# VALUATION OF AUSTRALIA'S GREEN INFRASTRUCTURE: HEDONIC PRICING MODEL USING THE ENHANCED VEGETATION INDEX

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ABSTRACT –

The benefits of a robust green infrastructure network are frequently overlooked by policy makers. Hence, there is a need to assign a monetary value to green infrastructure. The Hedonic Pricing Model is used in conjunction with Australian property sales to indirectly determine an implicit price property owners are willing to pay for green infrastructure in their postcode. The Enhanced Vegetation Index (EVI) aggregated annually at postcode level is used as a proxy for green infrastructure. To address endogeneity issues due to the EVI regressor, the Instrumental Variable approach is implemented using precipitation data as the instrument. Using clustered standard errors at postcode-year level a one standard deviation increase in EVI leads to increases in housing prices of 8.62% using year fixed effects and 15.57% using state-year fixed effects. For an average house this translates to an increase of $32,139.23 and $57,991.41.

## INTRODUCTION -

It would be hard to imagine a typical Australian suburb devoid of parks, trees and urban greenery. The value of this "green infrastructure" is well-recognised in modern Australian society. However, policy makers generally do not fully understand the costs and benefits of green infrastructure. Furthermore, most of the green infrastructure is a public good and therefore non-excludable and non-rivalrous. As a result there is typically a market failure due to a sub-optimum level of private investment in urban green infrastructure (Choumert & Salanié, 2008). Hence, there is a need to value environmental assets to quantify monetarily the benefits of improvements in green infrastructure. Wolf (2004) stated that "Green infrastructure… in cities should be administered in an integrated way, just as grey infrastructure (i.e. roads, power, water etc.) systems have been".

Green infrastructure comprises "all natural, semi-natural and artificial networks of multifunctional ecological systems within, around and between urban areas" (Tzoulas et al., 2007). Essentially, green infrastructure is the aggregate of all urban vegetation including environmental assets such as parks, trees and backyards (Cameron et al., 2012). It is assumed that the bulk of utility derived by consumers from green infrastructure is a non-use value and therefore non-tradable. Due to this property of non-tradability, stated preferences cannot be observed easily. This motivates the use of an indirect method of valuation, namely the Hedonic Pricing Method (HPM), to measure the value of green infrastructure through Australian property prices. Essentially, the HPM determines property owners' willingness to pay for the benefits of green infrastructure. The need to value ecosystems is essential in order to address the issues that relate to improving green infrastructure (Schäffler & Swilling, 2013).

Green infrastructure plays a vital role in reducing pollution, minimising the effects of climate change, limiting the heating of metropolitan areas (heat island effect), encouraging ecological diversity and sustainable economic growth (Gill, Handley, Ennos, & Pauleit, 2007; Sandström, Angelstam, & Mikusiński, 2006). This was outlined by Chen and Warren (2011) who emphasised the urgent need for expenditure on green infrastructure in China to enable sustainable economic growth and increasing living standards. Gill et al. (2007) analysed the benefits of increasing green infrastructure with respect to reducing the impact of climate change in Australia. Gill et al. also outlined the benefits of green infrastructure networks during times of drought, an important issue given Australia's long history of susceptibility to droughts. There are flow on effects from improved green infrastructure. In Georgia, USA, the mere presence of trees increased housing prices by approximately 4.5%, which had the subsequent effect of increasing tax revenue for the city by roughly 0.46% of the budget (Anderson & Cordell, 1988). Furthermore, cities of all sizes derive benefits from green infrastructure including cities experiencing rapid growth and towns with a declining population (Chen & Warren, 2011; Schilling & Logan, 2008).

There is substantial research with respect to green infrastructure's role in improving the health of society. A robust green infrastructure network decreases the severity of heat waves and improves air quality within cities, resulting in improvements in public health (Rosenzweig, Solecki, & Slosberg, 2006). Heat waves have been occurring at an increasing rate in the 21st century causing major health concerns, particularly among the elderly (Meehl & Tebaldi, 2004). Mitigating heat waves through green infrastructure can significantly improve social utility. There is also evidence that green infrastructure is implicated in decreasing obesity, stress, anxiety and better self reported health (Tzoulas et al., 2007).

The HPM is an indirect valuation method that analyses the variance in property prices that relate to changes in the characteristics that are packaged with the property (Rosen, 1974). There are numerous studies using the HPM to value environmental assets. However, these typically focus on a specific environmental asset or on a small geographical area. Our study aims to find the implicit price of aggregate green infrastructure at nation-wide level through fluctuations in housing prices, as there is a gap in literature for a study of this kind. The dataset used for this study consists of 2,531,803 observations of housing sales transactions between the years 2000 and 2010.

To quantify green infrastructure we used the satellite measured Environmental Vegetation Index (EVI). EVI is a measure of the amount of photosynthesis occurring in the environment. Photosynthesis is correlated with the "greenness" of the environment which is directly proportional to the quantity of green infrastructure (Lymburner & Australia, 2011). Consequently, EVI is used as a proxy for green infrastructure. EVI is aggregated annually at postcode level using Geographic Information Systems (GIS)[1]. Therefore, we are analysing what property owners are willing to pay for improvements in green infrastructure within their postcode. However, as EVI is an endogenous regressor due to omitted variable bias, measurement error and simultaneity bias. The Instrumental Variable (IV) approach is implemented to address endogeneity and precipitation data is used as an instrument for annual EVI at postcode level. Our results show that a one standard deviation increase in EVI increases housing prices by between 8.62% and 15.57%. For an average house this translates to an increase of between $32,139.23 and $57,991.41.

[1] Clustered standard errors are used at postcode-year level due to autocorrelation between standard errors with EVI measured at postcode level

## LITERATURE REVIEW –

The theoretical model for the HPM was pioneered by Rosen (1974). His model attempts to observe variations in property prices with respect to the characteristics that they are packaged with. Doing so enables the user to determine implicit prices for these characteristics. Rosen (1974) defines hedonic prices "as the implicit prices of attributes and are revealed to economic agents from observed prices of differentiated products and the specific amounts of characteristics associated with them" (p.34).

Since Rosen's paper there has been extensive research using the HPM to value a variety of goods. These include economic factors such as price elasticity, income distribution and the depreciation index. However, the HPM is generally used to value neighbourhood factors or other observable non-tradable characteristics that effect communities. These include both environmental (such as air pollution, open space, wetlands, beaches and parks) and non-environmental (such as crime, racial factors, infrastructure factors and zoning) characteristics (Herath & Maier, 2010).

Typically, for environmental assets the HPM is used to value a specific environmental landmark: the effect of an environmental good on a small area or a specific type of green infrastructure. This was undertaken in a recent Australian study in which the value of Lake Illawarra in New South Wales was determined using 521 housing price sales and their respective distance to the lake (Hodgkinson & Valadkhani, 2009). In Belgium a study was completed on the effect increasing agriculture has on rural tourism (Vanslembrouck, Huylenbroeck, & Van Meensel, 2005), while in Perth, Australia, the value of street trees with respect to housing prices was estimated (Pandit, Polyakov, Tapsuwan, & Moran, 2012). Despite these studies, there is little research investigating the effect of aggregate green

infrastructure from a nation-wide perspective, and it is this gap in the literature that this paper hopes to fill.

The EVI is used as a measure of green infrastructure and is aggregated at postcode level using GIS. GIS has been used previously with the HPM for valuation of environmental assets and has been shown to help improve the accuracy of HPM's (Kong, Yin, & Nakagoshi, 2007). Cavailhès et al. (2009) used GIS imagery to value the urban area of Dijon located in France, with 2,667 property sales. The paper demonstrated that houses within the proximity of trees produced a positive effect, whilst if houses were located near a road there was a negative effect. Stobbe, Cotteleer, and Cornelis Van Kooten (2009) analysed the effect of small scale "hobby farms" using both GIS and the HPM. Bastian, McLeod, Germino, Reiners, and Blasko (2002) analysed Wyoming's rural landscape to determine the value per acre of both productive agricultural land and natural habitat. Typically, HPM research using GIS has been primarily focused on rural areas or valuing open spaces.

Vegetation indexes similar to the EVI have been used before in conjunction with the HPM. Mansfield, Pattanayak, McDow, McDonald, and Halpin (2005) used the Normalised Difference Vegetation Index (NDVI) in conjunction with other environmental aspects in North Carolina. Using OLS, they found an inverse relationship between NDVI and housing prices. This is contrary to Payton, Lindsey, Wilson, Ottensmann, and Man (2008) research in Indianapolis, USA, that found NDVI had a small positive and significant effect on housing prices. Sengupta and Osgood (2003) used NDVI to control for unobserved variations in temperature and presence of water in a hedonic analysis of ranchette land value in Arizona.

A central issue for many hedonic models is omitted variable bias. This stems from the inability to quantify unobserved characteristics such as crime, proximity to schools or shopping centres (Kuminoff, Parmeter, & Pope, 2010). Kuminoff et al. (2010) completed a

Monte Carlo analysis with over 54,000 regressions to determine the effect of omitted variable bias has on the accuracy of hedonic models and what functional form is optimal in minimising the endogeneity bias. Samples of 2,000 out of a pool of 104,000 property transactions from Wake Forest, USA were taken. Various neighbourhood characteristics subsets were omitted selectively to determine the robustness of the functional forms. The findings were that spatial fixed effects most effectively captured the effects of the omitted variables. Although spatial fixed effects do not control for the variation within the omitted variables, they are effective in reducing omitted variable bias. In a valuation of urban forestry in Finland, Tyrväinen and Miettinen (2000) excluded all property types except terrace houses in order to minimise bias. Our paper uses similar methods to minimise the omitted variable bias including spatial fixed effects and excluding property types.

The EVI regressor is endogenous due to omitted variable bias, measurement error and simultaneity bias and therefore OLS produces biased and inconsistent estimates (Kuminoff et al., 2010). This paper uses the IV approach using precipitation data as an instrument for green infrastructure. Angrist and Krueger (1992) pioneered the IV approach by using birth date as an instrument for the years of schooling. The IV approach has been used in conjunction with the HPM in order to value environmental assets. Irwin (2002) used the HPM and IV approach to analyse the marginal effects of open space using land slope as an instrument for land use. Ready and Abdalla (2005) used GIS to analyse how the externalities from farmland in Southeastern Pennsylvania impacted housing prices. Their paper addressed endogeneity using a variety of land characteristics as instruments for an IV model. Recently (Gopalakrishnan, Smith, Slott, & Murray, 2011) analysed the impact of erosion of beaches on housing prices. This was completed using eight beaches in North Carolina, USA. To address endogeneity of cheaper beaches eroding quicker due to human factors geomorphologic variables was used as an IV for beach width. The results were that erosion of beaches diminishes housing prices by

up to 52% or houses will increase by $8,800 for each foot of beach width. What is interesting about this result is that it is around five times greater than the OLS regression. This highlights the importance of using IV when endogeneity exists. It should be noted that the aggregate median house price cannot be used in the HPM due to unobserved changes in the quality of houses rather than the amenities results endogeneity bias (Bayer, Keohane, & Timmins, 2009).

In order to address endogeneity precipitation data will be used as an instrument for green infrastructure. For this to be a valid instrument it has to be exogenous with housing prices and correlated with EVI. Rehdanz (2002) in a HPM analysis of the effect of climate change on house prices in Great Brittan found that average precipitation is exogenous with housing prices. This finding is contrary to Englin (1996) who estimated an implicit price of $0.05 for a one mm reduction in annual rainfall. However, both articles found that agents prefer more seasonal variation (wetter winters and dryer summers).

## DATA SECTION

To complete this research, 2,531,803 observations of property transactions across mainland Australia[2] were analysed. The challenge of obtaining, cleaning and preparing the housing price data and the EVI data was non-trivial. The housing data was the aggregate of 2,127 individual tables[3], each of which held up to 10,000 observations. The housing pricing data was supplied by Property Data Solutions Pty Ltd [4] and the merging of this data was completed as part of this research. Standard methods of data cleaning were also used to ensure data quality.

[2] Data from all States and Territories was used, with the exception of Tasmania.
[3] The data was imported from the website into Microsoft Excel
[4] The data sourced by Property Data Solutions was from the various state governments

The dataset encompasses all properties sold from 1 January 2000 until 31 December 2010[5]. The dependent variable is the natural log of the sales price. We restricted the number of bedrooms, bathrooms and car parks to a maximum of 10 in order to minimise measurement errors. These thresholds have been used in previous HPM studies (Gopalakrishnan et al., 2011). All commercial properties were excluded, area was limited to 10,000m$^2$ and the maximum sales price was limited to $20m. The decision was made to exclude units and apartments and only include houses was due to the data relating to units and apartments being inconsistent and incomplete. The area of the unit was inconsistent as it varied between the area of the unit, and the area of the land the unit is located on. Furthermore, data that is vital for the valuation of a unit e.g., how many apartments are collocated, the age of the building, or the size of the unit, was not available. Consequently, the unit data is very noisy.

In total 2,000,524 observations were dropped, leaving 2,651,962 housing observations. 2,531,803 observations were used in our regressions due to incomplete data in the EVI and precipitation data[6]. The average Australian house has 869.7m$^2$, 3.2 bedrooms, 1.3 bathrooms, 1.4 car parks, and sells for $372,456. The average postcode has an EVI of 0.295 and average daily precipitation (determined from average monthly totals) was 2.372cm.

The amount of photosynthesis in plants is directly correlated to the quality of green infrastructure, or 'greenness' of vegetation. Using satellite imagery, we can use the EVI as a measure of the amount of photosynthesis occurring in a sample area (Lymburner & Australia, 2011). As such, the EVI can be used as a proxy for a measure of green infrastructure.

EVI is derived from the NASA satellite images obtained from Terra and Aqua Moderate Resolution Imaging Spectroradiometers (MODIS), the MOD13Q1. MOD13Q1 is the product composites 16 of sequential days of MODIS satellite data into a single image (Lymburner et

[5] See appendix A1 for description of variables
[6] See appendix A2 for summary statistics

al, 2011). EVI is a standard product of the composite data using 250 metre (for $\rho_{NIR}$ and$\rho_{RED}$) and 500 metre ($\rho_{BLUE}$) spatial resolution bands (Lymburner & Australia, 2011). EVI can take an annual value between 0 and 1.

The EVI is measured by the following equation:

$$EVI = G \times \frac{(\rho_{NIR} - \rho_{RED})}{(\rho_{NIR} + C_1 \times \rho_{RED} - C_2 \times \rho_{BLUE} + L)}$$

where $\rho_{NIR}$, $\rho_{RED}$ and $\rho_{BLUE}$ are spectral reflectance's in MODIS bands 1, 2 and 3 respectively(Sims et al., 2008). G is the gain factor, C1 and C2 are the coefficients of the aerosol resistance term which uses blue band to correct for aerosol influences on red band and L acts as a soil adjustment function (Jiang, Huete, Didan, & Miura, 2008). For the EVI calculations L, C1, C2 and G are constants set to 1, 6, 7.5 and 2.5 respectively.

Within each postcode there are multiple pixels[7]. These pixels are aggregated together using GIS at postcode level. The mean pixel value across each postcode is taken and assigned to the specific postcode for that year. This is done for each of the 10 years in the sample. The result is a value for green infrastructure that illustrates the growth or decline in green infrastructure between 2000 and 2010 for each postcode. See figure 1 for an extract of the EVI images of Victoria during 2010. The darker green the pixel is the more photosynthesis is occurring, hence, the more green infrastructure.

[7] The median number of pixels in each postcode is 1,278

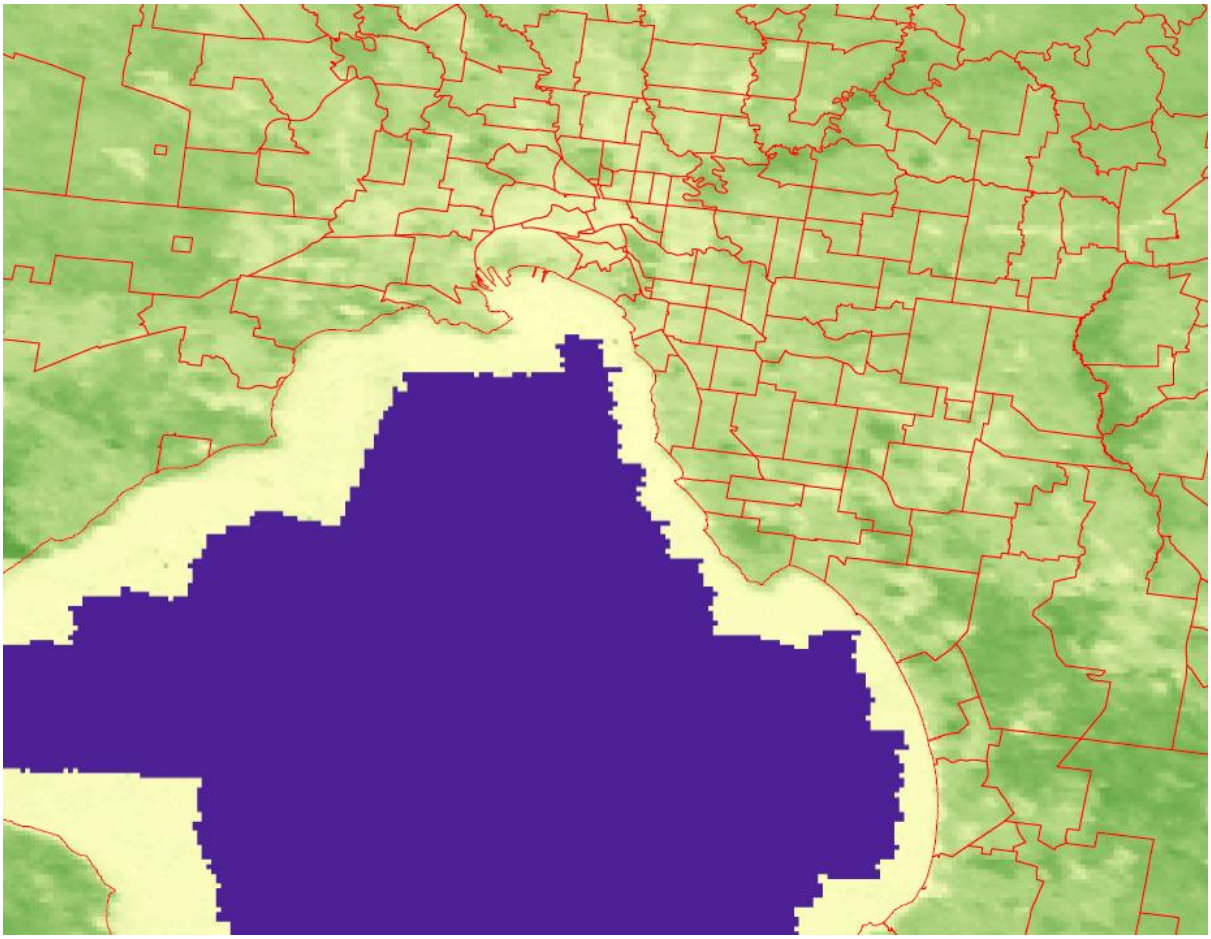

FIGURE 1: EVI EXTRACT OF VICTORIA IN 2010.

Most past HPM research focuses on city or local government area level, and attempts to value local assets. This paper's research is novel in both its data size and geographical setting, using 2,531,803 observations across the entire Australian housing market. Analysis at the national level was primarily motivated by the need to capture sufficiently large variation in the EVI, allowing valuation of green infrastructure to be possible.

The precipitation data taken from over 8,000 weather stations located across Australia and was obtained from the Bureau of Meteorology. Using GIS we assign each weather station a postcode and collect precipitation data at each postcode for the years 2000 to 2010. See figure two for a map of the weather station locations. It can be seen that the weather stations are situated across most of Australia with the exception of areas in Central Australia. However, there are very few property transactions in these areas. The daily precipitation data was

aggregated using multiple methods in order to determine the best fit for predicting EVI. These included positive shocks such as average monthly rainfall, total annual rainfall, total monthly rainfall and consecutive days of rainfall. Negative shocks were also used including multiple measures of consecutive days without rainfall. The aggregation methods chosen for our analysis was a twostep approach of taking the average monthly rainfall and then taking the daily average of this value. After aggregating the precipitation data we have an instrument that is measured at postcode level on a yearly basis which is used for our first stage to predict the values of annual EVI.

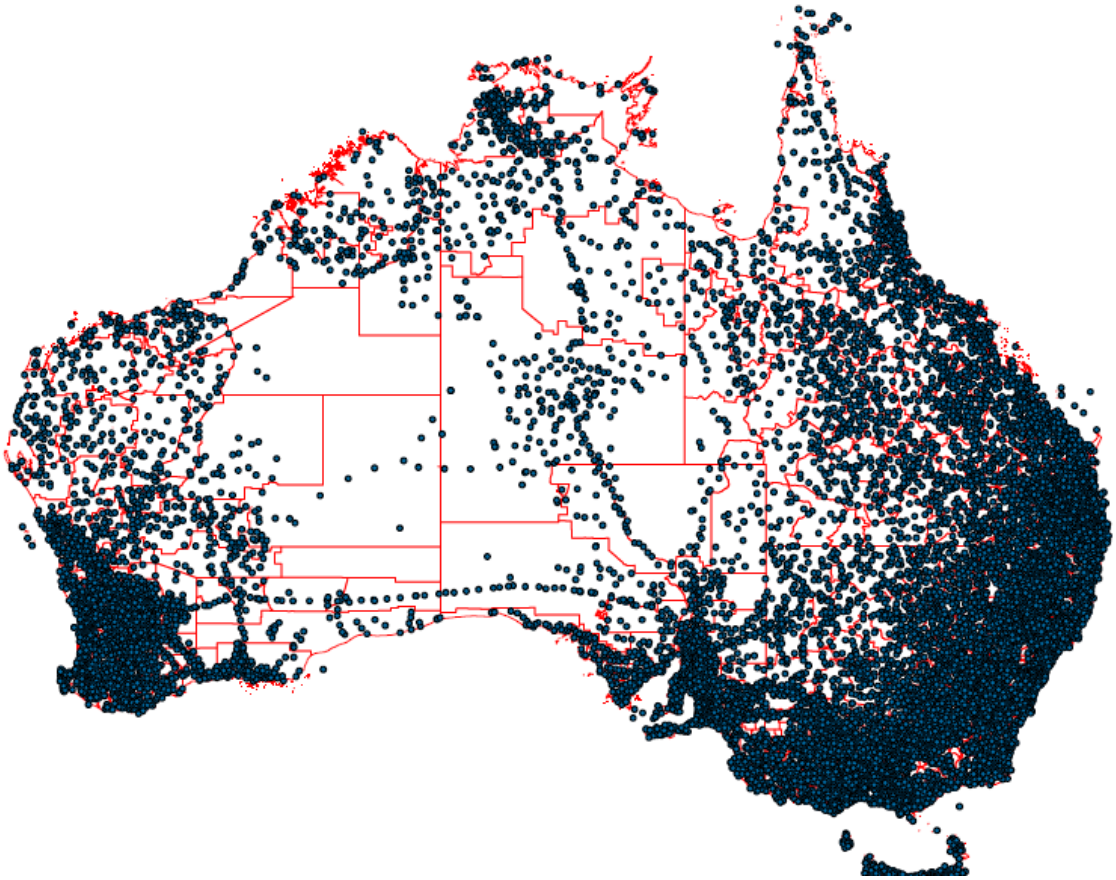

FIGURE 2: WEATHER STATION LOCATIONS ACROSS AUSTRALIA.

## METHODOLOGY

This paper attempts to estimate the value consumers place on green infrastructure through the indirect method of the HPM. Essentially, the HPM illustrates through fluctuations in housing prices that property owners are willingness to pay for green infrastructure. The model is structured such that the price ($P_{ijkt}$) of property (i) in a postcode (j) in the year (t) in the state (k) is a function of the following:

$$\log(P_{ijkt}) = \alpha_j + \gamma_{kt} + \rho + \boldsymbol{X_{ijkt}}\phi + \beta EVI_{jkt} + \varepsilon_{ijkt}$$

Such that $\boldsymbol{X_{ijkt}}$ is a vector of the following housing characteristics: the number of bedrooms, the number of bathrooms, the area of the property (per 100m$^2$) and the number of car parks. $EVI_{jt}$ is the annual EVI at postcode level which is used as a proxy for the level of green infrastructure. $\alpha_j$ is the area fixed effects that measure the time invariant differences at the postcode level. $\gamma_{kt}$ is the state and year fixed effects that capture any proportional changes in housing prices between each state and year. $\rho$ is the variable for the month the property was sold in to capture monthly differences in sales price.

The model employs an unbalanced panel data model using a log-linear transformation and fixed effects in order to predict housing prices. There are many omitted variables affecting housing prices that result in a biased and inconsistent prediction of price. For example, a house price is affected by factors such as crime rate, quality of schools in the suburb, presence of shopping centres, government housing in the suburb, natural disaster risk, distance to CBD and many more. To address this, spatial fixed effects have been found to significantly help address omitted variable bias in a HPM (Kuminoff et al., 2010). Assuming these omitted variables do not change over time, the spatial fixed effects at postcode level will capture the fixed omitted variable bias, whilst the state-year fixed effects capture the time variant omitted variables at state level. An example of this was a state policy that

stimulated the housing market of that state relative to the other states. The log-linear transformation chosen has been commonly used among HPM and has been found to perform well with omitted variable bias (Cropper, Deck, & McConnell, 1988).

For our regressions clustered standard errors are used. Clustered standard errors are relevant when micro observations are aggregated together in an attempt to measure macro effects. When these micro observations do not have independent disturbances the standard errors are significantly biased downwards (Moulton, 1990). In the model, multiple observations are aggregated together at postcode-year level to give the marginal effect for EVI. These observations all have correlated standard errors when predicting EVI of the postcode. Therefore, clustered standard errors at postcode-year level are used. Clustering has been used previously alongside the HPM to address the issue of standard errors being correlated within groups (Poudyal, Hodges, & Merrett, 2009).

Using OLS to determine $\beta$ would produce biased and inconsistent results due to the green infrastructure being an endogenous regressor. This is due to omitted variable bias, measurement error and simultaneity bias.

There are unobservable events and variables that affect both the housing prices and the level of green infrastructure. These omitted variables result in $\beta$ not being a true estimate of the effect of changes in green infrastructure. For example, if a suburb experiences an increase in government support through policy changes, the postcode could experience an improvement of schools, public transport and infrastructure. However, this would also result in improvements in green infrastructure. That is, an unobserved factor has increased both the house prices and also the green infrastructure. An example of this was the American policy to improve cities with declining population ("shrinking cities"). Green infrastructure was identified as a way to improve the housing sector and stimulate the local economy (Schilling

& Logan, 2008). Omitted variable bias such as this would result in the $\beta$ being overestimated. However, omitted variables can result in $\beta$ being underestimated. An example of this is urbanisation and urban sprawl which increase house prices but reduce green infrastructure. In Kansas City, USA urban sprawl has been found to significantly decrease the city's urban vegetation (Ji, Ma, Twibell, & Underhill, 2006). An Australian example is Berwick. Berwick was a small country town 60km east of the Melbourne CBD that has expanded rapidly over the past decade. As a result EVI has decreased from 0.41 in 2000 to 0.31 2008, or by 1.35 standard deviations of EVI. However the average housing price has increased from $185,689 to $376,912. Consequently, there is an inverse relationship between housing prices and EVI, resulting in $\beta$ being underestimated.

Furthermore, green infrastructure and housing prices are simultaneously determined. It is assumed that property owners are willing to pay for greener infrastructure. However property prices in a suburb will also determine the amount of green infrastructure. More affluent postcodes attract wealthier individuals or families who invest more into a green backyard. Moreover, these postcodes collect higher council rates that improve green infrastructure (and vice-versa for less affluent suburbs). Postcode fixed effects addresses much of the simultaneity bias because more affluent suburbs will always have more robust green infrastructure network. However the bias may still exist if this occurs independently of the postcode.

Our final source of endogeneity is through measurement area. As we are using EVI as a proxy for green infrastructure, it is not an exact measure for what property owners are willing to pay for improvements in green infrastructure. The presence of measurement errors results in t statistics declining and a biased estimate of sales price (Hausman, 2001). EVI measures the aggregate level of green infrastructure in a suburb. However, there may be "useable green" (UG) which property owners are willing to pay for and "unusable green" (UUG)

which property owners gain no utility from. Consequently we have $UG = EVI + UUG$. The unusable green infrastructure could be a vacant lot of land covered in weeds whilst the useable green infrastructure could be park or street trees. Property owners are only willing to pay for the improvements in UG infrastructure, while the presence of UUG infrastructure may decrease prices or have no effect (Panduro & Veie, 2013). Therefore we have measurement error due to EVI not being an exact measure of property owners' utility from green infrastructure. Furthermore, EVI does not give weight to the quality of green infrastructure. For example, the marginal effect on housing prices for a leafy park in an inner city suburb would be larger compared to open farmland in a country town. This is outlined in Panduro and Veie (2013) paper that states "green space is not a uniform environmental amenity but rather a set of distinct goods with very different impacts on the housing price" (p.1). The result is the OLS model suffering from attenuation bias where $\beta$ is biased towards zero.

Overall, we hypothesise that the most significant causes of endogeneity are measurement error and the omitted variable bias. Australia's increasing population and the housing boom results in urbanisation and urban sprawl being the most significant of the omitted variable bias. A significant variety in quality of green infrastructure and therefore the presence of UUG results in significant attenuation bias. We believe the net effect of these is a $\beta$ biased towards zero and understated.

In order to achieve an unbiased and consistent estimator of green infrastructure the IV approach was implemented. The method has been used previously in HPM's to account for endogeneity Gopalakrishnan et al. (2011). A valid instrument for green infrastructure must be correlated with green infrastructure but is exogenous to property values. Our first stage of the regression is as follows:

$$EVI_{jkt} = \alpha_j{}' + \gamma_{kt}{}' + \boldsymbol{X_{ijkt}}\phi' + \rho' + \delta R_{jkt} + u_{ijkt}$$

$R_{jkt}$ is the average daily precipitation determined from the average monthly precipitation measured at postcode level. The literature gave little guidance on the relationship between vegetation indexes and precipitation except that it was significant and complex (Nightingale & Phinn, 2003). Consequently we used various range of precipitation aggregated in different methods. Negative measures such as days without rainfall gave insignificant results while positive measures such as average or total precipitation gave significant positive results. A study in Great Britain found that average rainfall is exogenous with housing prices (Rehdanz, 2002). Furthermore, we believe that precipitation is intuitively exogenous. It is unlikely consumers will base their housing decisions on variation of precipitation at postcode level within a state. As such, we believe consumers will not pay a premium for variation in precipitation at postcode level within a state. Therefore we chose our instrument of daily precipitation determined from the average monthly precipitation and believe it is valid. We note that the excess precipitation in the form of floods will decrease property prices. However, we rely on the assumption that flood prone areas already have depreciated housing prices due to the known risk. Therefore flood risk is captured in the postcode fixed effects. Hence, the precipitation variable is still exogenous with housing prices.

Our second stage is as follows:

$$\log(P_{ijkt}) = \alpha_j + \gamma_{kt} + \boldsymbol{X_{ijkt}}\phi + \rho + \beta\widehat{EVI_{jkt}} + \varepsilon_{ijkt}$$

After addressing endogeneity using the instrumental variable approach $\beta$ produces unbiased and consistent estimate of the marginal effect of green infrastructure on housing prices.

## RESULTS & HYPOTHESIS

Our hypothesis is that an increase in EVI, and consequently the greenness and quantity of green infrastructure, will have a positive effect on housing prices in Australia. The hypothesis is based on the assumption that consumers gain utility from green infrastructure. Therefore, consumers will be willing to pay a premium for increases in green infrastructure in their postcode.

For our results, we split the regressions using state-year fixed effects and year fixed effects (FE). We modelled state-year fixed effects by assigning a dummy variable for each state per year. This is in order to account for the growth in prices and EVI between states relative to the rest of Australia between years. For year fixed effects, a dummy variable for year is used and the postcode fixed effects account for the variation from state to state. The results with log of price as the dependent variable are as follows[8]:

[8] Due to computational limitations these results are based on demeaned values of the variables. Stata's centre' command was used to demean the dependent and independent variables. Therefore, the standard errors need to be interpreted with care. However, considering the large number of observations, we are confident that the discrepancies between the standard errors for these estimates and the ones using a proper fixed effects estimator are negligible.

Table 1: Results of OLS and IV using both state-year and year FE. Standard errors clustered at postcode-year level.

| **Dependent Variable: log(Price)** | **OLS** | **OLS** | **IV** | **IV** |
|---|---|---|---|---|
| **EVI** | -0.154* | -0.016 | 1.946*** | 1.113*** |
| | (0.081) | (0.091) | (0.740) | (0.333) |
| **Bedrooms** | 0.150*** | 0.151*** | 0.149*** | 0.150*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| **Bathrooms** | 0.067*** | 0.065*** | 0.068*** | 0.066*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| **Car parks** | 0.014*** | 0.013*** | 0.014*** | 0.013*** |
| | (0.000) | (0.001) | (0.001) | (0.001) |
| **Area per 100m$^2$** | 0.007*** | 0.007*** | 0.007*** | 0.007*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| **Postcode FE** | Yes | Yes | Yes | Yes |
| **State-year FE** | Yes | No | Yes | No |
| **Months** | Yes | Yes | Yes | Yes |
| **Observations** | 2,651,962 | 2,651,962 | 2,531,803 | 2,531,803 |
| **$R^2$** | 0.504 | 0.474 | 0.500 | 0.473 |

***, ** AND * REPRESENT SIGNIFICANCE AT THE 1%, 5% AND 10% LEVEL RESPECTIVELY

*All results are using clustered standard errors at postcode-year level, postcode fixed effects and include a month variable. A log-linear model with log(Price) as the dependent variable. Column 1is and column 3 are the estimations using state-year fixed effects. Column 2 and column 4 are using year fixed effects. The IV results are using precipitation as an instrument for EVI.*

Table 2: First stage regression of IV. Standard errors clustered at postcode-year level.

| **Dependent Variable: EVI** | **IV** | **IV** |
|---|---|---|
| **Bedrooms** | -0.43 | 0.0001* |
| | (0.000) | (0.000) |
| **Bathrooms** | $3.33 \times 10^{-5}$*** | -0.0004*** |
| | (0.000) | (0.000) |
| **Car Parks** | $1.63 \times 10^{-5}$*** | $-8.5 \times 10^{-5}$*** |
| | (0.000) | (0.000) |
| **Area** | $6.56 \times 10^{-6}$* | $5.58 \times 10^{-6}$ |
| | (0.000) | (0.000) |
| **Precipitation** | 0.0028*** | 0.0055*** |
| | (0.000) | (0.000) |
| **Postcode FE** | Yes | Yes |
| **State-year FE** | Yes | No |
| **Months** | Yes | Yes |
| **Observations** | 2,531,803 | 2,531,803 |
| **$R^2$** | 0.4971 | 0.3891 |
| **F Statistic** | 56.6 | 193.66 |

***, ** AND * REPRESENT SIGNIFICANCE AT THE 1%, 5% AND 10% LEVEL RESPECTIVELY *All results are using clustered standard errors at postcode-year level, postcode fixed effects and include a month variable. The first stage regression EVI is the dependent variable and precipitation is the instrument. Column 1is is the first stage regression using state-year fixed effects. Column 2 is the first stage regression using year fixed effects.*

There is a large difference between OLS and the IV results in both significance and the magnitude of the marginal effect of the EVI regressor. The estimates of EVI using OLS produce a biased and inconsistent estimate of EVI. The endogeneity issues of EVI outlined previously result in our estimate for EVI being both understated and insignificant. The attenuation bias causes $\beta$ to be biased downwards whilst the omitted variable bias such as urban sprawl and urbanisation results in $\beta$ being understated. This is consistent with our previous hypothesis on the effect of endogeneity on the EVI regressor and previous studies. In North Carolina, USA, Mansfield et al. (2005) used the Normalized Difference Vegetation Index (NDVI) and GIS to determine the values of urban forests. The study used OLS and found a similar negative and significant correlation between the NDVI and house prices (Mansfield et al., 2005).

After accounting for the endogeneity of EVI through an IV specification, $\beta$ is positive and significant at a 1% significance level. This is consistent with the assumption that consumers would be willing to pay for an improvement in green infrastructure in their suburb. Both of the F statistics from the first stage of the IV regression are valid.

The marginal effect of a log-linear model is determined by the following equation: $ME = (e^{\beta} - 1) \times 100$. For bedrooms, bathrooms and car parks it is interpreted as a one unit increase whilst for area it is for every 100m$^2$ increase. The interpretation of EVI is different as a one unit increase is obsolete as due to the range of EVI being 0-1. Therefore we analyse it by a one standard deviation (0.074) increase in EVI. The following results are obtained:

Table 3: Marginal effects of dependent variables on sale price

| **Dependent Variable: log(Price)** | **OLS** | **OLS** | **IV** | **IV** |
|---|---|---|---|---|
| **EVI** | -1.139% | -0.119% | 15.57% | 8.629% |
| **Bedrooms** | 16.18% | 16.30% | 16.07% | 16.18% |
| **Bathrooms** | 6.929% | 6.716% | 7.037% | 6.823% |
| **Car parks** | 6.930% | 6.716% | 7.037% | 6.823% |
| **Area per 100m$^2$** | 0.702% | 0.702% | 0.702% | 0.702% |
| **State-year FE** | Yes | No | Yes | No |

*The marginal effects of the dependent variables in the log-linear model. The marginal effect of EVI is an increase of one standard deviation whilst for the other dependent variables is a one unit increase. Column 1is and column 3 are the marginal effects using state-year fixed effects. Column 2 and column 4 are using year fixed effects.*

The model predicts that a one standard deviation in EVI will increase housing prices by 15.57% using state-year fixed effects or by 8.629% using year fixed effects. The state-year fixed effects estimate is likely to be overstated due to multicollinearity in the model. In relatively small states such as Victoria, South Australia and the Australian Capital Territory, and states where the majority of property transactions occurs within a small geographical area such as Perth or Darwin the variation in EVI and precipitation do not vary significantly within the state per year. Hence, using state-year fixed effects the model suffers from

multicollinearity and $\beta$ is overestimated. However, by excluding state-year fixed effects the model fails to capture state by state difference in house price trends.

The mean price of a house in Australia is $372,456.1, so a one standard deviation increase in EVI will increase the average house by $57,991.41 using state-year effects or by $32,139.23 using year fixed effects. There has been little literature valuing aggregate green infrastructure or nation-wide green infrastructure. As such, it is difficult to compare these results with previous studies. Therefore, we will compare the results to similar valuations of environmental goods and analyse our results from a "real life" point of view.

A one standard deviation increase in EVI is hard to envisage compared to an increase in the number bedrooms. In order to visualise a one standard deviation increase in EVI below are two similar inner-city postcodes of Port Melbourne and Albert Park where the difference in EVI is approximately one standard deviation. The main difference between the two postcodes is that Albert Park has a 440 acre park (Albert Park) situated within it. The darker green pixels in the postcode where Albert Park is situated can clearly be seen in figure 1 below. Excluding the park, the two postcodes are very similar in appearance and green infrastructure.

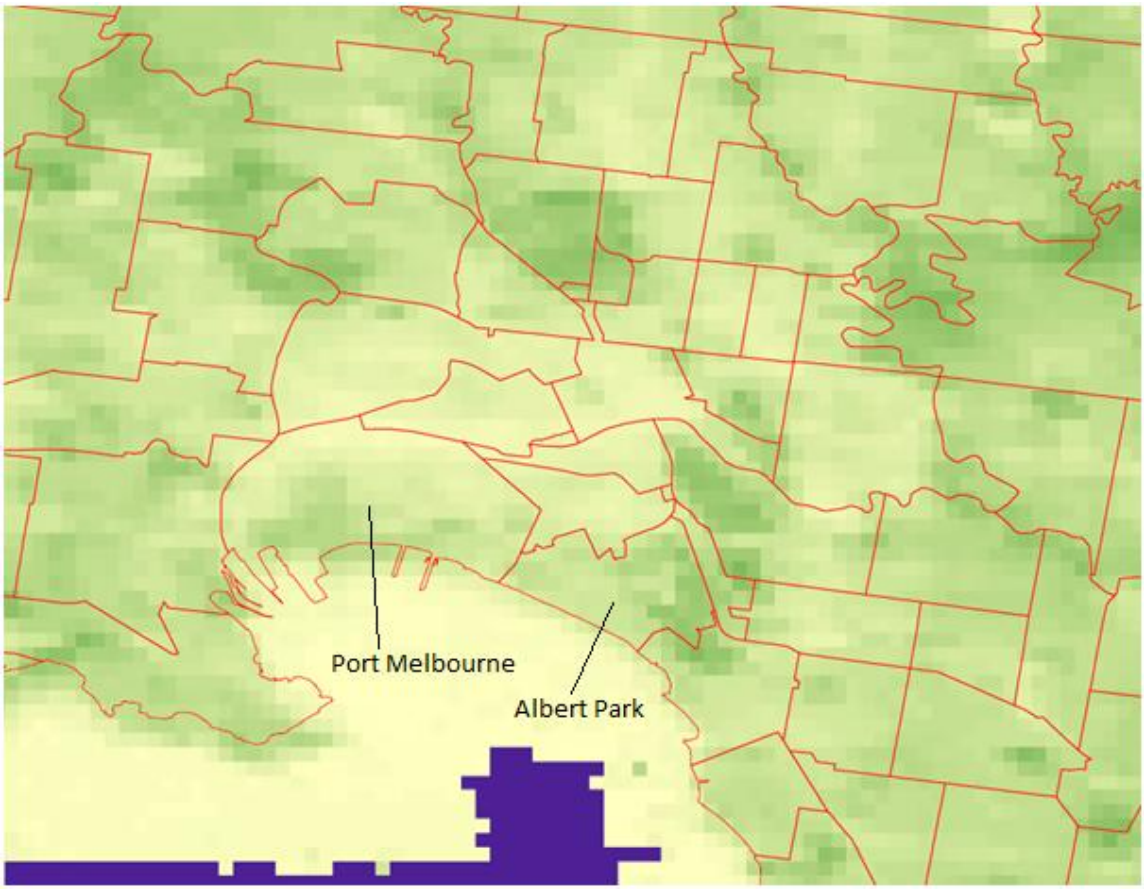


FIGURE 3 – PORT MELBOURNE & ALBERT PARK COMPARISON

From an intuitive point of view, if a postcode with little green infrastructure were to increase its EVI by the equivalent green infrastructure of a 440 acre park, it would not be unreasonable to assume that housing prices would increase by somewhere between 8% to 16%.

Our results are consistent with the few previous comparable studies. In Perth, Western Australia, it was found that the presence of street trees increases property values by $16,889 (4.27%) (Pandit et al., 2012). In Arizona consumers were willing to pay a 20% premium to live in densely vegetated wildlife corridors (Katz, Colby, Osgood, Bark-Hodgins, & Stromberg, 2005). In Virginia, increasing the average park size by 20% would translate to a $160 increase in consumer surplus per household (Poudyal et al., 2009). A study in the Netherlands found that environmental factors can increase housing prices by up to 28%

including an 8% premium for a park view and a 5%-12% for a more 'attractive' environmental view (Luttik, 2000). The mere presence of trees was found to increase housing prices from 1.7% and 4.5% (Dombrow, Rodriguez, & Sirmans, 2000) (Anderson & Cordell, 1988). Finally, Hatton MacDonald et al. (2010) found that consistently low quality parks have a negative impact on housing prices. Given the previous literature, a one standard deviation in EVI increasing housing prices by 15.57% or by $57,991.41 is economically justifiable.

There are limitations to the predictive ability of the model. We do not have access to many house specific factors such as age of the house, if it is a double story house or other housing characteristics not in the model. Furthermore, we are unable to determine distance related factors such as distance to schools, parks, shopping centres or train stations. However, house specific omitted variable would not significantly affect the results due to the magnitude of the sample size.

## ROBUSTNESS

To determine the robustness of our results we segregated the data into various subcategories. Using the Australian Standard Geographical Classification, we separated the data at postcode level into classifications of remoteness. The classification types for the postcodes are Major Cities of Australia, Inner Regional, Outer Regional, Remote and Very Remote. It is unnecessary to run the regression by postcode classification as the motivating factor of using Australia as a case study was sufficient variation in EVI. Running the regression by postcode segregates will not produce sufficient variation in EVI and precipitation for meaningful results. We therefore run regressions excluding remoteness categories one by one.

Table 4: Remoteness category results using IV and year fixed effects. Standard errors clustered at postcode-year level.

| **Dependent Variable: log(Price)** | **Exc. Major cities** | **Exc. Inner Regional** | **Exc. Outer Regional** | **Exc. Remote** | **Exc. Very Remote** |
|---|---|---|---|---|---|
| **EVI** | 3.129*** | 0.722* | 0.583* | 1.132*** | 1.128*** |
| | -0.499 | -0.394 | -0.344 | -0.338 | -0.334 |
| **Bedrooms** | 0.138*** | 0.152*** | 0.149*** | 0.150*** | 0.150*** |
| | -0.002 | -0.001 | -0.001 | -0.001 | -0.001 |
| **Bathrooms** | 0.077*** | 0.062*** | 0.065*** | 0.066*** | 0.066*** |
| | -0.003 | -0.001 | -0.001 | -0.001 | -0.001 |
| **Car Parks** | 0.019*** | 0.013*** | 0.010*** | 0.012*** | 0.013*** |
| | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| **Area100** | 0.006*** | 0.008*** | 0.007*** | 0.007*** | 0.007*** |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **Postcode FE** | Yes | Yes | Yes | Yes | Yes |
| **State-year FE** | No | No | No | No | No |
| **Months** | Yes | Yes | Yes | Yes | Yes |
| **Observations** | 806,366 | 1,966,750 | 2,327,390 | 2,500,048 | 2,524,758 |
| **$R^2$** | 0.443 | 0.477 | 0.479 | 0.474 | 0.473 |
| **F statistic** | 82.2 | 148.23 | 157.52 | 188.85 | 192.47 |

***, ** AND * REPRESENT SIGNIFICANCE AT THE 1%, 5% AND 10% LEVEL RESPECTIVELY *All results are using clustered standard errors at postcode-year level, postcode fixed effects, year fixed effects and include a month variable. Each regression excludes one type of remoteness category. A log-linear model with log(Price) as the dependent variable. These IV results are using precipitation as an instrument for EVI.*

These regressions do not use state-year fixed effects, as multicollinearity resulted in variables being dropped from the regression when state-year fixed effects were used. The results show that most of the significance is driven by the inner regional and outer regional postcodes. This is because outside the major cities, the postcodes are larger, so there is more variation in EVI and precipitation between postcodes. The results are still significant at a 10% significance level. It is important to note that this is not detrimental to robustness of our results. The entirety of Australia was required for sufficient variation in EVI and precipitation. With a significant proportion of Australia's property sales clustered in a relatively small geographical area, the inclusion of regional sales (25% of total sales) is required in order to achieve meaningful results. It is not surprising that when we begin segregate the postcodes the significance of $\beta$ decreases.

We completed a similar analysis excluding specific states one by one. There were similar conclusions to the remoteness categories where the significance was driven by specific subcategories. Queensland contributed significantly to the significance of the EVI coefficient. This is likely because unlike the other states, Queensland housing sales are not segregated into a small area. Furthermore, Queensland has a large variation in both rainfall and green infrastructure compared with other states. Using our current instrument when Queensland is excluded $\beta$ became insignificant. However, when total monthly rainfall is used as our instrument, $\beta$ is significant at a 5% significance level[9].

As stated earlier, units and apartments were excluded from the sample due to omitted variable bias. As a robustness test, we ran the regressions including all residential properties sold, and for units and apartments. (See table 5 for the output of the regression of all residential properties and only units and apartments using year fixed effects.) The marginal effect for EVI for apartments was higher than that of houses. This is intuitively expected as units and apartments either do not have a backyard or have a very small one. Furthermore, they are generally in highly populated suburbs which have less green infrastructure. For these reasons, it is intuitive for these apartment owners to want to pay a premium for increases in green infrastructure in their postcode. The results show that units are on average cheaper than a house which is as expected. However, we believe there are too many omitted variables for units and apartments which cannot be captured in our model to accurately predict the sale price. Therefore, we excluded units and apartments from our analysis. This is approach consistent with previous literature (Tyrväinen & Miettinen, 2000).

[9] See A3 and A4 of appendix for these results

Table 5: OLS and IV results using all properties types and only units and year FE. Standard errors clustered at postcode-year level.

| **Dependent Variable: Log(Price)** | **OLS all properties** | **IV all properties** | **OLS units only** | **IV units only** |
|---|---|---|---|---|
| **EVI** | -0.161* | 1.338*** | -0.662*** | 3.014*** |
| | (0.090) | (0.328) | (0.200) | (0.861) |
| **Bedrooms** | 0.165*** | 0.163*** | 0.213*** | 0.208*** |
| | (0.001) | (0.001) | (0.003) | (0.003) |
| **Bathrooms** | 0.070*** | 0.070*** | 0.098*** | 0.098*** |
| | (0.001) | (0.001) | (0.003) | (0.004) |
| **Car Parks** | 0.015*** | 0.015*** | 0.027*** | 0.025*** |
| | (0.000) | (0.001) | (0.002) | (0.003) |
| **Area per 100 $m^2$** | 0.005*** | 0.005*** | 0.002*** | 0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| **Unit/Apartment dummy** | -0.105*** | -0.100*** | | |
| | (0.003) | (0.004) | | |
| **Postcode FE** | Yes | Yes | Yes | Yes |
| **State-year FE** | No | No | No | No |
| **Months** | Yes | Yes | Yes | Yes |
| **Observations** | 3,359,609 | 3,177,833 | 708,122 | 646,505 |
| **$R^2$** | 0.477 | 0.474 | 0.422 | 0.405 |
| **F statistic** | | 183.86 | | 63.63 |

***, ** AND * REPRESENT SIGNIFICANCE AT THE 1%, 5% AND 10% LEVEL RESPECTIVELY *All results are using clustered standard errors at postcode-year level, postcode fixed effects and include a month variable. A log-linear model with log(Price) as the dependent variable. Column 1is and column 3 are the estimations using state-year fixed effects. Column 2 and column 4 are using year fixed effects. Columns 1 and 2 are using all property types whilst 3 and 4 only use units and apartments. The IV results are using precipitation as an instrument for EVI.*

The marginal effect of a one standard deviation increase in EVI for all properties is 10.46%, slightly above our estimate of 8.629% for houses. When the regression is run only including units and apartments the marginal effect increases to 25.96%. Interestingly, using OLS for only apartments it is a negative coefficient significant at 1%. This is likely because the effect of urbanisation is amplified in areas where there are apartments due to the population density of these locations.

## CONCLUSION:

The importance of green infrastructure should not be underestimated, although it is frequently overlooked by policy makers. As such, it is important to put a monetary value on the utility society gains from green infrastructure. The public good nature of green infrastructure motivates an indirect valuation method such as the HPM to determine the implicit price of green infrastructure.

Our model uses annual EVI measured at postcode level as a proxy for green infrastructure in an unbalanced fixed effects panel data model. Due to endogeneity in the EVI regressor from omitted variable bias, measurement error and it simultaneously determined, we used spatial fixed effects and IV to achieve an unbiased and consistent estimate of green infrastructure. The instrument for annual EVI is precipitation data aggregated at the postcode level using the average daily determined from the average monthly precipitation.

Our IV regression produces the marginal effect of a one standard deviation increase in EVI to result in an 8.62% increase in housing prices using year fixed effects or 15.57% using state-year fixed effects. For an average house this translates to an increase of between $32,139.23 and $57,991.41. Our research is novel as it is the first study valuing aggregate green infrastructure at a national level. However, comparing our results to similar valuations of green infrastructure and taking an intuitive approach, the results are economically justifiable. Valuation of environmental factors is essential in order for policy makers to understand the utility society gains from green infrastructure. Furthermore, a robust green infrastructure network reduces pollution, reduces the impact of climate change and has significant health benefits.

Future research could analyse the cost of climate change and consequently precipitation and green infrastructure on society. A simulation could allow us to determine how a decrease in green infrastructure due to climate change could affect the property market.

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## REFERENCES:

ANDERSON, LINDA, & CORDELL, KEN. (1988). INFLUENCE OF TREES ON RESIDENTIAL PROPERTY VALUES IN ATHENS, GEORGIA (USA): A SURVEY BASED ON ACTUAL SALES PRICES. *LANDSCAPE AND URBAN PLANNING, 15*(1), 153-164.

ANGRIST, JOSHUA, & KRUEGER, ALAN. (1992). THE EFFECT OF AGE AT SCHOOL ENTRY ON EDUCATIONAL ATTAINMENT: AN APPLICATION OF INSTRUMENTAL VARIABLES WITH MOMENTS FROM TWO SAMPLES. *JOURNAL OF THE AMERICAN STATISTICAL ASSOCIATION, 87*(418), 328-336.

BASTIAN, CHRIS, MCLEOD, DONALD, GERMINO, MATTHEW, REINERS, WILLIAM, & BLASKO, BENEDICT. (2002). ENVIRONMENTAL AMENITIES AND AGRICULTURAL LAND VALUES: A HEDONIC MODEL USING GEOGRAPHIC INFORMATION SYSTEMS DATA. *ECOLOGICAL ECONOMICS, 40*(3), 337-349.

BAYER, PATRICK, KEOHANE, NATHANIEL, & TIMMINS, CHRISTOPHER. (2009). MIGRATION AND HEDONIC VALUATION: THE CASE OF AIR QUALITY. *JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT, 58*(1), 1-14.

CAMERON, ROSS, BLANUŠA, TIJANA, TAYLOR, JANE, SALISBURY, ANDREW, HALSTEAD, ANDREW, HENRICOT, BÉATRICE, & THOMPSON, KEN. (2012). THE DOMESTIC GARDEN: ITS CONTRIBUTION TO URBAN GREEN INFRASTRUCTURE. *URBAN FORESTRY AND URBAN GREENING, 11*(2), 129-137.

CAVAILHÈS, JEAN, BROSSARD, THIERRY, FOLTÊTE, JEAN-CHRISTOPHE, HILAL, MOHAMED, JOLY, DANIEL, TOURNEUX, FRANÇOIS-PIERRE, . . . WAVRESKY, PIERRE. (2009). GIS-BASED HEDONIC PRICING OF LANDSCAPE. *ENVIRONMENTAL AND RESOURCE ECONOMICS, 44*(4), 571-590.

CHEN, ANDREW, & WARREN, JENNIFER. (2011). SUSTAINABLE GROWTH FOR CHINA. *CHINESE ECONOMY, 44*(5), 86-103.

CHOUMERT, JOHANNA, & SALANIÉ, JULIEN. (2008). PROVISION OF URBAN GREEN SPACES: SOME INSIGHTS FROM ECONOMICS. *LANDSCAPE RESEARCH, 33*(3), 331-345.

CROPPER, MAUREEN, DECK, LELAND, & MCCONNELL, KENENTH. (1988). ON THE CHOICE OF FUNTIONAL FORM FOR HEDONIC PRICE FUNCTIONS. *THE REVIEW OF ECONOMICS AND STATISTICS*, 668-675.

DOMBROW, JONATHAN, RODRIGUEZ, MAURICIO, & SIRMANS, C.F. (2000). THE MARKET VALUE OF MATURE TREES IN SINGLE-FAMILY HOUSING MARKETS. *APPRAISAL JOURNAL, 68*(1), 39-43.

ENGLIN, JEFFREY. (1996). ESTIMATING THE AMENITY VALUE OF RAINFALL. *THE ANNALS OF REGIONAL SCIENCE, 30*(3), 273-283.

GILL, S.E., HANDLEY, JOHN, ENNOS, A.R., & PAULEIT, STEPHAN. (2007). ADAPTING CITIES FOR CLIMATE CHANGE: THE ROLE OF THE GREEN INFRASTRUCTURE. *BUILT ENVIRONMENT*, 115-133.

GOPALAKRISHNAN, SATHYA, SMITH, MARTIN, SLOTT, JORDAN, & MURRAY, BRAD. (2011). THE VALUE OF DISAPPEARING BEACHES: A HEDONIC PRICING MODEL WITH ENDOGENOUS BEACH WIDTH. *JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT, 61*(3), 297-310.

HATTON MACDONALD, DARLA, CROSSMAN, NEVILLE, MAHMOUDI, PARVIN, TAYLOR, LAURA, SUMMERS, DAVID, & BOXALL, PETER. (2010). THE VALUE OF PUBLIC AND PRIVATE GREEN SPACES UNDER WATER RESTRICTIONS. *LANDSCAPE AND URBAN PLANNING, 95*(4), 192-200.

HAUSMAN, JERRY. (2001). MISMEASURED VARIABLES IN ECONOMETRIC ANALYSIS: PROBLEMS FROM THE RIGHT AND PROBLEMS FROM THE LEFT. *THE JOURNAL OF ECONOMIC PERSPECTIVES, 15*(4), 57-67.

HERATH, SHANAKA, & MAIER, GUNTHER. (2010). THE HEDONIC PRICE METHOD IN REAL ESTATE AND HOUSING MARKET RESEARCH: A REVIEW OF THE LITERATURE.

HODGKINSON, ANN, & VALADKHANI, ABBAS. (2009). COMMUNITY VALUATIONS OF ENVIRONMENTAL QUALITY IN COASTAL LAKES: LAKE ILLAWARRA CASE STUDY. *ECONOMIC PAPERS: A JOURNAL OF APPLIED ECONOMICS AND POLICY, 28*(2), 155-168.

IRWIN, ELENA. (2002). THE EFFECTS OF OPEN SPACE ON RESIDENTIAL PROPERTY VALUES. *LAND ECONOMICS, 78*(4), 465-480.

JI, WEI, MA, JIA, TWIBELL, RIMA, & UNDERHILL, KAREN. (2006). CHARACTERIZING URBAN SPRAWL USING MULTI-STAGE REMOTE SENSING IMAGES AND LANDSCAPE METRICS. *COMPUTERS, ENVIRONMENT AND URBAN SYSTEMS, 30*(6), 861-879.

JIANG, ZHANGYAN, HUETE, ALFREDO, DIDAN, KAMEL, & MIURA, TOMOAKI. (2008). DEVELOPMENT OF A TWO-BAND ENHANCED VEGETATION INDEX WITHOUT A BLUE BAND. *REMOTE SENSING OF ENVIRONMENT, 112*(10), 3833-3845.

KATZ, BARBARA, COLBY, BONNIE, OSGOOD, DANIEL, BARK-HODGINS, ROSALIND, & STROMBERG, JULIET. (2005). *DO HOMEBUYERS CARE ABOUT THE'QUALITY'OF NATURAL HABITATS?* PAPER PRESENTED AT THE 2005 ANNUAL MEETING, JULY 24-27, PROVIDENCE, RI.

KONG, FANHUA, YIN, HAIWEI, & NAKAGOSHI, NOBUKAZU. (2007). USING GIS AND LANDSCAPE METRICS IN THE HEDONIC PRICE MODELING OF THE AMENITY VALUE OF URBAN GREEN SPACE: A CASE STUDY IN JINAN CITY, CHINA. *LANDSCAPE AND URBAN PLANNING, 79*(3), 240-252.

KUMINOFF, NICOLAI, PARMETER, CHRISTOPHER, & POPE, JAREN. (2010). WHICH HEDONIC MODELS CAN WE TRUST TO RECOVER THE MARGINAL WILLINGNESS TO PAY FOR ENVIRONMENTAL AMENITIES? *JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT, 60*(3), 145-160.

LUTTIK, JOKE. (2000). THE VALUE OF TREES, WATER AND OPEN SPACE AS REFLECTED BY HOUSE PRICES IN THE NETHERLANDS. *LANDSCAPE AND URBAN PLANNING, 48*(3), 161-167.

LYMBURNER, LEO, & AUSTRALIA, GEOSCIENCE. (2011). *THE NATIONAL DYNAMIC LAND COVER DATASET*: GEOSCIENCE AUSTRALIA.

MANSFIELD, CAROL, PATTANAYAK, SUBHRENDU, MCDOW, WILLIAM, MCDONALD, ROBERT, & HALPIN, PATRICK. (2005). SHADES OF GREEN: MEASURING THE VALUE OF URBAN FORESTS IN THE HOUSING MARKET. *JOURNAL OF FOREST ECONOMICS, 11*(3), 177-199.

MEEHL, GERALD, & TEBALDI, CLAUDIA. (2004). MORE INTENSE, MORE FREQUENT, AND LONGER LASTING HEAT WAVES IN THE 21ST CENTURY. *SCIENCE, 305*(5686), 994-997.

MOULTON, BRENT. (1990). AN ILLUSTRATION OF A PITFALL IN ESTIMATING THE EFFECTS OF AGGREGATE VARIABLES ON MICRO UNITS. *THE REVIEW OF ECONOMICS AND STATISTICS*, 334-338.

NIGHTINGALE, JOANNE, & PHINN, STUART. (2003). ASSESSMENT OF RELATIONSHIPS BETWEEN PRECIPITATION AND SATELLITE DERIVED VEGETATION CONDITION WITHIN SOUTH AUSTRALIA. *AUSTRALIAN GEOGRAPHICAL STUDIES, 41*(2), 180-195.

PANDIT, RAM, POLYAKOV, MAKSYM, TAPSUWAN, SORADA, & MORAN, TIMOTHY. (2012). THE EFFECT OF STREET TREES ON PROPERTY VALUE IN PERTH, WESTERN AUSTRALIA. *LANDSCAPE AND URBAN PLANNING*.

PANDURO, TOKE, & VEIE, KATHRINE. (2013). CLASSIFICATION AND VALUATION OF URBAN GREEN SPACES: A HEDONIC HOUSE PRICE VALUATION. *LANDSCAPE AND URBAN PLANNING, 120*, 119-128.

PAYTON, SETH, LINDSEY, GREG, WILSON, JEFF, OTTENSMANN, JOHN, & MAN, JOYCE. (2008). VALUING THE BENEFITS OF THE URBAN FOREST: A SPATIAL HEDONIC APPROACH. *JOURNAL OF ENVIRONMENTAL PLANNING AND MANAGEMENT, 51*(6), 717-736.

POUDYAL, NEELAM, HODGES, DONALD, & MERRETT, CHRISTOPHER. (2009). A HEDONIC ANALYSIS OF THE DEMAND FOR AND BENEFITS OF URBAN RECREATION PARKS. *LAND USE POLICY, 26*(4), 975-983.

READY, RICHARD, & ABDALLA, CHARLES. (2005). THE AMENITY AND DISAMENITY IMPACTS OF AGRICULTURE: ESTIMATES FROM A HEDONIC PRICING MODEL. *AMERICAN JOURNAL OF AGRICULTURAL ECONOMICS, 87*(2), 314-326.

REHDANZ, KATRIN. (2002). HEDONIC PRICING OF CLIMATE CHANGE IMPACTS TO HOUSEHOLDS IN GREAT BRITAIN: FNU-13.

ROSEN, SHERWIN. (1974). HEDONIC PRICES AND IMPLICIT MARKETS: PRODUCT DIFFERENTIATION IN PURE COMPETITION. *THE JOURNAL OF POLITICAL ECONOMY, 82*(1), 34-55.

ROSENZWEIG, CYNTHIA, SOLECKI, WILLIAM, & SLOSBERG, RONALD. (2006). MITIGATING NEW YORK CITY'S HEAT ISLAND WITH URBAN FORESTRY, LIVING ROOFS, AND LIGHT SURFACES. *REPORT TO THE NEW YORK STATE ENERGY RESEARCH AND DEVELOPMENT AUTHORITY*.

SANDSTRÖM, GREGORY, ANGELSTAM, PER, & MIKUSIŃSKI, GRZEGORZ. (2006). ECOLOGICAL DIVERSITY OF BIRDS IN RELATION TO THE STRUCTURE OF URBAN GREEN SPACE. *LANDSCAPE AND URBAN PLANNING, 77*(1), 39-53.

SCHÄFFLER, ALEXIS, & SWILLING, MARK. (2013). VALUING GREEN INFRASTRUCTURE IN AN URBAN ENVIRONMENT UNDER PRESSURE: THE JOHANNESBURG CASE. *ECOLOGICAL ECONOMICS, 86*, 246-257.

SCHILLING, JOSEPH, & LOGAN, JONATHAN. (2008). GREENING THE RUST BELT: A GREEN INFRASTRUCTURE MODEL FOR RIGHT SIZING AMERICA'S SHRINKING CITIES. *JOURNAL OF THE AMERICAN PLANNING ASSOCIATION, 74*(4), 451-466.

SENGUPTA, SANCHITA, & OSGOOD, DANIEL. (2003). THE VALUE OF REMOTENESS: A HEDONIC ESTIMATION OF RANCHETTE PRICES. *ECOLOGICAL ECONOMICS, 44*(1), 91-103.

SIMS, DANIEL, RAHMAN, ABDULLAH, CORDOVA, VICENTE, EL-MASRI, BASSIL, BALDOCCHI, DENNIS, BOLSTAD, PAUL, . . . MISSON, LAURENT. (2008). A NEW MODEL OF GROSS PRIMARY PRODUCTIVITY FOR NORTH AMERICAN ECOSYSTEMS BASED SOLELY ON THE ENHANCED VEGETATION INDEX AND LAND SURFACE TEMPERATURE FROM MODIS. *REMOTE SENSING OF ENVIRONMENT, 112*(4), 1633-1646.

STOBBE, TRACY, COTTELEER, GEERTE, & CORNELIS VAN KOOTEN, GERRIT. (2009). HOBBY FARMS AND PROTECTION OF FARMLAND IN BRITISH COLUMBIA. *CANADIAN JOURNAL OF REGIONAL SCIENCE, 32*(3), 393.

TYRVÄINEN, LIISA, & MIETTINEN, ANTTI. (2000). PROPERTY PRICES AND URBAN FOREST AMENITIES. *JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT, 39*(2), 205-223.

TZOULAS, KONSTANTINOS, KORPELA, KALEVI, VENN, STEPHEN, YLI-PELKONEN, VESA, KAŹMIERCZAK, ALEKSANDRA, NIEMELA, JARI, & JAMES, PHILIP. (2007). PROMOTING ECOSYSTEM AND HUMAN HEALTH IN URBAN AREAS USING GREEN INFRASTRUCTURE: A LITERATURE REVIEW. *LANDSCAPE AND URBAN PLANNING, 81*(3), 167-178.

VANSLEMBROUCK, ISABEL, HUYLENBROECK, GUIDO, & VAN MEENSEL, JEF. (2005). IMPACT OF AGRICULTURE ON RURAL TOURISM: A HEDONIC PRICING APPROACH. *JOURNAL OF AGRICULTURAL ECONOMICS, 56*(1), 17-30.

WOLF, KATHLEEN. (2004). TREES AND BUSINESS DISTRICT PREFERENCES: A CASE STUDY OF ATHENS, GEORGIA, US. *JOURNAL OF ARBORICULTURE, 30*(6), 336-346.

# APPENDIX:

## A1: Variable Descriptions

| Variable: | Description |
|---|---|
| **Sales Price** | Sale price of the property in $AU |
| **Bedrooms** | Number of bedrooms. Properties were excluded if they had more than 10. |
| **Bathrooms** | Number of bathrooms. Properties were excluded if they had more than 10. |
| **Car Parks** | Number of car parks. Properties were excluded if they had more than 10. |
| **Area** | Area of the land the property is located on per $100m^2$ |
| **Postcode** | The postcode the property is located in |
| **State** | The state the property is located in |
| **Year** | The year between 2000 and 2010 the property was sold in |
| **Month** | The month the property was sold in |
| **Property Type** | Type of property, either house or units/apartments |

A2: Descriptive statistics table.

| Variable | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Sale Price** | 2,651,962 | 372,456.1 | 362,743.4 | 1,000 | 20,000,000 |
| **Area** | 2,651,962 | 869.7 | 934.7 | 0.1 | 10,000 |
| **Bedrooms** | 2,651,962 | 3.280 | 0.797 | 1 | 10 |
| **Bathrooms** | 2,651,962 | 1.328 | 0.831 | 1 | 10 |
| **Car Parks** | 2,651,962 | 1.424 | 1.105 | 0 | 10 |
| **EVI** | 2,531,803 | 0.295 | 0.074 | 0.059 | 0.597 |
| **Precipitation** | 2,531,803 | 2.372 | 1.340 | 0 | 31.48 |

A3: IV results excluding states. Standard errors are clustered at postcode-year level.

| **Dependent Variable Log(Price)** | **Exc. VIC** | **Exc. NSW** | **Exc. ACT** | **Exc. QLD** | **Exc. NT** | **Exc. SA** | **Exc. WA** |
|---|---|---|---|---|---|---|---|
| **EVI** | 3.309*** | 2.338*** | 1.942*** | 0.153 | 1.955*** | 2.018*** | 1.958*** |
| | (1.004) | (0.904) | (0.740) | (0.742) | (0.743) | (0.762) | (0.752) |
| **Bedrooms** | 0.107*** | 0.157*** | 0.149*** | 0.158*** | 0.149*** | 0.149*** | 0.152*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| **Bathrooms** | 0.137*** | 0.060*** | 0.068*** | 0.054*** | 0.068*** | 0.065*** | 0.060*** |
| | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| **Car Parks** | 0.034*** | 0.009*** | 0.014*** | 0.015*** | 0.014*** | 0.014*** | 0.008*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) |
| **Area per 100 $m^2$** | 0.008*** | 0.008*** | 0.008*** | 0.008*** | 0.007*** | 0.007*** | 0.007*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| **Postcode FE** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **State-year FE** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **Months** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **Observations** | 1,711,987 | 1,958,128 | 2,507,946 | 2,000,719 | 2,521,854 | 2,390,082 | 2,100,102 |
| **$R^2$** | 0.519 | 0.545 | 0.500 | 0.472 | 0.501 | 0.495 | 0.481 |
| **F statistic** | 70.58 | 32.6 | 56.54 | 35.03 | 56.11 | 54.14 | 53.35 |

***, ** AND * REPRESENT SIGNIFICANCE AT THE 1%, 5% AND 10% LEVEL RESPECTIVELY

A4: IV results using total monthly rainfall as the instrument excluding QLD. Standard errors are clustered at postcode-year level.

| Dependent Variable Log(Price) | Exc. QLD |
|---|---|
| **EVI** | 1.307** |
| | (0.624) |
| **Bedrooms** | 0.148*** |
| | (0.002) |
| **Bathrooms** | 0.067*** |
| | (0.002) |
| **Car Parks** | 0.018*** |
| | (0.001) |
| **Area per 100 $m^2$** | 0.007*** |
| | (0.000) |
| **Postcode FE** | Yes |
| **State-year FE** | Yes |
| **Months** | Yes |
| **Observations** | 1,103,532 |
| **$R^2$** | 0.455 |
| **F statistic** | 104.65 |

***, ** AND * REPRESENT SIGNIFICANCE AT THE 1%, 5% AND 10% LEVEL RESPECTIVELY