighbourhood and location amenities and spatial dependencies (Table 4). Our model specification has a limited number of environmental and locational attributes; however, both SFEM (Kuminoff *et al.* 2010) and SEM (Polyakov *et al.* 2015) are able to control for unobservable spatial characteristics.

The SEM has better fit than the OLS model with a highly statistically significant spatial error coefficient. However, the SFEM provides a better fit than the SEM (Table 4). Moran's I test for spatial dependency indicates a clustering pattern in SFEM residuals only at the 10 per cent level, while the LM and the RLM tests do not indicate the presence of any spatial dependencies (Table 4).

The PV capitalisation effect ('PV Premium Average') has the expected sign but is statistically insignificant in the baseline model. This effect becomes

[5] The SA1s are the second smallest statistical units under the new Australian Statistical Geography Standard (ASGS) and have an average population of 400 persons.

statistically significant once spatial dependencies are controlled for in SEM and SFEM. The magnitudes of effects are consistent between SEM and SFEM and indicate a PV premium of 2.3–3.2 per cent on average.

5.2 Repeated sales and hybrid model results

Table 5 provides regression results of the repeated sales and hybrid models. The static RS model assumes constant implicit prices over time. Thus, all structural and locational variables drop out. It is possible 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 heteroscedasticity in the error term. A 3-stage GLS model was estimated where observations in the final stage were weighted based on the fitting of first-stage residuals on linear and quadratic specifications for time between the two sales (Δt).

The dynamic RS model assumes that implicit prices of structural variables change linearly with time. Tests for spatial dependencies (Table 4) indicate the presence of spatial error dependency but no spatial lag dependency in the presence of spatial error. Thus, SEM and SFEM were estimated for the dynamic RS model (Table 5). Moran's I and RLM tests indicate the presence of spatial error dependence which seems to suggest that SFEM overcorrected

Table 5 Repeated sales and hybrid model results

Variables	Repeated sales model			Hybrid GLS model†
	Static GLS‡	Dynamic SEM‡	Dynamic SFEM‡	
PV premium	0.0282* (2.24)	0.0320** (2.64)	0.0282* (2.27)	0.0232** (2.82)
Structural variables	-	-	-	YES
Structural Var.*Delta T	-	YES	YES	-
Other variables				
SA1 dummies	-	-	-	YES
Year.Quarter dummies	YES	YES	YES	YES
(Log Dist. Amenities)* Delta T	-	YES	-	-
SA1 dummies*Delta T	-	-	YES	-
Spatial error	NA	0.2587** (10.39)	NA	NA
R-squared	0.8463	NA	0.8938	0.9987
AIC	−5923	−6777	−6329.5	165,699
N of Obs.	15,164	15,164	15,164	41,139‡
N of PV properties	258	258	258	671

Note ** and * refer to significance level at 1 per cent and 5 per cent. Figure in the parenthesis indicates *t*-statistic. †Hybrid GLS is a stacked regression model in which the number of observations 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). ‡The dependent variable for all repeated sales models is Log (Price 1/Price 2).

spatial autocorrelation. Furthermore, the Akaike Information Criteria (AIC) also show SEM is superior to SFEM for the dynamic RS model.

The hybrid GLS model estimates a stacked equation system. Consequently, the observations were also stacked resulting in an augmented 41,154 total observations and 671 PV property observations.

Both RS models and hybrid models show strong evidence of a PV capitalisation effect (Table 5). The dynamic SEM provides the best model fit among all RS models. The PV premium estimates vary from 2.32–3.20 per cent depending on the model specifications. The PV premium estimate in the hybrid model is slightly smaller than the repeated sales model estimates[6] .

5.3 To Buy or to install

The results in Tables 4 and 5 demonstrate that property price premium associated with a PV system ranges between 2.32 and 3.20 per cent. Based on this range, a PV system adds between \$16,124 and \$22,240 to the value of a median-priced (\$695,000) home. We compare this range of values with the costs and benefits of a typical PV system (Table 6).

To calculate the costs, we use average turnkey price of a typical PV system on the market. Medium sizes of installed residential PV systems for each year of the sample period are calculated using data provided by the Clean Energy Regulator. Unit turnkey prices \$(/Wp) for 2009–2012 are sourced from Watt and Passey (2013). These prices are discounted by the value of the Small-scale Technology Certificate (STC). The costs presented in Table 6 do not include the charges of a grid connection and meter upgrade. Furthermore, installing a PV system involves transaction costs such as searching for the best deals, checking eligible financial incentives and negotiating tariff contracts with the utility company.

The benefits of a PV system consist of (i) savings due to reduction of electricity consumption from the grid and (ii) buyback or FIT payments for the electricity exported to the grid. To calculate the benefits, we assumed that average household consumption is 7100 kWh pa (CEC 2014). We further assumed that on an ‘average’ day, a PV system produces equivalent to 3.5 h of electricity at PV capacity, of which 2.0 h equivalent is used to reduce electricity consumption from the grid and 1.5 h equivalent is exported to the grid (Burtt and Dargusch 2015). There are several schemes of paying owners of PV systems for exported electricity. The default buyback electricity rate is

[6] The PV premium may be heterogeneous across market segments and over time. Although not reported here, we have also examined the heterogeneous premium across different market segments. We expect that the absolute marginal contribution of a PV panel to a property price 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 estimated all our models on 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 PV premium in the low-end market but a smaller capitalisation effect in the high-end market. These results are available from the authors upon request.

Table 6 PV capitalisation in the housing market

Year	Average unit price ($/W)	Median size of a system (kW)	Average price for a median-sized system ($)†	NPV‡ with Buyback at 7.13 c/kWh	NPV‡ with Buyback at 7.13 c/kWh and FIT at 20 c/kWh	NPV‡ with Buyback at 7.13 c/kWh and FIT at 40 c/kWh	PV capitalisation§
2009	$9.0	1.19	$10,710	$3993	NA	NA	-
2010	$6.0	2.21	$13,260	$8329	$10,750	$13,805	-
2011	$3.8	2.65	$10,335	$10,717	$13,618	$17,283	-
2012	$3.0	2.66	$7980	$11,553	$14,466	$18,144	$16,124 ~ $22,240

Note †Average price for median-sized system ($) = Average unit price ($/Watt)*Median size of system (kW)*1000. ‡Assuming a 5 per cent discount rate, a 5 per cent annual increase in electricity prices, a 20-year life of PV systems and 10-year FIT contracts. §PV capitalisation ($) = Median property price ($695,000)*PV premium (per cent). The range corresponds with largest and smallest expected PV premiums across all models.

7.13 c/kWh. In addition, the government introduced the residential net FIT scheme, which is a subsidy encouraging the use of renewable energy systems. The scheme was open to applications on 1 July 2010 and ended on 1 August 2011. Residential customers who applied to become qualified FIT customers before 30 June 2011 and had their system approved by 30 September 2011 receive FIT 40 c/kWh. The customers who applied after 30 June 2011 or had their system approved after 30 September 2011 receive FIT 40 c/kWh from 1 July to 9 December 2011 and 20 c/kWh after 10 December 2011. A customer who moves into a premise that qualified for a FIT is qualified for the same tariff. This means that purchasing a house with a PV system and a FIT contract after the scheme was suspended has greater benefit than purchasing a similar house and installing a new PV system. About half of all existing residential PV systems in WA are signed up to the government scheme. However, we do not have information on which PV systems in our sample had a FIT contract. Therefore, we calculated present value of the benefits generated by a PV system using electricity savings and three possible options of being compensated for exporting excess electricity to the grid: buyback at 7.13 c/kWh, FIT at 20 c/kWh and FIT at 40 c/kWh (Table 6). In 2010 and 2011, the present value of a PV system without FIT was similar to the cost of installation. In 2012, the cost of installation was lower than the present value of a PV system and substantially lower than the present value of a system with FIT. The estimated range of PV capitalisation is comparable with the present value of a PV system with FIT. It is likely that a substantial number of houses sold with PV systems in our sample were also sold with the FIT contract at 40 c/kWh.

In closely related studies from the United States, Dastrup *et al.* (2012) and Hoen *et al.* (2013) both found that property owners in California, on average, fully recover the costs of installing PV systems upon the sale of the property. The findings of the present study suggest that property owners in Western Australia upon the sale of their properties not only fully recover costs of PV investments, but also are able to capture windfalls generated by the FIT contracts (Kwon 2015). The PV premiums could change over time. In general, the older the system becomes, the less value it would add to the property. The time frame of our study coincides with the rapid growth of the PV market in Australia; therefore, the premiums reported in this study largely reflect the values of new PV systems. Furthermore, the capitalisation effect could be influenced by changes in policy parameters. For instance, removal of the carbon tax will reduce residential electricity price from roughly 27 cents per unit to 24.6 cents per unit in the study area, which is likely to lower the PV premiums. In order to investigate dynamics of the PV premiums and the influences of changing policy parameters, a larger data set of properties with PV installed at different times over a longer period would be required.

6. Conclusion

Discussions about policy design to encourage investments in green technologies such as PV systems in residential sector are focused on private and public benefits of a technology and often ignore the fact that a substantial fraction of residential properties are transacted annually. The adoption of such technologies by homeowners who anticipate selling their properties in the near future depends on whether homeowners perceive investments in PV being capitalised in property values. While there has been research on capitalisation of green technologies, including PV systems, elsewhere (Dastrup *et al.* 2012; Hoen *et al.* 2013), the extent to which investment in PV systems has been capitalised in the Australian property market has not been studied. Using a comprehensive set of property sales data from Perth, Western Australia, this study finds strong evidence that residential properties with PV systems attract a premium of 2.3–3.20 per cent. This corresponds to a capitalisation of \$19K $\pm$ \$3K (\$16,124–\$22,240) for a median-priced property. There is a chance that this effect is inflated due to omitted variables correlated with the presence of PV panels, such as investment in renovation. However, these results are generally consistent across hedonic, repeated sales and hybrid models and with different controls for spatial autocorrelation (SEM or SFEM).

The estimated capitalisation of PV systems implies at least a full return on PV investment. Furthermore, PV systems that carry government FIT contracts appear to be superior to new installations and the sellers are able to capture rents associated with FIT contracts. However, judging from the low proportion of PV systems among the properties being sold (3.3 per cent) in comparison with the PV penetration in the property market (13.6 per cent) in the study area in 2012, it appears that homeowners who anticipate selling their properties in the near future hesitate to invest in PV systems. This finding had not been reported in the literature before. One possible reason for this is a lack of awareness about capitalisation of investment in PV systems in property values.

Our results have significance for the government to improve residential renewable energy policy instruments and for the PV retailers to better target potential customers. The government policies are focusing on economic instruments such as subsidies and FITs. Informing potential PV adopters about the fact that investment in a PV system is recouped upon the sale of the property would encourage additional households to consider the adoption of a PV system. Similarly, PV retailers could use this information to improve their marketing strategies for targeting the most promising market areas.

There are a number of important questions that could not be addressed in this paper but warrant further research in the future. Given a strong incentive from the private property market, what would be the optimal level of government subsidy? What is the contribution of PV-generated power to the peak loads (i.e. how much has the government benefited from the reduced investment in reserve capacity through PV programs?). It is also important to explore the dynamic nature of the PV premiums and how various government programs have influenced the dynamics. As shown in Table 1, there are substantial differences in the attributes of the houses with and without PV systems. An important policy issue to be addressed is the distributional effects of the various subsidy programs. The present study is limited in time span (2009–2012) and geographic coverage (Perth) in Australia. Given the increased market share of PV systems in Australia, it would be ideal and relevant to examine how the premium dynamics change over a longer time and across multiple locations within Australia using more recent data.

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