CAN EXCLUSION FACTORS BE PRICED?

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ABSTRACT

Social exclusion defines the degree to which an individual is limited in their access to the services and facilities to engage with their local and broader community. This paper investigates the relationship between exclusion and the level of accessibility to services provided by locality and transport. We provide household valuations of the factors that affect access and which can inform various policy directions.

A Hedonic Price Analysis of an urban residential area is used to estimate implicit household monetary valuations on some key exclusion indicators. The value of access to schools, shops, parks and transport facilities is observed in the market price of the house. The application to social exclusion focuses on the outer suburbs of Perth, Western Australia with low socio-economic status. Locations are drawn from a prior cluster analysis that identifies local areas with distinct accessibility differences. Depending on the model structure, these evaluations may differ. Current results reveal a 6-8% premium for houses conveniently located near local shops, schools, a railway station and to the CBD, a 20-25% premium for the quality of the neighbourhood, the remaining being embedded in the dwelling features.

The analysis has both practical and academic implications: i) it informs policies that aim to alleviate social exclusion. The implicit pricing is an important advance in this area because the household valuations may be imported into cost-benefit analysis of transport or service provision projects; ii) the implicit prices are important inputs into the designing of experiments for follow-up stated choice surveys aimed at understanding residential choice; however, differences in evaluations lead to different designs, supporting the wider adoption of Bayesian designs, which can be more robust to variations of prior parameters. The models accounting for spatial effects provide more robust estimates, however the interpretation and prediction are not straightforward.

Keywords: social exclusion, accessibility, transport

1 INTRODUCTION

It is without doubt that the housing market sorts households into areas of advantage and areas of disadvantage. High property values and consequent high rental costs effectively price out the less affluent families from access to quality neighbourhoods. United States housing prices show a rapid decline once the concentration of poverty exceeds about 10 per cent (Galster *et al.*, 2008). The composition of the social community can present the locality as more or less attractive (higher or lower land value) to prospective residents. Gibbons and Machin (2008) suggest that the quality of local government schooling and crime rate have an effect on housing values. Furthermore, the value of the quality of schooling, capitalised in housing prices, is a function of the school's composition as well as the educational performance of the school (Gibbons *et al.*, 2012). The effect of socio-economic agglomeration may "*seriously distort the valuation of specific amenities"* and hedonic regression analysis must carefully consider the effect of spatial correlation (Theriault *et al.*, 2003).

Whilst acknowledging the evident social segregation within urban areas, it is still worth investigating whether the lower socio-economic areas differ in terms of access to services. Furthermore, are residents paying a premium for access to transport and other services? The Social Exclusion Unit (SEU) reported a link between lower socio-economic households and their increased challenge to access education, employment, health services and cultural or leisure activities (Social Exclusion Unit, 2003). Whilst transport disadvantage does not necessarily lead to transport-related exclusion (Lucas, 2012), mobility is a predictive indicator of a person's self-reported level of inclusion (Stanley *et al.*, 2011). Currie *et al.* (2010) suggest that residents on the fringe of Melbourne, Victoria, exercised a choice between household affordability and vehicle ownership. Some residents opted for a higher valued property with better access to services and forwent a private vehicle; others invested in a car by moving to a more affordable area.

The purpose of this paper is to identify whether the neighbourhood attributes, in particular access to services and transport, are valued by those at highest risk of exclusion: Do the lower socio-economic groups value access? We use the implicit prices for closeness to services, estimated in spatial hedonic regression models, to proxy the value of accessibility. The sample is limited to lower socio-economic areas in Perth and the values do not represent the average 'market' values. Given the importance of spatial effects in obtaining unbiased parameter estimates and understanding the role of dwelling characteristics, neighbourhood features and access in housing prices, we estimated a sequence of spatial models starting with models including only coordinates of the house location and distances to various services, to models incorporating lagged and error effects. The final model, we are discussing here, has a mixed structure, with both lag and error, and meets the assumptions of normality, independence of errors, heteroscedasticity.

The paper opens with a discussion on social exclusion and the relationship with location choice (Section 2.1) and mobility (Section 2.2). The hedonic regression modelling incorporating spatial autocorrelation is presented in Section 3. The data and statistical modelling results are given in Section 4, followed by a discussion of the policy implications.

2 SOCIAL EXCLUSION

Rene Lenoir (1974) was the first to regard the disadvantaged section of the population as "socially excluded" in his assessment of the French population who were not covered by the social security net. These included: mentally and physically handicapped, suicidal people, the aged, invalids, abused children, substance abusers, delinquents, single parents, multi-problem households, marginal, asocial persons, and other social "misfits" (Silver, 1995: 63). These people made up around 10% of the French population. The concept has since broadened and is currently used to refer to a range of dimensions which marginalise people and reduce their opportunities to engage in social or political life (Scutella *et al.*, 2009: 7).

The concept of social exclusion became prominent in Britain under the Blair Labour government in the 1990's when they introduced the Social Exclusion Unit (SEU). The unit outlined social exclusion as *"what can happen when people or areas suffer from a combination of linked problems such as unemployment, poor skills, low incomes, poor housing, high crime, poor health and family breakdown"* (Social Exclusion Unit, 2004). The unit has addressed a number of different areas including elderly disadvantage, youth unemployment, and teenage pregnancy, repeat criminal offenders, homelessness and transport disadvantage.

What became apparent was the breadth and complexity of issues associated with the term social exclusion. Hence, a coherent definition and framework for the concept is imperative so that we can identify which individuals are socially excluded, the extent of their exclusion and what type of policies can effectively lessen exclusion.

Burchardt (2000) attempted to fill the definitional void by defining social exclusion based on Townsend's concept of relative deprivation.

> *"An individual is socially excluded if he or she does not participate to a reasonable degree over time in certain key activities of his or her society and*
> *(a) This is for reasons beyond his or her control*
> (b) *He or she would like to participate" (*Burchardt, 2000: 388)

The key point here is that for an individual to be socially excluded they must *want* to participate in an activity that is customary or common in society, without being able to do so. These activities are multi-dimensional and address various facets of an individual's life. Burchardt (2000) developed four dimensions addressing a diverse spectrum of activities, which were thought to be important for people to participate in Britain in the 1990s:

1) *Consumption* is having a reasonable standard of living;
2) *Production* is engaging in a socially valued activity such as paid work or volunteering;
3) *Political engagement* is participation in the democratic process, or 'having a voice' in society;
4) *Social interaction* is relations with friends and family – or the opposite of isolation.

The first two dimensions identify the economic contribution of individuals in society. Limited access to the job markets, due to a lack of transport infrastructure or education and training, not only affects engagement in the labour force, but also the level of consumption undertaken by the household to which the individual belongs. In a sense, social exclusion is self-fortifying in that limited access to social infrastructure limits the household's capacity to buy their way out of exclusion.

Most contemporary measures of social exclusion are derived from Burchardt's four-factor model. For example, the Australian government's new social inclusion agenda aims to allow Australians to have the resources, opportunities and capability to:

- *Learn* by participating in education and training;
- *Work* by participating in employment, in voluntary work and in family and caring;
- *Engage* by connecting with people and using their local community's resources; and
- *Have a voice* so that they can influence decisions that affect them (Social Inclusion Agenda, 2011).

2.1 Social Exclusion and Household Location

Given the percentage of income allocated to it, housing is an extremely important factor in lower socio-economic consumption decisions. Housing stress has become a debilitating influence on low-income families in the last decade in Australia as house prices have increased by 400%, while incomes have only risen 120%. Using a measure of median house prices compared to median income, every Australian capital city is rated as severely unaffordable. Sydney, Melbourne, Adelaide, Brisbane and Perth are among the top 14 most expensive cities in the world (Demographia, 2012: 11). This has led to over one million low and middle income Australians spending more than 30% of their entire budget on housing (Healey, 2011: 2).

A major determinant on a person's risk of social exclusion is her/his residential location. Kelly and Lewis (2002) suggest that spatial frictions may occur that prevent complete integration of a metropolitan labour market, such as access to employment rich areas like the CBD. Donaghy *et al.* (2004) identify that the high cost of transport for low-wage workers restricts their ability to engage with the community, reinforces a local lifestyle and increases the likelihood of further social exclusion. This is especially true for their children as subsequent generations of transport-disadvantaged families are then put at further risk of social exclusion; being limited from accessing the education and employment limits their possibility to gain income to become more mobile (Donaghy *et al.*, 2004: 683).

A major reason to this problem has been the gentrification of cities with its associated movement of high-income and high labour market status populations to previously declining inner urban locations, resulting in housing market price displacing the existing less advantaged residents. The effect was driving out low-income households to urban fringes, where they are put at greater risk of social exclusion, as transport, employment and services may be more restricted. As high paying jobs are usually located in inner city areas and routine, low paying production work is more peripheral, households on the urban fringe may be excluded from certain employment, due to spatial labour market segmentation (Dodson *et al.*, 2004: 5). In Melbourne, Delbosc and Currie (2011) identified that one in 15 of fringe and regional respondents could not find work and half of these said they could not interview for jobs because of transport difficulties.

Fringe dwelling households are further disadvantaged in the face of rising fuel costs because they have fewer available alternatives of transport. The consequence is that while inner city people have the possibility to walk or cycle more to get to activities, outer suburban people are likely to participate less in activities (Delbosc and Currie, 2011: 1134). If oil prices and house prices continue to rise we would continue to see residents in suburban and regional areas finding it harder to participate in society.

2.2 Social Exclusion and Mobility

The ability of an individual to be mobile is highly significant in reducing their chance of becoming socially excluded. As indicated, the UK's Social Exclusion Unit identified that problems with transport provision and the location of services can reinforce social exclusion, as they prevent people from accessing key services or activities, such as jobs, learning, healthcare, food shopping or leisure. The unit found that 40% of job seekers considered lack of transport as a barrier to getting a job, 50% of 16-18 year old students had trouble with transport costs associated with education, and 31% of people without a car had difficulties travelling to their local hospital (Social Exclusion Unit, 2003). In addition, motoring costs account for a quarter of all household expenditure.

Stanley *et al.* (2011) found that the number of daily trips a person makes strongly reduces their chance of becoming socially excluded. Transport disadvantage is more relevant to young people, single parents, the unemployed, low-income families (Delbosc and Currie, 2011) and non-drivers (Engels and Liu, 2011).

Household mobility decisions are embodied in their housing location choices. For example, Debrezion *et al.* (2007) explained that dwellings within a 400m range to a station are on average about 4.2% more expensive. A trade-off exists between living in inner city areas, which are more expensive, yet offer more services within walking distances and better public transport, and living in a cheaper outer suburb where they will face higher transport costs. Currie *et al.* (2010) studied the residential and transport patterns of two different groups, Low income no car ownership (LINCO) and low-income high car ownership (LIHCO) households. LIHCO households considered housing affordability as the greatest influence on their housing choices; LINCO chose proximity to public transport as their most important location factor. Around a third of LIHCO households reported transport costs as a major portion of their income, while another third limited travel to reduce costs. LINCO were asked to explain their reasons for not having a car. While over half said they could not afford to drive a car, another third preferred to save money by not owning a car. However, without adequate provision of public transport households may be restricted from engaging in certain activities or forced into car ownership.

3 HEDONIC PRICE THEORY

Hedonic Price (HP) Theory quantifies the value of underlying characteristics in goods. Its usefulness arises from the ability to infer the value of these characteristics, many unobservable in the market place. We use here HP to assess the implicit value of access to various urban facilities. The model is applied to data from the low income housing market in order to price main exclusion factors such as metropolitan accessibility, public transport, shopping facilities, education, etc.

1.1 The Consumption of Characteristics Rather than Goods

The hedonic pricing, HP, model is based on a Lancastrian perception of consumer theory. Consumers perceive goods as bundles of characteristics (Lancaster, 1966). A hedonic price model is a relation between prices of varieties or models of heterogeneous goods – or services – and the quantities of characteristics contained in them:

$$P = \beta X \tag{1}$$

where *P* is an *n*-element vector of prices of varieties, X is a *k* × *n* matrix of characteristics, and β is a vector of coefficients that can be interpreted as implicit prices. They are called 'implicit' because the prices are not directly observed in the market place. Consumers purchase the good based upon the price of the good relative to all other goods, their budget constraint and their utility function (Lancaster, 1966: 133).

Sherwin Rosen's (1974) work was highly influential in the development of Hedonic Theory as he identified that the attributes of goods were subject to 'implicit markets'. Rosen's primary goal was *to "exhibit a generating mechanism for the observations in the competitive case and to use that structure to clarify the meaning and interpretation of estimated implicit prices"* (Rosen, 1974: 35). Implicit prices of goods are driven by an interaction between bid functions of households and offer functions of suppliers. Rosen assumed perfect competition, whereby producers maximise profit, consumers maximise utility, prices are exogenous for an individual agent, information is perfect, where there are a large number of buyers and sellers, and all optimum choices are feasible. Rosen departed from Lancaster on the assumption of indivisibility. He outlined that packages of goods cannot be untied and mixed with portions of another bundle to optimise utility (Rosen, 1974: 38), which means we cannot arbitrage characteristics and must assume diminishing marginal utility.

3.1 Rosen's Model of Consumer Choice

Rosen identified that utility, U, is strictly concave and a function of how the consumer values the characteristics, $z_{1,\dots,}z_n$, , of a particular good, and the goods a consumer can purchase with their residual income, *x*. Utility is expressed as:

$$U(x, z_{1,\dots,}z_n) = u \tag{2}$$

An optimal choice is made by a consumer based on their budget constraint (y), y=$p(z_i) + x$, the amount of characteristics in a good, $(z_{1,...}, z_n)$ and their utility function, U. Rosen used these concepts to formulate the following bid function for a good: ϴ=$(z_{1,...}, z_n; u, y)$. If utility is maximised subject to the non-linear budget constraint, we get the first order conditions:

$$U(z_i, x) + \lambda(y - p(z_i) - x) \tag{3}$$

$$\frac{\partial u}{\partial z_i} - \lambda p_i = 0 \tag{4}$$

$$\frac{\partial u}{\partial x} - \lambda = 0 \tag{5}$$

$$\frac{\lambda p_i}{\lambda} = \frac{\partial u}{\partial z_i} / \frac{\partial u}{\partial x} \tag{6}$$

$$\frac{\partial p}{\partial z_1} = p_i = \frac{u_{zi}}{u_x}, i = 1, \ldots, n, \tag{7}$$

Marginal utility of money income is denoted as λ. The first derivative p_i is the implicit price of z_i and must be equal to the marginal rate of substitution between the characteristic z_i and x, all other goods. If we set the price of x equal to unity and measure income in terms of units of x: y = x + p(z), we can derive the second order conditions by maximisation of utility subject to the non-linear budget constrain. Differentiating (2), where x = y – ϴ, and where p(z) is not sufficiently concave, we obtain:

$$\frac{U_{zi}}{U_x} > 0 \;;\; \Theta_u = -\frac{1}{U_x};\text{ and } \Theta_y = 1 \tag{8a-c}$$

The relation 8a explains the relationship between the utility of characteristics and utility of all other goods. As all other goods represent our residual income, we can interpret the derivative as the marginal rate of substitution between z_i and money income. The partial derivative $\partial\Theta / \partial z_1$ gives the rate at which the household would be willing to change their bid in response to a change in the characteristic z_1, holding utility constant. The bid function, which is the amount the consumer is willing to pay at a fixed income and utility level, is tangential to the price function at the optimum, that is $\frac{\partial\Theta}{\partial z_i} = \frac{U_{z1}}{U_x} = p_i$.

Since $\frac{U_{zi}}{U_x} > 0$, the characteristics a person consumes increase as their income increases. However, this increase may not be proportionate. Higher income groups may desire certain characteristics over others. For example, in a housing market, higher income groups may value proximity to public goods such as parks and beaches, more than their marginal valuation on an additional bedroom. Rosen accounts for this by allowing for a parameterisation of tastes across consumers. The utility function is expressed as U(x, $z_{1,...,} z_n; \alpha)$, where α is a taste parameter that differs from person to person. An additional challenge is the dependence of many attributes on the neighbours' attributes. This means that *z* and *a* are not enough for evaluating accurately the valuation of the housing bundles.

3.2 Application of HP to Location Choice

Starting from (1) a variety of multivariate methods can be applied for the analysis of spatial variation of housing prices (see Paéz and Scott, 2004 and Anselin, 2006 for reviews of these models). Because houses in neighbourhoods have similar characteristics and they may vary from other parts of the city, to address the spatial structure we apply a series of models accounting for spatial autocorrelation and dependence. The general structure of the model is given in (9), where the house sales price P_h includes the characteristics (z), W, a matrix of geographic weights calculated as a distance-based or a contiguity matrix between the houses (in this research using binary indicators for the closest five neighbours), and μ, an error term accounting for spatial dependence (ε is assumed independent and possibly homogeneous). The coefficients β give an indication of the implicit price of each characteristic, after accounting for relationships with the neighbours. If ρ and λ are both zero, (9) is the expression of the a-spatial multivariate OLS regression. The other two particular cases occur when only ρ=0 (spatial error model) or only λ=0 (spatial autoregressive model). The vector z of explanatory variables includes three categories of characteristics: locality, dwelling features (age, block area, bedrooms), and transport accessibility to various urban services (education, health, recreation, etc.).

$$P_h = \rho W P_h + z\beta + \mu_h \quad \text{and} \quad \mu_h = \lambda W \mu_h + \varepsilon_h \qquad (9)$$

Generally, a two-step approach is applied (Paéz and Scott, 2004: 55; Anselin *et al.*, 2010), with a non-spatial model estimated first and then checking the spatial associations using indicators of spatial association (e.g., Gamma, Moran's I, Geary's c, Ripley's K, in Getis, 2010) or spatial statistical tests. Significant Lagrange multipliers, LM (Anselin, 1988; Anselin *et al.*, 2010) support the estimation of more sophisticated spatial models, whereas failure to reject the null hypothesis of spatial errors and lags indicates that the OLS model accounts for the variability in the data. This modelling strategy is also applied in this research and the results are provided in Section 4.

The theory outlined in this section was applied to sales prices from the Perth housing market. The transacted prices of houses were regressed against their characteristics in order to estimate the implicit price, μ_i, of each characteristic. Prices of factors like public transport, quality of surrounding education, local recreational amenities, and metropolitan accessibility are embodied in household valuations and, as such, HP allow us to estimate the value of these factors, even though they are not directly observable in the market place. Then, using an example, we evaluated the impact of location and transport access as a social exclusion measure.

4 DATA AND RESULTS

This research combines three sources of secondary data: housing market, Census data (ABS, 2005-2011), and transport GIS information from WA Department of Planning and Department of Transport. Section 4.1 describes how the data set was prepared for hedonic regression analysis. Residential house property sales from 23,277 transactions, between April 2011 and March 2012, were made available by Landgate for the greater Perth metropolitan area. The data contains a series of variables relevant for hedonic regression of the sales price and for this analysis we selected suburbs that displayed the lowest socio-economic indicators provided by ABS and were the most remote in terms of transport access. Although, in most circumstances, low-income households will usually be in the rental market and assisted social housing, we used the sales price as a proxy for value of the underlying characteristics. In this geographical setting the rental price is highly correlated with the sales price.

4.1 Focus on Socially Excluded Households

We applied cluster analysis (two-stage approach, including Ward method with Euclidean distance and followed by quick clustering with seeds from previous hierarchical cluster analysis), to identify Perth suburbs with similar socio-demographic fabric and similar access to various urban services (Olaru and Smith, 2012). Through this analysis we were able to spatially differentiate areas with good access from zones of the city, remote in terms of their opportunities for economic and social participation/integration. The cluster analysis identified five residential types. The analysis was based on:

- Seventeen city-wide and local accessibility variable such as population density, employment density, the distance from the CBD, road accessibility, public transport accessibility and distance to services;
- The structure of the household, employment and car ownership;
- Additional ABS socio-economic indicators;
- Characteristics of the dwelling; median house price and average number of bedrooms.

Table 1 describes the five clusters, which are significantly different from each other at significance level of less than 1% (Multivariate Analysis of Variance, MANOVA, tests).

Table 1: Cluster Analysis of Perth Metropolitan Region

Cluster	**Description**
Cluster 1	Inner city, high value land, highest population density, small houses
Cluster 2	Highest income, highly connected locations, highest property values
Cluster 3	Lowest income and car ownership, low property value, lowest socio-economic indicators
Cluster 4	Lowest population density, income and education advantage, suburban housing, largest household size with most children
Cluster 5	Outer coastal suburbs, lowest property values, big houses

Cluster 3, including 82 suburbs, displayed the deepest economic disadvantage, the lowest indicators of development and access to facilities, whereas cluster 5 (21 suburbs) is the furthest in terms of geographical city access and includes the lowest price properties. These 103 suburbs were considered to have significant levels of socio-economic exclusion and further analysed in this research, with a sample of them used in the hedonic pricing analysis (51 suburbs were chosen based on having greater than 25 observations, i.e. 25 transactions during the analysed time period). Finally, the houses in these suburbs were grouped geographically in 13 areas, presented in Appendix.

As the focus of the research is on the consumption patterns of socially excluded households, only sales below $500,000 were used in the analysis. Given that the weekly repayments for a $500,000 home are of $790.73 (based on the average variable rate, of 6.67% of Australia's big four banks - CANSTAR, 2011), and the median household weekly income of $1,234 (ABS, 2011), we appreciated that households who can afford homes greater than $500,000 should be excluded from the dataset. A lower bound of $150,000 was set to eliminate unusual transaction values, as low as $20, judged as occurring either between family members or being data coding errors (i.e., including only arm's length transactions).

Only properties classed as "HOUSE" were considered for the hedonic regression, with household structures such as vineyards, farmland or boatsheds being ignored. The variable used for lot size the area of the property polygon in m^2. The variable describing the area of the house size was omitted from the analysis because 70% of the data was missing. All the garage and carport variables are combined to one single variable measuring the facility of parking space. Some other variables were combined when the functionality was similar (e.g. the 'service' of rooms is assumed to be interchangeable for FAMILY, GAMES and LOUNGE rooms, thus they have been pooled into one variable, RECREATION, whereas DINING and MEALS rooms became the variable EATING). The filtering and augmentation of the variables has narrowed down the dataset to 2,649 observations.

Locational attributes have also been incorporated into the dataset to capture the surrounding amenities, transport services, recreational features and aesthetic qualities of the dwelling and neighbourhood. Shopping precincts, the central business district, healthcare centres, rivers, oceans, schools, universities, technical college (TAFE), parks and negative locations such as airports have all been geocoded using *Google Maps.* The minimum Euclidean distance has then been calculated between each household and the locational attribute.

Other locational effects have been taken into account by the inclusion of dummy variables for suburbs and regions. Table 2 displays the descriptive statistics for each geographical cluster shown in the Appendix and the spatial distribution of the houses and facilities is presented in Figure 1. Two Rocks has the highest average sale and Midland the lowest. The most established areas are Guildford and South River, with new development in the North Inner and Coastal areas. Most houses have access to shops and healthcare within a 2 km radius. The average block size is around $660m^2$, which is slightly smaller than the national average of 735 (State of the Environment, 2003). The distance to the CBD reveals the extent of the city, with suburbs located at distances ranging from 4 to 67km from the city. The closest to the city are suburbs in the Belmont area and the furthest Mandurah and Two Rocks.

The map (Figure 1) shows that with few exceptions (Spearwood, Mandurah), the areas potentially excluded are further from the coast, aligned N-S on the inland side of the major Mitchell-Kwinana Freeways and near four of the five the railway lines (Clarkson, Mandurah, Armadale, and Midland). Although most facilities seem to be dispersed evenly across the metro area, the 'negative features' (power lines, airport, water treatment plants) are dominating in the Eastern groups.

Table 2: Descriptive Statistics by Geographical Cluster

Area	Sale ($)	Age of the house (years)	Lot-size (ha)	Dist. from tertiary ed.(km)	Dist. from shops (km)	Dist. from schools (km)	Dist. from train (km)	Dist. from TAFE (km)	Dist. from health/ hospital (km)	Dist. from river/ ocean (km)	Distance from negative features (km)	Dist. from CBD (km)
South River	365,077	33.42	0.069	10.62	1.36	1.94	1.14	2.89	0.58	1.59	7.34	11.89
Spearwood-South Lake	386,439	32.91	0.071	4.71	1.19	*1.34*	3.05	9.64	0.92	1.55	3.94	16.45
North Rockingham	364,574	29.12	0.068	7.48	1.59	1.54	1.15	*0.94*	0.53	4.23	5.24	32.12
Rockingham	336,717	26.66	0.066	*2.38*	1.68	1.83	1.30	1.40	0.92	1.92	7.10	38.88
Mandurah	359,334	18.82	0.066	28.94	1.66	1.87	1.17	17.78	0.70	1.26	**33.98**	**65.50**
Broodale-Kenwick	365,552	28.21	0.069	15.78	**3.20**	1.42	0.98	2.63	1.09	2.03	10.98	19.18
North Coastal	316,637	13.29	0.062	8.09	1.08	2.31	1.87	13.89	*0.45*	4.77	4.56	31.55
North Inner	327,422	*13.06*	0.063	5.31	1.20	**5.93**	2.18	9.42	0.73	1.85	1.53	24.96
Two Rocks	**478,389**	26.56	**0.079**	**32.78**	1.08	7.03	**15.70**	**29.38**	**12.89**	*0.73*	*1.30*	56.50
Balga	364,180	32.35	0.069	8.45	1.15	1.36	3.73	1.66	0.62	**5.03**	9.53	12.09
Guildford	319,367	**46.98**	0.060	5.65	*0.88*	2.40	*0.75*	4.50	0.79	1.92	4.17	8.44
Midland	*287,703*	23.45	*0.055*	16.61	0.92	3.75	2.54	1.23	1.72	2.51	2.91	19.17
Belmont	326,120	30.36	0.060	8.09	1.80	1.60	2.19	6.59	0.60	1.18	*1.31*	*8.03*

Note: For each column the highest value is given in **bold** and the lowest value is in ***italic***.

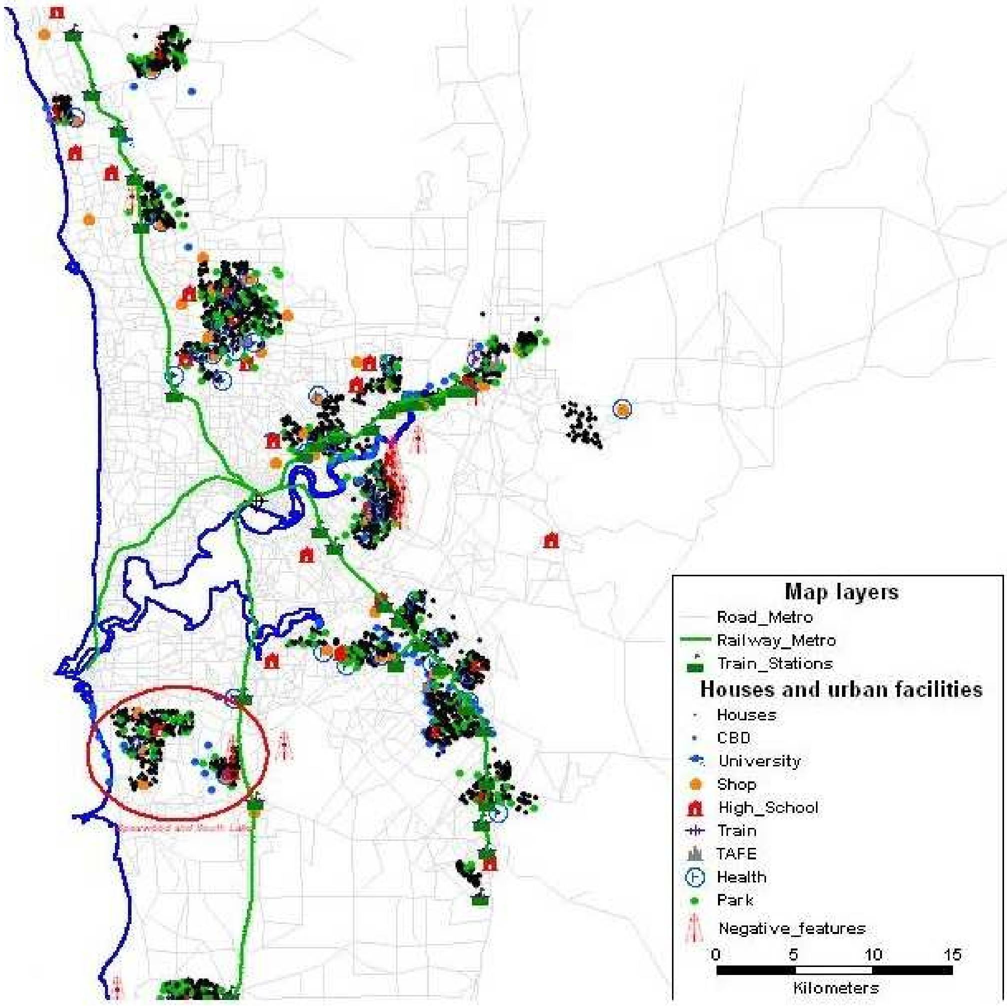

Figure 1: Map of households and locational features

Figure 2 is a zoom-in view for the Spearwood-South Lake area, an “average” cluster both in socio-demographic characteristics and access to urban facilities.

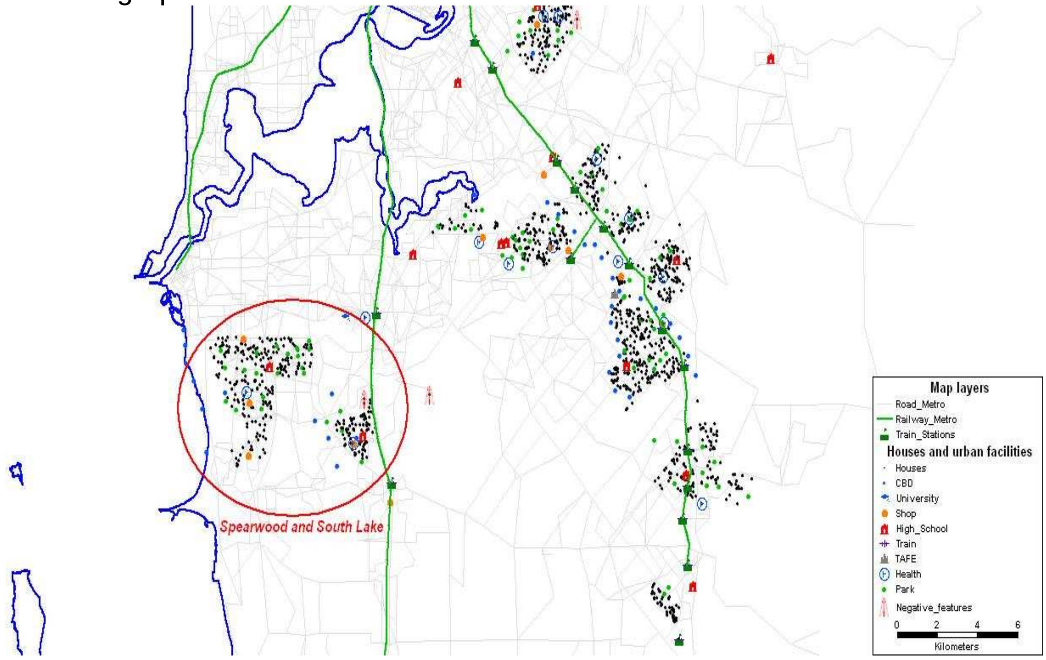

Figure 2: Cluster Example: Spearwood

Overall, the houses in our sample are located at an average of 23km from the city, have access to a park nearby (in less than 500m), and have a high school or a train station in 2km distance from them.

4.2 Empirical Results and Findings

Table 3 displays the results of four models: ordinary least squares (OLS), spatial error (SEM), spatial autoregressive lagged (SAR) and spatial combined model (SAC).

Their overall goodness-of-fit is remarkable. Even the OLS model explains 91% of the variance in the transaction prices using dwelling and location characteristics. The standard error of the estimate ($22,363) of 6.2% of the average house price, confirms again the quality of the model and suggests that outliers may affect the results of the analysis.
However, the condition index shows significant multicollinearity (1892.745), primarily due to location variables. The extremely significant Jarque-Bera test indicates strong non-normality of residuals (57.180; p<0.001) and there is also strong heteroscedasticity, as illustrated by Breusch-Pagan (175.228, p<0.001) and Koenker-Bassett tests (261.003, p<0.001). The Moran's I for residuals indicates significant autocorrelation = 0.2023 (I=17.895), which is further confirmed by the Lagrange Multiplier tests. They suggest that the data displays a complex spatial structure including both lag and error effects (116.860 and 23.753 ordinary and robust tests for error effect; 312.590 and 219.483 for the lag effect). Finally, the LM-SARMA confirms the complex autoregressive nature of the process (336.343, p<0.001)[1]. All this evidence supports the need for more advanced spatial models, which means that the parameter estimates of OLS are biased.

[1] Results obtained in GeoDa software, avaiable from: https://geodacenter.asu.edu/projects/opengeoda.

Table 3: Hedonic Pricing Models

Predictors	OLS		SEM		SAR		SAC	
	Par. est.	t-stat	Par. est.	t-stat	Par. est.	t-stat	Par. est.	t-stat
Age 0-19 years	1,865.399	1.144	2,408.168	1.628	2,942.035	1.883	2,617.453	1.781
Age 20-39 years	-10,197.210	-8.335	-7,511.302	-6.725	-9,410.114	-7.904	**-7,459.894**	**-7.389**
Three bedrooms	4,178.483	4.440	3,679.065	4.267	3,756.380	4.101	**3,631.398**	**4.223**
d CBD	-905.795	-4.118	-648.365	-3.164	-886.531	-4.216	**-652.842**	**-5.056**
d health	2,504.885	3.194	1,810.816	2.548	2,105.719	2.845	**1,773.651**	**2.572**
d highschool	407.606	0.837	272.579	0.614	464.672	0.983	298.285	0.680
d negative features	152.342	0.452	259.658	0.840	222.498	0.707	261.896	1.234
d park	-256.734	-0.163	-119.124	-0.084	-340.684	-0.224	-156.201	-0.112
d shop	1,033.673	2.360	851.274	2.146	953.604	2.247	**842.823**	**2.160**
d TAFE	1,610.631	3.448	1,539.693	3.555	1,662.545	3.763	**1,546.184**	**10.933**
d train	-637.868	-0.924	-796.875	-1.276	-570.316	-0.853	-788.107	-1.463
d university	844.504	2.799	587.381	2.105	846.357	3.040	**601.725**	**2.472**
d ocean/river	-618.595	-1.350	-785.332	-1.873	-652.064	-1.487	**-776.910**	**-2.206**
Northing	-35.914	-1.643	-30.655	-2.208	-44.393	-11.848	**-35.655**	**-3.265**
Easting	-120.342	-1.989	-120.483	-1.486	-165.323	-3.038	-146.726	-0.894
Block land (m^2)	639.249	122.740	630.743	127.918	622.310	123.780	**630.735**	**129.660**
Av. Car ownership	-19,499.866	-4.913	-19,673.349	-5.466	-19,826.422	-5.291	**-19,875.737**	**-6.011**
index SE advantage	46.905	4.194	51.160	5.043	48.057	4.430	**51.585**	**6.141**
Balga (dummy)	7,224.579	2.071	9,608.995	3.008	7,846.564	2.311	**9,708.267**	**3.737**
North Inner (dummy)	8,613.599	2.765	7,524.271	2.532	8,794.097	2.902	**7,656.341**	**3.003**
North Rockingham (dummy)	25,794.194	3.864	21,257.703	3.427	25,609.782	3.979	**21,394.791**	**9.144**
Rockingham (dummy)	19,985.884	2.447	12,873.878	1.690	19,815.900	2.494	**13,071.328**	**2.729**
Mandurah (dummy)	13,928.228	1.554	813.174	0.099	9,431.041	1.083	652.993	0.109
Spearwood (dummy)	3,680.580	1.449	2,065.025	0.878	3,725.579	1.579	2,220.096	0.959
Midland (dummy)	12,353.734	2.661	13,609.661	3.159	13,534.131	3.114	**13,699.620**	**4.389**
ρ					0.118	111.622	**0.041**	**64.715**
λ			0.471	322.165			**0.458**	**8.817**
R^2-adj /Pseudo R^2		0.910		0.924		0.915		0.923
LL		-30,255.1		-30,112.09		-30,199.4		-27,679.153

Note: parameter estimates for SAC significant at 0.05 level are in **bold** text.

SEM, SAR, and SAC, all provide better goodness-of-fit measures (all LL ratio tests significant) and more robust parameter estimates, however, only SAC accounts completely for the spatial effects, being the only model that leads to uncorrelated residuals (Moran's I = 0.0143). Before discussing in detail the SAC model, it is worth noting that the direction of relationships is the same in all four models (larger properties, closer to the city, in less disadvantaged areas and less car dependent are valued more). Nevertheless, the significance level of the predictors changed.

Focusing on SAC, the most significant parameters are for lot size, distance from CBD, and location, followed by several accessibility indicators. Most of them have the expected signs, although multicollinearity affected the significance and direction of some relationships (distance from shops, parks, schools and health services). The parameter for land is $630.74/m^2, being 1km further from the city decreases the value by $652.82, and being away from the ocean/river decreased the value by $776.91. This shows that people value broad metropolitan accessibility and amenity highly. The significance in proximity to CBD is intuitive considering the density of employment, education, transport, shopping, entertainment and health care facilities in the CBD, as well the location on Swan River's shore. Moreover, all of the major train lines originate from the CBD and are not connected to each other. Therefore, to change train lines patrons must change over at the Perth city stop. This makes proximity to the CBD very desirable for public transport mobility. The results show that although nearby local shopping centres or higher education may not be desired, the array of services available in the city is important for low income households.

As indicated, the dummy variables, identifying the geographical area play a big role in the value of houses. The relatively expensive, northern coastal region of Two Rocks was used as the reference. Regions located furthest south – on the coastal region of Rockingham and Mandurah seem to be preferred. This is also reflected in the fact that distance to water features is significant and, as expected, has an inverse relationship between distance and price. Wealthier and more established neighbourhoods are located closer to the rivers and oceans. Hence, the valuation of proximity to the river and ocean could reflect both the recreational and visual aesthetic of the water, as well as the access to high quality established amenities and services in those regions. The data seems to imply that consumers use suburbs and sub-regions as proxies for lifestyle and accessibility factors rather than specifically trading-off distances to various features.

In regard to dwelling characteristics, three-bedroom house represents the standard and is preferred. Variables Eating, Recreation and Bathrooms, as well as the presence of a Pool were initially included in the models, then removed due to their lack of significance and expected multicollinearity issues. Compared to houses built before 1970s, new houses are valued higher and houses between 20 to 40 years old are cheaper (-$7,460). This may be due to certain architectural/aesthetics features of that time period compared to the 'newness' of recently built homes, as well as consumers' desire for older, historic buildings. Moreover, suburbs with older homes are typically well established and have better amenities, which explains their higher housing prices. Intuitively, distance to negative features is important and decreases house prices, but this is not shown in our data. Houses that are within close proximity to universities are valued less, possibly due to student housing being located closely to university campuses. Surprisingly, proximity to shopping centres and health facilities have a positive sign. These sign reversals could be explained by the noise and congestion associated with such areas. Living in areas that require car mobility detracts substantially from the house value (-$19,875.74). Although not significant, train proximity is important and the parameter value seems to be comparable in magnitude with that of distance to the CBD or water features.

Alternative models were also estimated using: a) only the structural attributes of the house; b) only the location characteristics; and c) applying aggregated socio-economic characteristics - density, employment, household structure, and indices of disadvantage, resources, education (ABS). The models (not included here) reveal that only 11% of the variance in the transaction prices is explained by aggregated indicators, 20% by location, with almost 90% of the variation in house prices captured by structural characteristics, particularly calculated land area, age, and number of bedrooms.

Before further discussing the implications of these findings and apply the SAC model for prediction, we must note the non-negligible spill over effect (4.1%) of neighbouring units.

4.3 Implications for Socially Excluded Households

The hedonic regression models provide estimated implicit prices for the transport access indicators, which can be used to assess the relative exclusion of a location/suburb related to others. Using the SAC model we separated the dwelling, access, and location parts of the housing prices and computed the proportion in the sale price represented by access. Current results reveal a 6-8% premium for houses conveniently located near local shops, schools, a railway station and to the CBD, a 20-25% premium for the quality of the neighbourhood (suburb or geographical cluster), the remaining being embedded in the dwelling features. Parameter estimates from Table 3 and the weights matrix were applied to hypothetical examples of new housing properties in each geographical cluster, with blocks of $600m^2$ and with 3 bedrooms, for households owning only one car (Table 4).

Compared to the Northern cluster of Two Rocks, being located in the Balga area is translated in a decrease of the house prices of $43,231 or living in Rockingham means the house prices are lower by $52,452 (everything else being equal). Although the coefficients do not represent marginal rates of substitution (because of the W matrix), the results suggest that households in the 51 suburbs selected for analysis, are willing to pay a similar amount for access to the city or for access to the train, or twice as much to be further away from TAFE and medical centre, compared to being close to the ocean or to the river. Finally, the willingness to pay for locations where car is not required is an order or magnitude larger than for the distance accessibility.

The geographical clusters are presented in the ascending order of the estimated housing prices. At the top we notice suburbs from the Rockingham area (Rockingham, Medina, Parmelia, Leda, Orelia) and North – Coastal (Carramar, Iluka, Balga, Balcatta, etc.). They are approximately $40-50k less expensive than the emergent groups at the bottom of the table, including Belmont, Midland, and Mandurah. Good access to facilities, combined with suburban lifestyle seems to be traded-off by households living in those areas. The table also suggests that despite its significance in the regression model, the distance from the city is not the only prominent factor differentiating 'most excluded suburbs' from the 'least excluded' in the group of 51 suburbs we analysed here.

Table 4: Transport Exclusion Estimates

Geographical area	Average estimated house price (SAC model)	Characteristics of the cluster
Rockingham	**$341,598.15**	Well established area (>30 years), 35-40km from CBD, close to the ocean
Balga	$350,819.38	Inner area, with poor access to train and to amenity (river/ocean), 12km from CBD
North Coastal	$354,963.63	New developments, 30km from CBD
South River	$355,766.88	Good access to urban facilities, established area, only 12km from the CBD
North Rockingham	$356,186.24	Older area, closest to Technical Colleges and health services, 35-40km from CBD
Broodale-Kenwick	$356,452.56	Large properties, quite isolated, 20km from CBD
Guildford	$360,356.40	Oldest housing area, closest to shops, trains, but >2.4km from education, 8.5km from CBD
Spearwood-South Lake	$362,255.82	Large properties, good access to school, shops, health, and to ocean, 16.5km from CBD
North Inner	$362,278.39	New developments, quite poorly catered in terms of education access, 25km from CBD
Midland	$362,524.51	Low housing prices, smallest properties, isolated in terms of access to education, close to negative features, 19km from CBD
Mandurah	$362,872.44	Furthest South from the city (66-70km), from higher education, but also from negative features (34km)
Belmont	$365,364.98	Low value properties, closest to the city (8km), but also closest to negative features (airport)
Two Rocks	**$394,050.86**	Furthest North from the city (56km), train and education, close to negative features, but highest lot sizes and housing prices

4.4 Conclusions and Further Research

This research has both methodological and practical implications.

The presence of spatial autocorrelation is known to bias the results (Basu and Thibodeau, 1998; Dubin, 1988; Sheppard, 1999; Anselin, 2001; Getis, 2010. Under such conditions the measurements are not influenced by a single location, but surrounding locations as well. Hence, houses that are close to each other are more likely to be effected by the same variables, and as a result will have correlated error terms. Although our models have taken into account these aspects, the interpretation is less obvious and the prediction time consuming, which limits their wide use, especially for practitioners. Further modelling, such as geographic weighted regression, expansion models, or market segmentation (spatial filtering) should be tested and compared to ascertain their benefits over the econometric models applied here.

An important benefit of the analysis is represented by possibility to use implicit prices as inputs into the designing of experiments for follow up stated choice surveys aimed at understanding residential choice (see Olaru et al., 2011). However, differences in evaluations as shown in our models, would lead to different designs. In order to create more "immune"/robust designs to variations of prior parameters Bayesian designs are recommended.

For practice, the results may assist planning to better incorporate household preferences. The findings of the Hedonic Regression Analysis indicate that lot size, the regional location, distance to the CBD and distance to water features as well as aggregated socio-economic (dis)advantage are the most influential variables in explaining house prices. Although the dwelling features prevailed (more than 70% of the housing value), the results provided insights into the valuations low-income households place on certain exclusion factors. They showed that consumers value broadly complex accessibility to various urban facilities. Limited access to quality employment markets or to other services, located near the CBD affects not only engagement in the labour force, but also the consumption level undertaken by the household, and implicitly their wellbeing. The results show that improving access to the CBD and good public transport that alleviates car dependence would be highly valued by low income consumers. This has interesting policy implications particularly for urban planning and public transport. The supply of inner urban housing could be increased by raising the residential density of inner urban areas. Moreover, the long-term plan to decentralise the city's focus from the CBD may reduce some of the pressure on inner urban areas for demand of services, and provide better services across the metropolitan area. This could be done through improving outer suburban transport, containing urban sprawl and increasing the residential density of existing suburbs. This would make the provision of infrastructure and services for communities more viable.

Although distance to CBD and water bodies is important to low income consumers, it seems as though estimating monetary valuations for accessibility to specific features like shopping centres, healthcare and education facilities is harder to model. This may be due to a number of factors regarding data and modelling limitations (e.g., lack of information about the types of households/consumers in the model, incomplete data, quality of establishments).

Rosen (1974) highlighted that tastes and preferences play an important role in shifting the bid function for certain characteristics. Further research needs to be done in order to discover the influence of demographics, and consumer segmentation, on consumption patterns of household sales. For example, a seniors' couple, compared to a young family, will have vastly different implicit prices for public transport, education and accessibility to various locations. Obviously, the affordability may limit the household's capacity to express their way of valorising various urban facilities and future research agendas should account for this endogeneity of implicit prices.

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6 Appendix

Region	Suburbs
1 South River	Beckenham, Langford, Lynwood, Riverton
2 Spearwood	South Lake, Hamilton Hill, Spearwood
3 North Rockingham	Parmelia, Leda, Orelia, Medina
4 Rockingham	Rockingham, Shoalwater, Coolongup, Hillman
5 Mandurah	Dudley Park, Greenfields, Coodanup, Mandurah
6 Kenwick-Brookdale	Gosnells, Brookdale, Kenwick, Maddington, Kelmscott
7 North-Coastal	Merriwa, Iluka
8 North-Inner	Banksia Grove, Carramar, Woodvale
9 Two Rocks	Two Rocks
10 Balga	Mirrabooka, Balcatta, Balga, Marangaroo, Koondoola
11 Guildford	Guildford, Eden Hill, Bayswater, Inglewood, Lockridge, Embleton
12 Midland	Midland, Stratton, Middle Swan
13 Belmont	Redcliffe, Cloverdale, Kewdale, Belmont