University of New South Wales

School of Economics

Honours Thesis

Stuck in Traffic (Data)

Analysing the Spatial Structure of Sydney with Travel Time Data

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Bachelor of Economics (Honours) (Econometrics & Economics)

and

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November 2019

Declaration

I hereby declare that this submission is my own work and that, to the best of my knowledge, it contains no material which has been written by another person or persons, except where due acknowledgement has been made. This thesis has not been submitted for the award of any degree or diploma at the University of New South Wales, or at any other institute of higher education.

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Aaron Wong,
22nd November 2019

Acknowledgements

I would first like to thank my supervisor Glenn Otto, for all the time and effort you have invested in my research this year. I am grateful for your guidance and support. Thank you for patiently answering all my questions, contemplating my ideas and reading all of my drafts. Your advice has been invaluable in making this thesis possible. Thank you also for your encouragement throughout the year when I was having doubts. Hopefully your students next year will write shorter theses!

Thank you to everyone who took the time to read my drafts and provide valuable advice on my writing. My thanks go to Jono, Tash, Elif and Max for your suggestions and feedback. Thank you to Federico Masera for your insightful comments and suggestions on Part II. Thanks also go to Jim for assisting with data acquisition.

This year has been an amazing year of learning and intellectual challenge not only in the thesis but in the coursework. Thank you to all the course lecturers who have taken our understanding and appreciation of economics to new heights and pushed us past all our intellectual limits. To Anuj Bhowmik and Gabriele Gratton, thank you for completely rebuilding our understanding of microeconomics. To Stanley Cho and Pratiti Chatterjee, thanks for the sheep and the beers, and for teaching us macro from the very microfoundations. To Denzil Fiebig, for taking us on a fascinating journey through discrete choice models every Monday night. To Pauline Grosjean and Federico Masera, for giving us the tools to identify what is really happening.

Thank you to Tess Stafford for your work in co-ordinating this year. This year has gone by about as smoothly as it could have. Without your efforts, Honours would not have been possible. Thanks for looking out for us and keeping us in the loop with the sudden move upstairs this year. Thank you also to Pauline Grosjean and Sarah Walker for facilitating the Honours seminars this year. The practical guidance and feedback on our presentations have been invaluable in making this thesis as polished as can be.

I would like to thank the Reserve Bank of Australia and Herbert Smith Freehills for their generous financial support this year. Thank you also to the Microeconomics 1 and Introductory Econometrics teams for employing me this year. I am grateful for the opportunity to share my love of economics with a new crop of undergraduates and hopefully at least one of them will be motivated to take Honours in the future.

HONOURS! We made it to the finish line! Through the struggles, achievements and struggles again this has been an incredible year spent with incredible people. Thank you. I am astounded every day by the quality and volume of work that everyone has managed to accomplish this year, and the incredible endurance and motivation in the hours that some of you have pulled. I am surprised we did not get cabin fever with the amount of time we spent together this year. I want to make a special mention to those with whom I endured three courses in Term 1. An absolutely moronic decision, but I couldn't ask for a better group to persevere with. A special thanks to Jono, Jack and Nick for your friendship this year. Jono, it has been an honour to share a desk with you for the better part of the year. I will always remember our conversations and the random thoughts we have shared thanks to our spatial proximity. I look forward to seeing the great things every one of you will go on to accomplish and coming together again in the future to reminisce about the challenging but rewarding year that was Honours 2019.

It has been an absolute privilege to get to know such a highly motivated and fun group of people. Our "hour in the yard" and desk-side conversations were a highlight, with our awful humour echoing through the corridors. Thanks to everyone who organised drinks and other social events where we could forget the stress of the year for a night. Thank you especially for your delicious BBQs this year Jono! This year has also been surprisingly active, which has been invaluable for keeping me motivated and sane. I enjoyed kicking the footy around with everyone and improving my hand-eye co-ordination. Thanks to Gabriele for starting the climbing crew with me, Jack and others, and I am keen to ascend to new heights with you all next year. I thoroughly enjoyed our hike, Nick and Jack, and am looking forward our next trip.

Finally, I want to thank those who have seen far too little of me this year. Thank you to my family for supporting me these last two and a bit decades. Mum and Dad, thank you for fostering my love of learning and encouraging me to pursue my interests. Without your unconditional love and support, I would never have made it here in the first place. To Kristie, thank you for your support this year and encouraging me through rough patches. Thank you for putting up with my grumpiness. I always looked forward to our time together this year as a welcome change from my thesis.

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Attributions

This research includes computations using the computational cluster Katana supported by Research Technology Services at UNSW Sydney.

A Guide to this Thesis

This thesis estimates the willingness to pay of commuters to reduce their cost of travel to employment in Sydney using a unique dataset of Google Maps travel time data. I divide my thesis into two Parts in order to answer this question from two related perspectives.

The first Part considers a cross-sectional equilibrium approach to estimating the value of commuting time from a Sydney-wide perspective. The second Part uses a difference in differences estimator to measure the value of commuting time by exploiting variation in travel times from the opening of Sydney Metro Northwest.

Although the two Parts are related, each Part has its own story to tell, with the literature, dataset and methodology being sufficiently different such that combining the parts would muddle the motivation for my research.

While each Part is structured as a separate thesis, I make several references throughout Part II to content contained within Part I to avoid repeating myself excessively. Thus, I recommend that the reader read this two-part thesis sequentially to avoid loss of information. This is especially the case for the chapters relating to the conceptual framework, theory and methodology.

Abstract

Most studies of urban rent gradients and estimates of land value uplift from infrastructure projects use distances from employment and transport facilities as a proxy for accessibility. However, commuters value reducing travel times to their destinations, not distances. In this thesis, I construct a novel dataset of travel time data scraped from Google Maps to analyse the spatial structure of Sydney. I use travel times to the Sydney CBD, Parramatta and Macquarie Park to estimate rent gradients using a spatially correlated hedonic pricing model for a cross-section of residential properties using data on sales prices and land valuations (Part I). I exploit variation in travel times caused by the opening of the Sydney Metro Northwest railway line on a panel dataset of land valuations to estimate willingness to pay (WTP) for reduced travel time to employment in Sydney using a difference in differences estimator (Part II). I find that travel time models materially improve goodness of fit and out-of-sample predictive power relative to distance-based models. I calculate the WTP of commuters to reduce travel times in Sydney, finding that commuters positively value accessibility to Sydney and Parramatta by road and public transport, and negatively value additional travel time caused by congestion. My results have applications in increasing the predictive power of land valuers' automated valuation models, improving assumptions on the value of travel time savings used in cost-benefit analysis and land value capture mechanisms for funding new infrastructure, and optimising the setting of motorway tolls and congestion charges for entering congested city centres.

Part I

Estimating Rent Gradients in Greater Sydney: A Travel Time Data Approach

Chapter 1

Introduction

In addition to speculating on property prices, complaining about urban sprawl and long commutes is a popular pastime of Sydneysiders (Livingston, 2019; Riga, 2019). Most individuals aim to minimise commuting because it is a mental and physical burden (Stutzer & Frey, 2008). From an economic perspective, commuting creates disutility due to the opportunity cost of time and monetary costs of travelling (McArthur, Kleppe, Thorsen & Ubøe, 2011). Thus, commuters are willing to pay to avoid these costs by living in a location that minimises their travel costs, subject to financial constraints. This willingness to pay for accessibility to employment and amenities is capitalised into the value of land and hence variation in land values can be used to quantify variation in accessibility across cities (Grislain-Letrémy & Katossky, 2014).

It is likely that travel time to a location matters more than commuting distance, despite the preference in most of the literature to use distances as a proxy for accessibility (see Bowes and Ihlanfeldt (2001), Hill (2012), S. Ryan (1999) for a review). This hypothesis is supported by research that shows land value uplift surrounding new transport infrastructure projects (Bowes & Ihlanfeldt, 2001; Du & Mulley, 2006, 2012; McIntosh, Trubka & Newman, 2014; Mulley & Tsai, 2016; Yen, Mulley, Shearer & Burke, 2018). An infrastructure project that physically reduces the distance between work and home would be quite expensive. Instead most transport projects aim to increase the speed at which people can move from A to B, so changes in travel time should be what is valued by commuters — a proposition I investigate in this thesis. I examine whether travel time models improve the explanatory and predictive power of hedonic pricing models compared to models that use distances as a proxy for accessibility. I also examine whether the inclusion of employment sub-centres improves model estimation compared to monocentric models. By measuring variation in travel times and property values in Sydney, I estimate the value that the average commuter associates with reduced commuting times to employment.

I construct a unique dataset of driving and public transport travel times scraped from Google Maps. Using this dataset, I estimate the impact of changes in travel time to major

Sydney employment centres on residential property sales prices and land values using spatial regression methods to estimate hedonic price models. The travel time data takes into account traffic congestion for drive times, and delays and interchange times for public transport, providing a dataset that is as close as possible to being representative of real commutes. The results provide an estimate of commuters' willingness to pay to live closer to these centres, controlling for property characteristics, zoning effects and neighbourhood demographics. I source these datasets from Australian Property Monitors (APM), the NSW Valuer General and from the 2016 Census conducted by the Australian Bureau of Statistics (ABS).

I examine whether travel times are a better measure of accessibility to employment and amenities compared to straight-line distances. Existing theoretical models of cities such as the Alonso-Muth-Mills model — and most research that is based upon it — include the assumption that commuting costs can be measured as a function of Euclidean distance from a single Central Business District (CBD). I replace this with a more accurate measure of commuting costs — travel times by car and public transport. Given that commuters experience disutility from increased commuting time rather than distance (McArthur et al., 2011), I hypothesise that replacing distance measures with time measures should increase the explanatory power of spatial models. I also generalise from the assumption of a monocentric and homogeneous city by including commuting times to Parramatta and Macquarie Park in Sydney, non-employment amenities (beaches) and neighbourhood heterogeneity in the form of socio-economic variables.

My results present the first direct estimates of the present value of travel time savings and the value of congestion for commuters in Sydney using unit record data, improving on previous rent gradients estimated using distance-based models at the more aggregate suburb level (Abelson, Joyeux & Mahuteau, 2013). I find that including travel times as a measure of accessibility improves the explanatory power of hedonic models of property prices relative to models using distances to centres. For out-of-sample prediction, the travel time models also outperform the distance models, with my measure of prediction accuracy — root mean squared error (RMSE) — improving by over 30% for some specifications. However, the land value models exhibit different performance characteristics, with travel time models not outperforming distance models — a finding I attribute to the methodology used by the valuers in constructing the dataset.

I find that households are willing to pay for properties that are more accessible to the Sydney CBD and Parramatta by road or public transport. The magnitudes of estimates vary between models, but the signs are robust to model specification. For the model containing travel time data to Sydney, Parramatta and Macquarie Park, I find that the average commuter is willing to pay about $3,400 (all currency values are in Australian dollars) more (0.30% of the property price) to be 1 minute closer to the Sydney CBD by road and $4,100 (0.36% of the property price) to be closer by public transport. For the land value models, I estimate the value of 1 minute in road accessibility improvements to be worth about $3,500 (0.42% of land value) and about $2,200 (0.26% of land value) for improved public transport accessibility. This calculation assumes a property with a sales price of $1.15 million and a land value of $826,800, with a commute to Sydney of 49 minutes' drive and 69 minutes by public transport.

Commuters also value improved accessibility to employment in Parramatta by road and public transport. I find that these effects diminish as travel times increase, suggesting commuters closest to the centre are most sensitive to changes in travel times. I also find that accessibility to Macquarie Park is not valued positively by commuters, with marginal effects that suggest accessibility to Macquarie Park diminishes property values. This result may be the result of interactions between the variables measuring accessibility to the other major centres, rather than a significant result in itself. In a cross-sectional framework, travel times and property values are likely to be endogenous and Sydney residents are also likely to have sorted themselves into preferred locations, hence these results should be interpreted from a long-run equilibrium perspective, as opposed to a causal effect.

I find that commuters negatively value road congestion that increases drive times above free flowing uncongested drive times. A 1 minute increase in congestion is associated with a $2,200 decrease in land values for the average property in Sydney, holding free-flowing drive times to the Sydney CBD constant. Similarly, this effect is present for commutes to Parramatta and Macquarie Park, with commuters valuing a 1 minute reduction in congestion at $1,500 and $1,900 for the average property.

These results are useful for industry with applications such as automated valuation modelling. By using regression techniques to complement traditional land valuation, the scale and consistency of valuations can be improved. My results also support previous research (McIntosh et al., 2014) finding evidence of land value uplift in Australia around infrastructure projects that improve commute times. Estimates of the willingness to pay for reducing commute times are a key input into cost-benefit analysis of infrastructure projects. Thus, my more direct estimates of willingness to pay for travel time savings may improve the appraisal of transport projects and hence contribute to the better allocation of public funds for infrastructure. These estimates can be used for pricing land value capture mechanisms that tax part of the land value uplift associated with new infrastructure to fund transport projects (Medda, 2012). For example, enabling a levy to be designed that is proportional to travel time savings rather than just distance. My estimates of the value of the disutility of congestion can also inform the pricing of congestion charges for travel into city centres during peak times.

CHAPTER 2

Literature review

The spatial economics literature began as the study of land rent by Ricardo (1821), which was developed by von Thünen (1826) into a model of agricultural land use. This model predicts the use of a piece of land at a given distance from a market town as a function of the cost of transport and the maximum rent that the farmer is willing to pay. For developed urban areas, the theoretical basis for much of the urban economics literature is based on the model of urban spatial structure developed by Alonso (1964), Muth (1969) and Mills (1967) (AMM model). This model formalises the observation that there is a compensatory trade-off between commuting costs within an urban area and the price of land and living space. The AMM model assumes a stylised city with all residents commuting to work in a central business district at the centre of the urban area. The costs of commuting are simply expressed as a function of the cost of commuting per unit of distance and the distance travelled by each resident. The model predicts that the price per square metre of housing is a decreasing function of distance to the CBD (Brueckner, 1987). I discuss the model in greater detail in section 3.1.

Using hedonic methods first developed by Rosen (1974), I estimate the empirical relationship between commuting times and property values in Sydney. Hedonic regressions are a widely used revealed preference method that reveal consumers' marginal willingness to pay (WTP) for individual attributes of a differentiated product. Hedonic models have been used to determine the impact on house prices of particular characteristics. A survey of the literature by Hill (2012) explored previous work examining the effect of environmental bads such as pollution (Anselin & Lozano-Gracia, 2008; McMillen, 2004; Zabel & Kiel, 2000); goods such as public parks, public services provision; and crime (Gibbons & Machin, 2003; Rouwendal & van der Straaten, 2008; Song & Knaap, 2004). However, hedonic regression models can produce misleading results in the event of functional form misspecification, omitted variables and failure to control for spatial effects (Kuminoff, Parmeter & Pope, 2010). Hill (2012) argues that researchers should make greater use of spatial econometric methods and geospatial data to improve hedonic estimations of the value of housing attributes. I contribute to improving these estimates by using spatial econometric methods in this Part.

There are opportunities for my analysis to extend the use of spatial hedonic regression modelling. According to a survey of the literature by Higgins and Kanaroglou (2016), about 40% of the 104 North American studies they surveyed did not use any spatial methods in the econometric analysis. Hill (2012) notes that house prices are likely to be spatially dependent as many of the determinants of price are neighbourhood characteristics that are difficult to quantify explicitly (consider the "character" of a wealthy neighbourhood versus a more disadvantaged one). In a study of the WTP to live away from hazardous industrial plants in France, Grislain-Letrémy and Katossky (2014) show that a parametric ordinary least squares model performs less well compared to semi-parametric models that estimate a series of local regressions that weight observations inversely by distance, such that more distant properties are weighted less. They found that this model is less sensitive to small changes in the sample or specification of the functional form. More importantly, the parametric model leads to a significant bias in the estimation of the marginal WTP, with statistical tests showing that the distributions estimated by the parametric and semi-parametric models are substantially different. Similarly, Du and Mulley (2012) analyse the effects of accessibility on property values and note that spatial dependence (where there is interdependence between observations as a result of their relative locations in space) will result in biased estimated coefficients. The presence of spatial error dependence (where the error terms follow a spatial autoregressive process) leads to unbiased, but inefficiently estimated coefficients. Prior research examining the performance of non-parametric spatial models find that they almost always outperform parametric approaches in terms of the mean-square error for out-of-sample prediction (Bao & Wan, 2004; Martins-Filho & Bin, 2005; Pace, 1993). Thus, implementing spatial econometric techniques in this Part is essential for credible estimation.

I use data on both property transaction prices and assessed land values in this Part. Property sales data is the best representation of the market value of property, but as this Part is interested in the accessibility of land, the value of the structure on top of the land must be partialled out using hedonic price modelling techniques. On the other hand, land valuations data appears to be better suited for this task as it aims to provide the unimproved value of the land on a property (NSW Valuer General, 2017a, 2017b). However, this dataset relies on professional valuers accurately isolating the value of the land from the rest of the property. In addition, anecdotal comments from some researchers have suggested that this dataset may be prone to downward biases, such as Kendall and Tulip (2018), who wrote that valuations may be biased downwards if property owners only challenge high estimates of their land value, but not low estimates. While property sales data is more popular in the literature (Higgins & Kanaroglou, 2016), statutory land values have also featured in the literature. One example is work by

McIntosh et al. (2014), who used land valuations for residential properties in Perth to estimate the WTP for transport access.

Commuting cost is the key parameter that my research examines. Past empirical studies of the effect of transport costs focused on using distance to transport facilities or the city centre as the measure of accessibility. However, transportation facilities are not a final destination for commuters, merely an intermediary providing connectivity between origins and destinations. Thus, studies that focus on access to transport facilities may not accurately reflect changes in travel costs (Bowes & Ihlanfeldt, 2001; S. Ryan, 1999). My research builds on the AMM model by treating commuting costs as a function of travel times using Google Maps travel time data (Google, 2019), which is superior to straight-line distance proxy for accessibility.

Outside of the economics literature, recent research has started making use of travel time data. In the civil engineering literature, Wu and Levinson (2019) examine the number of jobs and workers accessible within a 30 minute commute from the population-weighted average household. Terrill, Batrouney, Etherington and Parsonage (2017) use Google Maps data to examine road congestion in Sydney and Melbourne at different times of the day and week. They find that congestion varies greatly across Sydney, worsening closer to the Sydney CBD, but relatively minor around other sub-centres. Congestion is also much less severe than commonly believed, with the average commute into the Sydney CBD incurring an average delay of only 11 minutes compared to free-flow drive time. For commuters to locations other than the Sydney CBD, average delays are rarely more than 5 minutes longer than free flowing traffic. However, trip times are unreliable, which forces commuters to leave earlier to take into account potential extra delays, which are an additional commuting cost.

Palm and Niemeier (2019) measure the effect of accessibility to employment using data from a limited subset of the urban transportation network. They examine the effects of accessibility improvements from private bus shuttle services provided by technology firms in San Francisco to their employees on rents in the city. They compare a simple distance-based model to a more complex model that groups locations into bands determined by travel time-weighted accessibility to employment. They conclude that the more complex model does not produce any significant improvement in explanatory power relative to the distance-based model. While this research is related, the focus on private shuttle buses limits the external validity of the results to broader commuter choices compared to the wider scope of my research.

Ibeas, Cordera, dell'Olio, Coppola and Dominguez (2012) examine the effects of increased density of transit lines present in areas of housing in Santander, Spain. They find that property values increase by 1.8% for each additional transit line within each district. They also find a positive relationship between accessibility by car and property values, with a 1 minute reduction in travel times to the Santander city centre increasing property values by 0.5% to 1.1% depending on the model specification. Their research found that the spatial error model, which incorporates spatial autocorrelation in the error term, to be the most suitable model for modelling spatial relationships in their dataset as measured by model fit and theoretically consistent parameter estimates. More broadly, there is a wide body of literature examining the spatial structure of cities globally. However, given that the structure of cities vary considerably around the world, overseas results may not be applicable to an Australian context. As a result, I now turn to two key papers investigating the spatial structure of cities in Australia by Kulish, Richards and Gillitzer (2012) and Abelson et al. (2013).

From a more theoretical perspective, Kulish et al. (2012) calibrate the AMM model to a representative Australian city, finding that the model reasonably represents Australian urban centres. Their representative city matches the characteristics of a large Australian city with a population of around 2 million people and simulates a coastal location by restricting housing construction to half the circular area around the CBD. From their results, the AMM model suggests that a doubling in transport costs will result in a significantly stronger incentive to live closer to the CBD, shrinking the representative city from a radius of 35 km to 21 km. Dwelling prices closer to the CBD rise, while those further away fall. Households face higher housing costs but have smaller dwellings under this scenario. Conversely, lower transport costs through well-directed infrastructure investment will enable households to live further from the CBD and reduce the cost of housing. These findings show that the AMM model is an appropriate framework for estimating Sydney's rent gradient using travel time data.

Previous research focusing on Sydney has only been conducted at a more aggregate level, which limits the detail of conclusions that can be drawn. Abelson et al. (2013) examine median house prices across 626 suburbs across Sydney, comparing the explanatory power of three spatial hedonic models. They use three models that take into account spatial correlations in the dependent variable, independent variables and error term. These are referred to as spatial lag, spatial Durbin and spatial error models. Their work explained median house prices by Euclidean distance from the CBD and amenities, housing characteristics, regional location in Sydney, crime rates and suburb density. They find that access to the CBD and coastline, larger house and lot sizes, and lower crime rates increase house values. The effects of access to transport infrastructure were more ambiguous, but this is likely to be an effect of the use of suburb-level data instead of individual property data. They also find that access to sub-centres have no impact on house prices. However, Euclidean distance approaches can be problematic as distance is only a proxy for accessibility and in the case of geographically challenging cities, the proxy can be especially weak. As a measure of proximity, travel times to employment are a more direct approach, as people value transit times more than distance travelled. Higgins and Kanaroglou's (2016) extensive review of literature on land value uplift modelling using hedonic techniques discusses the issues associated with the use of distance as a proxy for accessibility and its drawbacks relative to more direct measures. I improve on this paper by extending the analysis to unit record data on individual properties and incorporating travel time data as my accessibility measure.

CHAPTER 3

Methodology

This chapter describes the theoretical and empirical models used in this Part. The theoretical basis of this Part is the Alonso-Muth-Mills (AMM) model, which I discuss in section 3.1. While I extend this model using new approaches to commuting costs, the core model remains through its key insight into the trade-off between commuting costs and housing costs (Alonso, 1964; Mills, 1967; Muth, 1969). In section 3.2, I introduce the hedonic pricing framework that is used to capture the predictions of the AMM model and describe the various spatial regression models that are used in my thesis.

3.1 Alonso-Muth-Mills model of urban spatial structure

The AMM model is a workhorse model in urban economics that is used in and extended by a number of different studies around the world, illustrating its versatility (Abelson et al., 2013; Brueckner, 1987; Kulish et al., 2012). Furthermore, Kulish et al. (2012) calibrate the AMM model to a representative Australian city as shown in figure 3.1, finding that the model is a good approximation of the structure of Australia's large capital cities including Sydney.

The spatial structure of the city predicted by the AMM model is created by the key observation that commuting is costly and this must be balanced by differences in the price of living space (land). Because commuting costs increase with distance from the city centre, people would prefer to live closer to the CBD (Central Business District). However, not everyone can live close to the city, so the price and density of housing adjust to clear the market. The inverse relationship between housing costs and commuting costs is illustrated in figure 3.2. Line A represents the outside option for urban land, which is the value obtained from using it for agricultural purposes. This opportunity cost causes the radius of the city to be $\bar{x}$, beyond which the land reverts to agricultural use.

The AMM model considers a circular city with a fixed population made up of residents with identical utility functions and incomes. Each resident commutes to a job in the

Figure 3.1: The AMM model calibrated to a representative Australian city by Kulish et al. (2012)

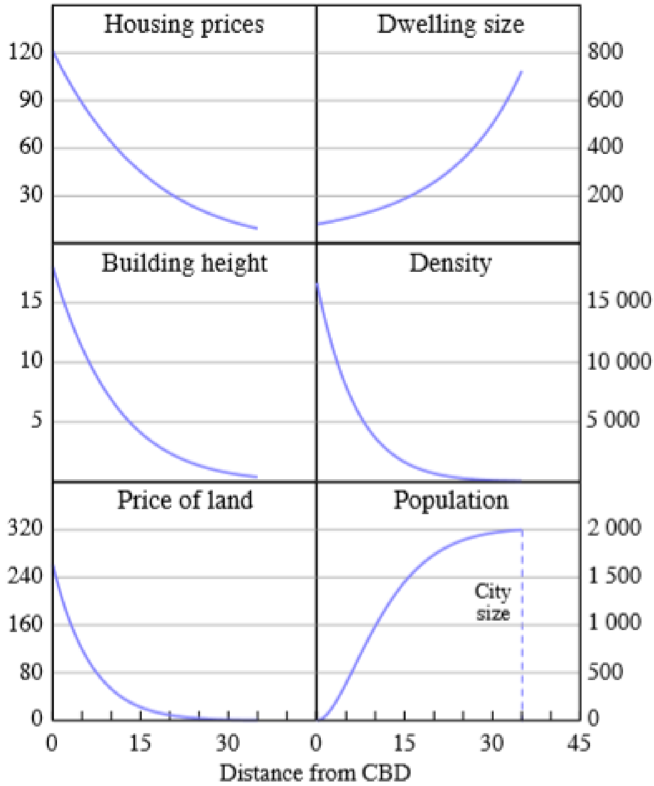
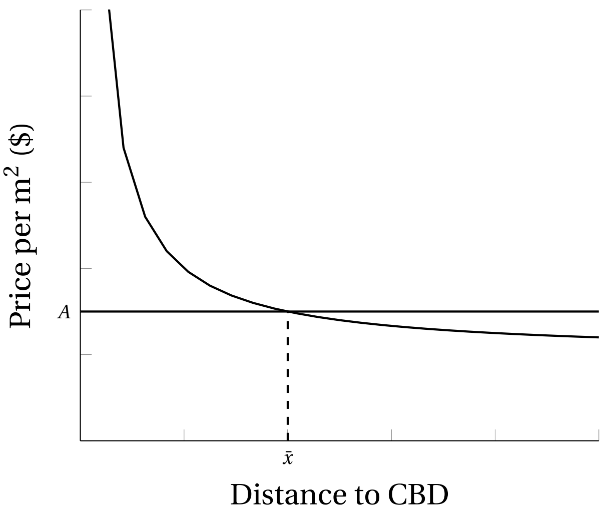


Figure 3.2: Idealised rent gradient



CBD located in the centre of the city along a dense radial road network. Each resident earns identical incomes which are used to purchase a housing good (of which land is an input) and a composite non-housing good that represents all other consumption. The original AMM model assumes that the only parameter of interest in relation to housing is land area, even though real-world dwellings are characterised by a vector of different attributes. Because land prices increase closer to the CBD, residents will economise on the use of land by building more dwellings per unit of land, e.g. building smaller dwellings in apartment towers instead of detached houses. Hence, the city structure is characterised by dense and small dwellings close to the CBD, and less dense and larger dwellings further away.

In the model, households maximise their utility function $v(c,q)$, a function of a composite non-housing good c and quantity of housing q (in m^2). If we replace c using the budget constraint $pq + c = y - tx$, where p is the price per unit of housing, y is income, t is commuting cost per unit of distance, x is distance from the CBD and u is the constant utility level attained by all households, then the maximisation problem becomes:

$$\max_{\{q\}} v(y - tx - pq, q) = u \tag{3.1}$$

The optimality conditions of the model are given by:

$$\frac{v_q(y - tx - pq, q)}{v_c(y - tx - pq, q)} = p \tag{3.2}$$

$$v(y - tx - pq, q) = u \tag{3.3}$$

By solving the maximisation problem, it can be shown that equations 3.2 and 3.3 give solutions for q and p as functions of y, t, u and x.

Because transport costs vary between locations, the price per unit of land must vary to allow this condition to hold. Brueckner (1987) shows that:

$$\frac{\partial q}{\partial x} = \eta \frac{\partial p}{\partial x} > 0 \tag{3.4}$$

$$\frac{\partial p}{\partial t} < 0, \frac{\partial q}{\partial t} > 0 \tag{3.5}$$

where $\eta < 0$ is the slope of the demand curve.

Equation 3.4 implies that with increasing distance from the CBD, the quantity of land consumed is increasing and the unit price of land is decreasing. This result makes sense, as consumers living far from the CBD need to be compensated for their longer commutes, otherwise no one would voluntarily live far away from the centre. Similarly, equation 3.5 implies that increasing commuting costs (t) decrease the unit price of land (p) and increase the quantity of land (q) consumed.

Naturally, the AMM model's simple yet powerful structure results in some limitations. First, the model assumes that individuals have identical incomes and preferences, which is unrealistic. However, the basic structure and insights from the model do not change even in models that allow for heterogeneity. Many analyses using the AMM model also assume a monocentric city, with no sub-centres or other amenities outside of the city centre affecting household location choices. However, the model can be easily extended to take these factors into account (Henderson & Mitra, 1996), which I do by including three employment centres throughout my analysis. The AMM model also exists in partial equilibrium, as other markets such as labour or capital markets are exogenous to the model. Finally, the model is static, providing insights into long-run equilibrium structure of the city, rather than the dynamics of urban change (Kulish et al., 2012).

3.2 Econometric modelling approaches

Econometric modelling links the theoretical predictions of the AMM model to real life data. In this Part, the focus is on estimating the magnitude of the first order conditions of prices with respect to travel times as shown in equation 3.5. The AMM model predicts that this parameter should take on a negative value, so I expect that the regression coefficients on travel time should also be negative. Spatial data require the use of modelling approaches that take the additional spatial information into account. While I start with a brief exposition of hedonic pricing models, the focus of this section is on specifying a variety of spatial regression models that are able to handle the challenges and opportunities posed by spatial data.

3.2.1 Hedonic pricing models

Hedonic pricing models were conceptualised by Rosen (1974) and consider the observed price of a product to be the sum of the implicit values of a vector of observable characteristics. The implicit prices of each attribute are estimated through multiple linear regression analysis (Abelson et al., 2013). The equation that is estimated is of reduced form, as we only observe the equilibrium of supply and demand, as opposed to estimating the individual supply and demand structural equations (Kuminoff et al., 2010).

Hedonic pricing is useful for products that are highly differentiated, with an extensive literature estimating prices for products subject to rapid technological change, such as computers. Property is a special case where each individual observation has a unique vector of characteristics, which makes the hedonic method more powerful compared to other approaches to pricing housing such as repeat-sales methods or regional median pricing approaches (Hill, 2012).

The ability for hedonic models to incorporate a wide variety of observable characteristics in a relatively flexible, yet simple, parametric approach makes hedonic models the model of choice for a large body of literature in urban economics (Hill, 2012). For housing, observable characteristics can be roughly divided into physical or locational characteristics. For the models using land valuations data as the dependent variable, I am able to avoid estimating most physical characteristics of the property as these factors are supposed to be excluded from the value of land by the valuation process (NSW Valuer General, 2017a). Locational attributes include the geographic location of the property relative to amenities such as parks, schools and beaches; proximity to employment centres; and the characteristics of the surrounding neighbourhood.

Hedonic models are not without their drawbacks. Standard hedonic models assume that the observations in the regression are independent of one another, which is very likely to be violated in the case of spatial data such as housing (Du & Mulley, 2012). The second assumption of hedonic modelling is that the price is obtained through a perfectly competitive market equilibrium. This is a problematic assumption with regards to housing, given that each unit of housing has unique characteristics due to its location.

Finally, misspecifying the hedonic price function will seriously undermine estimation of economic values through omitted variable bias. Frequently, the source of this problem for housing models are neighbourhood characteristics that are valued by households, but not observed by the researcher (Kuminoff et al., 2010). In recent years, more literature is correcting for this by using spatial hedonic models that reduce the issue of omitted variable bias by adding spatial fixed effects that absorb the price effect of spatially clustered omitted variables. Monte Carlo analysis by Kuminoff et al. (2010) found that including spatial fixed effects substantially reduces the bias from omitted variables in cross-sectional data.

3.2.2 Spatial models

There exist several classes of models that incorporate the spatial nature of the data I am using. To motivate the use of these models, I introduce the concept of spatial dependence and discuss what this means for traditional regression methods. The following explanation borrows from LeSage and Pace (2008).

To contrast the nature of non-spatial and spatial data, I begin by considering the properties of the data generating process for conventional cross-sectional non-spatial data. Consider n independent observations y_i, $i = 1, \ldots, n$ that are linearly related to a matrix $\mathbf{X}$ of explanatory variables. This can be expressed in the following form:

$$y_i = \mathbf{X}_i \beta + \epsilon_i \tag{3.6}$$

$$\epsilon_i \sim N(0, \sigma^2) \quad i = 1, \ldots, n \tag{3.7}$$

Where $\mathbf{X}_i$ represents a $1 \times k$ vector of covariates, β are a $k \times 1$ vector of parameters, and ϵ_i is an iid normal error component with mean 0 and variance σ^2. These are the typical assumptions for linear regression models and imply that each observation i is independent of other observations. If this assumption is applied to spatial data, then this claims that an observation at one location is completely independent of observations made at other locations (including immediate neighbours). This assumption may be dubious when applied to spatial data, as demonstrated by the following examples.

By allowing for spatial dependence, values of observations at one location are able to be influenced by, or depend on the values of nearby observations. To illustrate this, consider a very simple example of two neighbouring observations $i = 1$ and $j = 2$ with the following data generating process.

$$y_i = \alpha_i y_j + \mathbf{X}_i \beta + \epsilon_i \tag{3.8}$$

$$y_j = \alpha_j y_i + \mathbf{X}_j \beta + \epsilon_j \tag{3.9}$$

$$\epsilon_i \sim N(0, \sigma^2) \quad i = 1 \tag{3.10}$$

$$\epsilon_j \sim N(0, \sigma^2) \quad j = 2 \tag{3.11}$$

As we can see, the observed values of y_i now depend on y_j and y_j depends on y_i.

As a concrete example, consider a hedonic pricing model of sales prices of houses as the dependent variable and a vector of observed physical and location characteristics as the explanatory variables. Suppose a house sells for a much higher price than predicted by its characteristics and this coincides with the opening of a new train station nearby. We would expect that this higher price will signal to nearby homeowners that the value of their houses may have also increased. Consequentially, they will also increase the asking price of their own properties. In the absence of a spatially dependent model, this flow-on effect from nearby properties is not captured. As a result, a model that incorporates the selling prices of neighbouring properties has improved explanatory power relative to a model that does not.

Spatial spillover effects create problems with model estimation. These spatial spillover effects can be considered from two perspectives: as spatial dependence in the explanatory variables or a spatially correlated error term (Abelson et al., 2013). At minimum if the error term is spatially correlated, ordinary least squares (OLS) estimates are unbiased but inefficient (similar to serial correlation problems with time-series regression). However, in the presence of omitted spatially correlated variables, the OLS estimate will be biased and inefficient (Du & Mulley, 2012). Models of spatial dependence consider the spatial spillover effects to be an integral part of the model, and hence directly model for it as one of the explanatory variables. In contrast, a model with a spatially correlated error term considers the spatial spillovers to be a nuisance term that needs to be addressed through the disturbance term of the model (LeSage & Pace, 2008). This motivates the different classes of spatial model which I discuss.

Spatial error model

The spatial error model (SEM) restricts the effects of spatial dependence to the disturbance term, as specified in the structural equation, equation 3.12. Compared to the standard OLS, the SEM does not assume the disturbances ϵ_i are i.i.d., but rather follow a spatially autocorrelated process. In the SEM, the spatial autoregressive term (λ) is contained within the error term, which implies that unobserved neighbour effects are shared by nearby properties. The presence of spatial autocorrelation is assumed to bias the standard errors (inefficient estimates) but not the point estimates (LeSage & Pace, 2008).

In the structural form (equation 3.12), y is a $n \times 1$ vector of observations of the dependent variable, $\mathbf{X}$ is a $n \times k$ matrix of explanatory variables, β is a $k \times 1$ vector of regression coefficients, u is a vector of $n \times 1$ composite error terms, λ is the spatial autoregressive coefficient, $\mathbf{W}$ is the $n \times n$ spatial weights matrix, and ϵ is a vector of $n \times 1$

i.i.d. error terms. The reduced form of the structural equation is expressed in equation 3.14.

$$y = \mathbf{X}\beta + u \tag{3.12}$$

$$u = \lambda \mathbf{W} u + \epsilon \tag{3.13}$$

$$y = \mathbf{X}\beta + (I_n - \lambda \mathbf{W})^{-1} u \tag{3.14}$$

$$\epsilon \sim N(0, \sigma^2 I_n) \tag{3.15}$$

Spatial autoregressive model

The spatial autoregressive (SAR) model, also known as a spatial lag model, incorporates spatial dependence in the form of a spatially lagged dependent variable on the right-hand side of the structural regression equation as shown in equation 3.16. Compared to the traditional OLS model, the SAR model adds the $\rho\mathbf{W}y$ term, which captures the spatial interaction effects as the weighted average of the price (dependent variable) of other properties in the sample.

In the structural form, y is a $n \times 1$ vector of observations of the dependent variable, $\mathbf{X}$ is a $n \times k$ matrix of explanatory variables, $\mathbf{W}$ is the $n \times n$ spatial weights matrix, ϵ is a vector of $n \times 1$ i.i.d. error terms, ρ is the spatial autoregressive coefficient and β is a $k \times 1$ vector of regression coefficients. To form the weighted average of the other properties ($\mathbf{W}y$), the value of the other properties y_j is weighted by the inverse of the Euclidean distance between the jth property and property i for all i properties in the sample. Spatial weights are strictly positive for observations i and j where $i \neq j$, and 0 otherwise.

$$y = \rho \mathbf{W} y + \mathbf{X}\beta + \epsilon \tag{3.16}$$

$$\mathbf{W}y = \sum_{j=1}^{n} w_{ij} y_j, \quad i = 1, \ldots, n \tag{3.17}$$

$$y = (I_n - \rho \mathbf{W})^{-1} \mathbf{X}\beta + (I_n - \rho \mathbf{W})^{-1} \epsilon \tag{3.18}$$

$$\epsilon \sim N(0, \sigma^2 I_n) \tag{3.19}$$

The model estimated is the reduced form equation specified in equation 3.18. The reduced form equation implies that land values of any property are a function of the property's own characteristics and the characteristics of neighbouring properties, with the effect of neighbours diminishing with the spatial weight operator. This model can be estimated by maximum likelihood (Abelson et al., 2013).

Interpreting spatial autoregressive models is different to interpreting standard linear regression models. The coefficients on a spatial model are partial derivatives only in the case of the spatial error model, but this is not true in the case where spatial dependence is present in the dependent variable or explanatory variables. Simple partial derivative interpretations fail due to the need to take into account the effect of spatial spillovers in the model, which require the consideration of direct and indirect effects. The direct effect of a variable x_r on y is the average over all observations of the marginal effects of x_{ir} on y_i: $(1/n)\sum_{i=1}^{n}(\partial y_i/\partial x_{ir})$. The indirect effect is defined as $\sum_{i=1}^{n}\sum_{j=1,i\neq j}^{n}(\partial y_i/\partial x_{jr})$. The total effect is simply the sum of the direct and indirect effects (LeSage & Pace, 2008). Golgher and Voss (2015) derive the direct and indirect effects of changes in the explanatory variables on the observed outcomes.

CHAPTER 4

Data

This chapter provides a descriptive and preliminary analysis of the data used in the empirical analysis. The aim of this Part is to estimate the value that households place on access to employment and amenity. This is done using an estimate of the rent (price) gradient for Sydney and requires data on property values, a measure of commuting costs and property attributes unrelated to the cost of commuting.

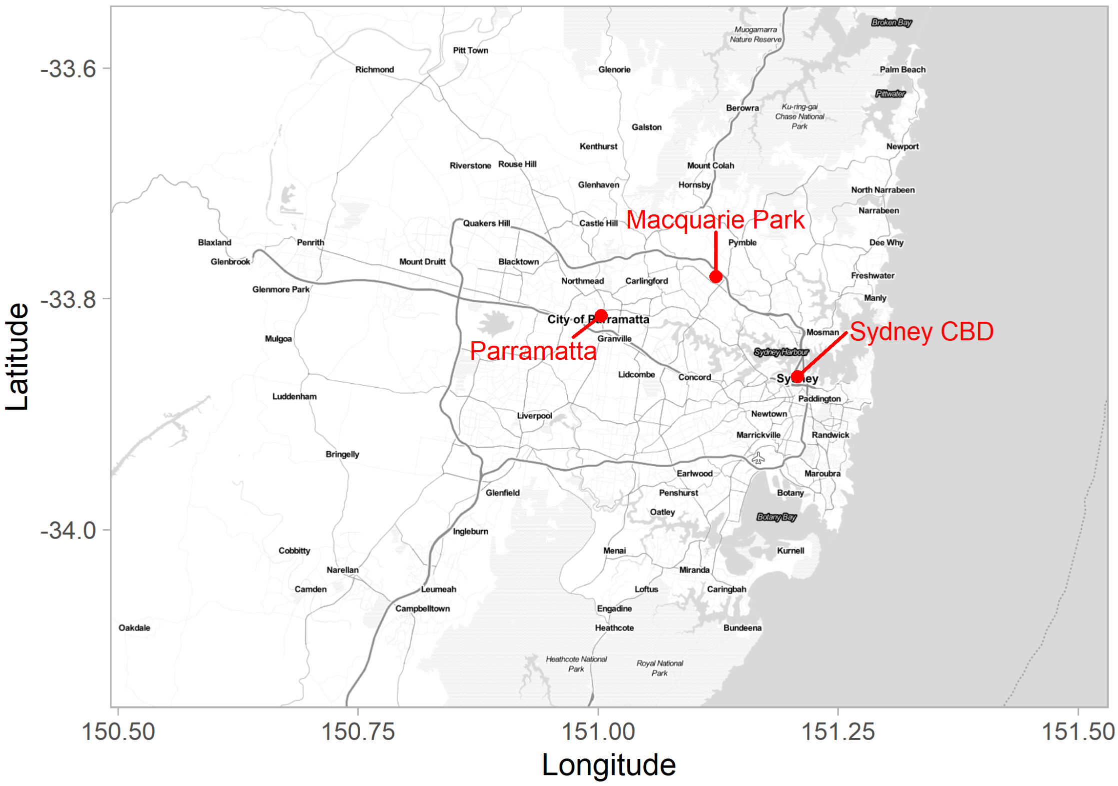
I measure property values using transaction prices and land valuations. Property sales prices best reflect the value that the market is willing to pay for property. However, property price data can complicate estimation as hedonic price modelling needs to be used to partial out the value of the structure, which is not influenced by the accessibility of the property. Land valuation data is used as it has the advantage of eliminating the need to control for the characteristics of residential structures (houses or apartments), but these valuations reflect the judgement of professional valuers rather than the market price. I use sales of residential housing in Sydney in 2018 as my property price dataset and a random sample of July 2018 land values for 40,000 locations obtained from the NSW Valuer General as my land valuations dataset. These properties are then linked with travel time data from Google Maps and neighbourhood characteristics information from the 2016 Census using the Australian National Geocoded Address Dataset (PSMA Australia, 2018).

I describe the collection of the travel time data in section 4.1. I discuss and provide visualisations of the sales data and land valuations data in sections 4.2 and 4.3. I analyse the descriptive statistics for the data in sections 4.5 and 4.6, along with some maps which illustrate the spatial distribution of travel times in section 4.7. I conduct a statistical test for spatial dependence in the data in section 4.8.

4.1 Travel time data

Variation in commuting costs are the key driver of differential property prices under the AMM model. As discussed previously, most of the existing literature has focused on explaining commuting costs using straight-line distances from the CBD. In this study, I use Google Maps travel time data as a novel measure of variation in commuting costs. The commuting cost data used in this Part consists of the travel times for a random sample of 40,000 residential properties with associated land values and 8,073 residential properties that transacted in 2018 within the Greater Sydney GCCSA (Greater Capital City Statistical Area) during the morning peak (7AM–9AM) to the three largest employment areas in Sydney (Sydney/North Sydney, Parramatta and Macquarie Park). Figure 4.1 shows the locations of the three centres. Collecting data on more than just the Sydney CBD also extends this paper beyond the monocentric cities examined by the existing literature.

Figure 4.1: Location of the Sydney CBD, Parramatta and Macquarie Park



I use Google Maps data because it is the most accurate source of live travel time data available that can be collected in bulk. My data consists of both driving and public transport travel times. Driving times include the effects of traffic congestion as calculated by Google's traffic model, while public transport times include walking times to transit stops and interchange times. Functionally, the data are identical to what commuters would see if they entered a start location (e.g. their home address) and end location (e.g. their work address) into maps.google.com.au. I collect data for travel times from each of the properties in my datasets (an origin), to each of the three employment centres analysed (a destination). I refer to this as an origin-destination pair.

I construct this dataset by coding an R script that calls the Google Maps Distance Matrix API (Application Programming Interface). This API takes an origin-destination pair and transit mode and returns the duration and distance travelled. For the land valuations dataset, I collected travel times between July 2018 and May 2019, and for the sales dataset, I collected travel times between September 2019 and October 2019. Collecting data during the morning peak allows me to capture the effects of congestion.

As part of the data collection and cleaning process, some observations were removed due to errors in the collection of travel time data. Outlier travel time values were discarded if the drive times exceeded 240 minutes or if the public transport times exceeded 300 minutes. These outliers were caused by the Google Maps script erroneously computing travel times to the incorrect locations. For example, one address was incorrectly parsed as being from outside NSW and hence produced a completely incorrect travel time. Occasional server connectivity errors also resulted in missing data points. This process only affected a small share of the sample; in the land values data the number of observations was reduced from 40,000 to 38,514.

Some limitations of the data include the lack of information on traffic flows/volumes for specific routes as the API is only able to provide travel times between origin-destination pairs. Public transport travel time data is also not disaggregated into walking, waiting and actual travelling time in the data provided by the API. Google also limits the number of API calls that can be made for free to 40,000 each month, which forced the collection of data over a long period of time, meaning there is potentially some variation in the comparability of data collected in different months. However, I was careful not to collect data during periods of known reduced commuter flow, such as public holidays and the Christmas/New Years and Easter holiday periods.

4.2 Property sales data

As a measure of property values, I source property sales data from Australian Property Monitors, a commercial provider of property transactions data. The data cover all recorded residential property sales within Greater Sydney for 2018. The property sales data includes information on the sale price, sale date, address, geographical coordinates, land area, count of bedrooms, count of bathrooms, and count of parking spaces among other property characteristics. I compare estimates using this dataset to my estimations using land valuations data, improving the robustness of my analysis. Property sales data are also preferred by the literature as they reflect the actual valuations placed by the market on the value of property, rather than the value that professional valuers believe an unimproved land lot is worth. However, unlike land values data, the sales data may not reflect the overall housing stock as it only contains properties that were sold in 2018.

The data cleaning process involved filtering out duplicates, sales outside the Sydney GCCSA and properties that were missing key characteristics data (transaction price, transaction date, bedrooms, bathrooms and area). The original dataset contained around 163,000 entries, but most of these were duplicates as data was recorded at each stage of the sales process until settlement. After this initial cleaning, I took a random sample of 9,000 properties from the whole dataset in order to fit within financial constraints of scraping Google Maps travel time data. After geocoding properties to their corresponding ASGS (Australian Statistical Geography Standard) Statistical Area 1 (SA1), I merged neighbourhood demographics data from the 2016 ABS Census with each property sale. I calculated the Euclidean distance from each property to the Sydney CBD, Parramatta, Macquarie Park and the nearest coastline using the `geosphere` GIS package in R (Hijmans, 2019). I removed remaining duplicates and outliers based on sales prices that were higher than $10 million or below $100,000 as they are unrepresentative of the property market in Sydney, which removed less than 200 properties from the data. Properties with extremely large or small prices per square metre were also omitted as these indicate that the property area was incorrectly recorded. As previously described, properties with erroneous travel time measurements were also omitted. Together, this process reduced the dataset from the original 163,000 entries to 8,073 sales.

I provide two visualisations of median sales prices in Greater Sydney. Figure 4.2 shows the median sales price in each Sydney SA2, while figure 4.3 shows the median sales price per square metre in each Sydney SA2, which provides a view that is not distorted by variation in land lot sizes across Sydney. This effect is most evident on the North Shore region, where large lot sizes combined with relatively strong accessibility combine to increase overall property prices, while prices per square metre are relatively lower compared to areas closer to the Sydney CBD. “NA” areas denote SA2s without any recorded property sales. There is a clear pattern of falling sales prices further away from the Sydney CBD and the coastline. We can also see that there are areas with greater average sale prices that are equidistant from other areas with lower sale prices that appear to fall along major transport infrastructure (roads, railways). This observation suggests that heterogeneity in transport costs influence the pattern of sale prices in the Sydney region.

Figure 4.2: Median property sales price at SA2 level

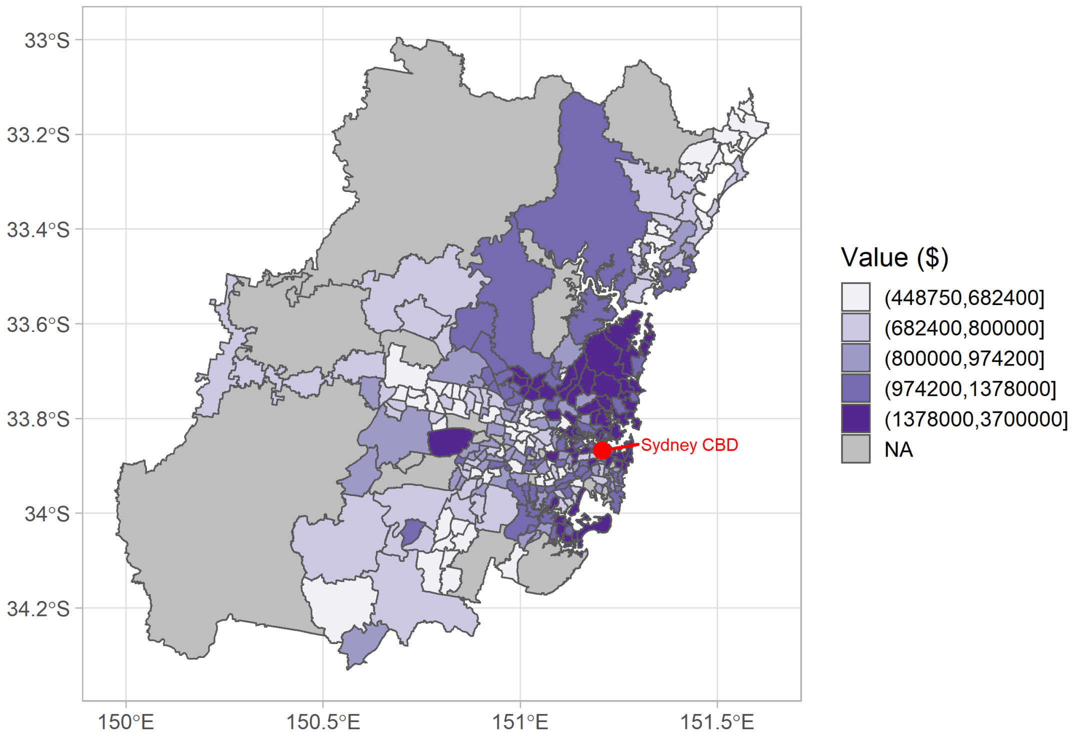
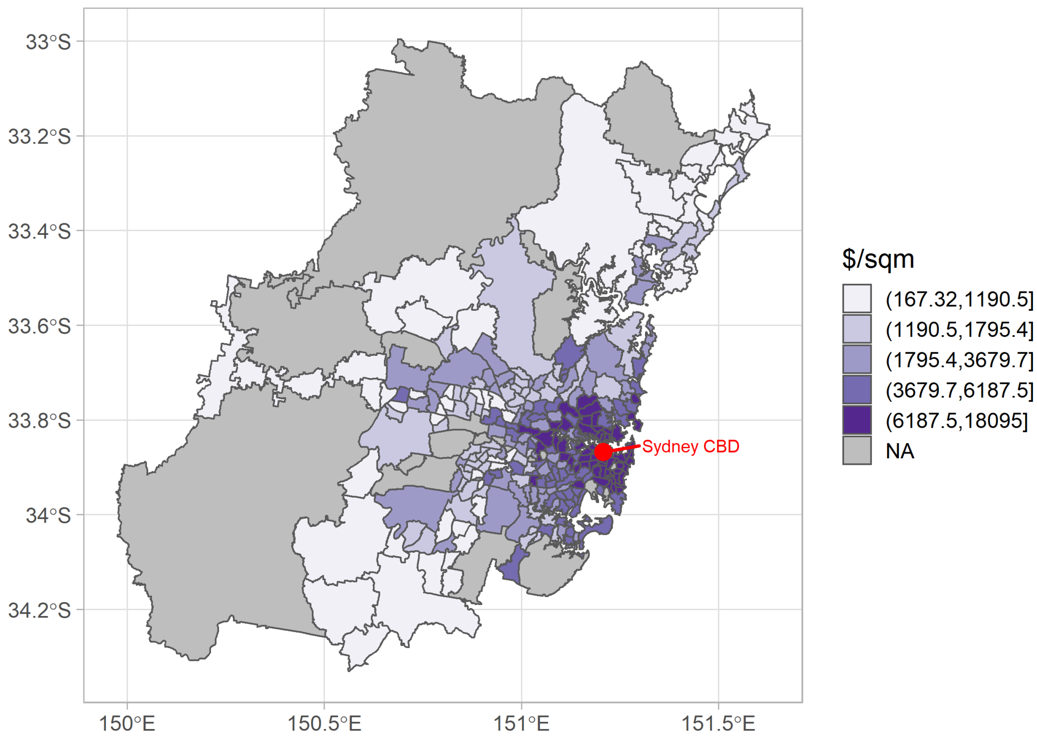


Figure 4.3: Median property sales price per square metre at SA2 level



4.3 Land valuations data

Property valuations data is sourced from the NSW Valuer General's Bulk Land Values dataset. The Valuer General provides land valuations for every property (about 1.3 million addresses) in New South Wales. This is the unimproved value of the land on a property that excludes the value of the structures or other improvements on top of the land (NSW Valuer General, 2017b).

The Valuer General supplies land value information containing the annual valuations of every property in NSW. This dataset includes values for residential, commercial, mixed-use, industrial and government properties. The data include a unique identifier, address and other locational attributes, zoning code, and up to five years of land values. Land in NSW is valued in groupings of similar properties based on their location, size and amenity. This process applies to both single residential and high density properties. The value is based on a hypothetical sale of land that is vacant and has no improvements other than land improvements (NSW Valuer General, 2017a, 2017b).

The data cleaning process involved removing non-residential properties from the dataset based on their zoning code. Entries with addresses that were missing a house number or missing land areas were also omitted. In order to match the dataset with ABS Census data, each address had to be geocoded using the Geocoded National Address File (G-NAF) compiled by PSMA Australia (2018). This process involved converting property addresses to a standardised format that followed the G-NAF conventions, which allowed me to match each address to an ASGS Mesh Block (MB) and geographic coordinates. Using the MB codes, I further filtered the data to include only properties within the Greater Sydney GCCSA. This process reduced the initial 1.3 million addresses in the dataset to 1,050,000 addresses. Finally, I took a random sample of 40,000 properties within the remaining subset of the data, which was used as the origin point for which travel time data was collected.

Using the land valuations data provides an alternate perspective by providing an estimate of the value of land without having to control for the attributes of the structure sitting on top of the land. Land value data simplifies the design of the hedonic regression model and allows me to focus on the relationship between land values, travel times and other proximate amenities. However, Kendall and Tulip (2018) have suggested anecdotally that the land values data may be susceptible to downward biasing due to individuals challenging land values that they believe are too high, while not challenging undervalued land in order to minimise their land tax owed.

I provide two visualisations of the median land values in Greater Sydney. Figure 4.4 shows the median land value in each Sydney SA2, while figure 4.5 shows the median value of land per square metre in each Sydney SA2, which provides a view that is not distorted by variation in land lot sizes across Sydney.

Like with the sales price data, land values exceed land values per square metre mostly in the North Shore region. Similarly, there is also a clear pattern of falling land values further away from the Sydney CBD and the coastline. Like the sales data maps, we can see that there are areas with greater average land values that are equidistant from other areas with lower land values that appear to fall along major transport infrastructure routes. This observation indicates that, like the sales data, heterogeneity in transport costs influence the pattern of land values in the Sydney region.

Figure 4.4: Median land values at SA2 level

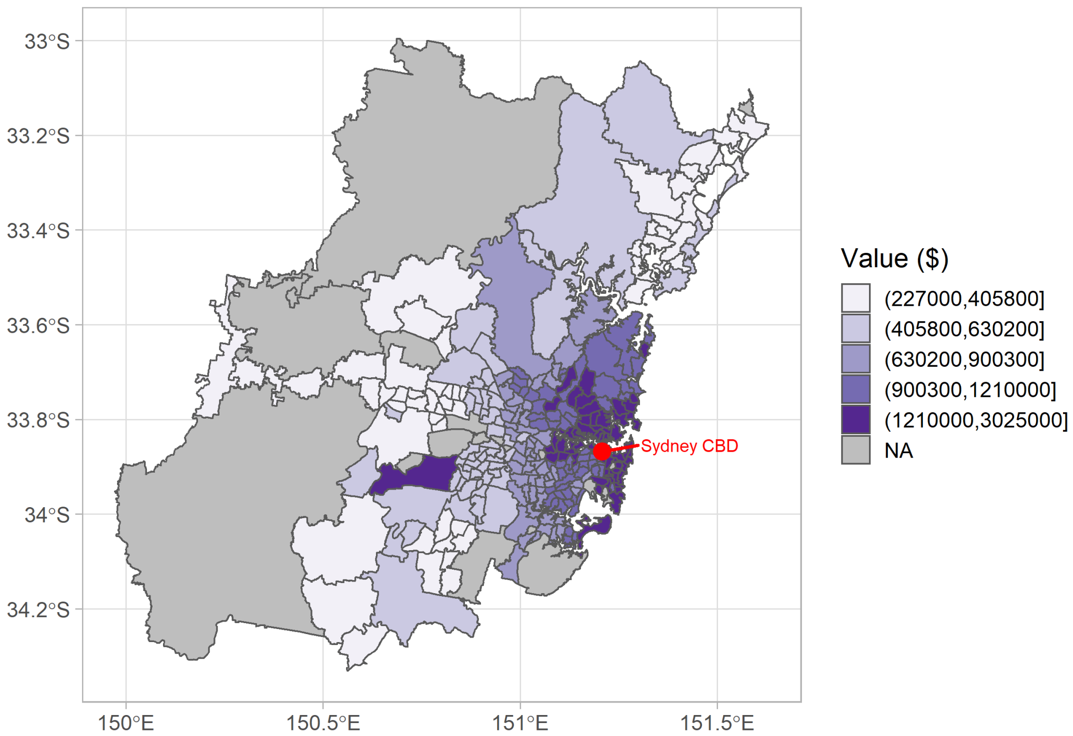
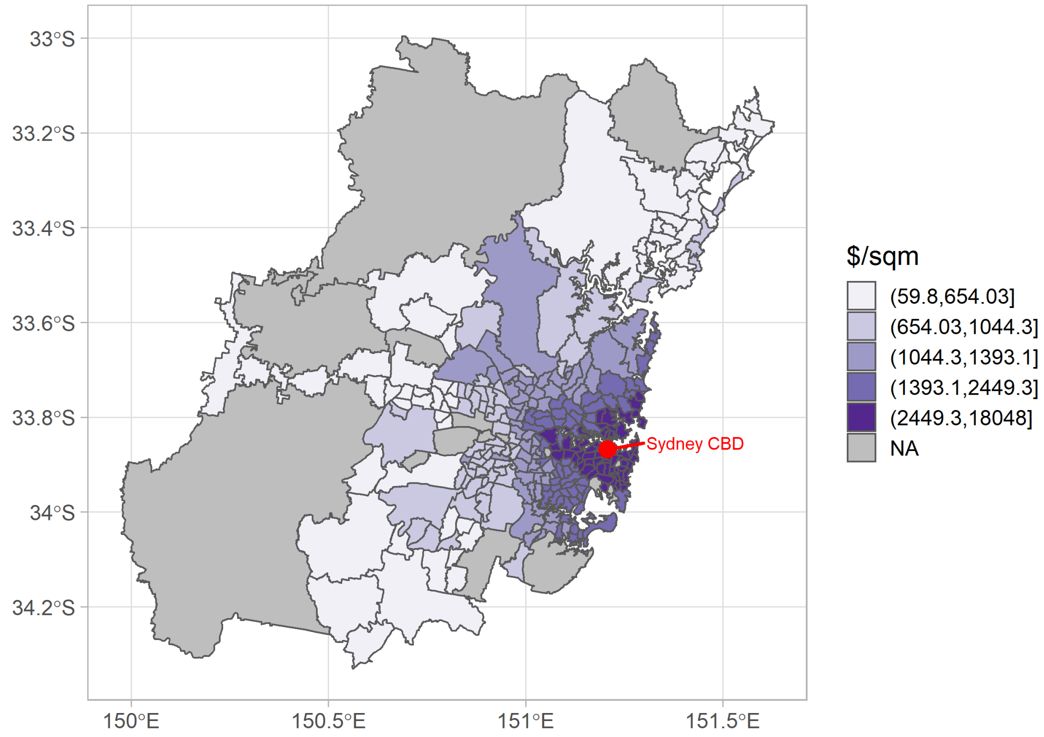


Figure 4.5: Median land values per square metre at SA2 level



4.4 Neighbourhood controls

Property prices are affected by factors in addition to commuting costs (Abelson et al., 2013; Grislain-Letrémy & Katossky, 2014). As a result, it is necessary to control for nearby amenities and characteristics of the neighbourhood. These controls are sourced from ABS 2016 Census data on population density, proportion of high income earners, unemployment, educational attainment, ancestry, socio-economic index scores and other demographic variables (see Appendix B for further details). These data are collected at the SA1 level, which captures local neighbourhood dynamics while working within the legal restriction on matching unit record data to non-confidentialised geographic locations. In addition, I also compute the distance to the nearest coastline using Geographic Information System (GIS) software for each property, given that access to beaches and the coast are such integral parts of the Sydney lifestyle (Abelson et al., 2013). Once each of the datasets were constructed, I geocoded the land value and property sales data with the corresponding travel time data and neighbourhood controls data using the `sf` package in R (Pebesma, 2018).

4.5 Property sales data summary statistics

Table 4.1 shows summary statistics for the sales data in this analysis. The mean land size is 515 square metres with a small number of small inner city lots and larger semi-rural lots. The mean property sale price in 2018 for this sample is $1.15 million, incorporating both house and unit sales. Table 4.2 shows that about half the dataset is made up of houses (defined as detached houses and cottages) and slightly less than half are sales of units (defined as units, studios and townhouses), with a small number of other property types making up the balance.

Table 4.1: Summary statistics for the property sales data

Statistic	Mean	Std. Dev.	Min	Max
Land area (sqm)	514.70	713.56	48.00	9,624.00
Sale price ($)	1,147,109.00	829,226.00	130,000.00	9,500,000.00
Price per sqm ($)	5,339.20	4,725.19	84.90	24,456.52
Driving time to Mac. Park (no traffic)	34.82	17.19	2.82	101.27
Driving time to Mac. Park (with traffic)	40.60	18.04	3.03	100.98
Transit time to Mac. Park	83.55	39.83	6.17	251.70
Driving time to Parramatta (no traffic)	39.99	17.30	4.25	99.35
Driving time to Parramatta (with traffic)	45.17	18.15	5.47	103.25
Transit time to Parramatta	74.06	34.29	3.52	240.90
Driving time to Sydney (no traffic)	37.04	20.22	5.28	112.65
Driving time to Sydney (with traffic)	49.38	24.23	5.77	122.22
Transit time to Sydney	68.74	40.36	5.42	221.58
Straight-line distance to Mac. Park	23.35	16.80	0.63	84.25
Straight-line distance to Parramatta	23.57	15.83	0.29	91.95
Straight-line distance to Sydney	24.21	20.17	0.26	94.56
Straight-line distance to coastline	15.01	15.64	0.01	83.14
Number of bedrooms	2.92	1.29	1.00	12.00
Number of bathrooms	1.86	0.76	1.00	8.00
Number of parking spaces	1.63	1.07	0.00	14.00
% with Australian ancestry	15.16	8.73	0.00	41.83
% holding Bachelor's degrees or above	26.63	13.29	0.00	61.54
% households speaking English at home	59.44	25.80	3.60	100.00
% individuals earning more than $156,000 per year	4.31	4.84	0.00	32.50
% individuals in professional occupations	14.14	7.38	0.00	36.00
% individuals unemployed	3.13	1.93	0.00	9.88
ABS Index of Disadvantage	1,038.05	88.14	573.00	1,176.00

Number of observations: 8,073. Travel times are in minutes. Straight-line distances are in kilometres. Demographic variables refer to the proportion of residents in the assigned SA1 for each property with those characteristics. The ABS Index of Disadvantage is sourced from the ABS Socio-Economic Indexes for Areas (SEIFA) Index of Relative Socio-Economic Disadvantage.

The sample of properties sold in 2018 is broadly reflective of Sydney's housing stock. Properties in the sample have an average of 2.9 bedrooms, 1.9 bathrooms and 1.6 parking spaces. The mean drive time to the Sydney CBD is 49 minutes, which is greater than that of Parramatta (45 minutes) and Macquarie Park (41 minutes). These average drive times make sense as Parramatta and Macquarie Park are more centrally located relative to most of Sydney's housing stock than the Sydney CBD, as well as being less affected by traffic congestion in inner city areas. In contrast, public transport travel times to the Sydney CBD (69 minutes) are shorter than that of Parramatta (74 minutes) and Macquarie Park (84 minutes), reflecting the CBD-centric design of Sydney's public transport network.

I report neighbourhood demographics data at the SA1 level on ancestry, educational attainment, income and occupation to capture a range of neighbourhood effects that may affect property values. Other socio-economic characteristics are also summarised into the SEIFA Index of Relative Socio-economic Disadvantage.

Given that Sydney is a coastal city, with a coastline that provides considerable amenity, I have included a proxy for accessibility to the coast in the form of straight-line distances to the nearest coastline for each property. This variable measures distance to the coastline, which includes both ocean-facing and other waterways such as Sydney Harbour or Broken Bay. The data contain properties on the coast as well as up to 83 km inland.

Table 4.2: Residential property type counts

Property type	Observations	%
Houses	4,033	50.0%
Units	3,950	48.9%
Other	90	1.1%

Houses are defined as detached properties and cottages. Units are defined as units, studios and townhouses. Other properties are defined as semi-detached, duplexes, terraces and villas.

I plot the bivariate relationship between sale prices, and drive times and public transport travel times to the Sydney CBD in figures 4.8 and 4.9. As implied by the AMM model, there is a negative and non-linear relationship between travel times and sale prices (per square metre). Sale prices per square metre initially decrease rapidly with increasing travel times from the CBD, before flattening out as the travel time increases beyond approximately 60 minutes.

Figure 4.6: Scatter plot of sale prices and drive times to Sydney CBD

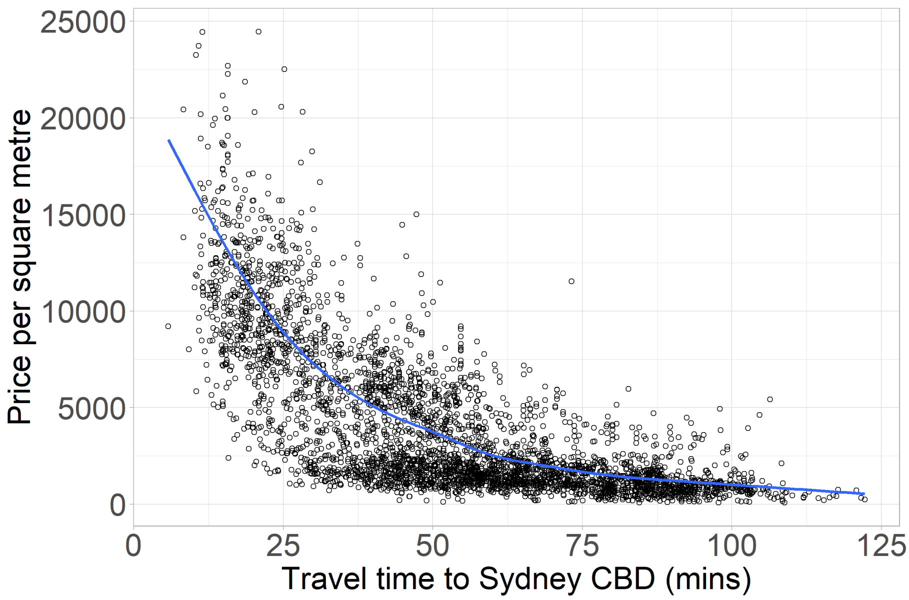
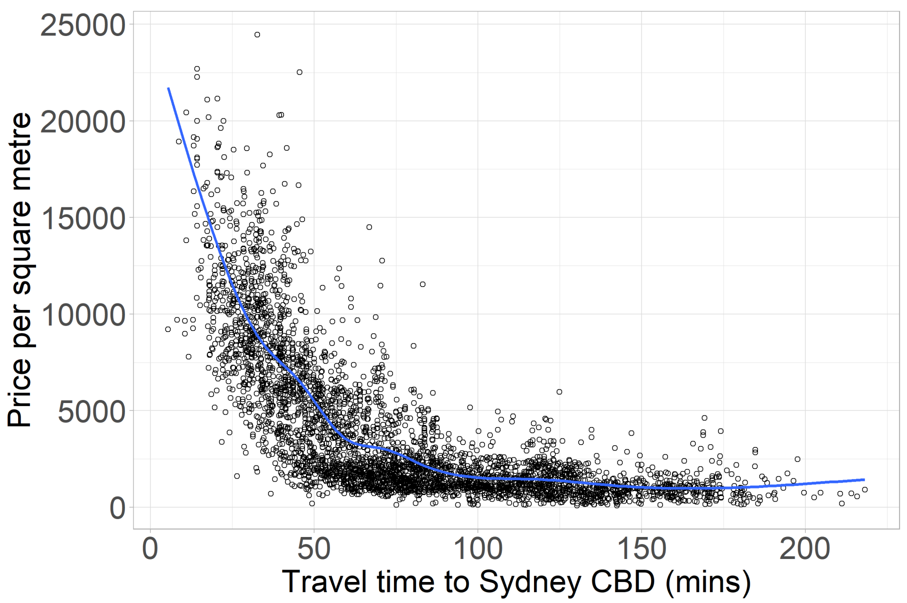


Figure 4.7: Scatter plot of sale prices and public transport travel times to Sydney CBD



4.6 Land values data summary statistics

Table 4.3: Summary statistics for the land value data

Statistic	Mean	Std. Dev.	Min	Max
Land area (sqm)	671.64	865.98	101.00	46,250.00
Land value ($)	826,774.90	539,164.90	200,000.00	3,790,000.00
Value per sqm ($)	1,605.30	1,497.55	17.95	26,872.25
Driving time to Mac. Park (no traffic)	37.40	15.89	2.22	157.97
Driving time to Mac. Park (with traffic)	47.32	19.07	2.35	161.28
Transit time to Mac. Park	87.59	34.64	5.35	248.12
Driving time to Parramatta (no traffic)	39.87	18.15	5.62	128.30
Driving time to Parramatta (with traffic)	47.23	20.84	6.38	130.97
Transit time to Parramatta	74.84	35.10	8.15	235.12
Driving time to Sydney (no traffic)	41.78	18.05	7.22	111.43
Driving time to Sydney (with traffic)	55.82	22.60	6.73	122.43
Transit time to Sydney	77.99	37.31	4.78	249.88
Straight-line distance to Mac. Park	24.13	15.57	0.70	84.10
Straight-line distance to Parramatta	22.54	16.68	0.70	93.27
Straight-line distance to Sydney	27.04	17.51	1.12	93.98
Straight-line distance to coastline	16.57	13.21	0.01	84.96
% with Australian ancestry	17.49	7.80	0.00	77.19
% holding Bachelor's degrees or above	20.26	11.09	0.00	59.31
% households speaking English at home	62.92	22.18	2.72	100.00
% individuals earning more than $156,000 per year	3.43	4.16	0.00	26.00
% individuals in professional occupations	11.51	6.00	0.00	38.26
% individuals unemployed	2.86	1.43	0.00	11.26
Persons	515.07	341.32	44.00	3,867.00
ABS Index of Disadvantage	1,021.83	95.43	433.00	1,176.00

Number of observations: 38,514. Travel times are in minutes. Straight-line distances are in kilometres. Demographic variables refer to the proportion of residents in the assigned SA1 for each property with those characteristics. The ABS Index of Disadvantage is sourced from the ABS Socio-Economic Indexes for Areas (SEIFA) Index of Relative Socio-Economic Disadvantage.

Table 4.3 shows summary statistics for the land valuations data in this analysis. The mean land size is 708 square metres, but varies considerably with a small number of outliers at the small end and a handful of large area lots, which are associated with greenfield developments that have yet to be subdivided. Land values also vary a large amount, which makes sense as this dataset captures the full range of properties from new greenfields developments to small strata lots in inner city areas. Table 4.4 shows that 80% of the properties in the data are low-density residential zoned (R2), about 11% are medium-density (R3), 2% are high-density (R4), 7% are zoned for general residential (R1) and the remainder are rural large-lot residential properties (R5).

Driving and public transport travel times to the three centres are in line with expectations. The mean drive time to the Sydney CBD at 56 minutes is greater than that of Parramatta (47 minutes) and Macquarie Park (47 minutes), which is likely the result of

Table 4.4: Residential zone code counts

Zoning code	Number of properties	%
R1	2,633	6.8%
R2	30,899	80.2%
R3	4,118	10.7%
R4	731	1.9%
R5	133	3.5%

R1 is General Residential; R2 is Low Density Residential; R3 is Medium Density Residential; R4 is High Density Residential; and R5 is Large Lot (Rural) Residential.

the more easterly location of the CBD, combined with greater traffic congestion in inner city areas. In contrast, mean public transport travel times to Sydney and Parramatta are similar at 78 minutes and 75 minutes, while Macquarie Park is less accessible with a mean travel time of 88 minutes.

The neighbourhood demographics data is reported at the SA1 level (in urban areas this covers an area of around 4–6 street blocks), with each property geocoded to its corresponding SA1. I report data on ancestry, educational attainment, income and occupation to capture a range of neighbourhood effects that may affect property values. Other socio-economic characteristics are also summarised into the SEIFA Index of Relative Socio-economic Disadvantage.

Like the sales data, I control for coastal amenities by including a proxy for accessibility to the coast in the form of straight-line distances to the nearest coastline for each property. This variable measures distance to the coastline, which includes both ocean-facing and other waterways such as Sydney Harbour or Broken Bay. The data contains coastal properties as well as up to 85 km inland.

I plot the bivariate relationship between land values, and drive times and public transport travel times to the Sydney CBD in figures 4.8 and 4.9. As implied by the AMM model, there is a clear negative and non-linear relationship between travel times and land prices (per square metre). Like with the sales price data, land values per square metre initially decrease rapidly with increasing travel times from the CBD, before flattening out as the travel time increases beyond approximately 60 minutes.

Figure 4.8: Scatter plot of land values and drive times to Sydney CBD

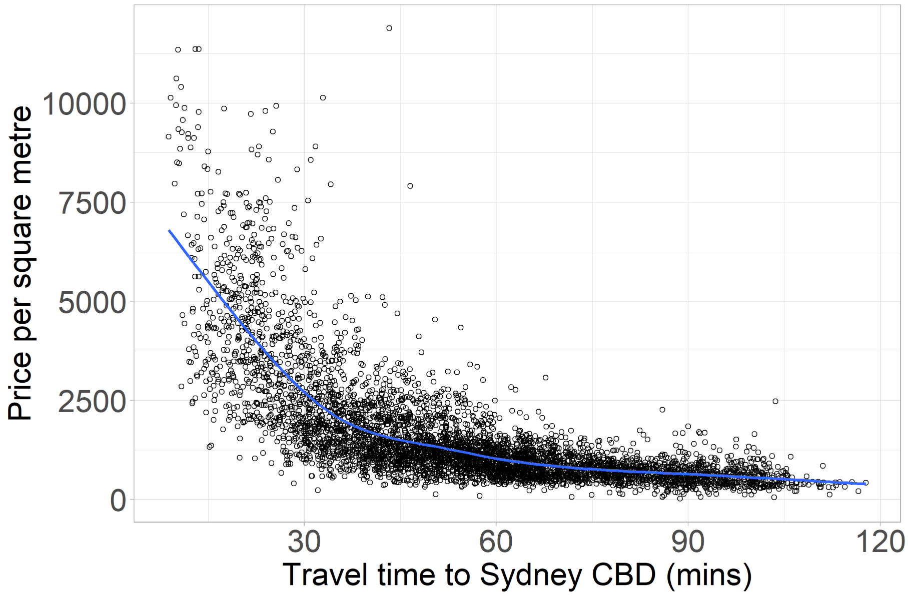
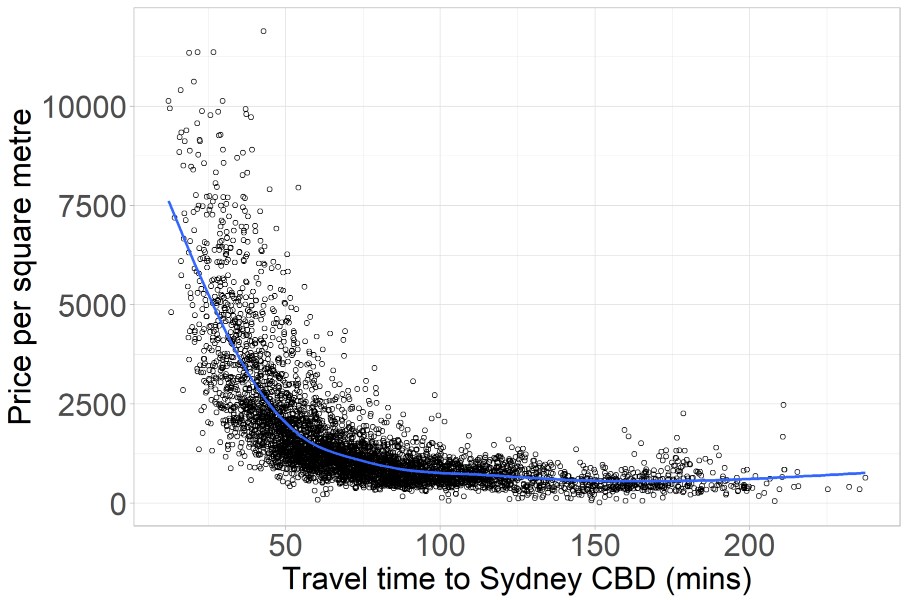


Figure 4.9: Scatter plot of land values and public transport travel times to Sydney CBD



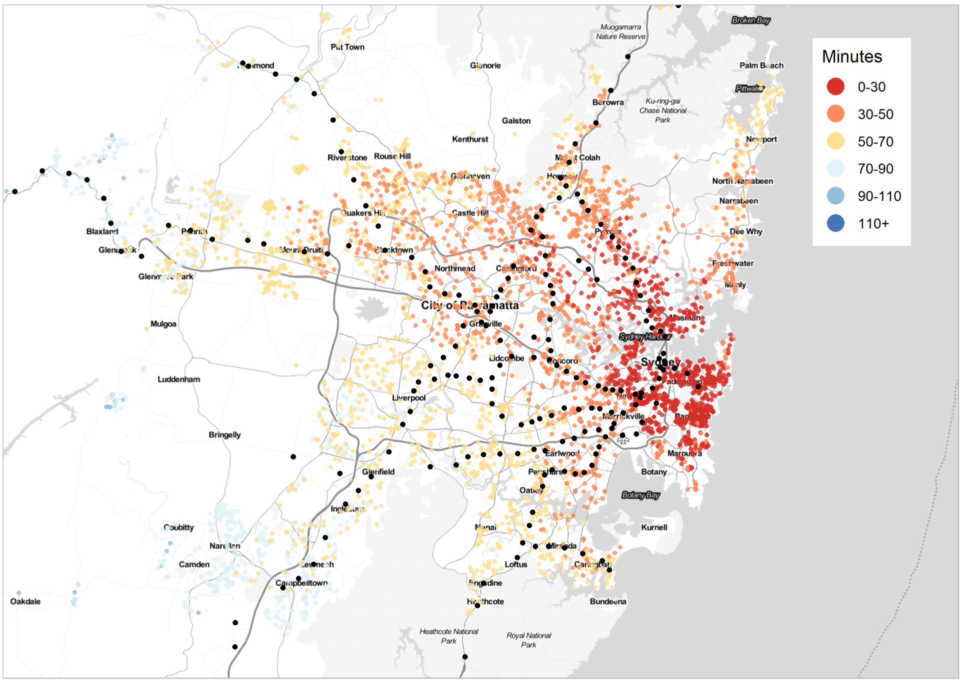
4.7 Mapping the data

Given the spatial nature of the data, we can better understand the relationships in the data by mapping key variables onto a map of Sydney. The key variables of interest are land values and travel times to various employment centres. I map the travel times for all properties to Sydney, Parramatta and Macquarie Park by road and public transport in the next two subsections. This map allows us to better visualise the relationship between proximity to the city centre and travel time, and also observe heterogeneity in travel times at a given distance from each city centre. This heterogeneity is a key reason I hypothesise travel times will be a better indication of commuting costs than distance from city centres. Using the maps for public transport travel time, such as figure 4.11, we can see that the location of transport infrastructure (the black dots represent train stations) strongly affects accessibility to the CBD.

4.7.1 Property sales data travel time maps

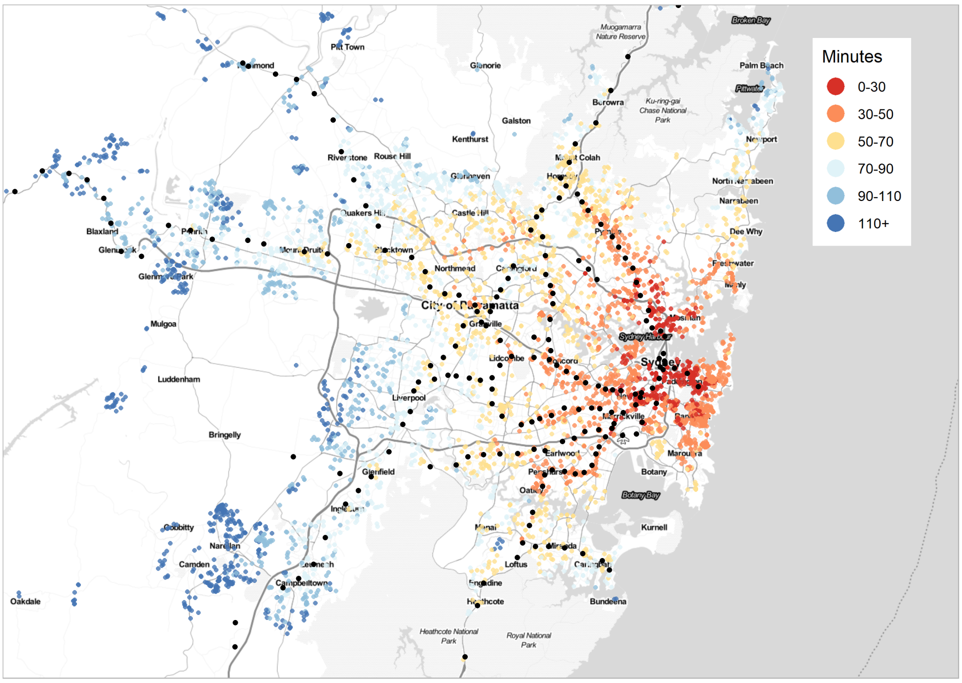
This subsection contains maps of the travel times for all 8,073 properties for which I have sales price data to Sydney, Parramatta and Macquarie Park by road and public transport. I only present the maps for travel times to the Sydney CBD and present the remainder in Appendix A. Accessibility to the Sydney CBD by road is much more closely related to distance, which is a function of the radial road network of Sydney. In comparison, accessibility by public transport varies for a given distance, with properties closer to public transport nodes (such as railway stations) having shorter travel times than equidistant properties that are not close to transport facilities.

Figure 4.10: Drive times to Sydney CBD



Notes: Black circles are locations of railway stations.

Figure 4.11: Public transport times to Sydney CBD

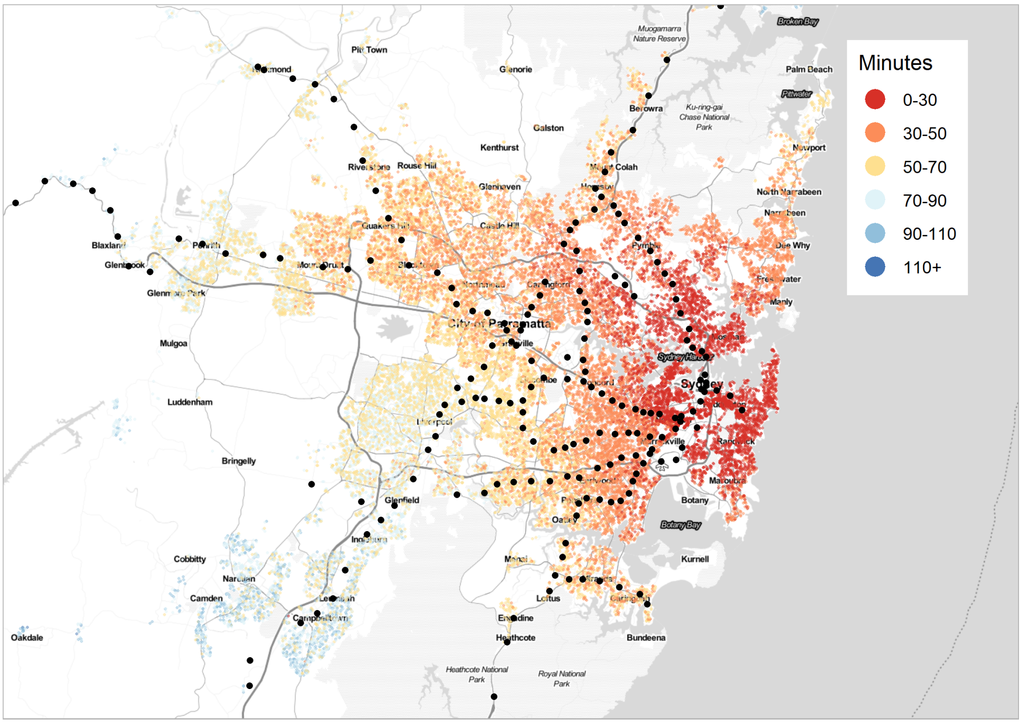


Notes: Black circles are locations of railway stations.

4.7.2 Land valuations data travel time maps

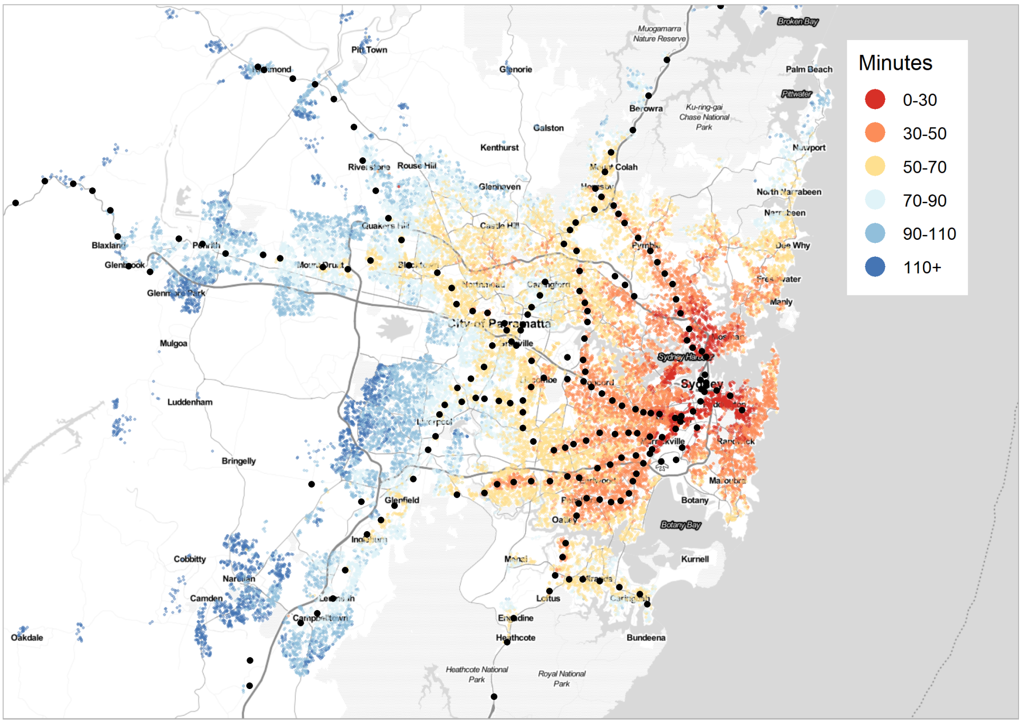
This subsection contains maps of the travel times for all 38,514 properties for which I have sales price data to Sydney, Parramatta and Macquarie Park by road and public transport. These maps show a similar pattern to the travel times for the sales price data properties. I only present the maps for travel times to the Sydney CBD and present the remainder in Appendix A.

Figure 4.12: Drive times to Sydney CBD



Notes: Black circles are locations of railway stations.

Figure 4.13: Public transport times to Sydney CBD



Notes: Black circles are locations of railway stations.

4.8 Testing for spatial dependence in the data

Spatial data points are likely to be related to one another across space. As stated by Tobler (1970), "everything is related to everything else, but near things are more related than distant things". This is a concept known as spatial dependence, which violates the assumption of independence of observations required for OLS estimation, as values observed in one location depend on the values of neighbouring observations in nearby locations (LeSage & Pace, 2008).

It is possible to formally test for the presence of spatial dependence in the data. One such test is to compute Moran's I, which is a measure of spatial autocorrelation in the dependent variable (property values) (Moran, 1950). The null hypothesis is that there is no spatial autocorrelation and the expected value of the statistic equals $-1/(N-1)$, which approaches 0 as $N \rightarrow \infty$. The test statistic (calculated using equation 4.1) is distributed χ^2. In equation 4.1, z_i is the deviation of an attribute for observation i from its mean $(x_i - \bar{x})$, w_{ij} is the spatial weight between observation i and j and S_0 is the sum of all spatial weights. The test uses the values of the dependent variable ($sqmvalue$) and a spatial weights matrix describing the spatial relationship between each observation in the data.

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{S_0 \sum_{i=1}^{n} z_i^2} \tag{4.1}$$

I present the results of the test in table 4.5 for both the sale price and land valuation datasets. The tests show that the null hypothesis of no spatial correlation is rejected (p-value = 0.000) for both datasets, which indicates that the presence of some form of spatial correlation is likely and this motivates the use of spatial regression models in the empirical analysis.

Table 4.5: Moran's *I* test results

	Moran's *I*	p-value
Sales price	42.274	0.000
Land valuation	82.709	0.000

CHAPTER 5

Results and discussion

In this chapter, I present estimates of the value of accessibility to employment in Sydney using a variety of model specifications. Starting with simple monocentric models of Sydney, I examine the explanatory and predictive power of traditional distance models, comparing them with travel time models and analyse the estimates of willingness to pay for increased accessibility to employment centres. I then examine how willingness to pay changes when the models are extended to include sub-centres. To account for the effects of spatial correlation across observations, I estimate these results using spatial regression methods in addition to linear regressions using OLS. The preferred functional form for the dependent variable is the natural logarithm as it addresses outliers in the right tail of the data, improves the normality of the residuals and is the preferred functional form in the literature. I then estimate alternative models that explicitly model for the effects of congestion on travel times to examine the premium that commuters place on avoiding congested roads. To investigate the predictive power of travel time models, I examine out-of-sample prediction performance of the model using spatial cross-validation techniques. These models are estimated using both the land valuations and property sales datasets, with the dependent variable in the model being land values and transaction prices. Finally, I discuss the limitations and areas that can be improved in future research. For brevity, I have excluded the coefficient estimates for the controls from the regression tables, the full regression tables are available in Appendix F and G.

Overall, the results support my new travel time data methodology. The results show that additional accessibility measures to sub-centres in Sydney are both statistically significant and improve the explanatory power of the hedonic models. The coefficients on accessibility to Sydney are negative and show a diminishing non-linear effect with decreased proximity, which concords with the predictions of the theoretical AMM model. Access measures to Parramatta also generally behave in line with expectations. I find that the travel time models materially improve the power of the model to explain variation in property sales prices compared to distance-based models when measured in terms of the Akaike information criterion (AIC) (Akaike, 1974; Lee & Ghosh, 2009) as shown in table 5.1. The AIC estimates the relative performance of models by comparing how much information is lost by one model relative to another (Akaike, 1974). The AIC is the preferred model selection method as it performs better at selecting models with good predictive properties relative to other information criteria (Dziak, Coffman, Lanza & Li, 2012). In contrast, the land value models do not show this improvement, with the distance models outperforming the travel time models in terms of goodness of fit. These differences in performance may reflect the methodologies used by the valuers in preparing the land value datasets as opposed to the market valuation that is revealed by the sale price data.

Table 5.1: Comparison of AIC scores for sales data models

Models	Distance	Travel time	ΔAIC
S	6,122.080	6,161.35	39.27
S+P	6,088.450	6,038.05	–50.40
S+P+M	5,990.440	5,947.64	–42.80
AIC(S+P+M) – AIC(S)	–131.640	–213.71	
AIC(S+P+M) – AIC(S+P)	–98.010	–90.41	

Models compared are the spatial error models estimated on the sales price data in section 5.2. A negative difference in AIC scores in the ΔAIC column indicates that the goodness of fit of the Travel time model is superior to the Distance model. A $\Delta AIC > 10$ indicates that the model with a higher AIC has essentially no support (Burnham & Anderson, 2004). A negative value in the last two rows indicates that the S+P+M model outperforms the simpler models. Model names: S (Sydney-only), S+P (Sydney and Parramatta), S+P+M (Sydney, Parramatta and Macquarie Park).

Including the travel time measures also substantially improves the out-of-sample predictive power of the hedonic pricing models when used to predict sales prices. Five of the six model specifications have improved predictive power when measured in terms of improvement in the root mean squared error (RMSE), with relative improvements in RMSE of over 33% compared to the equivalent distance models. In addition, half of the land valuation models have an improved ability to predict land values out-of-sample. Thus, based on the sales price data models, replacing distances with travel time as the measure of accessibility substantially improves both the goodness of fit and predictive power of hedonic pricing models.

Table 5.2 presents the estimated average value change in percentage and dollar terms for the average property as a result of a 1 minute change in travel times to the Sydney CBD. This estimate assumes a commute time by road of 49 minutes and by public transport of 69 minutes, and an average property sales price of about $1.15 million and land value of $826,800. The estimates reported come from the full S+P+M model. The results from the sales data models shows that a 1 minute reduction in drive times to the Sydney CBD increases property prices by between 0.30% to 0.62%, while a 1 minute increase in public transport times increases property prices by 0.36% to 0.52%. Similarly, I find that across the land value models, reducing driving times to Sydney tends to be more valued than public transport time, indicating a greater disutility from additional driving time relative to public transport travel time.

Table 5.2: Summary of property value changes for average property

Panel A: Sales price data models				
	Driving		Public transport	
	% change	$ change	% change	$ change
SUM	0.62%	$7148	0.52%	$5949
SEM	0.30%	$3396	0.36%	$4140
SARM	0.49%	$5635	0.49%	$5681
Panel B: Land valuations data models				
	Driving		Public transport	
	% change	$ change	% change	$ change
SUM	0.75%	$6210	0.58%	$4768
SEM	0.42%	$3479	0.26%	$2159
SARM	0.33%	$2693	0.16%	$1359

Models reported are the spatially uncorrelated model (SUM) estimated by ordinary least squares, spatial error model (SEM) estimated by maximum likelihood and spatial autoregressive model (SARM) estimated by maximum likelihood. Results reported are from the S+P+M (Sydney, Parramatta and Macquarie Park) model. Price changes are defined for the average property. The average property has a sales price of $1.15 million and land value of $826,800, drive time to Sydney of 49 minutes and transit time to Sydney of 69 minutes.

I discuss the model specification and tests of spatial autocorrelation in section 5.1. I analyse estimates using the sales price data in section 5.2 and land values data in section 5.3. I estimate models of the value of congestion in section 5.4. I present results for out-of-sample prediction in section 5.5 and compute willingness to pay estimates in section 5.6. I give an overview of robustness checks in section 5.7 and conclude with a discussion of the limitations in section 5.8.

5.1 Model specification

I estimate the hedonic models assuming spatially uncorrelated errors by ordinary least squares and two spatial regressions by maximum likelihood, first assuming a spatially correlated error term and then assuming a spatially correlated dependent variable. I use the natural logarithm of property values per square metre for each property (*lsqmvalue*) as the dependent variable as shown in equations 5.1 and 5.2 with three specifications: Sydney distance/travel times only (S), Sydney and Parramatta distance/travel times (S+P), and Sydney, Parramatta and Macquarie Park distance/travel times (S+P+M). For the sales price models, *lsqmvalue* is the natural logarithm of sale prices per square metre, whereas for the land valuation models, *lsqmvalue* is the natural logarithm of land values per square metre. Prices per square metre are used because the accessibility of a property is independent of land size. I estimate property values as a function of a vector of travel times ($\mathbf{T_i}$) and squared travel times ($\mathbf{S_i}$), individual property characteristics ($\mathbf{P_i}$) and neighbourhood demographic characteristics ($\mathbf{N_i}$).

$$\ln(\text{Sale price})_i = \alpha + \mathbf{T_i}\tau_1 + \mathbf{S_i}\tau_2 + \mathbf{P_i}\phi + \mathbf{N_i}\eta + \epsilon_i \tag{5.1}$$

$$\ln(\text{Land value})_i = \alpha + \mathbf{T_i}\tau_1 + \mathbf{S_i}\tau_2 + \mathbf{P_i}\phi + \mathbf{N_i}\eta + \epsilon_i \tag{5.2}$$

The log-level models are interpreted as the percentage change in property values. This change can be converted into dollar terms by multiplying it by some representative value. The log-level specification is useful as it better normalises the distribution of the residuals in the data (see figures C.1 to C.4 of Appendix C for regression residual plots). It also reduces the influence of outliers in the right tail (very high value properties) by compressing the scale of the dependent variable on the right-hand side. This approach is in line with the strategy taken in the literature (Abelson et al., 2013; Grislain-Letrémy & Katossky, 2014).

I include a vector of neighbourhood demographic and zoning controls to address non-accessibility related influences on the value of land. Neighbourhood controls are included at the SA1 level and incorporate measures of socio-economic disadvantage, employment, income and demographics that affect the character of a neighbourhood. I also include land zoning dummy variables because they are known to substantially affect the value of land (Kendall & Tulip, 2018). In all models, the base case is considered to be R1 General Residential, which can be considered the most flexible residential land zoning code. For additional details on variable descriptions see Appendix B.

The spatial regression models are estimated using the `spatialreg` package in R, written by Bivand, Pebesma and Gomez-Rubio (2013). I report results of the spatial error model (SEM) estimated using the `errorsarlm` function and spatial autoregressive model (SARM) estimated using the `lagsarlm` function, both by the method of maximum likelihood using approximate log-determinant methods (Bivand, Hauke & Kossowski, 2013). Spatial weight matrices are row-normalised inverse distance matrices calculated as the shortest distance between points on an ellipsoid using the `distm` function from the `geosphere` package by Hijmans (2019).

I find that the spatial error models generally outperform the equivalent spatial autoregressive models in terms of goodness of fit as measured by the AIC. Thus, I present one of the spatial error models in the main results section and provide the spatial autoregressive model tables as a robustness check in Appendix D and E.

5.1.1 Lagrange Multiplier test of spatial correlation

I test for the presence of spatial correlation in the error terms (spatial error) or spatial correlation in the dependent variable (spatial lag) in order to motivate the use of spatial regression methods. Table 5.3 reports the results from five tests of spatial correlation for the sales price models and land values models. The tests reject the null hypotheses that there is no spatial correlation in the error term and no spatial correlation in the dependent variable present in the data for both datasets and for all model specifications.

Table 5.3: Lagrange Multiplier tests of spatial autocorrelation

Panel A: Sales price data models						
	Distance			Travel times		
Statistic	S	S+P	S+P+M	S	S+P	S+P+M
Spatial error	11,335.876	4,751.729	3,513.632	3,705.323	2,721.034	1,555.057
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Spatial lag	419.447	45.387	33.216	106.645	113.476	29.197
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Robust spatial error	12,401.890	5,585.508	4,140.713	3,746.089	2,701.336	1,652.370
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Robust spatial lag	1,485.460	879.166	660.298	147.412	93.779	126.510
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: Land valuations data models						
	Distance			Travel times		
Statistic	S	S+P	S+P+M	S	S+P	S+P+M
Spatial error	33,237.825	18,843.794	8,417.614	20,834.487	13,601.128	5,834.728
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Spatial lag	9,280.042	4,809.657	2,668.571	5,386.688	5,006.939	2,831.782
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Robust spatial error	23,995.591	14,131.635	5,751.630	15,770.892	9,254.537	3,659.110
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Robust spatial lag	37.807	97.499	2.587	323.093	660.348	656.164
p-value	0.000	0.000	0.108	0.000	0.000	0.000

The Lagrange Multiplier tests are conducted on the linear regression models presented in Appendix D and E. Model names: S (Sydney-only), S+P (Sydney and Parramatta), S+P+M (Sydney, Parramatta and Macquarie Park). Test statistics and corresponding p-values are distributed $\chi^2(1)$.

The Lagrange Multiplier (LM) tests are a class of tests for spatially autocorrelated dependent variables and spatial error autocorrelation. Consider the following spatial general autoregressive model:

$$y = \mathbf{X}\beta + \rho\mathbf{W} + u \tag{5.3}$$

$$u = \lambda\mathbf{W}u + \epsilon \tag{5.4}$$

$$\epsilon \sim N(0, \sigma^2 I) \tag{5.5}$$

The spatial error LM test tests the null hypothesis that $\lambda = 0$. The test statistic is distributed $\chi^2(1)$. The data used in the test are the residuals of the linear regression model estimated by OLS (reported in section D.1 of Appendix D and section E.1 of Appendix E) and the same spatial weights matrix as in the Moran's I test. The robust LM test tests the same null hypothesis, but the results are robust to the presence of spatial autocorrelation in the dependent variable. The spatial lag LM test tests the null hypothesis that $\rho = 0$. The test statistic is distributed $\chi^2(1)$. Similarly, the robust version of this test is robust to the presence of spatial autocorrelation in the error term. However, in the absence of the other form of spatial autocorrelation, the robust form of the test has lower power compared to the non-robust version (Anselin, 2010; Anselin, Bera, Florax & Yoon, 1996).

The results of the LM tests show that the null hypotheses of no spatial correlation in the dependent variable or the errors are both rejected, indicating there is likely to be spatial autocorrelation in the dependent variable and/or the error term. Thus, it is likely that the results from the linear regressions have incorrect standard errors and/or biased coefficients, which motivates the use of spatial regression models analysed in this chapter.

5.2 Estimates from property sales data

The results from the spatial error model (SEM) show that the travel time models improve on the distance models in terms of goodness of fit. The results of the regression are reported in table 5.4. The models with all three sub-centres have greater explanatory power as measured by the AIC compared to the simpler monocentric models of Sydney, suggesting the inclusion of sub-centres adds information despite the additional complexity. The S+P+M and S+P travel time models outperform the equivalent distance models substantially in terms of goodness of fit as measured by the AIC. The difference in AIC for the S+P+M model is 65, which is a significant difference per the rule of thumb proposed by Burnham and Anderson (2004).

Table 5.4: Spatial error model regression results using $\ln\left(\text{Sales price per } m^2\right)$

	Distance (% change)			Travel time (% change)		
	S	S+P	S+P+M	S	S+P	S+P+M
Syd. distance	-4.5728^{***}	-4.6835^{***}	-5.9942^{***}			
	(0.23767)	(0.24597)	(0.27727)			
Syd. distance^2	0.0281^{***}	0.00100	0.0419^{***}			
	(0.00359)	(0.00729)	(0.00886)			
Par. distance		0.9652^{***}	-0.25246			
		(0.24442)	(0.27317)			
Par. distance^2		0.0198^{***}	0.0396^{***}			
		(0.00707)	(0.00755)			
Mac. distance			3.1321^{***}			
			(0.30875)			
Mac. distance^2			-0.0719^{***}			
			(0.00959)			
Syd. drive time				-1.9167^{***}	-1.7050^{***}	-1.9417^{***}
				(0.15474)	(0.15673)	(0.17171)
Syd. drive time^2				0.0140^{***}	0.0131^{***}	0.0168^{***}
				(0.00143)	(0.00147)	(0.00156)
Syd. transit time				-0.5579^{***}	-0.5721^{***}	-0.6498^{***}
				(0.09676)	(0.10788)	(0.11104)
Syd. transit time^2				0.00059	0.0017^{***}	0.0021^{***}
				(0.00047)	(0.00053)	(0.00055)
Par. drive time					-1.2329^{***}	-1.7390^{***}
					(0.24201)	(0.25286)
Par. drive time^2					0.0094^{***}	0.0171^{***}
					(0.00264)	(0.00280)
Par. transit time					0.16365	0.2908^{***}
					(0.10005)	(0.10327)
Par. transit time^2					-0.0024^{***}	-0.0029^{***}
					(0.00048)	(0.00053)
Mac. drive time						1.6793^{***}
						(0.25553)
Mac. drive time^2						-0.0244^{***}
						(0.00297)
Mac. transit time						-0.12088
						(0.09507)
Mac. transit time^2						0.00063
						(0.00049)
Coast distance	-2.7164^{***}	-0.7031^{*}	-0.57470	-3.3160^{***}	-4.5458^{***}	-4.5108^{***}
	(0.25078)	(0.40193)	(0.40052)	(0.23377)	(0.30764)	(0.31828)
Coast distance^2	0.0341^{***}	0.0205^{***}	0.0137^{**}	0.0264^{***}	0.0407^{***}	0.0412^{***}
	(0.00539)	(0.00590)	(0.00588)	(0.00461)	(0.00529)	(0.00541)
λ	0.9012^{***}	0.8930^{***}	0.8860^{***}	0.8833^{***}	0.8913^{***}	0.8875^{***}
	(0.00823)	(0.00926)	(0.00979)	(0.00927)	(0.00871)	(0.00911)
Neighbourhood controls	Yes	Yes	Yes	Yes	Yes	Yes
Zoning controls	Yes	Yes	Yes	Yes	Yes	Yes
Parameters	19	21	23	21	25	29
Log Likelihood	−3042.03841	−3023.22642	−2972.21888	−3059.67300	−2994.02729	−2954.82218
AIC (Linear model)	7985.79392	7574.62365	7377.23656	7766.01901	7696.05379	7377.83767
AIC (Spatial model)	6122.07682	6088.45284	5990.43777	6161.34600	6038.05458	5967.64436
LR test: statistic	1865.71710	1488.17081	1388.79880	1606.67300	1659.99920	1412.19331
LR test: p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

	Distance (% change)			Travel time (% change)		
	S	S+P	S+P+M	S	S+P	S+P+M

Standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Coefficients transformed to percentages. All travel times are in minutes. All distances are in kilometres. Results reported are spatial error models estimated by maximum likelihood. Number of observations in all models is 8,073. Model names: S (Sydney-only), S+P (Sydney and Parramatta), S+P+M (Sydney, Parramatta and Macquarie Park). Full model tables can be found in Appendix F and G.
Controls: Neighbourhood controls are demographic variables for the SA1 that each property belongs to and controls for ABS SEIFA Disadvantage Index, population % with Australian ancestry, population % with Bachelor's degree or above, population % unemployed, population % with income above $130,000 per year, population % speaking English at home, and population % working in a professional occupation. Zoning controls are dummy variables for Low Density Residential, Medium Density Residential, High Density Residential, Large Lot (Rural) Residential. The base case is General Residential.

The SEM is the preferred model as it controls for spatial dependency in the error term revealed in the Lagrange Multiplier test and outperforms the spatial autoregressive model in terms of goodness of fit as measured by the AIC. The log-level models also outperform the level-level models in terms of explanatory power, which are included in section D.2 of Appendix D as a robustness check. I also report the results and discussion of the spatial autoregressive model for the log-level and level-level specification in sections D.3 and D.4 of Appendix D.

The SEM incorporates a spatially autoregressive error term, which explicitly addresses spatial non-stationarity in the unobservables, which contrasts with the OLS estimation method which assumes spatial non-stationarity is not present. Assuming that the dependent variable is spatially uncorrelated, using the SEM means that the estimates are unbiased and the standard errors are efficient. The structure of the spatial error model is shown in equations 5.6 and 5.7.

$$y = \mathbf{X}\beta + u \tag{5.6}$$

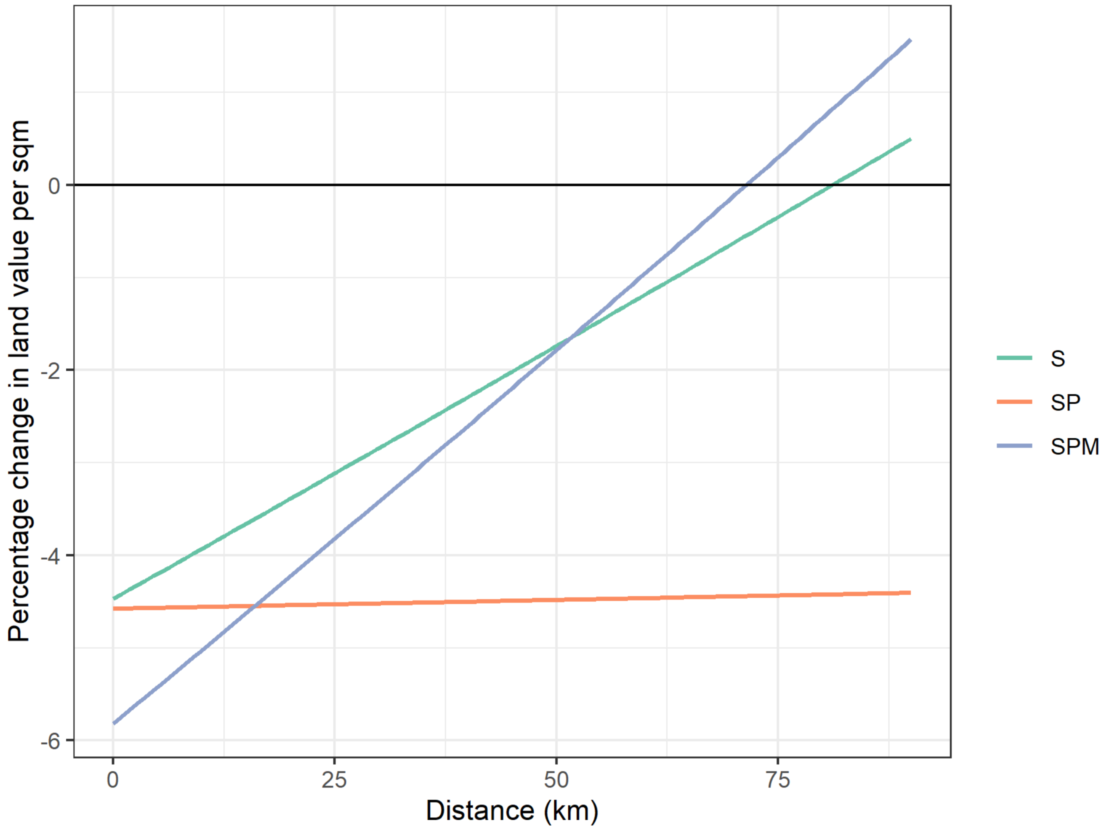
$$u = \lambda \mathbf{W} u + \epsilon \tag{5.7}$$

$$\epsilon \sim N(0, \sigma^2 I_n) \tag{5.8}$$

5.2.1 Distance specifications

The distance results from the spatial error models are in line with theoretical expectations, showing an inverse and non-linear relationship between distance from the Sydney CBD and property prices. My estimates show that a 1 km increase in distance to the Sydney CBD decreases property prices by around 6% in the vicinity of the CBD. This effect is non-linear and diminishes with distance, with the marginal effect decreasing to zero at a distance of 81 km from the CBD using the Sydney-only model compared to 72 km using the S+P+M model. This is equivalent to the straight-line distance from Sydney to Wollongong and is also illustrated in figure 5.1. Distance to the coastline also has a negative coefficient, indicating that proximity to the coast is positively valued in Sydney, which is in line with theory suggesting that proximity to amenities is positively valued. At a distance of around 21 km inland the marginal effect zeroes out, meaning that beyond this point, access to the coastline is not valued. In the context of Sydney, this is the distance from Bondi Beach to Sydney Olympic Park.

Figure 5.1: Marginal effect of Sydney distance on property prices per m^2



Parramatta is the second largest employment centre in Sydney and is often considered to be Sydney's second CBD. As a result, I hypothesise that accessibility to this important sub-centre will influence property price patterns. The Parramatta distance variables to the S+P model are highly significant, but have an unexpected positive sign. This unusual result is likely due to the fact that the Sydney CBD is a much more substantial employment centre compared to Parramatta, such that the effect spills over onto the Parramatta coefficient as well. This explanation is supported by the flatter slope of the Sydney distance coefficients that are illustrated in figure 5.1, suggesting that part of the effect of proximity to employment in Sydney has partially spilled over into the Parramatta measures of accessibility. The S+P+M model shows more conventional results. In this model, the coefficients are in line with theoretical expectations, with increased distance from Parramatta being associated with reduced sales prices. Under this specification, the model implies that a 1 km increase in distance away from Parramatta, holding proximity to other centres constant, decreases property prices by around 0.25%.

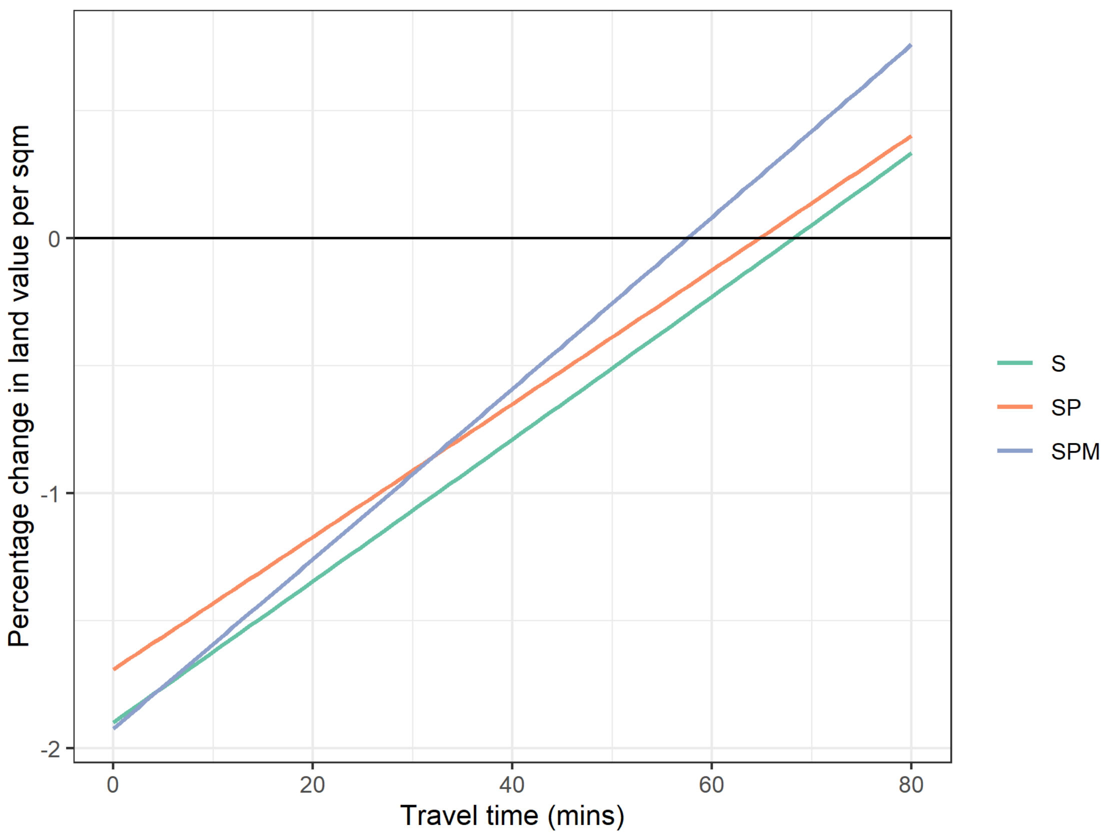
Macquarie Park is the third largest employment centre in Sydney (if Sydney and North Sydney are combined and treated as one centre), hence I include accessibility data to this location. However, the coefficients on distance to Macquarie Park are positive, which implies that access to Macquarie Park is negatively valued by commuters. However, it can be difficult to interpret the coefficients as they require everything else to be held constant. Consider the distance model with all three centres. It is impossible to change the distance from one CBD while holding the distance to the other two CBDs constant due to the trilateration problem. Trilateration refers to the property that given three distances or travel times to three different locations, it is possible to pin down a single unique location from that information. Nevertheless, the statistically and economically significant coefficients on Parramatta and Macquarie Park distance suggests that sub-centres are valued by commuters. This outcome is different to the conclusion reached by Abelson et al. (2013), who found that sub-centres do not have a significant effect on house prices. However, given that the sign of the coefficients are problematic, it is difficult to conclude whether sub-centres are truly valued or whether this is an artefact of the model specification. In addition, the problems with the coefficient estimates detract from the relative utility of the distance models compared to the travel time models, which are more consistent with theory.

5.2.2 Travel time specifications

Compared to the distance models, the behaviour of the coefficients in the travel time models are more consistent across the specifications and more in line with theoretical expectations. The travel time models also have superior explanatory power relative to the distance models as measured by the AIC, with the exception of the monocentric Sydney model. The S+P+M and S+P travel time models outperform the equivalent distance models substantially in terms of goodness of fit as measured by the AIC. The difference in AIC for the S+P+M model is 65 points and S+P model is 50 points, which indicates the travel time models are very likely to be more representative of the data generating process per the rule of thumb proposed by Burnham and Anderson (2004).

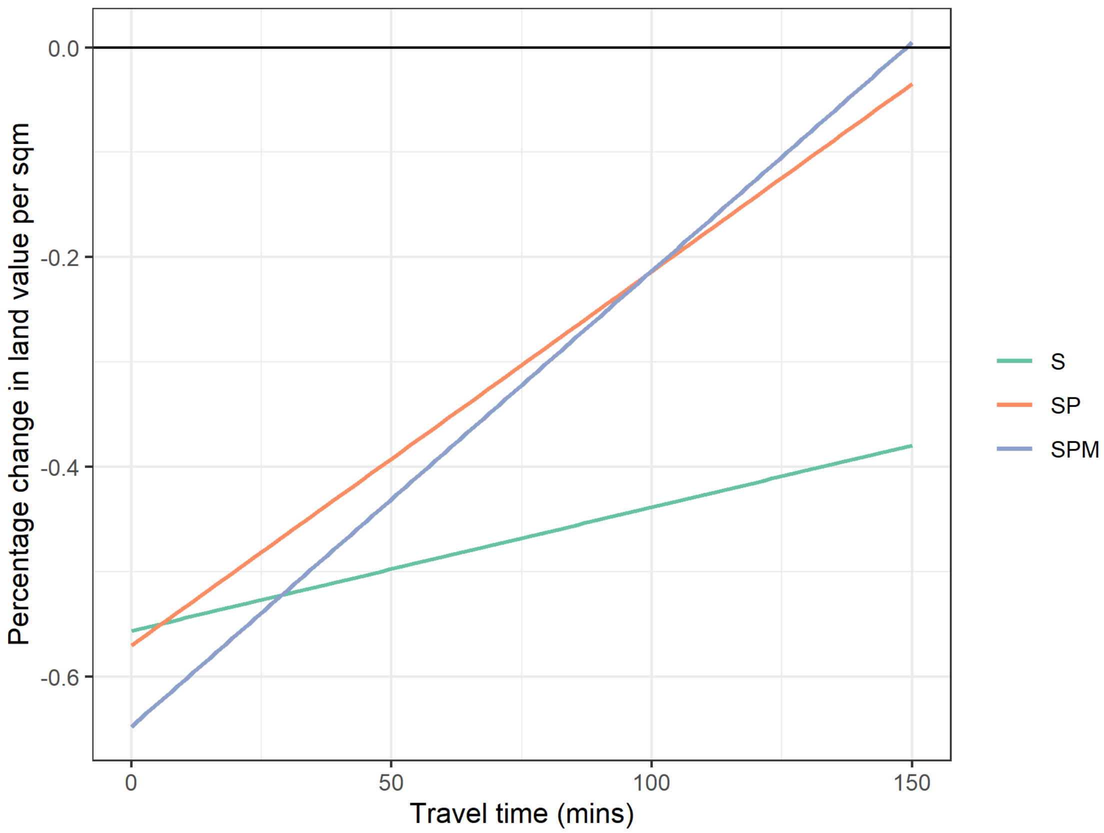
The coefficients on Sydney drive times behave in line with theoretical expectations, indicating an inverse and non-linear relationship between increased travel times and decreased property prices. Increased drive times to the Sydney CBD decrease property prices by a diminishing percentage effect. A 1 minute increase in drive time close to the Sydney CBD decreases prices by around 1.9%. This effect diminishes to a 0.9% decrease for a 1 minute increase in drive time when the property is located 30 minutes drive time from the CBD. The marginal effect of an increase in drive time zeroes out when the travel time increases to 58 minutes. This result is robust to model specification, as shown in figure 5.2, which indicates that the effect of changing travel times is similar across all model specifications.

Figure 5.2: Marginal effect of Sydney drive time on property prices per m^2



The marginal effect of a change in public transport travel times is smaller than the equivalent drive time effect. In the immediate vicinity of the Sydney CBD, an increase in public transport travel time by 1 minute decreases property prices by 0.65%. This effect falls to a 0.52% decrease 30 minutes away from the city centre. The marginal effect falls to zero when the travel time is greater than 155 minutes, which is almost three times further than the time taken for the marginal effect on drive times to reach zero. This result indicates that commuters experience greater disutility per minute from driving to work, as they are willing to pay more to reduce drive times compared to public transport travel times, holding all else equal. This outcome may result from the fact that it is possible to do other things on public transport, such as catching up on emails, whereas driving requires complete focus the entire time. As shown in figure 5.3, with the exception of the Sydney-only model, this result is robust to the inclusion of additional sub-centres as the slope and magnitudes of the marginal effects are fairly similar.

Figure 5.3: Marginal effect of Sydney transit time on property prices per m^2



In comparison, increased drive times from Parramatta are associated with a 1.7% drop in property prices in the immediate vicinity of Parramatta. This effect reduces to a 0.7% decrease in prices for a 1 minute increase in drive times for properties 30 minutes away from Parramatta. This result indicates that accessibility to Parramatta by road is valued by Sydneysiders. However, the coefficients on public transport travel times to Parramatta are positive, indicating that accessibility to Parramatta by public transport is not valued by commuters. This finding may be driven by the fact that Parramatta has worse public transport linkages compared to Sydney, combined with easier access by car due to lower traffic congestion.

The coefficients on drive times to Macquarie Park are also unusual as they have positive values, suggesting that improved accessibility to Macquarie Park reduces land values. This result goes against theoretical expectations, but there are some possible explanations. It is highly unlikely that the coefficients represent the true marginal value that commuters place on accessing Macquarie Park and the signs of the coefficients may instead be driven by spillover effects from the other centres. For example, imagine a straight line between Parramatta and Sydney. As you move further away from Sydney, you move closer to Parramatta simultaneously. The increasing travel time to Sydney decreases housing values according to the model, while the decreasing travel time to Parramatta also compounds the decreasing land value according to the model. In addition, directly interpreting the coefficients on the centres can be difficult due to trilateration. Thus, it is not possible to change only one travel time parameter while holding all else equal. In addition, the coefficients on public transport travel time to Macquarie Park are both insignificant, indicating that public transport access to Macquarie Park is not valued. However as the variables are jointly significant, I elect to retain the Macquarie Park variables in the final model as the explanatory power of the model is materially improved by including all three sub-centres.

The coast distance coefficients have the expected sign across all three travel time models. For the S+P+M model, a 1 km increase in distance from the coast reduces land values near the coast by 4.5%. This effect diminishes with increased distance from the coastline, with households further than 55 km from the coast no longer valuing proximity to the coastline. Thus, compared to the distance-only models, the marginal effect of coast access diminishes more slowly.

5.3 Estimates from land valuations data

I estimate the spatial error model (SEM) using the land valuations data and report the results in table 5.5. I find that both the distance and travel time models have high explanatory power. However, unlike the sales price data models, the travel time models do not outperform the distance models in terms of goodness of fit. The more comprehensive models that include sub-centres perform better than the simpler monocentric models, suggesting that including sub-centres adds information despite the added complexity.

The SEM is the preferred model as it controls for spatial dependency in the error term, making it superior to the linear models and also outperforms the spatial autoregressive model in terms of in-sample fit as measured by the AIC. I report the results and discussion of the spatial autoregressive model for the log-level and level-level specification in sections E.3 and E.4 of Appendix E as a robustness check. The log-level SEM also outperforms the level-level SEM, which I report in section E.2 of Appendix E. Due to the computational intensity of estimating the spatial models, I have used a random sample of 10,000 land value observations out of my full dataset for these regressions.

Table 5.5: Spatial error model regression results using ln(Sales price per m^2)

	Distance (% change)			Travel time (% change)		
	S	S+P	S+P+M	S	S+P	S+P+M
Syd. distance	-4.9678^{***}	-5.3061^{***}	-7.7090^{***}			
	(0.18895)	(0.20996)	(0.22834)			
Syd. distance^2	0.0345^{***}	0.0194^{***}	0.0630^{***}			
	(0.00258)	(0.00531)	(0.00617)			
Par. distance		0.9216^{***}	-1.2625^{***}			
		(0.17351)	(0.19201)			
Par. distance^2		0.0086^{*}	0.0226^{***}			
		(0.00471)	(0.00475)			
Mac. distance			4.9737^{***}			
			(0.22363)			
Mac. distance^2			-0.0662^{***}			
			(0.00620)			
Syd. drive time				-0.9978^{***}	-0.8917^{***}	-1.0284^{***}
				(0.11083)	(0.11098)	(0.11285)
Syd. drive time^2				0.0059^{***}	0.0054^{***}	0.0062^{***}
				(0.00090)	(0.00090)	(0.00091)
Syd. transit time				-0.6221^{***}	-0.4265^{***}	-0.6889^{***}
				(0.06572)	(0.06997)	(0.07168)
Syd. transit time^2				0.0025^{***}	0.0023^{***}	0.0031^{***}
				(0.00030)	(0.00033)	(0.00034)
Par. drive time					-0.2994^{**}	-0.6485^{***}
					(0.13999)	(0.14228)
Par. drive time^2					0.00091	0.0032^{**}
					(0.00132)	(0.00133)
Par. transit time					-0.3234^{***}	-0.2649^{***}
					(0.07128)	(0.07078)
Par. transit time^2					0.00030	0.00011
					(0.00037)	(0.00037)
Mac. drive time						0.5427^{***}
						(0.12027)
Mac. drive time^2						-0.0071^{***}
						(0.00109)
Mac. transit time						0.5583^{***}
						(0.06439)
Mac. transit time^2						-0.0017^{***}
						(0.00033)
Coast distance	-2.7403^{***}	-1.2292^{***}	-0.8300^{***}	-3.6066^{***}	-4.8082^{***}	-4.3210^{***}
	(0.18446)	(0.30342)	(0.29039)	(0.19445)	(0.21827)	(0.21716)
Coast distance^2	0.0428^{***}	0.0281^{***}	0.0098^{**}	0.0312^{***}	0.0488^{***}	0.0401^{***}
	(0.00387)	(0.00456)	(0.00436)	(0.00404)	(0.00428)	(0.00424)
λ	0.8905^{***}	0.8858^{***}	0.8602^{***}	0.9228^{***}	0.9189^{***}	0.9051^{***}
	(0.00790)	(0.00845)	(0.01038)	(0.00538)	(0.00571)	(0.00677)
Neighbourhood controls	Yes	Yes	Yes	Yes	Yes	Yes
Zoning controls	Yes	Yes	Yes	Yes	Yes	Yes
Parameters	18	20	22	20	24	28
Log Likelihood	−1414.13214	−1393.65904	−1138.12037	−1704.05107	−1609.20425	−1484.68042
AIC (Linear model)	5090.28271	4641.75601	3573.88262	6198.07007	5788.20127	4648.04811
AIC (Spatial model)	2864.26428	2827.31807	2320.24075	3448.10214	3266.40850	3025.36083
LR test: statistic	2228.01844	1816.43793	1255.64187	2751.96794	2523.79277	1624.68728
LR test: p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

	Distance (% change)			Travel time (% change)		
	S	S+P	S+P+M	S	S+P	S+P+M

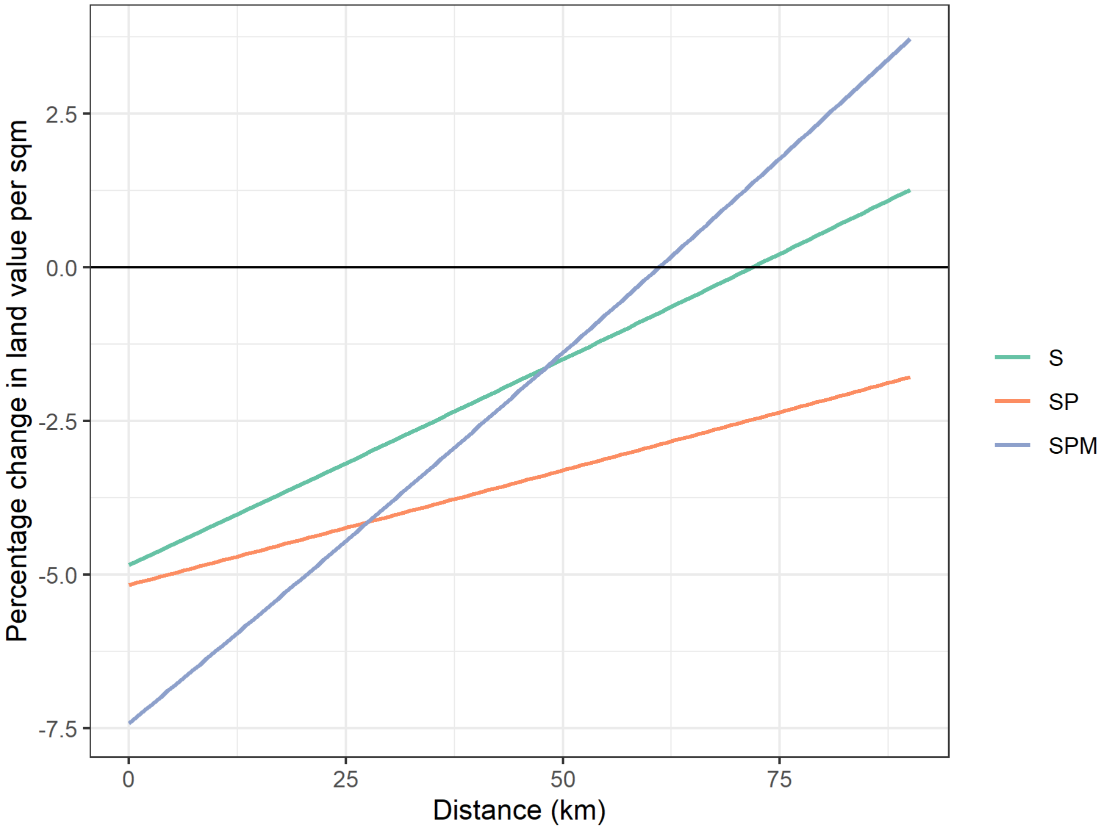
Standard errors in parenthesis. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Coefficients transformed to percentages. All travel times are in minutes. All distances are in kilometres. Results reported are spatial error models estimated by maximum likelihood. Number of observations in all models is 10,000. Model names: S (Sydney-only), S+P (Sydney and Parramatta), S+P+M (Sydney, Parramatta and Macquarie Park). Full model tables can be found in Appendix F and G.
Controls: Neighbourhood controls are demographic variables for the SA1 that each property belongs to and controls for ABS SEIFA Disadvantage Index, population % with Australian ancestry, population % with Bachelor's degree or above, population % unemployed, population % with income above $130,000 per year, population % speaking English at home, and population % working in a professional occupation. Zoning controls are dummy variables for Low Density Residential, Medium Density Residential, High Density Residential, Large Lot (Rural) Residential. The base case is General Residential.

5.3.1 Distance specifications

Similar to the sales data results, the spatial error models show that there is an inverse and non-linear relationship between distances and land values. A 1 km increase in distance from the Sydney CBD decreases land values by around 5.0% in the immediate proximity of the CBD. This effect is non-linear and diminishes with distance. Using the Sydney only model, this marginal effect diminishes to zero at a distance of 71 km from the CBD. This is equivalent to the straight-line distance from Sydney to Wollongong. When the additional sub-centres are included, this marginal effect zeroes out 61 km from the CBD as shown in figure 5.4. These results are consistent with the estimates from the sales data models. Distance to the coastline also has a negative coefficient, indicating an inverse relationship between distance to the coast and land values, which is in line with theory that implies proximity to amenities are positively valued. At a distance of around 32 km from the coast, the marginal effect zeroes out, suggesting there is no value placed on proximity to the coast once you are more than 32 km inland. In the context of Sydney, 32 km is the distance from Bondi Beach to Blacktown. Again, this is similar to the sales data results.

I find that proximity to Parramatta is positively valued by commuters using the S+P+M model specification. Under this specification, the model implies that a 1 km increase in distance away from Parramatta, holding proximity to other centres constant, land values decrease by around 1.3%. In contrast, proximity to Macquarie Park is not positively valued by commuters as the coefficients are positive, indicating that greater distance from Macquarie Park is positively valued by commuters, which goes against theoretical expectations. One possible explanation for this effect is that the employment density of the Sydney CBD dominates the model, such that part of its effect spills over onto the Macquarie Park coefficients. Another possible cause is the previously discussed trilateration problem that complicates the interpretation of the distance coefficients.

Figure 5.4: Marginal effect of Sydney distance on land values per m^2

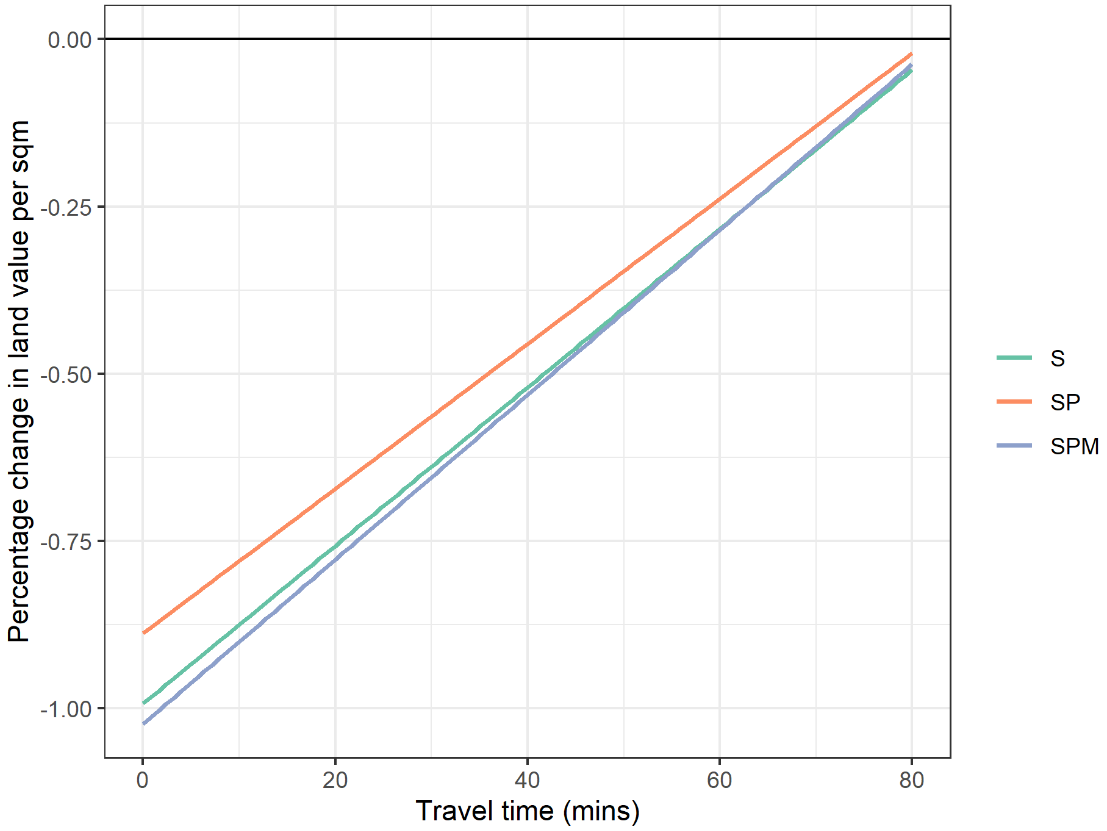


5.3.2 Travel time specifications

The behaviour of the coefficients in the travel time models tend to be more consistent and also more in line with theoretical expectations relative to the distance models. However, unlike the sales data models, the travel time models using land values data do not outperform the distance models in terms of goodness of fit. I discuss potential reasons for this in detail in the Limitations section. I find that commuters positively value increased accessibility to Sydney and Parramatta by car and public transport, but the estimates on Macquarie Park continue to confound expectations. I observe non-linear effects as predicted by the theory in all the accessibility measures, as shown by the highly significant level and squared terms.

Increased travel time to the Sydney CBD decreases land values by a diminishing percentage effect. This effect is stronger for drive times, with a 1 minute increase in drive times to the CBD decreasing land values by around 1.0% for the Sydney only model. This effect diminishes to a 0.6% decrease for a 1 minute increase in travel time 30 minutes' drive away from the CBD. The marginal effect of an increase in travel time zeroes out when the travel time increases to 85 minutes. This result is robust to the model specification, with the marginal effects not changing materially when the model is generalised to include additional sub-centres. This is shown in figure 5.5, which shows that the effect of changing travel times is similar across the three models.

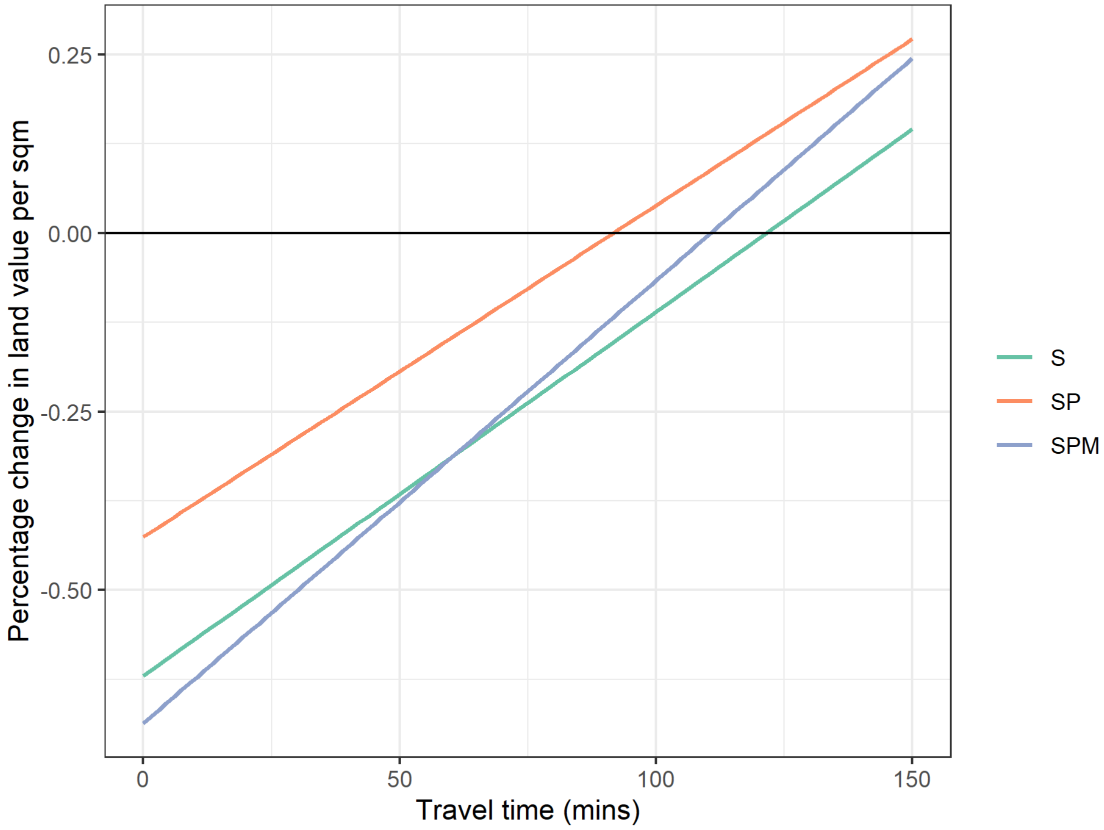
Figure 5.5: Marginal effect of Sydney drive time on land values per m^2



Consistent with sales data results, the marginal effect of a change in public transport travel times is smaller than the equivalent drive time effect. In the immediate vicinity of the Sydney CBD, an increase in public transport travel time by 1 minute decreases land values by around 0.62%. This effect falls to a 0.47% per minute decline 30 minutes away from the city centre. The marginal effect falls to zero when the travel time is greater than around 120 minutes, which is around 1.5 times as far as drive times. This result indicates the commuters experience greater disutility per minute from driving to work, as they are willing to pay more to reduce drive times compared to public transport travel times, holding all else equal. As shown in figure 5.6, this result is robust to the inclusion of sub-centres as the slope and magnitudes of the marginal effects are fairly similar.

The coefficients on the drive time and public transport times to Parramatta are statistically significant and negative, indicating that accessibility to Parramatta is valued by Sydneysiders. Using the S+P+M results, the data show that a 1 minute increase in drive times to Parramatta is associated with an approximate 0.65% decrease in land values in the immediate vicinity of Parramatta, while a 1 minute increase in

Figure 5.6: Marginal effect of Sydney transit time on land values per m^2



public transport time to Parramatta is associated with around a 0.32% decrease in land values. Like for Sydney, accessibility by driving appears to be more valuable than public transport, with the coefficient on drive times twice as large as that of public transport. This result may be driven by the fact that Parramatta has relatively worse public transport linkages compared to Sydney, combined with easier access by car due to lower traffic congestion.

In comparison, the coefficients on Macquarie Park travel times are unusual as they have positive values, suggesting that improved accessibility to Macquarie Park reduces land values, which is contrary to theoretical expectations. However, as the explanatory power of the model is materially improved by including Macquarie Park data, I elect to retain this in the final model. In contrast, accessibility to the coast continues to be positively valued by commuters across all model specifications. For the S+P+M travel time model, an increase in distance from the coastline by 1 km decreases land values near the coast by 4.3%. This effect diminishes with distance from the coast, with households no longer valuing proximity to the coastline at a distance of 54 km away from the coast.

5.4 Estimating the value of congestion

Commuters experience additional disutility from traffic congestion and the value of congestion is capitalised into land values as shown in table 5.6. Congestion is measured as the difference between the drive time in traffic less the drive time without traffic, which are unique datapoints that are available in my dataset. Commuters experience disutility from increased free-flow (without congestion) drive times, as shown by the negative coefficient on the *Free-flow drive time* variables for Sydney and Parramatta. Commuters also experience disutility from worsening congestion during peak hours, which is measured by the *Congestion delay* variables, which is constructed by subtracting the free-flow drive time (no traffic) from the congested (with traffic) drive time.

Using the log-level specification of the SEM, a 1 minute increase in congested drive time to the Sydney CBD is associated with a 0.26% decrease in land values. Similarly, commuters dislike increased road congestion to Parramatta, with a 1 minute increase in drive times corresponding to a 0.17% decrease in land values. Finally, while the sign on free-flow travel time to Macquarie Park exhibits the same unusual positive sign like in previous models, the negative coefficient on the congested drive time differential shows that commuters also value a reduction in congestion to Macquarie Park, with a 1 minute increase in congested drive time being associated with a 0.22% decrease in land values. These results are all statistically significant, although their significance is affected by model specification choices. Note that for interpretability reasons, I have specified a simplified model with only linear terms on the drive times instead of the fully featured models in previous sections that included squared terms on all accessibility variables.

These estimates have useful policy implications for congestion charging. I find that the average commuter values the present discounted value of 1 minute of congestion when driving into the Sydney CBD at about $2,200 for the average property, which can be converted to an hourly willingness to pay equal to $17.64 (per the method in Appendix K). This amount represents the value that the average commuter places on reducing congestion in their daily commute by one hour. Thus, this estimate can be used to set an upper bound on a congestion charge for travelling into the Sydney CBD. That is, if a hypothetical congestion charge was expected to reduce congestion by 1 hour for the average journey into the Sydney CBD, then commuters would be willing to pay up to $17.64 for the right to drive into the city. Naturally, if the scale of congestion improvements was expected to be smaller, then the congestion charge could be scaled down accordingly.

Table 5.6: Marginal value of congestion estimates

	Land value per m^2		ln(Land value per m^2)	
	SUM	SEM	SUM	SEM
Free-flow drive time (Syd)	-129.55^{***}	-21.11^{***}	-32.6940^{***}	-0.0071^{***}
	(5.35)	(1.97)	(1.8056)	(0.0007)
Congestion delay (Syd)	-23.00^{***}	-7.80^{***}	-12.4753^{***}	-0.0026^{***}
	(2.81)	(1.12)	(1.1697)	(0.0004)
Free-flow drive time (Par)	24.17^{***}	8.00^{***}	17.3675^{***}	-0.0040^{***}
	(5.10)	(2.23)	(1.8489)	(0.0008)
Congestion delay (Par)	-7.99	-3.42	1.0956	-0.0017^{**}
	(6.35)	(2.23)	(2.2984)	(0.0008)
Free-flow drive time (Mac)	122.82^{***}	5.99^{**}	6.7431^{***}	0.0030^{***}
	(6.62)	(2.52)	(2.2127)	(0.0009)
Congestion delay (Mac)	-7.91^{**}	-8.81^{***}	-15.2427^{***}	-0.0022^{***}
	(3.95)	(1.45)	(1.4889)	(0.0005)
λ		0.88^{***}		0.8816^{***}
		(0.01)		(0.0084)
Public transport times	Yes	Yes	Yes	Yes
Coastline distance	Yes	Yes	Yes	Yes
Neighbourhood controls	Yes	Yes	Yes	Yes
Zoning controls	Yes	Yes	Yes	Yes
R^2	0.74		0.7231	
Adj. R^2	0.74		0.7224	
RMSE	866.83		890.5742	
Parameters		28		28
Log Likelihood		–81,365.20		–2,349.8605
AIC (Linear model)		164,244.07		6,001.7601
AIC (Spatial model)		162,786.40		4,755.7210
LR test: statistic		1,459.67		1,248.0391
LR test: p-value		0.00		0.0000

Notes: Standard errors in parenthesis. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All travel times are in minutes. Number of observations in all models is 10,000. *Congestion delay* is calculated as the difference between free-flow (no traffic) drive times and congested (with traffic) drive times. SUM is the spatially uncorrelated model estimated by OLS. SEM is the spatial error model estimated by MLE. Full model tables can be found in table G.7 of Appendix G.

Controls: Neighbourhood controls are demographic variables for the SA1 that each property belongs to and controls for ABS SEIFA Disadvantage Index, population % with Australian ancestry, population % with Bachelor's degree or above, population % unemployed, population % with income above $130,000 per year, population % speaking English at home, and population % working in a professional occupation. Zoning controls are dummy variables for Low Density Residential, Medium Density Residential, High Density Residential, Large Lot (Rural) Residential. The base case is General Residential.

5.5 Out-of-sample predictive power

Out-of-sample prediction tests the power of the model to predict property prices given new data. Finding models with superior predictive power can have significant applications in the property industry, where these models are useful for developing automated valuation modelling tools capable of improving the scale and consistency of property valuation. Predicting the magnitude of land value uplift is also useful for infrastructure cost-benefit analysis by better predicting where and how much residents financially benefit from new infrastructure projects. For these applications, prediction and forecasting performance are more important than in-sample explanatory power.

Figure 5.7: Spatial cross-validation folds (repetitions 1-4)

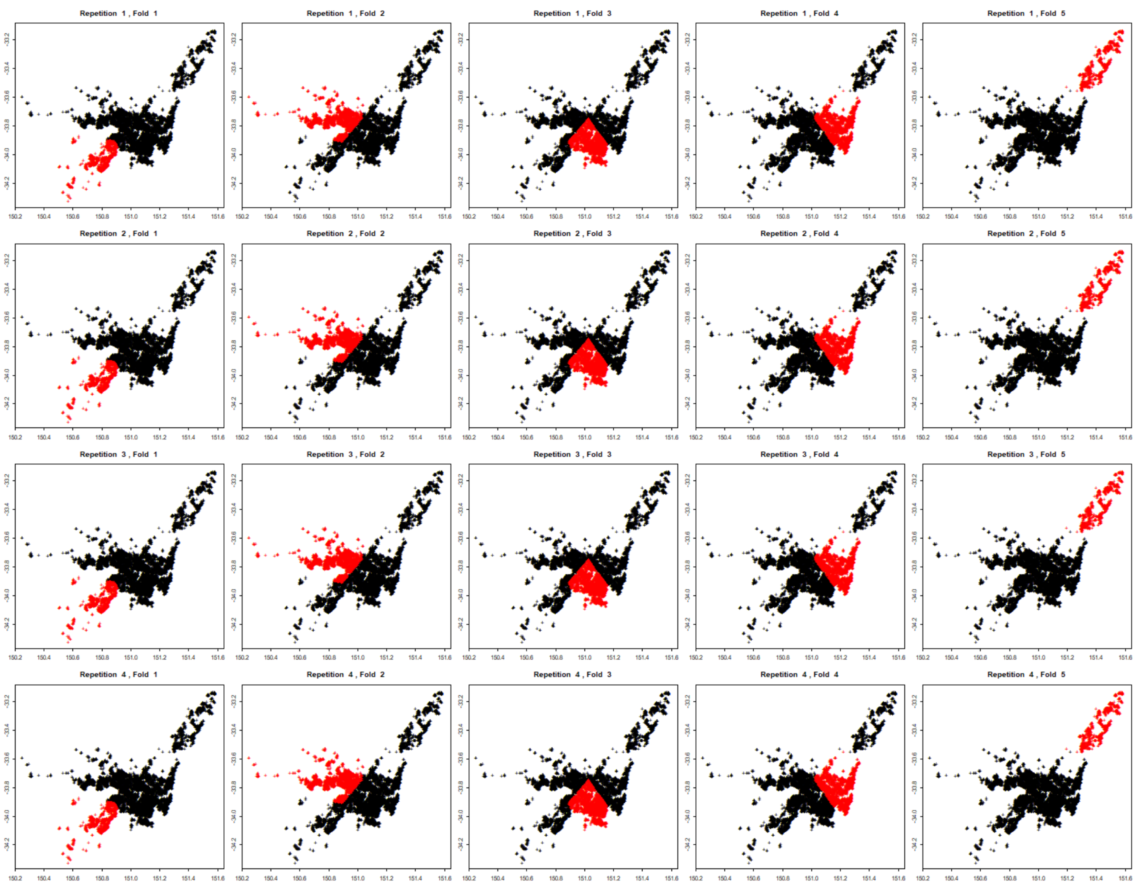


Figure shows the first 4 repetitions of the 5-fold spatial cross-validation routine. Red points denote properties that are in the test dataset and black points are properties that are in the training dataset. While the image size makes it hard to see, there is variation in the subsample used for the training/test data in each repetition.

Spatial data violate the assumption of independence of observations and as a result, the training and test datasets in cross-validation cannot be considered independent either. This property causes the out-of-sample predictive performance of the models to be biased upwards (Roberts et al., 2017). Conventional cross-validation methods are vulnerable to this bias, but this problem can be mitigated through cross-validation using spatially contiguous folds (Brenning, 2005, 2012). I address this problem by writing a cross-validation routine that slices the dataset in such a way that minimises the correlation across observations in the training and test sets. Using functions from the `sperrorest` R package by Brenning (2012), I use k-means clustering to construct spatially contiguous subsets of the data, as shown in figure 5.7, which form the training and test datasets. The subsets are spatially contiguous, minimising as much as possible the degree of spatial correlation between observations across the training and test data. Observations close to the boundaries of each grouping may still be correlated, but this process minimises the influence of this problem. I then run a 5-fold cross-validation routine on these spatially-selected folds, estimating the residuals by OLS.

Table 5.7: Spatial cross-validation out-of-sample prediction performance results

Panel A: Sales price data models						
	Sales price per m^2			ln(Sales price per m^2)		
Model	Distance	Time	% change	Distance	Time	% change
S	4,988	3,811	−30.90	0.780	0.710	−9.80
S+P	4,678	3,969	−17.90	0.760	0.810	+6.27
S+P+M	4,728	3,552	−33.10	0.730	0.730	−1.10
Panel B: Land valuation data models						
	Land value per m^2			ln(Land value per m^2)		
Model	Distance	Time	% change	Distance	Time	% change
S	1,366	1,355	−0.80	0.500	0.580	+15.20
S+P	1,156	1,378	+19.16	0.480	0.620	+28.91
S+P+M	1,795	1,236	−31.14	0.550	0.530	−2.78

Root mean squared error (RMSE) is the measure of out-of-sample fit reported. A positive % change indicates that the travel time models have a higher RMSE, that is they perform worse than the corresponding distance model. 5-fold CV with 100 repetitions using spatial folds selected by k-nearest neighbours on 8,073 observations for the sales price data models and 38,514 observations for the land valuation data models. Models are estimated by OLS. Model names: S (Sydney-only), S+P (Sydney and Parramatta), S+P+M (Sydney, Parramatta and Macquarie Park).

My measure of out-of-sample performance is the root mean squared error (RMSE) associated with each model. I refer to the model specifications as S (Sydney only), S+P (Sydney and Parramatta) and S+P+M (Sydney, Parramatta and Macquarie Park). Panel A of table 5.7 shows the results for the three model specifications using the sales price dataset. I find that the predictive power of the level-level travel time models are consistently higher than that of the distance-based models, indicating that replacing distance with travel times as the measure of accessibility significantly improves the ability of the models to predict house prices. This improvement is substantial, with the S+P+M travel time model performing over 33% better than the distance models in terms of RMSE. The results are more mixed for the log-level models. While two out of three travel time models perform better than their corresponding distance models, the scale of the improvement in predictive power is less substantial. In addition, the S+P travel time model does not outperform the equivalent distance model. Overall, these results strongly suggest that travel times are a better measure of accessibility to employment, especially for industry applications where predictive power is the most important measure.

I also compute out-of-sample prediction scores for the land value data models, where the results are more mixed. I find that half of the land value travel time models outperform their distance-based equivalents. For the Sydney-only model, the log-level distance model outperforms the log-level travel time model, while the level-level models have very similar predictive power. When using the S+P model, both the level-level and log-level travel time models perform worse than the distance models. Thus, when only accessibility to the Sydney CBD is considered, existing distance-based models are sufficient to explain the variation in land values across Greater Sydney. However, the level-level S+P+M travel time model improves out-of-sample fit by 31% compared to the distances-based model. Similarly, the log-level specification produces a smaller improvement of around 2.8%. Thus, incorporating additional travel time data leads to a substantial improvement in the predictive power of hedonic price models when a polycentric city structure is considered.

5.6 Willingness to pay calculations

I compute the present discounted value of reducing future travel times in this section and convert these estimates to hourly willingness to pay (WTP). Assuming an average land value of $826,700 and property sales price of $1.15 million, and commute times of 49 minutes by road and 69 minutes by public transport, I estimate that the average property price increase resulting from a 1 minute decrease in all future commuting trips by road is about $3,396. This value can be considered to be the present value of future travel time savings that are capitalised into the value of the house. For public transport, the present discounted value of a 1 minute reduction in trip times is about $4,140. For the land value data models, the average land value uplift from a 1 minute decrease in future road commutes is about $3,479. For public transport, the present discounted value of a 1 minute reduction in trip times is about $2,159. For the land value models, this value represents the present value of future travel time savings that are capitalised into the value of the land.

While the present value of total future travel time savings are interesting, converting these figures into willingness to pay for per trip savings are easier to understand and interpret. Using assumptions detailed in Appendix K on the relevant discount rate, number of hours worked per year and the number of working years remaining, I calculate that commuters value a 1 hour reduction in driving times to Sydney at $27.22 per hour and a 1 hour reduction in public transport travel times at $33.19 per hour. In comparison, I calculate from the land value models that commuters value a 1 hour reduction in driving times to Sydney at $27.89 per hour and a 1 hour reduction in public transport travel times at $17.31 per hour. This lower value for public transport for the land value estimates is in line with previous results that find that the disutility of public transport commute time to be lower than driving commute times. While the results for the value of driving are consistent across the datasets, the value of public transport times are divergent. I am unsure what is driving this difference and future research may wish to further investigate this discrepancy.

These figures represent the central scenarios, but within the full range of reasonable assumed values, this number varies from $18.76 to $52.05 per hour of driving and $22.33 to $61.94 per hour of public transport travel using the sales price models. In comparison, the range of reasonable assumed values from the land value models are $18.76 to $52.05 per hour of driving and $11.64 to $32.30 per hour of public transport travel.

As a comparison, transport agencies often use 40% of the average wage rate as a proxy for the amount that commuters are willing to pay to reduce their commute time. However, the reliability of this figure is strongly disputed, for example, see Hensher (2019) and Douglas and Jones (2018). Calculations using this assumption produce an estimate of $17.20 per hour (40% × $42.99) (data sourced from Australian Bureau of Statistics (ABS, 2019a, 2019b)). Thus, there are some substantial differences in the estimated WTP from my study compared with the assumed values used in industry, suggesting that if my results are more accurate, then transport improvements are likely to be undervalued under the existing methodology. For full calculations see Appendix K.

5.7 Robustness tests

I perform a range of robustness tests to check the sensitivity of results to different model specifications and estimation methods for both the sales data and land valuations data. I report the results of these tests in Appendix D and E. Overall, I find that my results are robust to model specification and while the magnitudes of some estimates change across estimation methods, for the most part the direction of the coefficients are unchanged.

I re-estimate my models by OLS to investigate whether ignoring the effects of spatial dependence have an effect on the results. I find that while the magnitudes of the coefficients vary compared to the SEM results, the direction of the estimates mostly remain the same. The magnitudes on the distance and travel time variables do not vary in any systemic manner, indicating the OLS estimates are not consistently over or underestimating the effects relative to the spatial models. These estimates are reported in table D.1 of Appendix D for the sales price estimates and table E.1 of Appendix E for the land valuation estimates.

Similarly, the results from estimating spatial autoregressive models (SARM) are also similar to the main results in this chapter. Including indirect spillover effects in the SARM increases the size of the effect observed as expected, but does not change the sign of the results. The initial effects of accessibility changes are consistently larger when indirect impacts are taken into account, but the marginal effect also diminishes more rapidly, such that when compared to the other models, the marginal effect of changes in accessibility zero out at similar distances and travel times. For the SARMs, estimates are reported in tables D.3 and D.6 of Appendix D for the sales price models and tables E.3 and E.6 of Appendix E for the land valuation models.

I test whether my results are robust to respecifying the dependent variable as land values and sales prices per square metre instead of the natural logarithms. I find that the level-level models perform worse in terms of explanatory power compared to the log-level models, likely due to the presence of outliers and a non-linear relationship in the dependent variable that the level-level models capture less well compared with the log-level models. However, the signs of the results mostly do not change, indicating that the results are robust to this change of specification as well. These results are reported in table D.2 of Appendix D for the sales price models and table E.2 of Appendix E for the land valuation models. I also compare the performance of log-log models with log-level models, finding that the preferred log-level specification outperforms in all cases. See table D.10 of Appendix D for sales data results and table E.10 of Appendix E for land value data results.

As an additional check, I run the sales price and land value models using sales price and land values as the dependent variable, without dividing the values by land area. The explanatory power of this model specification is consistently lower than both the level sales price/land value per square metre and the natural logarithm of sales price/land values. This result makes sense as the preferred models take into account the fact that accessibility does not change as a function of land area. While the magnitudes of the estimates vary, the results are qualitatively similar to the main models. I report the results for the sales price models in table D.9 of Appendix D and the land value models in table E.9 of Appendix E.

5.8 Limitations

This Part investigates whether travel time data is a useful addition to hedonic modelling of property prices. I find evidence supporting the use of travel time models over distance-based models in both explanatory and predictive applications, with these results mostly robust to different model specifications and estimation methods. However, it is important to discuss the limitations of my findings and suggest pathways for future researchers to address these issues.

While the sales data models outperform the distance models in terms of explaining in-sample variation of property sales prices, this is not true of the models estimated on the land valuations data. The AIC of the distance-based land valuations models indicates that they have a superior fit relative to the equivalent travel time models. A possible explanation for this is the way that the land value data is constructed. While the land values data is of high quality, it fundamentally does not reflect market outcomes in the way that housing sales data does. Land valuation data is constructed by professional valuers overseen by the NSW Valuer General and it is possible that their valuation of the land's accessibility uses distance as a proxy instead of travel times. Similarly, while the travel time specifications of the sales data models significantly outperform in terms of out-of-sample predictive ability compared to the distance specifications, the results are mixed for the land value data models. Some models provided large improvements in out-of-sample prediction using travel time data relative to distance data, while other specifications suggested that the travel time models actually performed worse. Future research should examine the discrepancy between the conclusions reached using sales data and land value data.

The behaviour of the coefficients on the Macquarie Park data cause some concern. In most of the models specified, the travel times and distance to Macquarie Park suggest that households would pay to live *further* away from that centre, which goes against theoretical expectations that people prefer to live closer to amenity and employment. There are some possible explanations for this result. The first is that Macquarie Park is not a sufficiently important centre to model, such that when it is included in the model, some of the effects of the larger centres, i.e. Sydney CBD, spill over into the coefficient. This explanation potentially makes sense, as moving further away from Sydney CBD necessitates moving closer to Macquarie Park if, for example you head in a northerly direction. As previously discussed, there is also a potential trilateration problem. As a result, the coefficients may have unexpected values as the model attempts to impose a ceteris paribus interpretation when one is not possible.

Future research should aim to incorporate monetary costs of travel as monetary travel costs and travel time costs are positively correlated, meaning that it is likely that the coefficients on the time travel cost parameters are biased upward. Note that the monetary cost differential between travel modes is quite small, especially compared to the increase in travel times that would be faced by commuters who choose to change modes to save money, meaning this bias should be relatively minor. It would also be interesting to decompose public transport travel times into walking, waiting, interchange and actual travelling times, as prior research has found that commuters tend to value these components differently. However, it is currently not possible to extract individual travel time components from the Google Maps travel time API data, but perhaps this will be added as a feature in the future.

While financial constraints prevented me from doing so in this thesis, including travel time measures to non-employment amenities is an important extension to modelling the value of variations in accessibility of different locations. Access to amenities such as schools, shopping centres and parkland are likely to be valued by commuters as well as employment. Another future extension to this project is to collect travel time data for the same sample of properties in the future, say in three to five years time. This allows the researcher to construct a panel dataset of travel times and land values, allowing for property-specific fixed effects to be controlled and better isolating the causal effect of changes in travel times. This would resolve a number of omitted variable problems that are associated with property-specific or neighbourhood-specific unobserved attributes.

The dispersed nature of employment in Sydney is a shortcoming of the theoretical basis and empirical methods used in this Part. My estimation method assumes that employment in three designated major centres are what are valued by households. This is a limiting assumption given that only 14% of workers (312,310 of 2,262,010) actually work in the Sydney CBD, 2% work in Parramatta and another 2% work in Macquarie Park. The second largest employment "location" in Sydney with 4% of workers is actually those with no fixed workplace address (ABS, 2016). In addition, access to other amenities such as parks, schools and shopping centres may also be valued by households and could be included in the travel time dataset with additional resources. However, compared to previous work that has generally assumed a monocentric city, my inclusion of three centres produces a more realistic model of Sydney.

One alternative specification that may ameliorate this issue are gravity models, which have been widely used in regional science and civil engineering (Ahlfeldt, 2010; Kau & Sirmans, 1979). With the collection of a large amount of additional data, it would be possible to estimate a gravity-based specification of the hedonic model estimated in this Part. The gravity model is based on two assumptions (Handy & Niemeier, 1997). The first is that areas with greater employment mass or greater amenity are more desirable. The second is that areas that are more accessible are also more desirable. By applying these principles, a gravity model approach would involve constructing a single employment-weighted travel time from each property.

One implementation would use granular employment data from the Census at the SA1 level and scrape travel times from Google Maps for each pair of SA1s i and j as the measure of travel cost c_{ij}. This measure is then used to weight employment E_j at each location j, creating a measure of accessibility A_i for each location i to employment as shown in equation 5.9. Properties can then be assigned their corresponding SA1, creating a more accurate summary measure of employment accessibility for each property that should be superior to the three centres approach I have used.

$$A_i = \sum_{j=1}^{n} E_j f(c_{ij}) \tag{5.9}$$

However, combining this specification with my travel time data approach is much more resource intensive. Using the idealised SA1 method involves computing travel times for $n(n-1)$ pairs of locations. Given there are 11,171 SA1s in Sydney, this results in over 124 million API calls. A less granular compromise is to use Travel Zones as defined by Transport for NSW, which are each designed to have standardised trip generation levels. There are 2,722 Travel Zones within Greater Sydney, which would require a comparatively smaller 7.4 million API calls.

CHAPTER 6

Conclusion

6.1 Policy implications

My research has numerous implications for industry and government. My new hedonic pricing models for property prices are a significant improvement on the existing distance-based modelling approaches. My results show that using travel times as a measure of accessibility instead of proxying using distances can substantially improve the out-of-sample predictive accuracy of these models, which is the key performance indicator for valuing new properties or land lots. This finding has implications for automated valuation modelling, which aims to automate the work performed by professional valuers to improve the scale and consistency of property valuations.

These results also have applications in infrastructure cost-benefit analysis (CBA). One of the main benefits measured by a CBA is the value of travel time savings for users of the new transport infrastructure. As previously discussed, existing CBA guidelines call for the use of a crude approximation that takes 40% of average hourly wages as the value of travel time savings to commuters (Douglas & Jones, 2018; Hensher, 2019). These assessments could be improved by replacing this measure with the more empirically-derived willingness to pay (WTP) estimates for travel time savings that I calculate in this Part using cross-sectional models, but also from my estimates in the next Part of my thesis using a difference in differences approach. Better measures of WTP mean that CBA more accurately quantifies the true costs and benefits of infrastructure, which would improve the allocation of scarce public investment funds to the projects that provide the greatest benefit to the community.

Infrastructure often suffers from funding difficulties leading to cancellations or delays. Value capture has been suggested as a mechanism for governments to fund projects by taxing those who benefit the most from new infrastructure (Medda, 2012). However, many proposed value capture mechanisms have been criticised for arbitrarily classifying some properties as beneficiaries of a project while other properties across the road are exempted from paying the tax due to a lack of accurate measures of who actually benefits from the project (Terrill & Emslie, 2017). Increasing the granularity of project benefit measurement by using travel time savings instead of distance cutoffs may improve the equity of value capture funding mechanisms by more accurately applying them to properties that are receiving benefits from new transport infrastructure.

My estimates of the value of congestion to road commuters provide insight into proposals to implement congestion charging for driving into the city centre during the morning peak. Congestion charging has been proposed as a method to ration scarce road space to the users who have the highest WTP to drive into congested city centres (Terrill, Moran & Ha, 2019). My estimates of the WTP to reduce additional travel time due to congestion are an upper bound on a potential congestion charge for travelling into the Sydney CBD. This estimate can be combined with traffic modelling that computes the reduction in congestion from imposing a congestion charge to predict the correct toll to levy on drivers. Similarly, motorway operators may also use the congestion estimates as a guide to setting motorway tolls by comparing the decrease in drive times from using the toll road versus untolled, but congested surface roads. For example, since the estimate of the value of 1 hour of congestion is \$17.64, then if the tolled motorway saved an hour in relative travel times, this implies drivers would be willing to pay up to \$17.64 to drive on it.

6.2 Concluding remarks

Variation in property values reveal commuters' willingness to pay to reduce their travel times. I extend existing hedonic modelling of property values in Sydney by constructing a unique dataset of travel times using Google Maps and estimating the relationship between property values and travel times in Sydney. I find that using travel times as the measure of accessibility significantly improves the goodness of fit of hedonic property pricing models compared to existing models using straight-line distances as measured by the AIC for the spatial regression models and R^2 for the linear models. Adding major employment sub-centres such as Parramatta and Macquarie Park improve explanatory and predictive power of models and provide evidence in favour of a polycentric city structure in Sydney. The travel time models also outperform distance models in predicting property prices out-of-sample as measured by which model minimises the RMSE. I also find evidence and estimate values for the disutility that commuters place on congestion on their drive to work. However, the models estimated using the land values dataset differ and do not find that travel time models outperform distance models, but this result is likely to be driven by the methodology used by valuers in constructing these estimates of land values.

I estimate two spatial hedonic models: spatial error models and spatial autoregressive models, in order to avoid spatial biases from autocorrelation in the errors and dependent variable. These models have improved fits compared to equivalent models estimated by OLS, which do not explicitly model the effects of spatial dependence. I find that in most cases, the spatial error model provides a superior fit as measured by the AIC.

These estimates of property value changes in relation to travel time changes are of policy significance in the context of funding urban transport infrastructure through capturing land value uplift. I find that drive times and public transit times significantly explain a large amount of variation in property values across Sydney after controlling for neighbourhood, demographic and zoning characteristics. I find that households value accessibility to the Sydney CBD and Parramatta through both driving and public transport modes and that these effects diminish as travel times increase, suggesting commuters closest to the centre are more sensitive to changes in travel times.

Commuters tend to value reducing driving times to employment centres more than reducing public transport travel times. This implies that commuters experience greater disutility from driving than taking public transport, which makes sense as commuters can do other things while on the train or bus, whereas distracted driving is dangerous. Commuters also experience disutility from increased road congestion in addition to that of free-flow drive times to all three employment centres.

However, access to Macquarie Park is not valued positively, with households significantly preferring to have less access to Macquarie Park, which is an unusual result that warrants further research. This may be the result of interactions between the variables measuring accessibility to the other major centres, rather than a significant result in itself. As travel times and property values are likely to be endogenous, especially in a cross-sectional framework, these results should be interpreted from a long-run equilibrium perspective, as opposed to a causal effect.

There is a discrepancy in the results from the sales price models and land valuation models. While the results from the sales price models show that travel times produce a material improvement in model fit and predictive power, the results are less clear for the land value models. It is possible that this result is driven by the methodologies used in constructing the land values dataset by the NSW Valuer General, as the valuers may be using distance as an accessibility proxy, hence driving the results in this Part. I propose a number of pathways for future research that may help to ameliorate these problems, including using a gravity model approach to modelling accessibility to address dispersed employment in Sydney and adding additional accessibility measures to better model household travelling preferences.

These findings have substantial implications for industry and research. They are the first direct estimates of the present value of travel time savings and the value of congestion for commuters in Sydney, improving on previous rent gradients estimated using distance-based models at more aggregate levels. These estimates are useful for industry with applications in automated valuation modelling, which would increase the scalability and consistency of property valuation. My results also provide improved valuations of commuter travel time savings, which are a key input into cost-benefit analysis of infrastructure projects and hence could contribute to the better allocation of scarce public funds for infrastructure.

Part II

Measuring Land Value Uplift: Difference in Differences Estimates from Sydney Metro Northwest

CHAPTER 1

Introduction

Five announcements, four cancellations and 21 years later, Sydney Metro Northwest opened to passenger service on 26 May 2019 and finally gave residents of northwest Sydney an alternative to often delayed and unreliable bus services (Kontominas, 2019). Unreliable buses are annoying, but commuting in general creates disutility. Commuters travelling from home to work incur monetary costs and the opportunity cost of time from travelling. Commuting is also a mental and physical burden for most individuals (Stutzer & Frey, 2008) and individuals have been shown to be willing to pay to avoid these costs (McArthur et al., 2011). Hence, properties located in more accessible locations contain the capitalised values of the willingness to pay for accessibility to employment and amenities (Grislain-Letrémy & Katossky, 2014). This observation motivates both Parts of this thesis, but in Part II, I address endogeneity challenges in my earlier analysis caused by a cross-sectional approach by using a quasi-experimental methodology. I conduct a difference in differences (DiD) analysis using a panel dataset that exploits land value uplift generated by the opening of the Sydney Metro Northwest rapid transit line. By exploiting variation in travel times and land values of properties in the vicinity of the Metro, I am able to estimate the value that the average commuter is willing to pay to reduce commute times.

I use a DiD approach with panel data to estimate the effect of changes in travel time on land values. This approach is uncommon in the literature, which is mostly made up of cross-sectional studies of housing prices on distances to transport facilities. These studies are affected by potential omitted variables and endogeneity issues, meaning they are limited in their causal interpretation. A smaller number of studies take a DiD approach to repeated cross-sectional data, an improvement on single-period cross-sections, but remain vulnerable to biased estimates if key determinants of house prices are omitted. Simulation studies by Kuminoff et al. (2010) suggest that DiD estimators are least prone to bias in the presence of omitted variables compared to cross-sectional regression designs.

My DiD exploits the opening of Sydney Metro Northwest, a rapid transit railway line in north-west Sydney running from Chatswood to Tallawong. The opening of this line created a change in travel times for commuters living in properties within the catchment area of stations while leaving other residents unaffected. Treated properties are defined as those for which travel times to the Sydney CBD by metro and rail are now faster than if they continued to take buses into the city. Control properties have a travel time to the Sydney CBD that is faster if they continue to catch buses to the city rather than switch modes to the new metro. Thus, the pre-existing location of properties acts as a treatment assignment mechanism by determining whether or not that property will benefit from the availability of the Metro. The magnitude of the treatment is the change in travel times as a result of switching modes to the Metro, which measures changes in accessibility to employment in Sydney. I use travel time data collected in May 2019 to measure pre-Metro travel times, while data collected in July 2019 measures post-Metro opening travel times. The value of accessibility is measured by changes in land values across properties and time. I use land values from July 2012 as the measure of pre-construction valuations and July 2018 as the measure of post-opening valuations (as July 2019 data are not yet available).

Transport infrastructure projects focus on reducing travel times, not physically moving locations closer to one another because it would be very expensive to attempt this. It is likely what is valued by commuters is the travel time to a location, not the physical distance travelled. Thus, I break with the traditional distance-based approach taken by most of the literature (Mohammad, Graham & Melo, 2015; Mulley, Ma, Clifton, Yen & Burke, 2016; Mulley & Tsai, 2016; Murray, 2016; Yen et al., 2018). Instead, I scrape Google Maps travel time data for morning peak travel times from locations in north-west Sydney to the Sydney CBD from before and after the Metro opened. Using travel time data brings us closer to a true measure of accessibility, as stations are an intermediary, not a final destination for commuters (S. Ryan, 1999). Thus, a travel time-based approach is likely to be a better measure of accessibility to employment and amenities.

Regressing changes in land values on changes in travel time across treated and control properties, I find that households in north-west Sydney are willing to pay 0.36% more for property that is located 1 minute closer to the Sydney CBD by public transport, which is equivalent to an increase in land value of $3,190 per minute saved for the average property relative to properties experiencing no accessibility improvement. By treating this land value change as the capitalised present value of all future commuting travel time savings, using assumptions on the relevant discount rate, number of hours worked per year and the number of working years remaining in the average commuters' career, I calculate that commuters value reducing their commute time at about $25 per hour.

My analysis is the first econometric analysis of the Sydney Metro Northwest project, which is the first rapid transit system in Australia. Thus, the results from this analysis are different from any other transport mode previously analysed in this country. Existing work has analysed most forms of transport around the world, including heavy rail, light rail, rapid transit and bus rapid transit (see Higgins and Kanaroglou (2016), S. Ryan (1999) for a review). There is a lack of consensus in the literature regarding the scale of value uplift due to transport improvements, with most studies finding a significant positive effect for decreasing distance and travel times. On the contrary, a number of papers find unexpected opposite impacts or no significant change, indicating that the returns of each transport project are highly influenced by idiosyncratic factors.

The DiD approach reduces the influence of omitted variable bias relative to other approaches by controlling for time-invariant individual property characteristics (Kuminoff et al., 2010). I also control for local demographic and socio-economic trends using data from the 2011 and 2016 Censuses to account for unbalanced pre-trends. The sign and significance of land value change estimates are robust to the functional form of the model and the results show the same direction when more traditional distance-based models are estimated as well. Despite this quasi-experimental approach taken to the data, endogeneity issues are not fully resolved. It is possible that some of the assumptions required for DiD estimators to identify a causal effect may not hold in both my data and the research designs employed in previous DiD studies of transport projects. Thus, while my results are an improvement on cross-sectional findings, I do not claim that the value uplift measured is a causal effect.

My estimates of hourly willingness to pay (WTP) for accessibility improvements have direct application in infrastructure cost-benefit analysis (CBA). The key economic benefit included in CBA is the value of travel time savings for infrastructure users and hence accurate measures of the value of time are essential for correctly appraising infrastructure projects. The more precise measures of WTP in this Part improve on existing approximations, which use a proportion of average wages. Better estimates of WTP enable policymakers to more accurately calculate the true costs and benefits of infrastructure, improving the likelihood that scarce public funds are allocated to the projects that provide the greatest benefit to the community.

My results also have implications for the development of value capture mechanisms for funding infrastructure investments that are increasingly part of the policy debate (Medda, 2012; Murray, 2016; Yen et al., 2018). Value capture is a proposed method for funding the cost of infrastructure by taxing part of the benefit that accrues to nearby residents in the form of increased property values as a result of the capitalisation of accessibility improvements in the land value. Existing value capture methods that are based on distance cutoffs are criticised for arbitrarily assigning properties within a certain distance to a taxed group, while neighbouring properties just outside are not taxed (Terrill & Emslie, 2017). In addition, the use of distances means that a proxy for accessibility is being used instead of a direct measure. By using travel times, a continuous variable that directly measures changes in accessibility, I provide a solution to this problem that may enable a mechanism that more equitably levies households proportionately to the accessibility gain they receive from new transport infrastructure investments.

Chapter 2

Literature review

There is a substantial literature measuring value uplift as a result of new transport projects (see S. Ryan (1999) and Higgins and Kanaroglou (2016) for a comprehensive review of the literature). These studies have examined most forms of transport, including rapid transit, heavy rail, light rail, bus rapid transit and motorways. This literature review focuses on railway studies as this is most similar to the Sydney Metro project I examine. I discuss the choices that previous researchers have made when measuring accessibility and land value, as well as model specification and functional form, and the implications this has for my research.

Improved accessibility is the main benefit imparted by transport infrastructure improvements. However, accessibility can be a difficult concept to quantify as shown by a substantial literature devoted to measurements of this concept that struggle to reach a consensus. Urban theory treats accessibility as having two dimensions: an attraction element and an impedance element. Commuters are attracted to certain locations that bring benefits such as amenities or employment. However, travel costs create an impedance to reaching these destinations and thus commuters engage in a personal cost-benefit decision process that aggregates into city-wide travel patterns (Handy & Niemeier, 1997). The most common way of measuring changes in accessibility effectively sidesteps the issue, using the distance of properties to the transport facility as a proxy (Cervero & Kang, 2011; Higgins & Kanaroglou, 2016; Mohammad et al., 2015; Mulley & Tsai, 2016; Murray, 2016; Yen et al., 2018). This approach may not accurately reflect changes in travel costs as "a transportation facility is not a final destination; it is an intermediary source of connection between an origin and destination." (S. Ryan, 1999). While many of these studies have found results that are in line with theoretical expectations (an inverse relationship between distance from the station and property values), this approach is problematic from a theoretical perspective.

The choice of distance cutoff is essentially arbitrary, with different papers specifying a variety of distances. The most popular approach is to group properties into discrete bins that are based on varying distances from the nearest station. For example, Mohammad et al. (2015) uses three bins, for properties located between 0–500 m, 500–1000 m and 1000–1500 m of Dubai Metro stations. Similarly, Murray (2016) classifies properties located within 2 km from Gold Coast Light Rail Transit (GCLRT) stops into a series of bins at 100 m intervals. This binning method allows for variation in the effect of the transport project across space to be captured. An alternative approach is to classify properties in a binary control/treatment way. Yen et al. (2018) uses this approach by classifying properties within 800 m of each GCLRT stop as treated properties, and properties between 800–1600 m away from stops as control properties. This method is more restrictive, as it averages out the effect on all treated properties into one value and does not allow varying accessibility to the transport facility to have a differing effect.

A more direct measure of commuting costs is to examine changes in travel times as a result of a project. While this measure does not capture the monetary component of transport costs, it better captures the time dimension of commuting costs as theorised in the AMM model compared to using distances to facilities. This approach is less common in the literature, with a review by Higgins and Kanaroglou (2016) finding that out of 106 North American studies surveyed, only four used changes in travel times as a measure of accessibility. However, usage of travel time data has started to appear in more recent work, such as in analysis of changes in accessibility from the Tyne and Wear Metro in north-east England by Du and Mulley (2012). Thus, I contribute to this literature by applying travel time data in a difference in differences (DiD) framework to analyse the effect of accessibility changes on land value.

The dependent variable in studies of value uplift needs to effectively measure the impact of the transport projects on property values. The majority of studies in the literature tend to favour the use of market sales data from property transactions (Higgins & Kanaroglou, 2016). They argue that this choice better represents the market price of transport accessibility compared to alternate measures (Mohammad et al., 2015; Mulley & Tsai, 2016; Yen et al., 2018). However, a number of papers elect to make use of land valuations data (Higgins & Kanaroglou, 2016; Murray, 2016). I have elected to follow this approach as it enables me to construct a balanced panel dataset, which controls for unobserved time-invariant heterogeneity in the individual properties (Murray, 2016), reducing the risk of omitted variable bias. In addition, using property sales data means that the DiD is performed using repeated cross-sections, which is vulnerable to omitted variable bias if all the properties of the land and structure are not controlled for (Kuminoff et al., 2010). Controlling for the characteristics of the structure sitting on top of the land is not a problem when land valuations data are used. Overall, out of all the studies surveyed by Higgins and Kanaroglou (2016), 80% use sales price data, 10% use land valuations data and the remaining 10% use market rents. An alternative approach is the pseudo-panel data method constructed by Mohammad et al. (2015), which groups similar properties together that were sold at different times into aggregate units for analysis. These time-aggregated units are then treated as if they were individual panel data observations.

Measures of willingness to pay for improved accessibility are sensitive to the choice of model structure and time scale, which in my case is affected by data availability. The choice of model structure has a substantial effect on the signs and magnitudes of estimated value uplift. Kuminoff et al. (2010) conduct a simulation study that compares cross-sectional models with and without spatial fixed effects, first differenced models and DiD models. The study finds that overall, the DiD estimator is best suited to hedonic estimation with panel data, when measured in terms of the bias of the estimates in the presence of omitted variables. The magnitudes of estimates from cross-sectional hedonic models also tend to be larger than the estimates produced by DiD class models (Mohammad et al., 2015). This difference further motivates my use of a DiD estimator using a panel dataset.

There is also variation in the extent of uplift measured in the literature as a result of choices of time scale. There is considerable variation in the timing of value uplift due to idiosyncrasies of individual projects (Yen et al., 2018). Most of the literature aims to capture the total amount of land value uplift as a result of a transport project by collecting property data from before the announcement of a project to well after a project has been opened to passenger service (Du & Mulley, 2007; Mohammad et al., 2015; Murray, 2016). For example, Mohammad et al. (2015) collect sales data between 2007 and 2011 to measure the effect of the opening of the Dubai Metro in 2009. In contrast, Murray (2016) uses up to 69 years of land valuation panel data for properties in the Gold Coast region to measure the total value uplift of the Gold Coast Light Rail. He finds that aggregate land values have increased by $300 million as a result of the project, which represents around 25% of the project cost. Yen et al. (2018) instead examine timing effects on land value uplift — a less well-researched area — using data from prior to project announcement (1996), before financial commitment (2002), post-commitment (2006), construction (2011) and opening (2016). They find that prices start to increase after announcement, but the largest increases do not occur until firm financial commitments have been made by government. Increases slow during construction and operation periods. While this is interesting, external validity may be of concern due to the unique circumstances of each infrastructure project. For example, the long history of announcements and cancellations of the project I am studying may affect the responsiveness of land values in north-west Sydney to the announcement of the line in 2011.

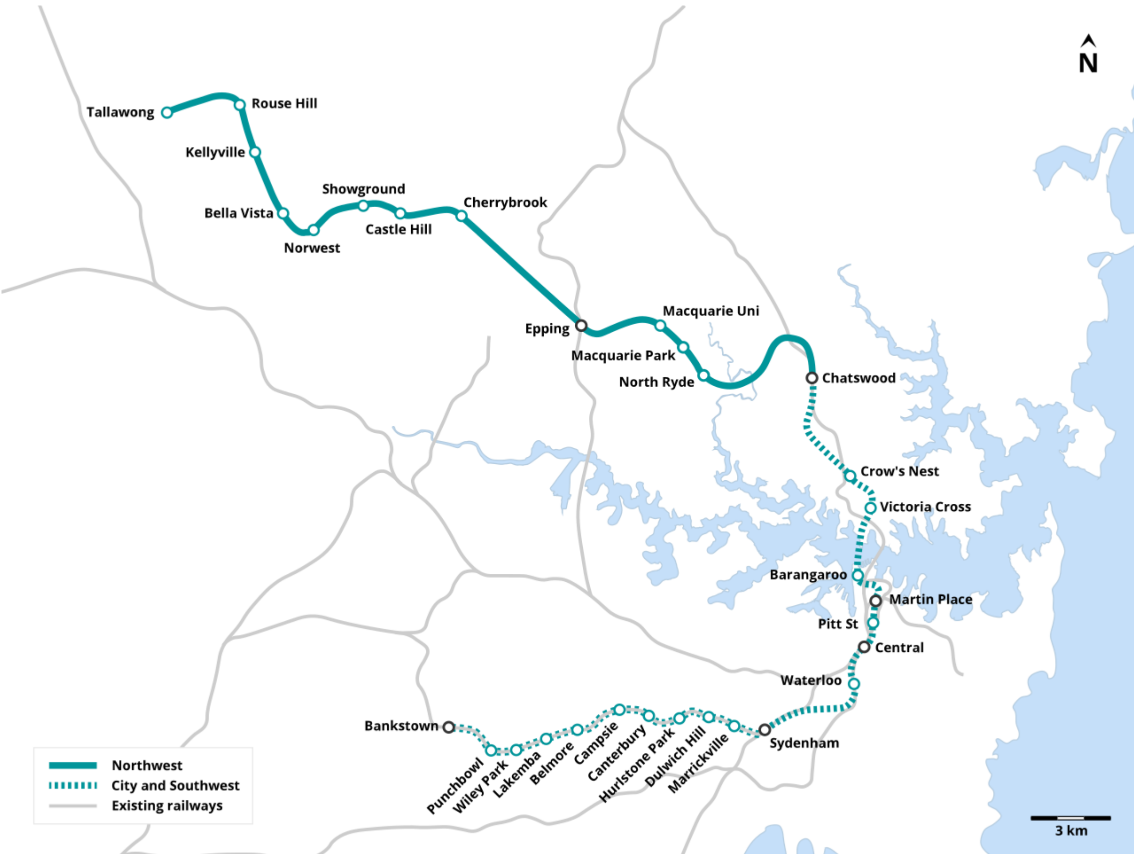
These differing specifications have resulted in variation in the size of estimated effects of changes in accessibility. It can also be difficult to compare projects due to their choice of transit mode (for example, value uplift from a motorway project is likely very different to light rail), distance measures, dependent variable and functional forms. A survey of the literature by Higgins and Kanaroglou (2016) finds very large variation in estimated effects of North American heavy rail projects, with value changes estimated for properties within 400 m of railway stations ranging from –49% to +49%. Analysis on the effects of the Mandurah railway line in Perth by McIntosh et al. (2014) find increases in land value of 28%, 13% and 8% for properties within 400 m, 800 m and 1600 m of stations. Although there has been previous research on value uplift effects from rapid transit lines internationally (for example, Du and Mulley (2007), Mohammad et al. (2015)), Sydney Metro is the first rapid transit system in Australia meaning there is little domestic research on this mode of transport. Mohammad et al. (2015) find significant and positive uplift for residential properties within 1 km of Dubai Metro stations (7.8% increase) and significant effects for commercial properties within 1.5 km of stations (41% increase). While international comparisons provide some guidance as to expected effects, there is a significant opportunity for me to contribute to the literature with my preliminary estimates of land value uplift and willingness to pay for improved accessibility from analysing Sydney Metro Northwest.

Chapter 3

Background

Sydney Metro is a NSW Government initiative to construct a rapid transit rail system in Sydney. It currently consists of a single line running from Chatswood on the lower North Shore to Tallawong in north-west Sydney. Further stages of the system are currently under construction, including an extension of the line from Chatswood to Bankstown through the Sydney CBD (Sydney Metro, 2019a). Figure 3.1 shows the route of the currently operating line in solid blue, the under construction section in dashed blue and existing railways in solid grey.

Figure 3.1: Sydney Metro route map



Source: strata8 (2019)

This Part analyses the impact that changes in travel times from Sydney Metro Northwest have had on land values in north-west Sydney. These changes in travel time come from the opening of the metro line and subsequent restructure of bus services in north-west Sydney, including express bus services to the Sydney CBD that run along the M2 Hills Motorway (O'Sullivan, 2019). I measure the change in travel times experienced by commuters who switch travel mode from bus to the new metro.

Sydney Metro Northwest was announced in 2011 as the North West Rail Link (Transport for NSW, 2011), following a change of government at the state election that year. The release of an Environmental Impact Statement (EIS) in 2012 indicated a firm commitment by the government to realising the project (Transport for NSW, 2012). Contracts to build and operate the rail line were awarded in 2013, creating a firm financial and legal commitment for the NSW Government (Transport for NSW, 2013). Major construction began in 2014, with the existing Epping to Chatswood railway line closed in September 2018 to allow for conversion to metro standards. The line opened to passenger services on 26 May 2019 (Sydney Metro, 2019b). As indicated by Yen et al. (2018), value uplift should occur at each of these stages, but the unique history of the project may affect the observed value changes.

Sydney Metro Northwest has been subject to repeated cancellations and broken promises until the line finally opened on 26 May 2019. The project was first conceptualised in 1998 as part of the *Action for Transport 2010* plan (Newman, 1999), but remained an aspiration until a North West Rail Link was announced as part of the Metropolitan Rail Expansion Program in 2005, to be delivered by 2017 as a heavy rail line incorporated into the CityRail network (Transport Infrastructure Development Corporation [TIDC], 2007). This line was cancelled and replaced by a stand-alone metro system called Sydney Metro in 2008 (Besser, 2008). In 2010, the metro was again cancelled and replaced by a heavy rail line to north-west Sydney (Department of Transport and Infrastructure, 2010). In 2012, the line was amended to run as a single-deck, privately operated metro (Saulwick, 2012; Transport for NSW, 2011).

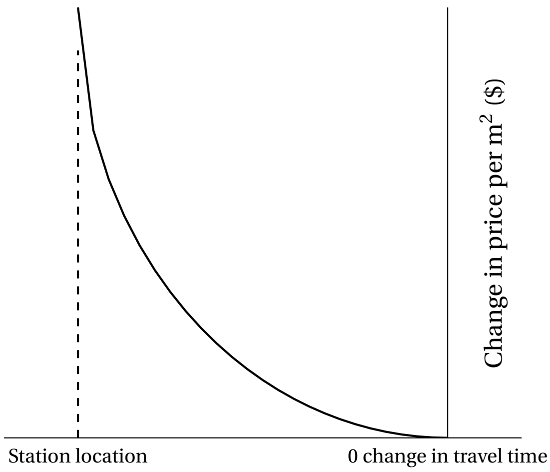
Following completion of the first stage of the Metro project, the second stage involves an extension of the line as an underground tunnel running from Chatswood (the current terminus) under Sydney Harbour and through the Sydney CBD before surfacing at Sydenham, where it will connect to the existing railway line to Bankstown. The existing line will be closed and converted to rapid transit standards as part of the project. This stage will open to service in 2024 (Sydney Metro, 2019c).

CHAPTER 4

Methodology

The Alonso-Muth-Mills (AMM) model provides a theoretical foundation for the results in this Part through its key insight into the trade-off between commuting costs and housing costs (Alonso, 1964; Mills, 1967; Muth, 1969). The AMM model is a suitable theoretical framework for conceptualising this analysis as shown by the large body of literature incorporating this model, including calibration exercises with Australian cities showing its suitability (Kulish et al., 2012), as well as my own work from Part I of this thesis. I expect a positive relationship between the size of the travel time saving as a result of the Metro project and the observed land value uplift. This is because a reduction in travel times is a reduction in commuting costs for residents, which will be at least partially capitalised into the price of living space.

Figure 4.1: Idealised land value uplift curve



This idealised relationship is illustrated in figure 4.1, which shows a hypothetical cross-section of accessibility gains due to a rail infrastructure project. In an ideal world, the maximum travel time reduction (x-axis) due to the project will be achieved in close proximity to the new station location, which is denoted by the vertical dashed line. If the AMM model holds, then this should correspond to the largest increase in land value (y-axis). As we move to the right along the x-axis, the change in travel time to the CBD falls towards zero and the model predicts that the corresponding positive change in land values should also fall to zero, until there is no change in travel time and no land value uplift.

Like in Part I of this thesis, I treat land values as a composite value made up of a bundle of individual observable attributes of the block of land, one of which is accessibility to employment. This framework draws on an extensive literature based on the hedonic pricing model conceptualised by Rosen (1974). Using a multiple linear regression model, I can estimate the implicit prices for each attribute, including the willingness to pay for accessibility to employment. The application of hedonic methods in this Part is otherwise the same as in Part I.

In order to measure the effect of changes in travel time on property values in Sydney, I use a difference in differences (DiD) approach to exploit variation in travel times as a result of the Sydney Metro Northwest project. The DiD approach is a quasi-experimental method that can be used to exploit natural experiments where only a fraction of a given population is exposed to a treatment and this population is observed both prior to and after the treatment takes effect (Abadie, 2005). I estimate the DiD model in Stata (StataCorp, 2015) using the `reghdfe` package written by Correia (2016), which estimates linear regression models with multi-level fixed effects.

The policy change is the opening of Sydney Metro Northwest and the treatment that results is improved accessibility to employment and amenities due to better rail access in the area. Treatment assignment is determined by whether post-Metro travel times by switching to a combination of metro and rail to the Sydney CBD are faster than the post-Metro travel time by bus to the Sydney CBD for each property. The treatment variable is a continuous variable measuring travel times, meaning that the magnitude of the effect is allowed to vary depending on the extent of the travel time savings. Variation in travel times are measured by collecting travel time in May 2019 (prior to the opening of Sydney Metro) and July 2019 (after the opening of the line). To measure the value placed on these improvements in accessibility, I use data from July 2012 measuring land values prior to the start of construction of the metro as the pre-treatment dependent variable and data from July 2018 as the post-treatment dependent variable to measure land values after opening. While the Metro did not open until late May 2019, July 2018 data is the most recent currently available and hence I have been forced to rely on older data.

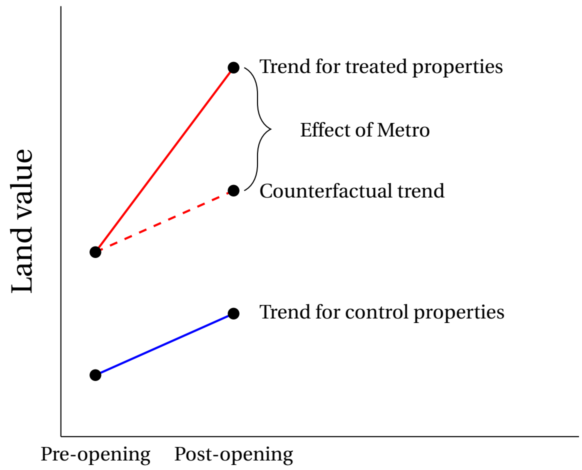
I model price changes in the following way using a log-level specification:

$$\ln(p_{it}) = \alpha_i + \mathbf{X_{it}}\gamma + \mathbf{T_i}\tau + \mathbf{D_t}\delta + (\mathbf{T_i} \times \mathbf{D_t})\theta + \epsilon_{it} \tag{4.1}$$

$\ln(p_{it})$ is the natural logarithm of the assessed land value of the ith property. α_i is the property-specific time-invariant fixed effect. The panel structure of the data means that including fixed effects will control for any time-invariant unobserved characteristics of the property, which improves the robustness of the analysis to one source of omitted variable bias. $\mathbf{X_{it}}$ is a vector of time-varying neighbourhood characteristics incorporating demographic and socio-economic data. $\mathbf{T_i}$ is a continuous variable measuring the change in public transport travel time from each property to the Sydney CBD, calculated as the difference before and after the Metro opens. $\mathbf{D_t}$ is a dummy variable taking a value of 1 for the period after the Metro opens and 0 prior to the Metro opening. The coefficient δ captures the trend in average prices pre- and post-Metro across the entire dataset. The DiD coefficient is θ, which captures the estimated value uplift from a 1 minute change in travel times as a result of the Metro opening. I use a continuous treatment effect that measures the treatment as the difference in pre- and post-Metro travel times. As previously discussed, this contrasts with most previous transport studies that use a discrete treatment effect based on an arbitrary distance cutoff from railway stations. As the treatment is assigned to individual properties, I cluster standard errors at the individual property level. I expect that the time coefficient (δ) will have a positive sign, indicating that prices have increased in the study area over time. I expect that the DiD coefficient (θ) will have a negative sign, indicating that a decrease (increase) in travel times as a result of the Metro opening is associated with an increase (decrease) in land values.

The DiD approach requires strong identifying assumptions. The treatment assignment (accessibility to Metro stations) must be unrelated to the outcome (property price) at the baseline (prior to Metro construction). DiD also requires that in the absence of the treatment, the difference in observed outcomes between the treatment and control groups is constant over time (Angrist & Pischke, 2009). This assumption means that the properties in the control group are similar to properties that are treated, other than the fact that the treated properties benefit from the Sydney Metro project. This assumption is known as the parallel trends assumption, which is illustrated in figure 4.2. The blue line indicates the change in land values (outcome variable) before and after the opening of the Metro (treatment) for the control properties. The solid red line shows the observed land values for the treated properties for the same time period. By assuming that the treated properties would otherwise follow the same price trend as the control properties, we assume that the unobserved counterfactual for the treatment properties is the red dashed line. Thus, the actual treatment effect is the difference in the observed actual and unobserved counterfactual outcomes for the treated properties. I discuss potential threats to the validity of this assumption and other assumptions in the next section.

Figure 4.2: Treatment effects in a DiD model



4.1 Challenges to identifying treatment effects

Much of the prior work applying DiD methods to transport projects come from the civil engineering or regional science literature (Cervero & Kang, 2011; Higgins & Kanaroglou, 2016; Mulley & Tsai, 2016; Yen et al., 2018) and do so with limited consideration as to whether the identifying assumptions are upheld. While the DiD approach is likely to be superior to cross-sectional approaches, which are even more exposed to endogeneity problems, I argue that there are a number of threats to identification which have not been fully addressed in the literature. In the following paragraphs I discuss the identifying assumptions for finding a causal effect using the DiD approach (A. Ryan, Burgess & Dimick, 2014).

Treatment assignment and baseline outcomes This assumption requires that the treatment assignment must be uncorrelated with the baseline observed outcome. In the context of this study, this means that the change in travel times as a result of commuters switching travel modes to the metro must be uncorrelated with land values prior to the announcement of the metro project, conditional on time-varying neighbourhood control variables. This is a potentially problematic assumption due to the idiosyncrasies of this project. As previously discussed, Sydney Metro Northwest has been a long-mooted rail link for north-west Sydney and while the exact design and way it integrates with the rest of the Sydney railway network has varied across all the cancelled proposals, the main stations and their approximate locations have been known well before the

2011 announcement date of the actually realised project. As a result, it is possible that developers and commuters have already started to bid up prices in the vicinity of the Metro stations and hence the baseline land valuations are predictors of the size of the treatment effect. This hypothesis can be empirically tested by regressing baseline land values on the change in travel times and a vector of time-varying neighbourhood controls (see table H.1 of Appendix H for regression tables). I find that there is no significant relationship between the two, indicating that treatment assignment and baseline land valuations are not predictors of each other.

Parallel trends assumption The parallel trends assumption (PTA) requires that in the absence of the treatment, the difference in observed outcomes between the treatment and control groups is constant over time. The usual method for investigating the validity of this assumption is to visually check for pre-trends in the data (Wing, Simon & Bello-Gomez, 2018). Unfortunately, the oldest land values data published by the NSW Valuer General dates back to July 2012, which is the year I use as the baseline year. While land values are likely available prior to this, enquiries with the Valuer General's office have gone unanswered as of the submission date of this thesis.

While it is not possible to perform pre-trends analysis on the outcome variable, I substitute this with data on the demographic control variables collected from the 2006, 2011 and 2016 Census. Ideally, the data should show a parallel trend between 2006 and 2011, which are time periods prior to the beginning of the treatment. For most of the control variables, the trend between these two years are roughly parallel, which provides some support for the PTA. I plot the data in figures H.1 and H.2 of Appendix H.

Despite this, there is a possibility that this assumption may not be upheld due to the long history of this project. The PTA would be violated if residents and developers started bidding up prices along the Metro route prior to the project being officially announced, as this pre-emptive purchasing prior to the project announcement would produce a deviation from a common trend compared to properties in the control areas. This violation would upwardly bias the size of the treatment effect as there would already be a pre-existing upward trend in prices in the treatment group above that of the control group.

Stable Unit Treatment Value Assumption The Stable Unit Treatment Value Assumption (SUTVA) assumes that there is no interference across treatment units, meaning that when the treatment (in this case a transport project) is applied to one unit, this does not affect the outcome (land value change) for another unit. SUTVA is not a plausible assumption in the case of spatial data (Clarke, 2017; Laffers & Mellace, 2016), where it is well established that spatial spillover effects exist (LeSage, 2008). These spillovers create a situation where it is likely that the value uplift effects of the Metro project on properties that directly benefit from a reduction in travel time will spill over onto neighbouring properties that do not directly benefit, especially given my strict definition of treated properties being only ones that receive a travel time reduction as a result of access to the Metro line.

Overall, there is the possibility that some of the identifying assumptions of the DiD estimator are violated. However, these issues are not isolated to my analysis, but also previously conducted research that uses this particular approach to assessing the effects of transport projects. As a result, it is difficult to claim that my results — or the results of previous research employing a DiD estimator — identify the causal effect of changes in travel time on property prices or land values. Despite this, as work by Kuminoff et al. (2010) show, DiD estimates are a step closer to finding the true effect relative to cross-sectional and other non-panel data methods.

CHAPTER 5

Data

Part II of this thesis aims to exploit the opening of a new metro train line in north-west Sydney to create variation in travel time to measure the value that commuters place on commuting costs. To measure changes in travel times, I scrape public transport travel time data from 7,007 locations in north-west Sydney to the Sydney CBD using the Google Maps API. The choice of properties was based on the number of data points that could be obtained for free from Google Maps in the time available to write this Part. To measure the value that commuters place on reducing travel times, I construct a panel dataset using land valuations data from the NSW Valuer General that aims to measure land values prior to the announcement of the project and after the opening of the project to the public. I also control for time-varying neighbourhood characteristics of the properties, such as demographic and socio-economic trends using ABS Census data from 2011 and 2016. To link these datasets together, I use the Australian Geocoded National Address File dataset compiled by PSMA Australia (2018).

5.1 Travel time data

My measure of the size of the treatment effect is the change in travel time to the Sydney CBD for each residential property that results from a modal shift from bus to metro rail that occurs after the opening of the Metro line, assuming that commuters take the transit mode that is fastest for them. This data was collected by scraping Google Maps using the Google Maps API as a novel measure of variation in commuting costs. This dataset is an improvement on the preferred methods in the literature of using a distance-based catchment area around new train stations, as discussed in the literature review. The travel time data used in this Part are travel times to the Sydney CBD, which is defined as 1 Martin Place, Sydney. I collected this data during the morning peak between 7 AM and 9 AM.

Google Maps data is used as it is the most accurate source of live travel time data available that can be collected in bulk. My data consists of public transport travel times that include walking times to transit stops and interchange times. The data are functionally identical to what commuters would see if they entered a start location (e.g. their home address) and end location (e.g. their work address) into maps.google.com.au. I collect data for travel times from each of the properties in my dataset (an origin) to the Sydney CBD (a destination). I refer to this as an origin-destination pair. I construct this dataset by coding an R script that calls the Google Maps Distance Matrix API. This API takes an origin-destination pair and transit mode and returns the duration and distance travelled. I collected this data in May 2019 and July 2019 during the morning peak in order to capture the effects of congestion.

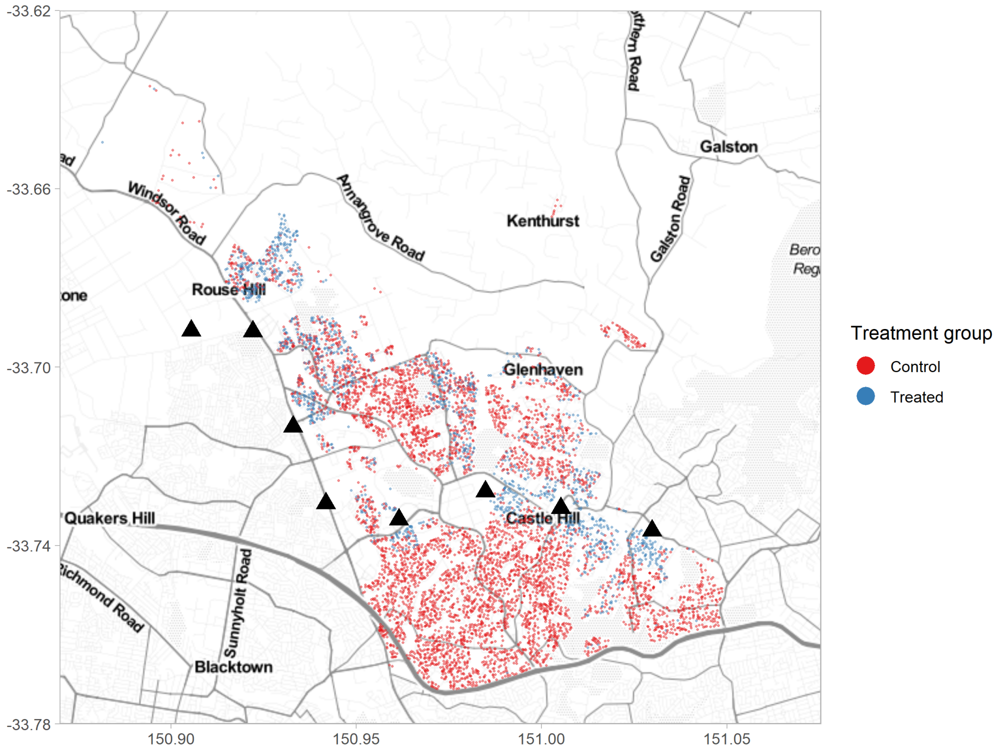
While it would have been ideal to collect the travel time data corresponding with the date of the pre-opening land values data (July 2012), Google Maps can only scrape travel times contemporaneously. As I had not yet had the idea for this thesis in 2012, I use May 2019 data as an approximation to public transport travel times for 2012. Given that bus infrastructure has not substantially changed in the intervening years, this is a reasonable approximation.

As part of the data collection and cleaning process, some observations were removed due to errors in the collection of travel time data. These omissions were the result of incorrect travel times that resulted from Google incorrectly locating the property and connectivity errors in receiving the data point that resulted in missing data. In addition, outlier travel time values were discarded if the public transport times exceeded 300 minutes. These outliers were caused by the Google Maps script erroneously computing travel times to the incorrect locations (for example, one address was incorrectly parsed as being from outside NSW and hence produced a completely incorrect travel time).

Some limitations of the data include the lack of information on traffic flows/volumes for specific routes as the API is only able to provide travel times between origin-destination pairs. Public transport travel times are also not broken up into walking, waiting and actual travelling times in the API-provided data. Google also limits the number of API calls that can be made for free, which restricted the size of the sample for which I was able to collect data in the time available.

Figure 5.1 shows the properties in the sample divided into treatment and control properties. Treated properties are classified by whether they have a public transport travel time to the Sydney CBD by metro and rail modes faster than the travel time by bus, after the Metro line opened. The figure shows that most of the treated properties lie in close proximity to the location of each of the new Metro stations, these are marked on the map as black triangles. One thing to note is that there are many properties that are close to the stations that do not experience any substantial improvement in

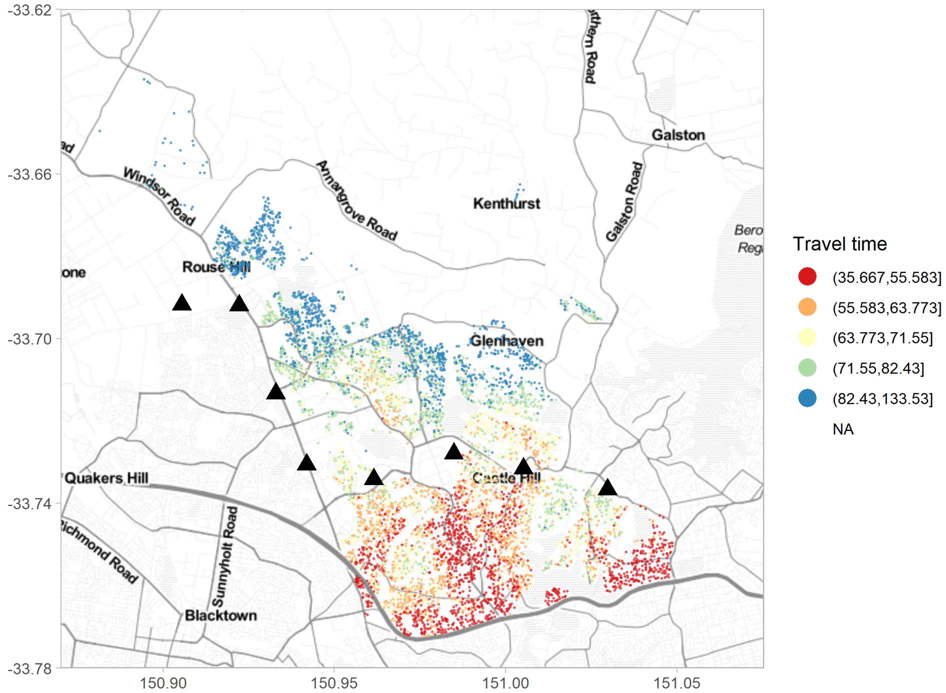
Figure 5.1: Treated and control properties



Notes: Black triangles refer to Metro station locations. Treated properties are properties where travel times to the Sydney CBD are faster by metro/train than by bus after the opening of Sydney Metro. Some gaps in the map are areas where greenfields developments are planned and subdivision of land lots has not yet occurred.

travel time, suggesting that for many residents, the new Metro does not represent a significant improvement in travel time relative to the express buses that run along the M2 motorway to the city.

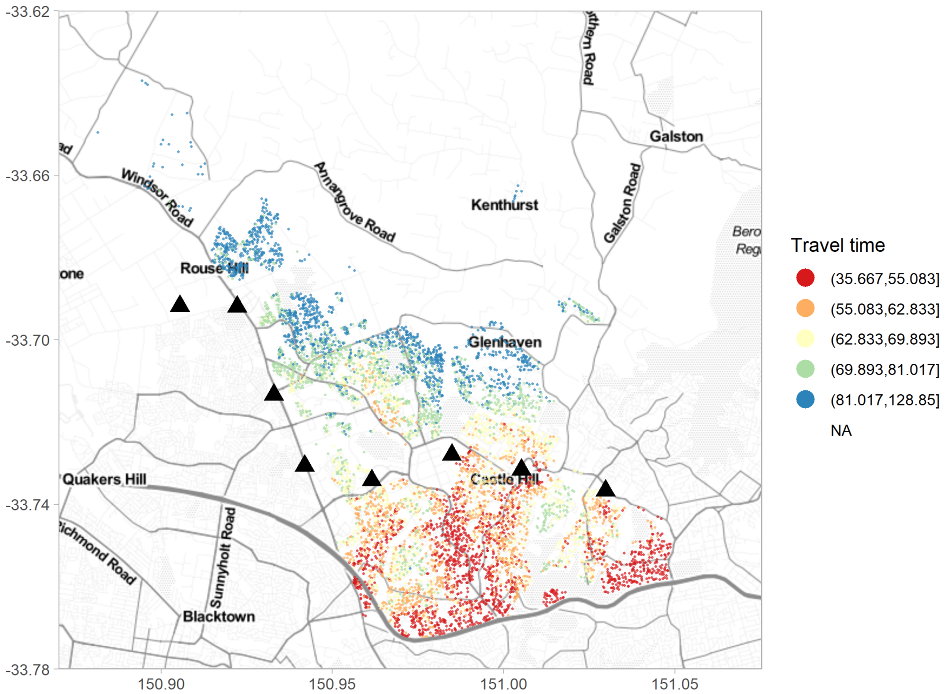
Figure 5.2: Travel times prior to Sydney Metro



Notes: Black triangles refer to Metro station locations. Map shows public transport travel time data collected in May 2019 to the Sydney CBD. Some gaps in the map are areas where greenfields developments are planned and subdivision of land lots has not yet occurred.

This minor change is reflected in figures 5.2 and 5.3 which show that for most properties, there has been almost no change in their travel times before and after the Metro started operating. There are only minor improvements in accessibility for properties in the immediate proximity of the Metro stations. Note that these are timetabled durations and may not reflect actual traffic conditions, especially for bus routes. For properties located closer to the M2 Hills Motorway and away from metro stations, buses remain the fastest mode of transport to the city, which is reflected by the lack of change in travel times for these locations. However, this may change in the future as increased patronage on the Metro may reduce traffic congestion in the area, which means that bus timetables will be adjusted in the future to reflect increased operating speeds, thus creating spillovers that positively affect residents throughout the Hills district.

Figure 5.3: Travel times after opening of Sydney Metro



Notes: Black triangles refer to Metro station locations. Map shows public transport travel time data collected in July 2019 to the Sydney CBD. Some gaps in the map are areas where greenfields developments are planned and subdivision of land lots has not yet occurred.

5.2 Land valuations data

Similar to Part I, I use property valuations data sourced from the NSW Valuer General's Bulk Land Values dataset. The Valuer General provides land valuations for every property (around 1.3 million addresses) in New South Wales. This is a valuation of the unimproved value of land on a property that excludes the value of the structures or other improvements on the land (NSW Valuer General, 2017b). Land valuations data is advantageous as it avoids the problems associated with controlling for the attributes of the property that is on top of the land, simplifying the design of the hedonic regression model.

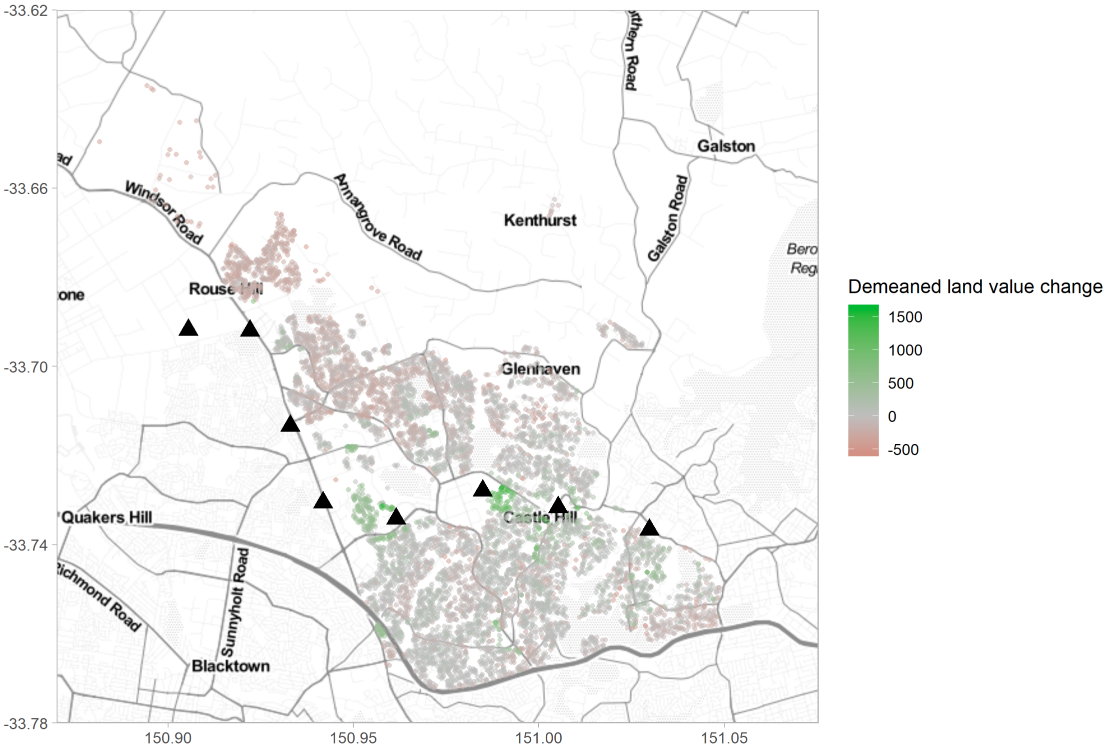
The specific land values that I have used for this study are a sample of valuations from properties located within the Hills Shire from July 2012 and July 2018. This represents the oldest and most recent publicly available land values data. Using the bulk land values file issued in July 2017, which is the oldest publicly available, I was able to encode property values from July 2012, while the most recent land values data provided the land values for July 2018. Data from July 2019 are not yet available and based on the dates that previous years' data were released by the Valuer General, are unlikely to be available until January 2020.

The data cleaning process involved removing non-residential properties from the dataset based on their zoning code. Entries with addresses that were missing a house number or missing land areas were also omitted. In order to match the dataset with ABS Census data, each address had to be geocoded using the Geocoded National Address File (G-NAF) compiled by PSMA Australia (2018). This step involved converting property addresses to a standardised format that followed the G-NAF conventions, allowing me to match each address to an ASGS Mesh Block (MB) and geographic coordinates.

As a simple filtering mechanism to capture only properties of interest, I subset the data to only include properties within the boundaries of The Hills Shire Local Government Area (LGA). Finally, I took a random sample of the data and collected travel times for this sample to leave me with my final sample of 7,007 properties. I later realised a more granular filtering mechanism would have also captured some properties of interest in the Blacktown City Council LGA to the west of Windsor Road, but unfortunately the travel time data had already been collected in May and as it was not possible to collect past travel time data from Google Maps, the study area could not be expanded.

Figure 5.4 shows the demeaned land value change in the Hills Shire. Overall, land values have risen significantly for all properties between 2012 and 2018. The figure shows the increase in land values above or below the mean increase of all the properties. That is,

Figure 5.4: Demeaned land value change (2012-18)



Notes: Black triangles refer to Metro station locations. Some gaps in the map are areas where greenfields developments are planned and subdivision of land lots has not yet occurred.

green areas have increased in value more rapidly than the mean increase in the area, while red areas have increased relatively slowly. As shown in the diagram, the relative increase in values is much higher for properties closer to the new metro stations as expected.

5.3 Neighbourhood variables

Property prices are affected by factors in addition to commuting costs (Abelson et al., 2013; Grislain-Letrémy & Katossky, 2014). Time-invariant amenities and characteristics are differenced away by the DiD methodology, however some time-varying characteristics remain and need to be controlled. For the two time periods analysed in the DiD model, I source equivalent data from the 2011 and 2016 Census. I collect data on average incomes, unemployment, educational attainment, ancestry and socio-economic disadvantage index scores at the SA1 level, which allows me to capture local neighbourhood dynamics. Given slight changes in SA1 boundaries between the 2011 and 2016 Censuses, the area that each property was assigned to over each wave may have adjusted slightly, but boundary adjustments are unlikely to have any influence on the results.

5.4 Summary statistics

Table 5.1: Summary statistics

Statistic	Mean	St. Dev.	Min	Max
Land area (sqm)	894.70	1,975.43	159.90	64,980.00
Pre-Metro Sydney CBD travel time	68.65	14.67	35.67	133.53
Post-Metro Sydney CBD travel time	67.43	13.80	35.67	128.85
Land value (2012)	423,889.80	235,349.00	192,000.00	9,590,000.00
Land value (2018)	886,625.80	738,663.30	337,000.00	35,000,000.00
Land value per sqm (2012)	576.78	151.55	53.75	1,521.02
Land value per sqm (2018)	1,161.85	300.36	133.57	3,500.26
% with Australian ancestry (2011)	20.08	4.99	6.88	38.46
% with Australian ancestry (2016)	16.70	4.64	4.66	29.51
% with Bachelor's degrees or above (2011)	22.33	5.30	5.92	38.17
% with Bachelor's degrees or above (2016)	26.89	5.01	7.88	43.77
% unemployed (2011)	2.24	0.99	0.00	5.94
% unemployed (2016)	2.48	1.11	0.00	8.13
% with incomes above $104,000 (2011)	9.52	3.02	3.40	18.68
% with incomes above $156,000 (2016)	4.78	2.19	0.00	13.55
% speaking English at home (2011)	70.65	9.60	39.50	94.99
% speaking English at home (2016)	64.80	10.50	29.13	94.90
% with a professional occupation (2011)	14.51	2.96	6.79	22.50
% with a professional occupation (2016)	15.22	2.63	4.62	23.59
SEIFA Disadvantage Index (2011)	1,108.08	26.68	983.70	1,158.34
SEIFA Disadvantage Index (2016)	1,110.39	24.49	982.00	1,165.00

Travel times are in minutes. Pre-Metro travel times refer to travel times in early May 2019. Post-Metro travel times refer to travel times in July 2019. Land values are in $. Demographic variables refer to the proportion of residents in each observation's corresponding SA1.

Table 5.1 shows summary statistics for the data in this analysis. The mean land size is 894 square metres, which is larger when compared to the mean of Greater Sydney at 708 square metres. The sample data contain properties with a variety of land sizes, ranging from semi-detached terrace-style housing or apartment units, to larger semi-rural lots. Table 5.2 shows that 77.9% of properties are zoned low-density residential (R2), while 20.2% are zoned medium-density residential (R3). These two classifications make up almost all properties in the dataset, with the small fraction remaining being zoned general residential (R1) or high-density residential (R4).

Table 5.2: Zoning classifications of sample data

Zone code	No. properties	% properties
R1	18	0.3%
R2	5457	77.9%
R3	1415	20.2%
R4	117	1.7%

Overall, commutes by public transport to the Sydney CBD average a little over 1 hour for residents in the Hills Shire. These journey times range from around half an hour for those closest to express bus services running along the M2 Hills Motorway, to over 2 hours for those residing further north in semi-rural parts of the Shire. Comparing pre-Metro and post-Metro travel times show a small decrease in average commute times, which are likely to be driven by the improvements from the Metro project.

Average land values in the Hills Shire more than doubled from about $424,000 in July 2012, to over $886,000 by July 2018. This is an annualised growth rate of around 13%. In comparison, Greater Sydney experienced relatively slower annualised median house price growth of 6.6%. This growth disparity highlights the rapidly developing nature of north-west Sydney with a substantial pipeline of housing being constructed during the study period as part of development plans for the North West Growth Area (Greater Sydney Commission, 2018). Despite this rapid growth over six years, the average socio-economic status of the area has changed little between the 2011 and 2016 Census as measured by the ABS Index of Socio-Economic Disadvantage (SEIFA).

Breaking down the data into treated and control groups, as measured by whether travel times decreased for each property after the Metro opened, reveals differences in the parameters of interest. For the key parameters, I test for whether the differences in means between the treatment and control groups are significant using a two-sample t-test as reported in table 5.4. The test shows that travel times to the Sydney CBD for control and treated properties are significantly different from each other both prior to and after the Metro opens. This difference is expected, as the Metro line was constructed in the southern part of the Hills Shire, which was previously well serviced by express buses along the M2 motorway. While land values are not significantly different across the groups, land values per square metre are significantly different both prior to and after the Metro opens, which is unsurprising as accessibility differs between the areas. The tests show that there are significant differences in socio-economic status between the control and treated areas in both the 2011 and 2016 Censuses. These findings justify my inclusion of these variables as controls in the regression model.

Table 5.3: Summary statistics by treatment status

Panel A: Control properties				
Statistic	Mean	St. Dev.	Min	Max
Land area (sqm)	900.16	1,947.56	159.90	64,980.00
Pre-Metro Sydney CBD travel time	65.03	13.39	35.67	128.85
Post-Metro Sydney CBD travel time	64.95	13.09	33.76	127.45
Land value (2012)	422,303.90	212,440.10	192,000.00	7,240,000.00
Land value (2018)	881,021.50	610,335.00	337,000.00	17,100,000.00
Land value per sqm (2012)	568.34	149.93	53.79	1,521.02
Land value per sqm (2018)	1,150.15	283.79	133.57	3,284.53
% with Australian ancestry (2011)	20.19	4.76	6.88	38.46
% with Australian ancestry (2016)	16.79	4.58	4.66	29.51
% with Bachelor's degrees or above (2011)	22.46	5.19	5.92	38.17
% with Bachelor's degrees or above (2016)	27.10	4.87	7.88	43.77
% unemployed (2011)	2.20	0.97	0.00	5.94
% unemployed (2016)	2.47	1.07	0.00	8.13
% with incomes above $104,000 (2011)	9.40	2.95	3.40	18.68
% with incomes above $156,000 (2016)	4.67	2.11	0.00	13.23
% speaking English at home (2011)	70.73	9.50	39.50	94.99
% speaking English at home (2016)	64.60	10.44	29.13	94.90
% with a professional occupation (2011)	14.67	2.91	6.79	22.50
% with a professional occupation (2016)	15.32	2.61	4.62	23.59
SEIFA Disadvantage Index (2011)	1,106.86	26.79	991.04	1,158.34
SEIFA Disadvantage Index (2016)	1,109.81	23.70	982.00	1,165.00
Panel B: Treated properties				
Statistic	Mean	St. Dev.	Min	Max
Land area (sqm)	875.54	2,070.71	170.60	45,660.00
Pre-Metro Sydney CBD travel time	81.36	11.57	41.82	133.53
Post-Metro Sydney CBD travel time	75.86	11.80	41.77	121.17
Land value (2012)	429,450.20	302,272.10	199,000.00	9,590,000.00
Land value (2018)	906,275.20	1,073,646.00	337,000.00	35,000,000.00
Land value per sqm (2012)	606.36	153.53	53.75	1,389.73
Land value per sqm (2018)	1,202.86	349.38	188.27	3,500.26
% with Australian ancestry (2011)	19.70	5.72	6.88	38.46
% with Australian ancestry (2016)	16.35	4.83	6.10	28.90
% with Bachelor's degrees or above (2011)	21.85	5.65	5.92	38.17
% with Bachelor's degrees or above (2016)	26.16	5.42	7.88	40.32
% unemployed (2011)	2.34	1.06	0.00	5.94
% unemployed (2016)	2.50	1.25	0.00	8.13
% with incomes above $104,000 (2011)	9.94	3.24	3.40	18.68
% with incomes above $156,000 (2016)	5.16	2.40	0.00	13.55
% speaking English at home (2011)	70.37	9.92	45.48	94.99
% speaking English at home (2016)	65.51	10.69	37.57	89.98
% with a professional occupation (2011)	13.96	3.07	6.79	20.85
% with a professional occupation (2016)	14.87	2.66	4.62	22.34
SEIFA Disadvantage Index (2011)	1,112.34	25.84	983.70	1,158.34
SEIFA Disadvantage Index (2016)	1,112.42	26.97	982.00	1,165.00

Travel times are in minutes. Pre-Metro travel times refer to travel times in early May 2019. Post-Metro travel times refer to travel times in July 2019. Land values are in $. Demographic variables refer to the proportion of residents in each observation's corresponding SA1.

Table 5.4: Difference in means tests

	Control		Treated			
Variable	Mean	Std. dev.	Mean	Std. dev.	t-stat	p-value
Land area (sqm)	900.16	1,947.56	875.54	2,070.71	0.42	0.675
Pre-Metro Sydney CBD travel time	65.03	13.39	81.36	11.57	–47.35	0.000
Post-Metro Sydney CBD travel time	65.03	13.39	75.86	11.80	–30.95	0.000
Land value (2012)	422,304.00	212,440.10	429,450.20	302,272.10	–0.87	0.383
Land value (2018)	881,022.00	610,335.00	906,275.20	1,073,646.00	–0.89	0.375
Land value per sqm (2012)	568.34	149.93	606.36	153.53	–8.66	0.000
Land value per sqm (2018)	1,150.15	283.79	1,202.86	349.38	–5.46	0.000
% with Australian ancestry (2011)	20.19	4.76	19.70	5.72	3.07	0.002
% with Australian ancestry (2016)	16.79	4.58	16.35	4.83	3.23	0.001
% with Bachelor's degrees or above (2011)	22.46	5.19	21.85	5.65	3.84	0.000
% with Bachelor's degrees or above (2016)	27.10	4.87	26.16	5.42	6.18	0.000
% unemployed (2011)	2.20	0.97	2.34	1.06	–4.68	0.000
% unemployed (2016)	2.47	1.07	2.50	1.25	–0.63	0.529
% with incomes above $104,000 (2011)	9.40	2.95	9.94	3.24	–5.96	0.000
% with incomes above $156,000 (2016)	4.67	2.11	5.16	2.40	–7.25	0.000
% speaking English at home (2011)	70.73	9.50	70.37	9.92	1.28	0.202
% speaking English at home (2016)	64.60	10.44	65.51	10.69	–2.98	0.003
% with a professional occupation (2011)	14.67	2.91	13.96	3.07	8.07	0.000
% with a professional occupation (2016)	15.32	2.61	14.87	2.66	5.94	0.000
SEIFA Disadvantage Index (2011)	1,106.86	26.79	1,112.34	25.84	–7.31	0.000
SEIFA Disadvantage Index (2016)	1,109.81	23.70	1,112.42	26.97	–3.46	0.001

Travel times are in minutes. Pre-Metro travel times refer to travel times in early May 2019. Post-Metro travel times refer to travel times in July 2019. Land values are in $. Demographic variables refer to the proportion of residents in each observation's corresponding SA1.

Chapter 6

Results and discussion

In this chapter, I present and discuss estimates of the willingness to pay for improved accessibility to employment in the Sydney CBD based on changes in travel times resulting from the Sydney Metro Northwest project. I perform robustness checks by estimating regressions using specifications measuring land value uplift with distance-based approaches and by randomising the travel time data to demonstrate that the significant results are unlikely to be the result of statistical noise. I then discuss potential limitations of this study.

6.1 Land value uplift estimates

I find that reducing travel times to the Sydney CBD results in an increase in land values for the affected properties. I present the estimation results from the DiD models in table 6.1. I estimate the results using three specifications. Column (1) shows a level-level model with the land value of each property as the outcome variable (model 1). Column (2) shows a level-level model with land value per square metre as the outcome variable (model 2). Column (3) shows a log-level model with the natural logarithm of land value as the outcome variable (model 3). All the models are run with controls for neighbourhood demographic and socio-economic characteristics, individual property fixed effects and heteroskedasticity-robust standard errors clustered at the individual property level. The models have high explanatory power, especially the square metre value (model 2) and logged land value (model 3) models.

The coefficient of interest is the interaction between the post-Metro time dummy and public transport travel time to the Sydney CBD in minutes. This coefficient is the DiD estimate of the land value uplift that accrues to the average property as a result of a 1 minute decrease in public transport travel times over the six years between July 2012 and July 2018. The results are highly significant and have the expected signs as predicted by theory. Model (2) shows that a 1 minute decrease in transit times to the Sydney CBD increases land values by about $3,400 for the average sized property. In percentage terms using model (3), a 1 minute decrease in travel times increases land values by 0.36%, which for the average property is equivalent to an increase in land value of $3,190, consistent with the estimates from model (2). The coefficient on the Post-Metro variable shows the pure effect of the time trend on land values in the Hills Shire. In the absence of the treatment, land values increased by about $757,000 between 2012 and 2018 using model (1), or around 97% using model (3).

For brevity, I have omitted the neighbourhood controls from the results table. Neighbourhood control variables were specified at the SA1 level and include data on the proportion of the resident population in each area: with Australian ancestry, who hold a Bachelor's degree or above, who are unemployed, with incomes above $130,000, who speak only English at home, and who work in a professional occupation. In addition, I also include each SA1's socio-economic index of disadvantage score. For the pre-Metro time period, these data were obtained from the 2011 Census, while for the post-Metro time period the data are from the 2016 Census. The signs on the demographic controls are as expected, and the inclusion and exclusion of these controls do not materially affect the magnitude of the estimates on changes in travel time. The full regression tables are available in Appendix I.

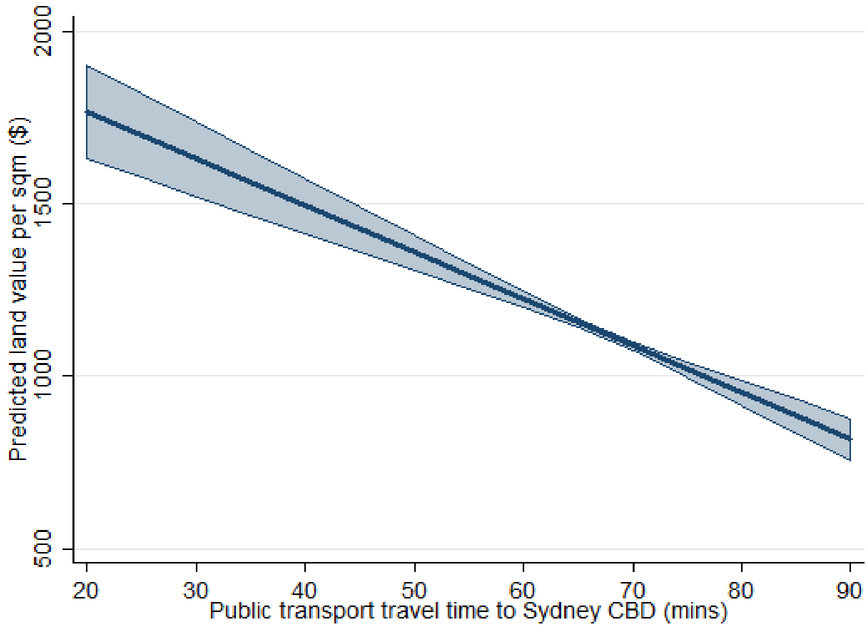
Table 6.1: Difference in differences regression estimates

	(1) Land value ($)	(2) Land value/sqm ($)	(3) ln(Land value)
Post-Metro=1	756,605.758***	748.698***	0.9686***
	(20.303)	(47.717)	(86.8326)
ΔPT travel time (mins)	−15,045.319***	−9.739***	−0.0050***
	(−3.267)	(−7.184)	(−4.5268)
Post-Metro=1 × ΔPT travel time (mins)	−2,754.159***	−3.810***	−0.0036***
	(−4.196)	(−22.968)	(−19.9391)
Neighbourhood controls	Yes	Yes	Yes
Property FE	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes
Adj. R^2	0.576	0.884	0.9558
Adj. within R^2	0.422	0.914	0.9651

t statistics in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Heteroskedasticity-robust standard errors clustered at property level. Number of observations in each model is 14,014 (7,007 properties observed at 2 time periods). ΔPT travel time refers to the change in public transport travel times to the Sydney CBD during the morning peak in minutes.
Controls: Neighbourhood controls are demographic variables for the SA1 that each property belongs to and controls for ABS SEIFA Disadvantage Index, population % with Australian ancestry, population % with Bachelor's degree or above, population % unemployed, population % with income above $130,000 per year, population % speaking English at home, and population % working in a professional occupation.

I plot the predicted land value per square metre as travel time to the Sydney CBD changes in figure 6.1. This figure illustrates the price gradient as estimated by the DiD model. The average property with a travel time to the Sydney CBD of 20 minutes is predicted to have a value of about $1.75 million in July 2018. In comparison, a property with a travel time of 90 minutes has a predicted value of less than $1 million. The blue areas indicate the 95% confidence intervals, showing that the predictions are estimated fairly precisely.

Figure 6.1: Predicted land values/m^2 with 95% CI



Predicted values estimated using land value/sqm model.

6.1.1 Willingness to pay calculations

The results from the DiD regression can be directly interpreted as the present discounted value that commuters place on saving 1 minute per commute for the rest of the life of the property. Using these results and assumptions on the relevant discount rate, number of hours worked per year and the number of working years remaining (detailed in Appendix K), I calculate that commuters value reducing their commuting time at \$26.15 per hour using the ln(Land value) model. This estimate is the central scenario, but within the full range of reasonable assumed values this number varies from \$17.60 to \$48.81 an hour as shown in table 6.2 (see Appendix K for full calculations). As a comparison, transport agencies often use 40% of the average wage rate as a proxy for the amount that commuters are willing to pay to reduce their commute time. However, the reliability of this figure is strongly disputed, for example, see Hensher (2019) and Douglas and Jones (2018). Calculations using this assumption produce an estimate of \$17.20 per hour (40% × \$42.99) (data sourced from ABS (2019a, 2019b)). Thus, the estimates from this study are within the expected range of willingness to pay.

Table 6.2: Willingness to pay for 1 hour of travel time savings

Model	Central estimate	Bounds
Land value	\$22.08	(\$14.85, \$41.21)
Land value/sqm	\$26.73	(\$17.98, \$49.88)
ln(Land value)	\$26.15	(\$17.60, \$48.81)

See Appendix K for assumptions underpinning WTP calculations.

6.2 Robustness tests

To check the robustness of my travel time results, I perform additional DiD regressions using the traditional distance-based methods used in the literature and also a regression where the travel time data is replaced with randomised data.

6.2.1 Alternative distance models

As a robustness check and comparison to previous work that focuses on the distance from new transport infrastructure, I present results using a variety of distance specifications in table 6.3. I estimate models using land values per square metre and also log of land value (measuring % changes). I find significant results indicating that the value uplift as a result of the Metro project is mostly robust to the choice of model specification with travel time and distance models both showing a large positive effect from a reduction in travel time.

Models (1) and (2) use a binary treatment assignment, where any property that experiences a reduction in travel times is considered to be part of the treatment group. The DiD estimate in model (1) has the expected positive sign and indicates that being located in the treatment area increases property values by about \$22 per square metre, which is an increase in land value of about \$20,000 for the average sized property in the Hills Shire. However, the log-level model in column (2) suggests that being part of the treatment group reduces land values. This conflicting result is likely caused by the crude nature of a binary treatment variable for a continuous treatment effect that the theory implies should have heterogeneous impacts. Hence, using a binary treatment assignment is a sub-optimal methodology compared to my continuous travel time method.

In models (3) and (4), I use a continuous distance measure that measures the distance of the property to the nearest Metro station. This variable measures accessibility as a function of the distance to the nearest transport node as opposed to measuring accessibility to an actual amenity such as employment. I find that a 1 km reduction in distance from a Metro station increases land values by \$49 per square metre or around

Table 6.3: Difference in differences regression alternative specification estimates

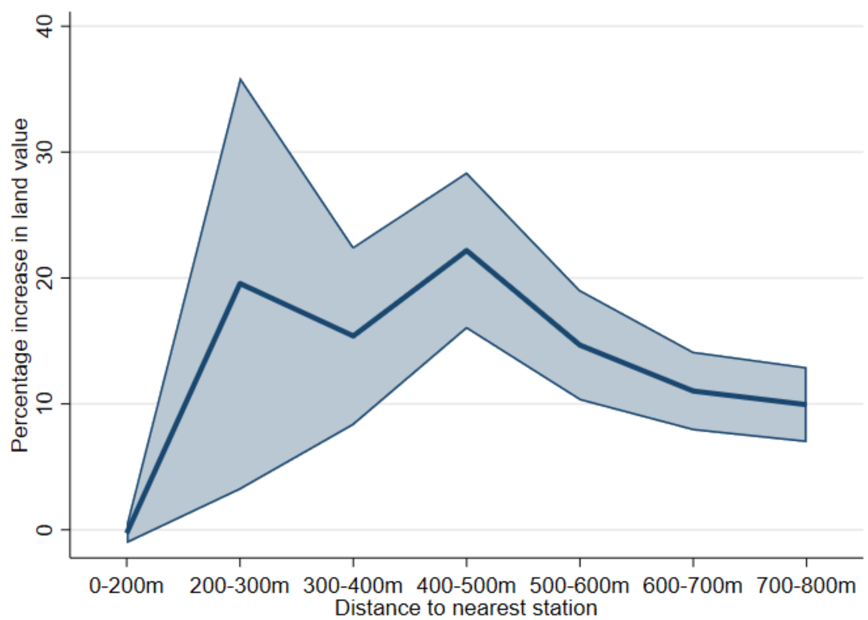
	Binary		Distance		Distance cutoffs	
	(1) $/sqm	(2) ln(·)	(3) $/sqm	(4) ln(·)	(5) $/sqm	(6) ln(·)
Post-Metro=1	486.230***	0.725***	631.894***	0.734***	489.968***	0.717***
	(49.713)	(78.220)	(46.949)	(71.404)	(55.739)	(78.838)
Post-Metro=1 × Treatment=1	22.266***	−0.024***				
	(3.086)	(−4.323)				
Post-Metro=1 × Station dist.			−49.116***	−0.005**		
			(−17.841)	(−2.490)		
Post-Metro opening and distance cutoff interaction terms						
Distance: 0–200 m					28.209***	−0.003
					(4.871)	(−0.685)
Distance: 200–300 m					433.817***	0.196**
					(3.897)	(2.339)
Distance: 300–400 m					352.384***	0.154***
					(6.931)	(4.249)
Distance: 400–500 m					401.380***	0.222***
					(8.225)	(6.980)
Distance: 500–600 m					250.789***	0.147***
					(8.222)	(6.538)
Distance: 600–700 m					207.739***	0.110***
					(8.788)	(6.887)
Distance: 700–800 m					181.393***	0.099***
					(9.489)	(6.510)
Neighbourhood controls	Yes	Yes	Yes	Yes	Yes	Yes
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.874	0.950	0.883	0.950	0.894	0.954
Adj. within R^2	0.906	0.961	0.912	0.961	0.921	0.964

t statistics in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Heteroskedasticity-robust standard errors clustered at property level. Number of observations in each model is 14,014 (7,007 properties observed at 2 time periods). Treated properties are defined as properties experiencing a travel time reduction if they switch modes from bus to metro in July 2019. Station distance is the straight-line distance to the nearest Metro station measured in kilometres.
Controls: Neighbourhood controls are demographic variables for the SA1 that each property belongs to and controls for ABS SEIFA Disadvantage Index, population % with Australian ancestry, population % with Bachelor's degree or above, population % unemployed, population % with income above $130,000 per year, population % speaking English at home, and population % working in a professional occupation.

1.5%. For the average-sized property in the Hills Shire, this is an increase in value of $44,100 for every 1 km closer to a Metro station.

Models (5) and (6) assign properties to distance-based cutoffs that group properties by distance from the nearest Metro station. These cutoffs reveal non-linearities in the level of value uplift. The first cutoff is properties within 200m of a station (100m was not used because not enough properties were within that distance). The coefficients on the level-level model show that for the average property within 200m, land values increased by about $28 per square metre. The effect using the log-level model is not statistically significantly different from zero. Notice that the estimated effect is much smaller compared to the other distances. This result is unsurprising, as there are likely to be some disamenities relating to being too close to a railway station (Yen et al., 2018). In contrast, properties located further from the station up to 500m away experience a large increase in land values of between 19.6% to 22.2% depending on the distance. As shown in figure 6.2, this effect then diminishes with increasing distance, which is expected as the benefit of the new transport project declines if it takes too long to travel to the station.

Figure 6.2: Average change in land values given distance to nearest Metro station with 95% CI



Predicted values estimated using ln(Land value) model.

6.2.2 Statistical noise DiD

As an additional robustness check, I perform a DiD regression using randomised data to ensure the results are not the result of statistical noise. This regression is done by randomly reallocating the pre- and post-Metro opening travel time data across the properties in the dataset and running the same DiD regression as in the main results. Because the time data are now randomised, there should be no statistically significant relationship between the change in travel time and the resulting change in land values and hence the coefficient on the DiD parameter should be highly insignificant. The results in table 6.4 confirm this expectation and show that it is unlikely that the significant results reported in table 6.1 are the result of statistical noise.

Table 6.4: Difference in differences robustness regression estimates

	(1) Land value	(2) $/sqm	(3) ln(Land value)
Post-Metro=1	570,219.279***	483.998***	0.71371***
	(11.071)	(29.925)	(53.87955)
ΔFake travel time (mins)	−160.316	−0.013	0.00008
	(−0.189)	(−0.043)	(0.34387)
Post-Metro=1 × ΔFake travel time (mins)	184.028	0.124	0.00008
	(0.425)	(0.634)	(0.53702)
Neighbourhood controls	Yes	Yes	Yes
Property FE	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes
Adj. R^2	0.572	0.874	0.95008
Adj. within R^2	0.416	0.905	0.96057

t statistics in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Heteroskedasticity-robust standard errors clustered at property level. Number of observations in each model is 14,014 (7,007 properties observed at 2 time periods). Existing travel times in the dataset were randomly reassigned to properties in the dataset to produce the Fake travel time variable. Travel times refer to public transport travel times to the Sydney CBD during the morning peak in minutes.
Controls: Neighbourhood controls are demographic variables for the SA1 that each property belongs to and controls for ABS SEIFA Disadvantage Index, population % with Australian ancestry, population % with Bachelor's degree or above, population % unemployed, population % with income above $130,000 per year, population % speaking English at home, and population % working in a professional occupation.

6.3 Limitations

This Part of my thesis aims to identify the willingness to pay of commuters to increase their accessibility to employment in the Sydney CBD through a difference in differences analysis of the Sydney Metro Northwest project. While the results are statistically and economically significant, there are a number of theoretical and data limitations to my analysis in addition to the previously discussed issues with satisfying the identifying assumptions.

The use of land values was motivated by difficulty obtaining contemporaneous housing sales data for the Hills Shire in time for the completion of this thesis and to take advantage of the panel structure of the land values dataset. However, using the land values data may be problematic. The oldest publicly available bulk land values data from the NSW Valuer General dates to July 2012, which I have used as the pre-Metro land valuations. However, the current incarnation of Metro Northwest was first exhibited by the NSW Government in July 2011, with the major construction program announced in December 2011 (Transport for NSW, 2011) meaning some land value uplift may have already started occurring. On the other hand, Yen et al. (2018) find that the largest value uplift occurs when firm financial commitments have been made by government, such as the signing of major construction contracts. Since the first major contract (for tunnelling) was signed in June 2013 (Transport for NSW, 2013), it is possible that most value uplift occurred after that date, reducing the magnitude of the downward bias. In addition, while the project has been conceptualised since the late 1990s (Newman, 1999), repeated cancellations and re-announcements are likely to have reduced the public credibility of the NSW Government's announcement of the project — at least until firm contractual commitments were made (Gordon, Mulley, Stevens & Daniels, 2013). However, overall it is likely that land values started increasing prior to July 2012. Furthermore, as discussed in the Methodology chapter, the lack of pre-2012 data also prevents me from conducting pre-trends analysis on the outcome variable to investigate whether the parallel trends assumption of the DiD estimator can be feasibly upheld. These limitations can be addressed by using older land value data, which are known to be held by the Valuer General. Unfortunately, I was unable to obtain it by the submission date of this thesis despite multiple attempts at contact.

At the other end of the timeline, I use land values data from July 2018 as an approximation of the post-Metro land valuations. However, Sydney Metro Northwest opened to revenue service in May 2019 (Sydney Metro, 2019b). Hence, it is likely that some of the value uplift due to the project has not yet been fully capitalised into the price of land in the study area. Furthermore, the literature show that value uplift is sometimes not fully capitalised into land values until a number of years after project opening (Higgins & Kanaroglou, 2016; McIntosh et al., 2014). The solution is to wait until land value data dating to July 2019 (or later) is released, likely by January 2020 based on the release timeline of previous land value data. These data issues likely lead to an underestimate of the total land value uplift as a result of the Metro project, if value uplift already started prior to July 2012 and did not fully conclude by July 2018. This is especially the case if price changes have a lagged response to changes in accessibility. These issues mean that the estimates of willingness to pay for increased accessibility will be downwardly biased compared to the true value.

There may also be further difficulties in land valuation due to the large number of greenfields developments occurring in the north west. As previously noted, there are some gaps in the maps where no properties are sampled, which correspond to areas where new developments were still being planned and lots were not yet subdivided in 2012. These missing areas primarily affect stations in the more northerly sections of the line and while analysis of the effects on land values of these new developments would be interesting, they cannot be captured as they are recorded in the land values dataset as very large blocks of land instead of individual subdivisions.

This study is affected by the multi-stage scope of the Sydney Metro project. The Northwest Metro is the first stage of the Sydney Metro project, with the second stage that connects Chatswood to Bankstown via the Sydney CBD currently under construction (Sydney Metro, 2019a). This stage will further reduce travel times from north-west Sydney to the Sydney CBD via a new route that is faster than the existing North Shore line, which has implications for my analysis. There is a high degree of credibility in the community that the travel time reductions will be realised upon completion and opening in 2024, because the project is already under construction. Thus, it is possible that part of the future value of this travel time saving will be in the process of being capitalised into land values in the study area, which would result in an overestimate of the true value of the willingness to pay, as the partial reduction in travel times from stage one is attributed to the rise in land values that represent residents responding to the cumulative gains from both stage one and two.

Similar to the limitations in Part I of this thesis, this part is also affected by the dispersed nature of employment in Sydney. My estimation method assumes that accessibility to employment in the Sydney CBD is the only location of employment that matters. Access to employment in other nearby major centres such as Macquarie Park and Parramatta are also likely to inform the locational decisions of households in north-west Sydney. Unfortunately, I was unable to collect travel time data to these locations due to time constraints. However, including additional centres still suffers from what is essentially an arbitrary choice of what employment centres matter. A more agnostic approach is to use a gravity model approach (see Ahlfeldt (2010), Kau and Sirmans (1979)) that allows me to construct a single employment-weighted travel time from each property. I have discussed this approach in depth in section 5.8 of Part I.

CHAPTER 7

Conclusion

This Part uses a difference in differences model to estimate commuters' willingness to pay for improved accessibility to employment in Sydney by exploiting variation in travel times and land values resulting from the opening of the Sydney Metro Northwest rapid transit rail line in north-west Sydney. I produce the first estimates of willingness to pay for the first rapid transit line in Sydney using a quasi-experiment panel data approach with a unique dataset constructed from Google Maps travel time data. This study demonstrates the feasibility of using travel time data as a means of separating properties into treatment and control groups that is more realistic than the existing distance-based approaches used in the literature.

After controlling for local demographics and socio-economic variables, I find that there is a significant relationship between reduced travel times and increased land values as assessed by the NSW Valuer General. The value uplift produced by the Metro project is robust to alternative specifications that are preferred in the literature, including a binary distance-based assignment into treatment and control groups, and also using multiple discrete distance-based bins to measure a varying effect over different distances from metro stations. Under both these specifications, I observe a significant effect of the Metro on land value uplift. Compared to the results from Part I, the estimated willingness to pay is lower. The cross-sectional approach produces magnitudes about double that of the baseline estimates using the travel time DiD model. This is in line with findings from the literature that show cross-sectional models tend to produce larger estimates than quasi-experimental approaches.

However, this is an early study and it is possible that estimates are underestimating the value uplift from the project due to the value change not yet fully capitalising into property values in the area. In addition, the multi-stage nature of the Sydney Metro project means there is a risk of confounding the benefits of future stages of the project with the benefits of the currently open stage, as some of the value uplift of future improvements may already be capitalising themselves into property values, possibly producing an overestimation of the gains. There can also be improvements to the measure of accessibility; future researchers could use a gravity-based approach to weighting employment across the whole of Greater Sydney, rather than solely measuring accessibility to the Sydney CBD.

My results improve on existing measures of the value of travel time savings for users of transport infrastructure, enabling more accurate cost-benefit analysis of transport projects compared to existing methods using assumed proportions of average wages (Douglas & Jones, 2018; Hensher, 2019). Better measures of willingness to pay improves the quality of cost-benefit analyses, ensuring that the most productive and beneficial infrastructure is funded first.

My research has implications for the policy debate surrounding the funding mechanisms for transport infrastructure projects. My results confirm that transport projects lead to significant land value uplift for the surrounding properties that benefit from this project. Value capture has been proposed as a mechanism for governments to fund projects by taxing those who benefit the most from new infrastructure (Medda, 2012). A common criticism of distance cutoff studies is that the cutoff is essentially arbitrary and applying such a mechanism to a tax would arbitrarily include some properties in the taxed group, while excluding neighbours from paying the tax (Terrill & Emslie, 2017). By using a continuous travel time approach to measuring value uplift from the project, I address this criticism of value capture mechanisms and provide a better mechanism design that ensures property owners equitably contribute to infrastructure investment.

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Appendices

APPENDIX A

Part 1: Additional travel time maps

A.1 Property sales data travel time maps

Figure A.1: Drive times to Parramatta

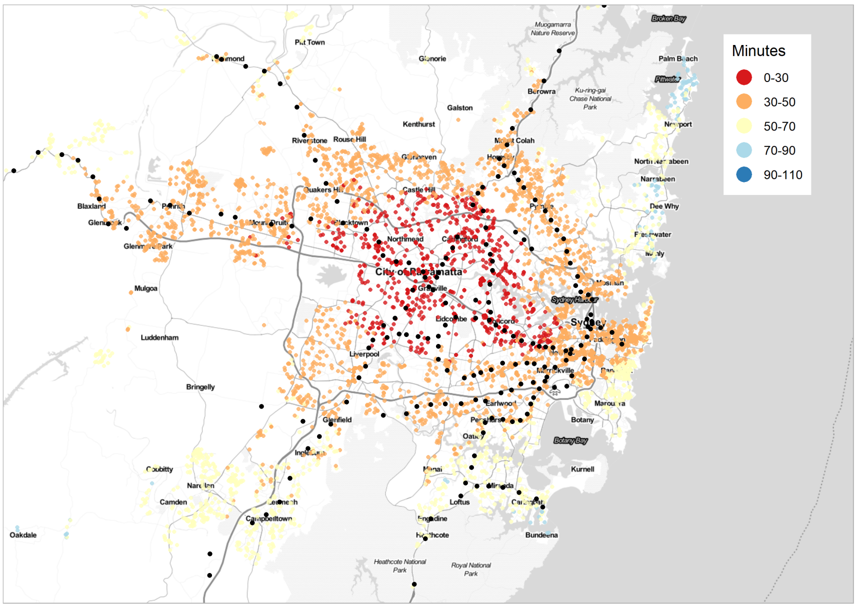


Figure A.2: Public transport times to Parramatta

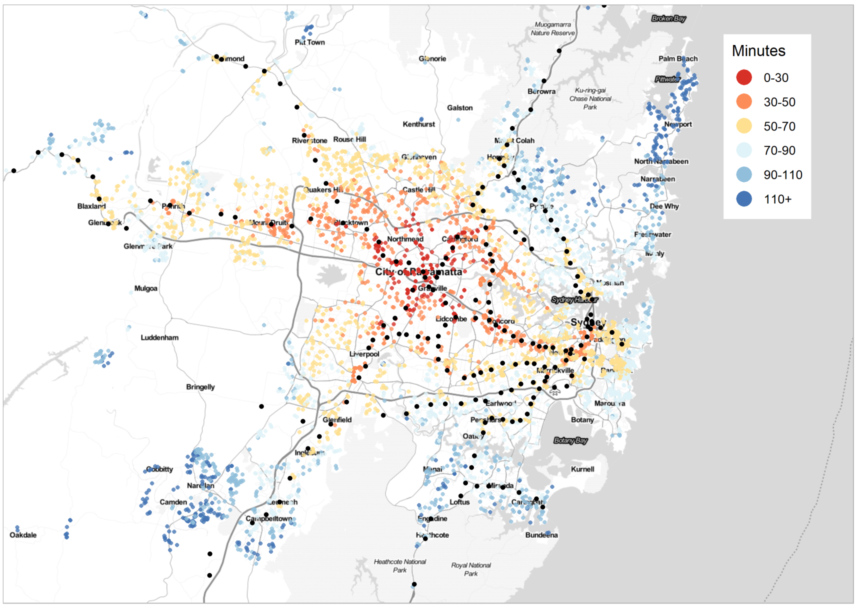


Figure A.3: Drive times to Macquarie Park

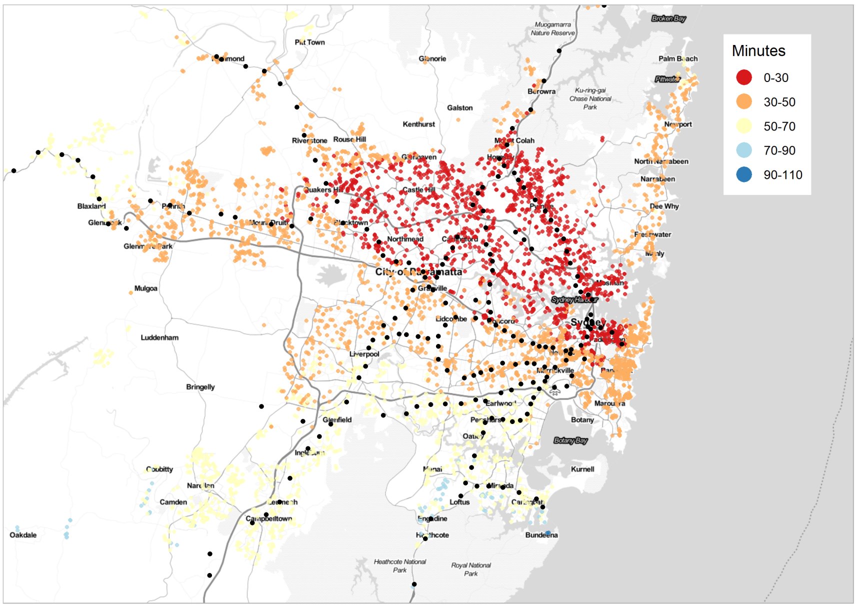
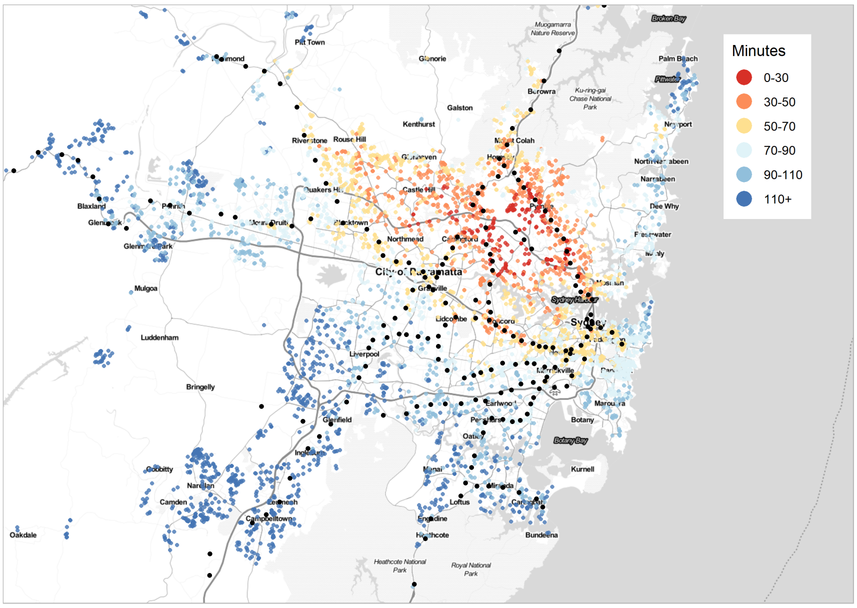


Figure A.4: Public transport times to Macquarie Park



A.2 Land valuations data travel time maps

Figure A.5: Drive times to Parramatta

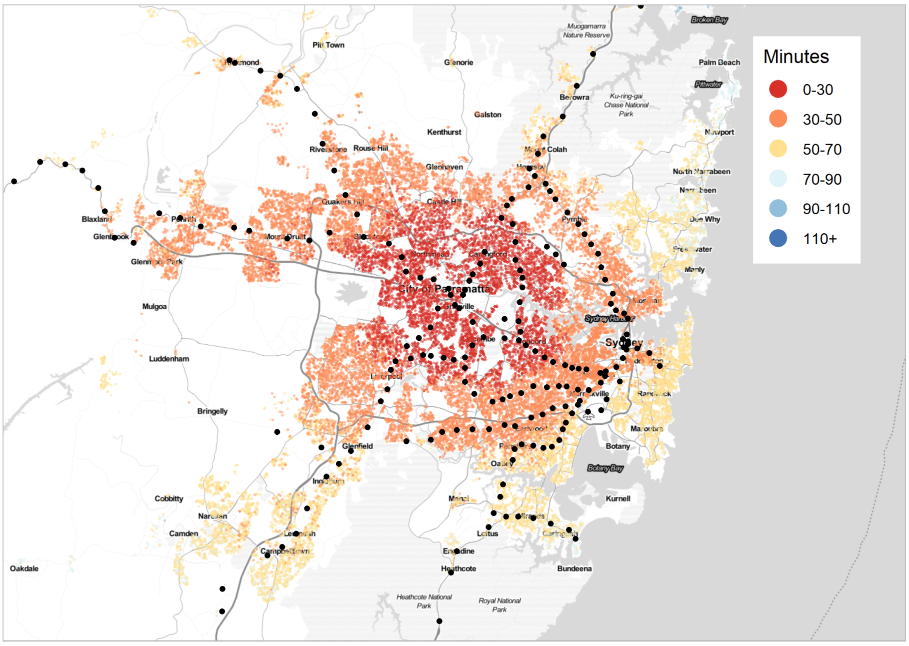


Figure A.6: Public transport times to Parramatta

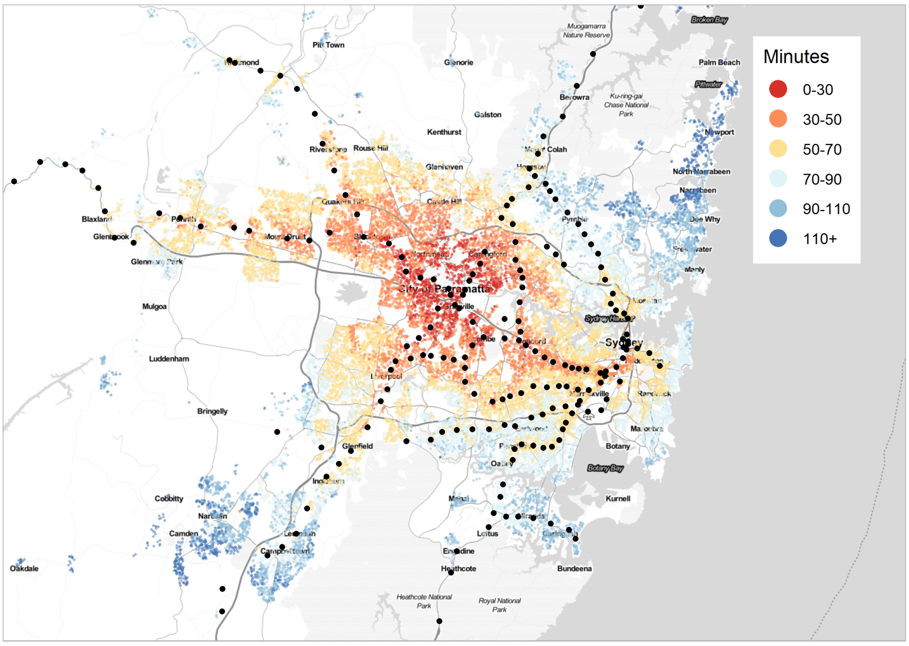


Figure A.7: Drive times to Macquarie Park

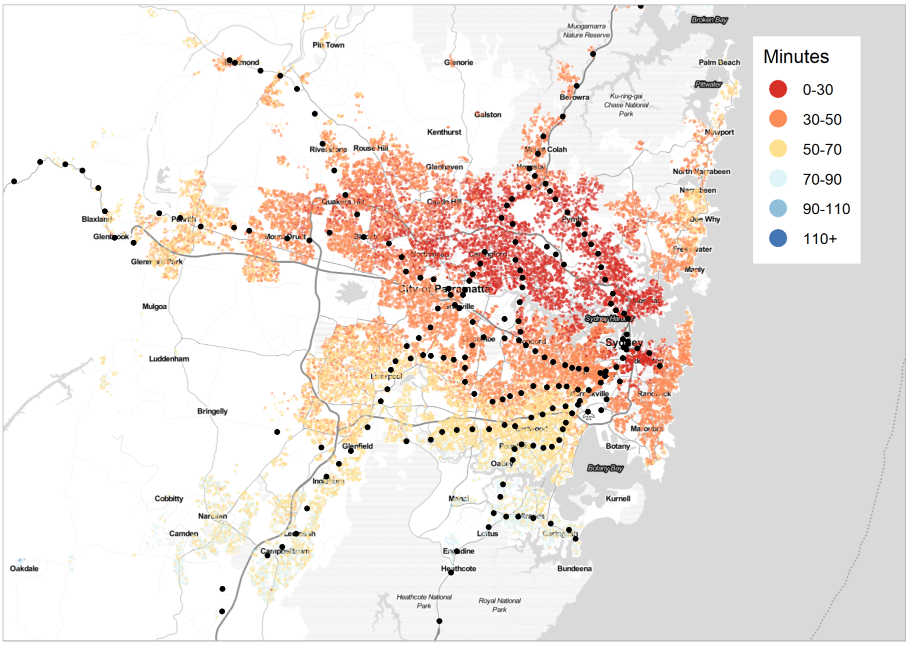
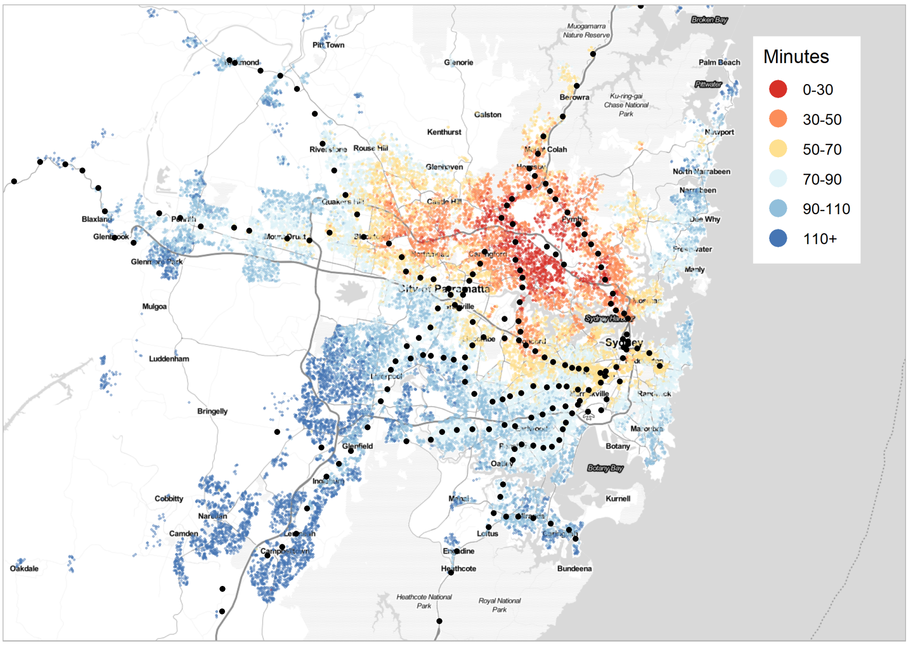


Figure A.8: Public transport times to Macquarie Park



Appendix B

Part 1: Variable names and descriptions

Table B.1: Variable names and descriptions

Variable name	Variable description
Accessibility measures (sale prices only)	
time_traffic_syd	In-traffic drive time (minutes) from property to Sydney CBD
time_transit_syd	Public transport travel time (minutes) from property to Sydney CBD
time_traffic_par	In-traffic drive time (minutes) from property to Parramatta
time_transit_par	Public transport travel time (minutes) from property to Parramatta
time_traffic_mac	In-traffic drive time (minutes) from property to Macquarie Park
time_transit_mac	Public transport travel time (minutes) from property to Macquarie Park
dist_syd	Straight-line distance from property to Sydney CBD
dist_par	Straight-line distance from property to Parramatta
dist_mac	Straight-line distance from property to Macquarie Park
coast_dist	Straight-line distance (km) to nearest coastline
Accessibility measures (land values only)	
S_time_traffic	In-traffic drive time (minutes) from property to Sydney CBD
S_transit_time	Public transport travel time (minutes) from property to Sydney CBD
P_time_traffic	In-traffic drive time (minutes) from property to Parramatta
P_transit_time	Public transport travel time (minutes) from property to Parramatta
M_time_traffic	In-traffic drive time (minutes) from property to Macquarie Park
M_transit_time	Public transport travel time (minutes) from property to Macquarie Park
Syd_dist	Straight-line distance from property to Sydney CBD
Par_dist	Straight-line distance from property to Parramatta
MP_dist	Straight-line distance from property to Macquarie Park
coast_dist	Straight-line distance (km) to nearest coastline
Property classifications (sale prices only)	
PropertyTypeHouse	Property is a detached house (base case)
PropertyTypeOther	Property is semi-detached, duplex, terrace or villa
PropertyTypeUnit	Property is a unit, studio or townhouse
Zoning dummy controls (land values only)	
zonecodeR1	General residential (base case)
zonecodeR2	Low density residential
zonecodeR3	Medium density residential
zonecodeR4	High density residential
zonecodeR5	Large lot residential
Property characteristics (sale prices only)	
Bedrooms	Number of bedrooms in the property
Bathrooms	Number of bathrooms in the property
Parking	Number of parking spaces in the property (garage and carport spaces)
SA1 Neighbourhood demographic controls (2016 data)	
SEIFA_disadv	ABS SEIFA Disadvantage Index
FracAustAncestry	Population % with Australian ancestry
FracBachAbove	Population % with Bachelor's degree or above
FracUnemp	Population % unemployed
FracHighInc	Population % with income above $130,000 per year
FracEngSpoken	Population % speaking English at home
FracOccProf	Population % working in a professional occupation

Appendix C

Part 1: Regression residual plots

C.1 Sales data residual plots

Figure C.1: Plot of Studentized residuals and fitted values of $sqmvalue$

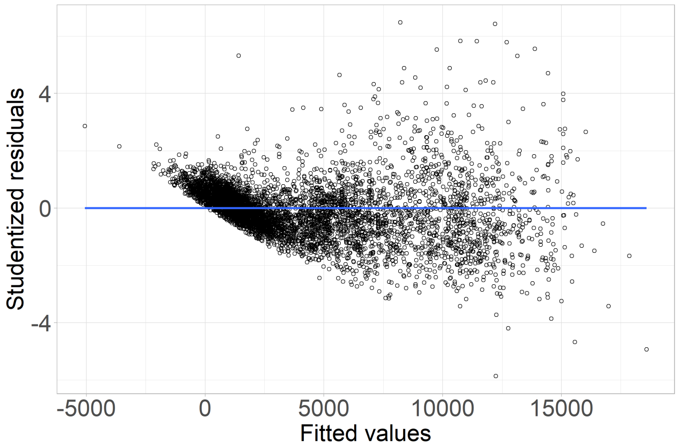


Figure shows the fitted values from the spatially uncorrelated regression estimated by OLS for the S+P+M model (see main Results for details on model specification) plotted against the Studentized residuals from the model.

Figure C.2: Plot of Studentized residuals and fitted values of $\ln(sqmvalue)$

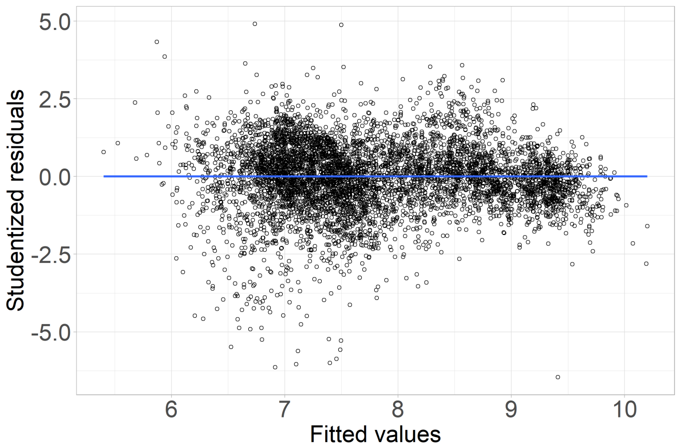


Figure shows the fitted values from the spatially uncorrelated regression estimated by OLS for the S+P+M model (see main Results for details on model specification) plotted against the Studentized residuals from the model.

C.2 Land value data residual plots

Figure C.3: Plot of Studentized residuals and fitted values of $sqmvalue$

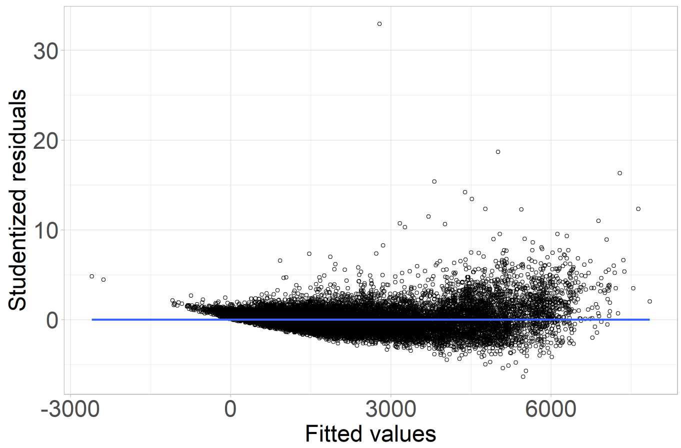


Figure shows the fitted values from the spatially uncorrelated regression estimated by OLS for the S+P+M model (see main Results for details on model specification) plotted against the Studentized residuals from the model.

Figure C.4: Plot of Studentized residuals and fitted values of $\ln(sqmvalue)$

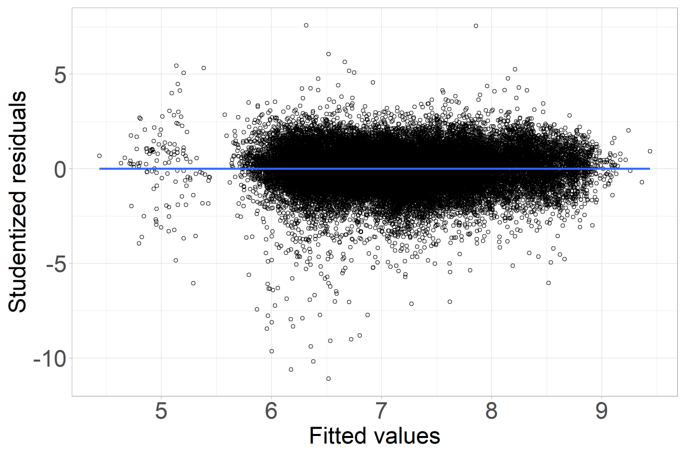


Figure shows the fitted values from the spatially uncorrelated regression estimated by OLS for the S+P+M model (see main Results for details on model specification) plotted against the Studentized residuals from the model.

Appendix D

Part 1: Sales data robustness tests

D.1 Log-level linear regression model results

Table D.1: Linear regression results ($lsqmvalue$)

	Distance			Travel time		
	S	S+P	S+P+M	S	S+P	S+P+M
Syd. distance	-3.4161^{***}	-4.2623^{***}	-5.6234^{***}			
	(0.13553)	(0.13845)	(0.17386)			
Syd. distance^2	0.0206^{***}	-0.0126^{***}	0.0298^{***}			
	(0.00161)	(0.00407)	(0.00577)			
Par. distance		2.4562^{***}	1.1915^{***}			
		(0.12572)	(0.17056)			
Par. distance^2		0.0153^{***}	0.0156^{***}			
		(0.00367)	(0.00379)			
Mac. distance			2.6426^{***}			
			(0.18821)			
Mac. distance^2			-0.0450^{***}			
			(0.00370)			
Syd. drive time				-2.0479^{***}	-1.9725^{***}	-1.9740^{***}
				(0.13725)	(0.14230)	(0.15770)
Syd. drive time^2				0.0119^{***}	0.0120^{***}	0.0138^{***}
				(0.00123)	(0.00136)	(0.00146)
Syd. transit time				-0.6581^{***}	-0.6499^{***}	-0.9037^{***}
				(0.08811)	(0.09953)	(0.10142)
Syd. transit time^2				0.0009^{**}	0.0022^{***}	0.0028^{***}
				(0.00041)	(0.00047)	(0.00048)
Par. drive time					0.6631^{***}	-0.9292^{***}
					(0.19174)	(0.21347)
Par. drive time^2					-0.0061^{***}	0.0120^{***}
					(0.00206)	(0.00231)
Par. transit time					-0.02736	0.4143^{***}
					(0.09505)	(0.09754)
Par. transit time^2					-0.0013^{***}	-0.0043^{***}
					(0.00046)	(0.00050)
Mac. drive time						2.0797^{***}
						(0.22357)
Mac. drive time^2						-0.0307^{***}
						(0.00242)
Mac. transit time						-0.08593
						(0.08328)
Mac. transit time^2						0.0021^{***}
						(0.00039)
Coast distance	-0.7589^{***}	2.5230^{***}	1.9505^{***}	-1.2975^{***}	-1.7061^{***}	-1.8668^{***}

	Distance			Travel time		
	S	S+P	S+P+M	S	S+P	S+P+M
	(0.12104)	(0.24439)	(0.24476)	(0.10919)	(0.17083)	(0.18578)
Coast distance^2	0.00311	-0.0174^{***}	-0.0209^{***}	0.0050^{***}	0.0066^{***}	0.0093^{***}
	(0.00196)	(0.00216)	(0.00221)	(0.00173)	(0.00209)	(0.00223)
Neighbourhood controls	Yes	Yes	Yes	Yes	Yes	Yes
Zoning controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.85324	0.86060	0.86404	0.85726	0.85863	0.86423
Adj. R^2	0.85295	0.86029	0.86370	0.85694	0.85824	0.86379
Num. obs.	8073	8073	8073	8073	8073	8073

Notes: Standard errors in parenthesis. Coefficients transformed to percentages. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

D.2 Level-level spatial error model

Table D.2: SEM regression results (Sales price per m^2)

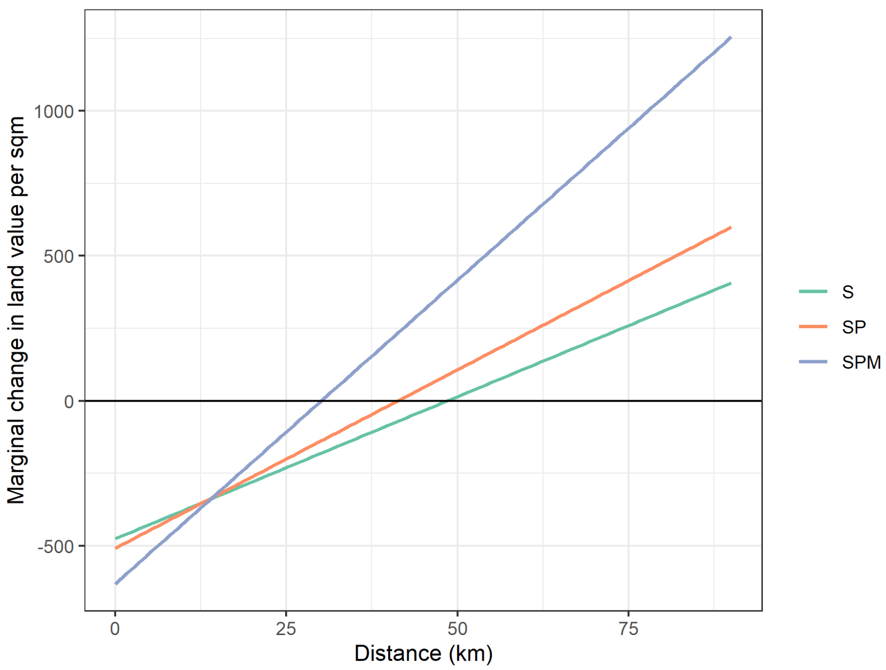
	Distance			Travel time		
	S	S+P	S+P+M	S	S+P	S+P+M
Syd. distance	-475.59^{***}	-508.18^{***}	-631.12^{***}			
	(13.145)	(13.384)	(14.747)			
Syd. distance^2	4.90^{***}	6.15^{***}	10.48^{***}			
	(0.212)	(0.398)	(0.472)			
Par. distance		154.70^{***}	36.73^{**}			
		(13.459)	(14.609)			
Par. distance^2		-2.70^{***}	-0.370			
		(0.393)	(0.411)			
Mac. distance			314.05^{***}			
			(16.506)			
Mac. distance^2			-7.94^{***}			
			(0.525)			
Syd. drive time				-194.00^{***}	-193.12^{***}	-176.84^{***}
				(8.091)	(8.191)	(8.939)
Syd. drive time^2				1.43^{***}	1.51^{***}	1.49^{***}
				(0.075)	(0.077)	(0.081)
Syd. transit time				-98.00^{***}	-84.08^{***}	-90.35^{***}
				(5.061)	(5.642)	(5.785)
Syd. transit time^2				0.40^{***}	0.42^{***}	0.42^{***}
				(0.025)	(0.028)	(0.028)
Par. drive time					49.12^{***}	45.71^{***}
					(12.612)	(13.093)
Par. drive time^2					-0.65^{***}	-0.44^{***}
					(0.137)	(0.145)
Par. transit time					-23.13^{***}	-20.21^{***}
					(5.232)	(5.384)
Par. transit time^2					0.004	-0.06^{**}
					(0.025)	(0.028)
Mac. drive time						-7.896
						(13.289)
Mac. drive time^2						-0.44^{***}
						(0.154)
Mac. transit time						9.29^{*}

	Distance			Travel time		
	S	S+P	S+P+M	S	S+P	S+P+M
						(4.946)
Mac. transit time^2						0.06**
						(0.025)
Coast distance	-160.94^{***}	-70.53^{***}	-53.34^{**}	-151.42^{***}	-229.36^{***}	-220.75^{***}
	(14.178)	(22.071)	(21.465)	(12.090)	(15.835)	(16.038)
Coast distance^2	2.69***	0.83**	0.057	2.09***	2.90***	2.63***
	(0.327)	(0.337)	(0.323)	(0.236)	(0.268)	(0.265)
λ	0.93***	0.91***	0.90***	0.87***	0.88***	0.86***
	(0.006)	(0.007)	(0.008)	(0.010)	(0.010)	(0.012)
Neighbourhood controls	Yes	Yes	Yes	Yes	Yes	Yes
Zoning controls	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	8073	8073	8073	8073	8073	8073
Parameters	19	21	23	21	25	29
Log Likelihood	−72402.189	−72340.289	−72161.860	−72189.425	−72123.879	−72068.369
AIC (Linear model)	147275.067	146178.635	145574.417	145554.367	145317.087	144943.411
AIC (Spatial model)	144842.378	144722.579	144369.719	144420.850	144297.757	144194.738
LR test: statistic	2434.689	1458.056	1206.698	1135.516	1021.330	750.673
LR test: p-value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

D.2.1 Distance specifications

Figure D.1: Marginal effect of Sydney distance on land values per m^2



D.2.2 Travel time specifications

Figure D.2: Marginal effect of Sydney drive time on land values per m^2

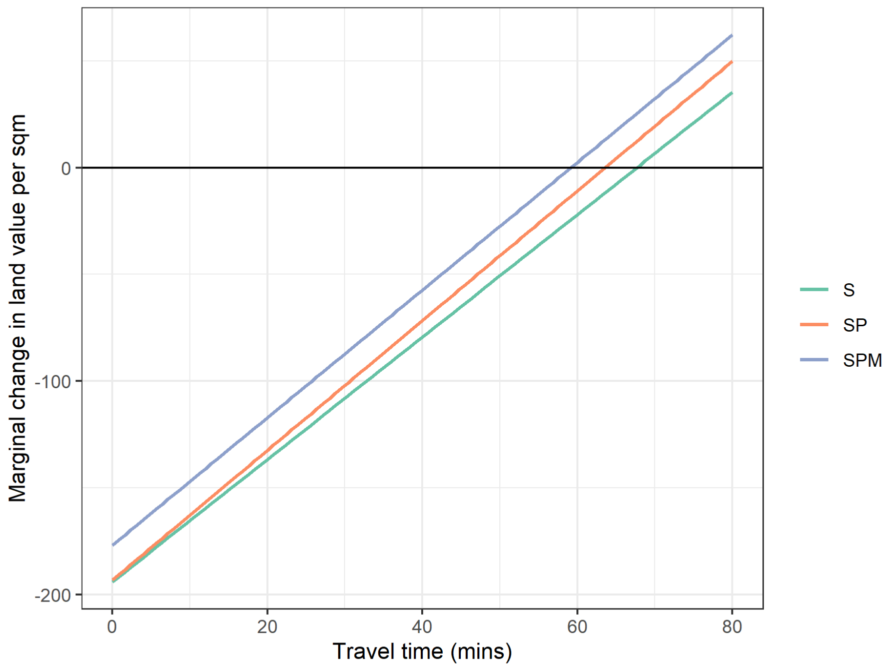
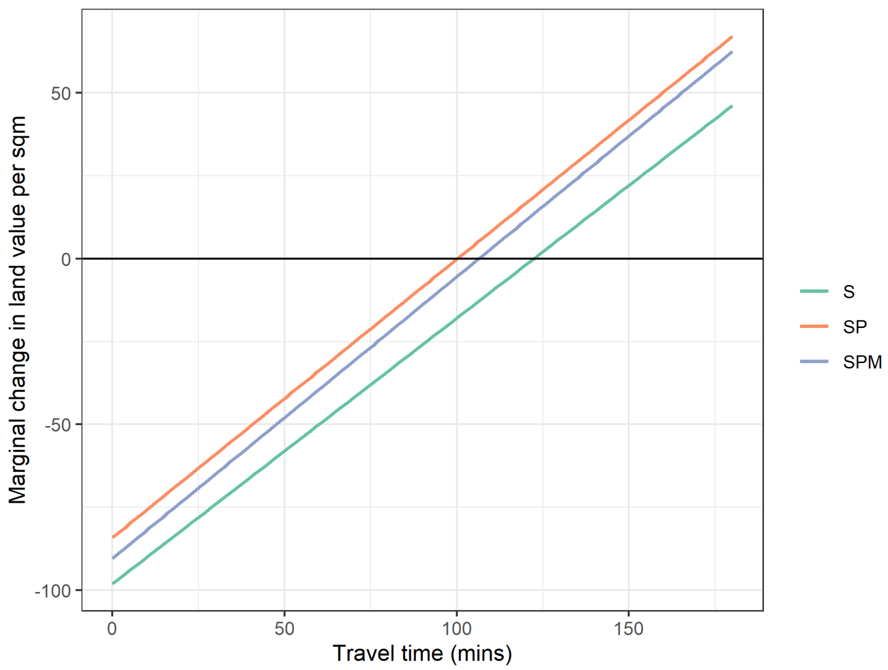


Figure D.3: Marginal effect of Sydney transit time on land values per m^2



D.3 Log-level spatial autoregressive models

Table D.3: SARM regression results ($lsqmvalue$)

	Distance			Travel time		
	S	S+P	S+P+M	S	S+P	S+P+M
Syd. distance	0.10296	-0.7164^{***}	-2.1967^{***}			
	(0.14553)	(0.16694)	(0.19012)			
Syd. distance^2	0.0058^{***}	-0.0075^{*}	0.0477^{***}			
	(0.00145)	(0.00396)	(0.00553)			
Par. distance		2.3295^{***}	1.5395^{***}			
		(0.12051)	(0.16257)			
Par. distance^2		-0.00317	-0.0088^{**}			
		(0.00361)	(0.00369)			
Mac. distance			2.3127^{***}			
			(0.17976)			
Mac. distance^2			-0.0525^{***}			
			(0.00353)			
Syd. drive time				-1.8750^{***}	-1.5975^{***}	-1.7129^{***}
				(0.13026)	(0.13440)	(0.14807)
Syd. drive time^2				0.0166^{***}	0.0118^{***}	0.0157^{***}
				(0.00117)	(0.00128)	(0.00138)
Syd. transit time				-0.2687^{***}	-0.3540^{***}	-0.6391^{***}
				(0.08359)	(0.09373)	(0.09600)
Syd. transit time^2				0.0010^{***}	0.0022^{***}	0.0030^{***}
				(0.00038)	(0.00045)	(0.00045)
Par. drive time					0.4278^{**}	-0.3574^{*}
					(0.17822)	(0.21051)
Par. drive time^2					0.0055^{***}	0.0144^{***}
					(0.00194)	(0.00224)
Par. transit time					-0.11736	0.13662
					(0.08737)	(0.09724)
Par. transit time^2					-0.0013^{***}	-0.0025^{***}
					(0.00042)	(0.00049)
Mac. drive time						1.3916^{***}
						(0.18314)
Mac. drive time^2						-0.0226^{***}
						(0.00197)
Mac. transit time						0.1097^{***}
						(0.03708)
Mac. transit time^2						0.0002^{**}
						(0.00011)
Coast distance	0.08060	2.2763^{***}	1.7074^{***}	0.6557^{***}	1.6674^{***}	1.5625^{***}
	(0.10690)	(0.23591)	(0.23463)	(0.12103)	(0.18488)	(0.19521)
Coast distance^2	-0.0037^{**}	-0.0222^{***}	-0.0284^{***}	-0.0115^{***}	-0.0224^{***}	-0.0201^{***}
	(0.00172)	(0.00208)	(0.00212)	(0.00172)	(0.00212)	(0.00221)
ρ	0.7360^{***}	0.7245^{***}	0.7368^{***}	0.6319^{***}	0.7013^{***}	0.6822^{***}
	(0.01935)	(0.02075)	(0.01997)	(0.02031)	(0.01905)	(0.02033)
Neighbourhood controls	Yes	Yes	Yes	Yes	Yes	Yes
Zoning controls	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	8073	8073	8073	8073	8073	8073
Parameters	19	21	23	21	25	29
Log Likelihood	-3635.86441	-3451.54166	-3339.16507	-3480.31021	-3383.25030	-3285.29233
AIC (Linear model)	7985.79392	7574.62365	7377.23656	7766.01901	7696.05379	7377.83767
AIC (Spatial model)	7309.72882	6945.08332	6724.33013	7002.62041	6816.50060	6628.58466
LR test: statistic	678.06510	631.54033	654.90643	765.39860	881.55319	751.25301
LR test: p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

	Distance			Travel time		
	S	S+P	S+P+M	S	S+P	S+P+M

Notes: Standard errors in parenthesis. Coefficients transformed to percentages. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table D.4: SARM total impact distance estimates (% points) ($lsqmvalue$)

	S		S+P		S+P+M	
Variable	Direct	Total	Direct	Total	Direct	Total
PropertyTypeOther	47.62	179.15	49.35	177.91	48.25	182.06
PropertyTypeUnit	76.52	287.86	73.92	266.50	73.56	277.55
Bedrooms	−2.94	−11.05	−3.26	−11.75	−3.02	−11.37
Baths	7.30	27.48	8.43	30.39	8.73	32.93
Parking	−8.27	−31.09	−8.11	−29.22	−7.87	−29.69
dist_syd	0.10	0.39	−0.72	−2.60	−2.21	−8.35
dist_syd^2	0.01	0.02	−0.01	−0.03	0.05	0.18
coast_dist	0.08	0.31	2.29	8.26	1.72	6.49
coast_dist^2	−0.00	−0.01	−0.02	−0.08	−0.03	−0.11
dist_par			2.35	8.46	1.55	5.85
dist_par^2			−0.00	−0.01	−0.01	−0.03
dist_mac					2.33	8.79
dist_mac^2					−0.05	−0.20

Table D.5: SARM total impact travel time estimates (% points) ($lsqmvalue$)

	S		S+P		S+P+M	
Variable	Direct	Total	Direct	Total	Direct	Total
PropertyTypeOther	48.71	131.69	48.64	161.83	48.80	152.70
PropertyTypeUnit	75.60	204.41	74.57	248.09	73.52	230.04
Bedrooms	−3.10	−8.39	−3.58	−11.91	−3.76	−11.76
Baths	8.32	22.49	8.98	29.87	9.35	29.25
Parking	−8.16	−22.06	−7.93	−26.37	−7.69	−24.07
time_traffic_syd	−1.88	−5.09	−1.61	−5.35	−1.72	−5.39
time_traffic_syd^2	0.02	0.05	0.01	0.04	0.02	0.05
time_transit_syd	−0.27	−0.73	−0.36	−1.19	−0.64	−2.01
time_transit_syd^2	0.00	0.00	0.00	0.01	0.00	0.01
coast_dist	0.66	1.78	1.68	5.58	1.57	4.92
coast_dist^2	−0.01	−0.03	−0.02	−0.08	−0.02	−0.06
time_traffic_par			0.43	1.43	−0.36	−1.13
time_traffic_par^2			0.01	0.02	0.02	0.05
time_transit_par			−0.12	−0.39	0.14	0.43
time_transit_par^2			−0.00	−0.01	−0.00	−0.01
time_traffic_mac					1.40	4.38
time_traffic_mac^2					−0.02	−0.07
time_transit_mac					0.11	0.35
time_transit_mac^2					0.00	0.00

D.4 Level-level spatial autoregressive models

Table D.6: SARM regression results ($sqmvalue$)

	Distance			Travel time		
	S	S+P	S+P+M	S	S+P	S+P+M
Syd. distance	-99.80^{***}	-267.38^{***}	-421.46^{***}			
	(10.436)	(14.224)	(14.700)			

	Distance			Travel time		
	S	S+P	S+P+M	S	S+P	S+P+M
Syd. distance^2	1.45***	2.10***	7.08***			
	(0.104)	(0.246)	(0.300)			
Par. distance		205.92***	138.99***			
		(8.740)	(9.014)			
Par. distance^2		−1.33***	−1.79***			
		(0.205)	(0.197)			
Mac. distance			207.42***			
			(9.854)			
Mac. distance^2			−4.69***			
			(0.192)			
Syd. drive time				−201.85***	−200.87***	−188.67***
				(7.341)	(7.571)	(8.282)
Syd. drive time^2				1.58***	1.56***	1.60***
				(0.063)	(0.069)	(0.074)
Syd. transit time				−76.61***	−64.66***	−87.83***
				(4.610)	(5.120)	(5.108)
Syd. transit time^2				0.31***	0.33***	0.40***
				(0.021)	(0.024)	(0.024)
Par. drive time					114.23***	61.47***
					(9.670)	(9.734)
Par. drive time^2					−0.84***	−0.24**
					(0.103)	(0.102)
Par. transit time					−32.77***	−16.66***
					(4.870)	(4.643)
Par. transit time^2					0.04**	−0.08***
					(0.024)	(0.024)
Mac. drive time						31.29***
						(10.867)
Mac. drive time^2						−1.00***
						(0.118)
Mac. transit time						15.23***
						(4.176)
Mac. transit time^2						0.04**
						(0.020)
Coast distance	29.71***	154.94***	107.38***	34.94***	23.74**	−25.47***
	(6.968)	(13.246)	(12.778)	(6.792)	(9.902)	(7.085)
Coast distance^2	−0.37***	−1.79***	−2.33***	−0.40***	−0.46***	0.084
	(0.112)	(0.142)	(0.114)	(0.099)	(0.117)	(0.079)
ρ	0.66***	0.30***	0.25***	0.29***	0.31***	0.17***
	(0.026)	(0.039)	(0.037)	(0.029)	(0.030)	(0.028)
Neighbourhood controls	Yes	Yes	Yes	Yes	Yes	Yes
Zoning controls	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	8073	8073	8073	8073	8073	8073
Parameters	19	21	23	21	25	29
Log Likelihood	−73430.914	−73042.461	−72746.352	−72703.396	−72579.541	−72429.156
AIC (Linear model)	147275.067	146178.635	145574.417	145554.367	145317.087	144943.411
AIC (Spatial model)	146899.828	146126.921	145538.705	145448.793	145209.083	144916.312
LR test: statistic	377.238	53.714	37.712	107.574	110.004	29.099
LR test: p-value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table D.7: SARM total impact distance estimates ($sqmvalue$)

	S		S+P		S+P+M	
Variable	Direct	Total	Direct	Total	Direct	Total
PropertyTypeOther	1,128.975	3,371.924	1,340.317	1,929.789	1,267.754	1,696.568
PropertyTypeUnit	2,875.268	8,587.599	2,787.504	4,013.448	2,783.012	3,724.358
Bedrooms	−171.832	−513.212	−171.721	−247.243	−148.495	−198.723
Baths	129.906	387.993	185.339	266.851	209.350	280.162
Parking	−240.020	−716.871	−243.546	−350.658	−223.922	−299.664
dist_syd	−100.360	−299.748	−267.636	−385.343	−421.734	−564.384
dist_syd^2	1.463	4.369	2.110	3.038	7.094	9.493
coast_dist	29.876	89.232	155.093	223.303	107.453	143.798
coast_dist^2	−0.376	−1.123	−1.794	−2.583	−2.338	−3.129
dist_par			206.121	296.773	139.080	186.123
dist_par^2			−1.339	−1.928	−1.793	−2.400
dist_mac					207.554	277.758
dist_mac^2					−4.698	−6.287

Table D.8: SARM total impact travel time estimates ($sqmvalue$)

	S		S+P		S+P+M	
Variable	Direct	Total	Direct	Total	Direct	Total
PropertyTypeOther	1,182.401	1,686.071	1,158.167	1,684.955	1,124.854	1,362.133
PropertyTypeUnit	2,821.740	4,023.724	2,765.868	4,023.912	2,720.434	3,294.290
Bedrooms	−205.533	−293.085	−224.112	−326.049	−253.141	−306.539
Baths	210.426	300.062	252.557	367.432	276.889	335.297
Parking	−232.837	−332.019	−235.269	−342.280	−224.064	−271.328
time_traffic_syd	−202.033	−288.094	−201.077	−292.536	−188.731	−228.542
time_traffic_syd^2	1.585	2.261	1.562	2.272	1.605	1.944
time_transit_syd	−76.682	−109.347	−64.733	−94.176	−87.865	−106.399
time_transit_syd^2	0.311	0.444	0.338	0.492	0.409	0.495
coast_dist	34.971	49.868	23.769	34.580	−25.482	−30.857
coast_dist^2	−0.404	−0.576	−0.460	−0.670	0.084	0.102
time_traffic_par			114.349	166.360	61.490	74.460
time_traffic_par^2			−0.850	−1.236	−0.242	−0.293
time_transit_par			−32.810	−47.734	−16.667	−20.182
time_transit_par^2			0.048	0.069	−0.084	−0.101
time_traffic_mac					31.299	37.901
time_traffic_mac^2					−1.001	−1.212
time_transit_mac					15.244	18.459
time_transit_mac^2					0.046	0.055

D.5 Sales price dependent variable regressions

I also conduct robustness tests by specifying the dependent variable as sales price instead of sales price per square metre. I add a level and squared area variable to control for variation in land sizes to the regression.

Table D.9: Linear regression results (Sales pric

	S	S+P	S+P+M	S
AreaSize	288.97***	317.76***	305.16***	
	(23.248)	(23.360)	(23.853)	
AreaSize^2	−0.03***	−0.03***	−0.03***	
	(0.004)	(0.004)	(0.004)	
PropertyTypeOther	−98157.43*	−77732.368	−73809.220	
	(51804.200)	(51601.564)	(51630.973)	
PropertyTypeUnit	−266600.17***	−270772.03***	−271739.99***	−
	(21458.344)	(21395.750)	(21427.212)	
Bedrooms	127896.54***	124096.49***	124438.02***	
	(8811.900)	(8790.925)	(8793.211)	
Baths	294350.81***	301104.79***	300246.01***	
	(10415.080)	(10388.597)	(10390.650)	
Parking	53009.23***	53041.86***	53004.99***	
	(6382.077)	(6356.095)	(6354.973)	
dist_syd	−25218.44***	−29975.80***	−27833.32***	
	(1635.065)	(1707.606)	(2187.317)	
dist_syd^2	115.76***	−64.689	−106.686	
	(19.486)	(50.383)	(71.873)	
coast_dist	−17213.05***	846.834	1772.379	
	(1459.567)	(3028.203)	(3059.468)	
coast_dist^2	249.99***	133.79***	134.66***	
	(23.656)	(26.744)	(27.706)	
dist_par		13692.01***	17434.85***	
		(1556.864)	(2125.781)	
dist_par^2		80.07*	60.614	
		(45.365)	(47.397)	
dist_mac			−6053.85**	
			(2392.885)	
dist_mac^2			64.694	
			(46.506)	
time_traffic_syd				
time_traffic_syd^2				
time_transit_syd				
time_transit_syd^2				
time_traffic_par				
time_traffic_par^2				
time_transit_par				
time_transit_par^2				
time_traffic_mac				

	S	S+P	S+P+M	S
time_traffic_mac^2				
time_transit_mac				
time_transit_mac^2				
Neighbourhood controls	Yes	Yes	Yes	Yes
Zoning controls	Yes	Yes	Yes	Yes
R^2	0.669	0.672	0.673	0.6
Adj. R^2	0.668	0.672	0.672	0.6
Num. obs.	8073	8073	8073	8073

Notes: Standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

D.6 Log-log comparison models estimated by OLS

Table D.10: Log-level and Log-log model comparisons ($lsqmvalue$)

	S	S+P	S+P+M	S	S+P	S+P+M
(Intercept)	8.4823^{***}	8.3174^{***}	8.1750^{***}	9.9650^{***}	10.0054^{***}	9.7126^{***}
	(0.09566)	(0.09777)	(0.09949)	(0.10857)	(0.11475)	(0.12068)
PropertyTypeOther	0.5277^{***}	0.5213^{***}	0.5120^{***}	0.5250^{***}	0.5244^{***}	0.5129^{***}
	(0.04208)	(0.04190)	(0.04112)	(0.04199)	(0.04196)	(0.04180)
PropertyTypeUnit	0.8032^{***}	0.8003^{***}	0.7760^{***}	0.8032^{***}	0.7987^{***}	0.7922^{***}
	(0.01624)	(0.01620)	(0.01597)	(0.01617)	(0.01620)	(0.01615)
Bedrooms	-0.0345^{***}	-0.0351^{***}	-0.0370^{***}	-0.0323^{***}	-0.0326^{***}	-0.0323^{***}
	(0.00721)	(0.00720)	(0.00707)	(0.00720)	(0.00720)	(0.00718)
Baths	0.0847^{***}	0.0888^{***}	0.0953^{***}	0.0839^{***}	0.0839^{***}	0.0863^{***}
	(0.00852)	(0.00850)	(0.00834)	(0.00850)	(0.00851)	(0.00847)
Parking	-0.0893^{***}	-0.0881^{***}	-0.0839^{***}	-0.0903^{***}	-0.0902^{***}	-0.0879^{***}
	(0.00503)	(0.00502)	(0.00494)	(0.00501)	(0.00501)	(0.00500)
SEIFA_disadv	0.0008^{***}	0.0008^{***}	0.0007^{***}	0.0008^{***}	0.0008^{***}	0.0008^{***}
	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)
FracAustAncestry	-1.5589^{***}	-1.4469^{***}	-1.1105^{***}	-1.5887^{***}	-1.5773^{***}	-1.5520^{***}
	(0.15375)	(0.15405)	(0.15275)	(0.15255)	(0.15259)	(0.15196)
FracBachAbove	-1.7822^{***}	-1.6402^{***}	-1.1166^{***}	-1.6582^{***}	-1.6403^{***}	-1.3619^{***}
	(0.12685)	(0.12964)	(0.13167)	(0.12634)	(0.12631)	(0.13019)
FracUnemp	3.3414^{***}	3.4536^{***}	3.6551^{***}	2.9052^{***}	2.7815^{***}	3.0717^{***}
	(0.33514)	(0.33499)	(0.33265)	(0.33165)	(0.33508)	(0.33598)
FracHighInc	2.9985^{***}	3.0503^{***}	3.0147^{***}	2.8115^{***}	2.8429^{***}	2.9240^{***}
	(0.17896)	(0.18383)	(0.18374)	(0.18005)	(0.18129)	(0.18339)
FracEngSpoken	-0.1261^{**}	-0.1187^{**}	-0.1545^{**}	-0.1472^{**}	-0.1314^{**}	-0.1279^{**}
	(0.05923)	(0.06026)	(0.06006)	(0.05866)	(0.05973)	(0.05948)
FracOccProf	1.8655^{***}	1.7495^{***}	1.2797^{***}	1.8423^{***}	1.7352^{***}	1.5561^{***}
	(0.18751)	(0.19106)	(0.18948)	(0.18699)	(0.18974)	(0.19007)
time_traffic_syd	-0.0204^{***}	-0.0197^{***}	-0.0197^{***}			
	(0.00137)	(0.00142)	(0.00158)			
time_traffic_syd^2	0.0001^{***}	0.0001^{***}	0.0001^{***}			
	(0.00001)	(0.00001)	(0.00001)			
time_transit_syd	-0.0065^{***}	-0.0065^{***}	-0.0090^{***}			
	(0.00088)	(0.00100)	(0.00101)			
time_transit_syd^2	0.0000^{**}	0.0000^{***}	0.0000^{***}			

	S	S+P	S+P+M	S	S+P	S+P+M
	(0.00000)	(0.00000)	(0.00000)			
coast_dist	-0.0129^{***}	-0.0170^{***}	-0.0186^{***}	-0.0132^{***}	-0.0144^{***}	-0.0122^{***}
	(0.00109)	(0.00171)	(0.00186)	(0.00093)	(0.00113)	(0.00118)
coast_dist^2	0.0000^{***}	0.0000^{***}	0.0000^{***}	0.0000^{***}	0.0000^{***}	0.0000^{*}
	(0.00002)	(0.00002)	(0.00002)	(0.00001)	(0.00002)	(0.00002)
time_traffic_par		0.0066^{***}	-0.0092^{***}			
		(0.00192)	(0.00213)			
time_traffic_par^2		-0.0000^{***}	0.0001^{***}			
		(0.00002)	(0.00002)			
time_transit_par		-0.00027	0.0041^{***}			
		(0.00095)	(0.00098)			
time_transit_par^2		-0.0000^{***}	-0.0000^{***}			
		(0.00000)	(0.00001)			
time_traffic_mac			0.0208^{***}			
			(0.00224)			
time_traffic_mac^2			-0.0003^{***}			
			(0.00002)			
time_transit_mac			-0.00086			
			(0.00083)			
time_transit_mac^2			0.0000^{***}			
			(0.00000)			
log_traffic_syd				-0.3519^{***}	-0.3703^{***}	-0.4147^{***}
				(0.02020)	(0.02117)	(0.02457)
log_transit_syd				-0.2959^{***}	-0.2632^{***}	-0.2669^{***}
				(0.02090)	(0.02248)	(0.02310)
log_traffic_par					0.0559^{**}	-0.01554
					(0.02738)	(0.02858)
log_transit_par					-0.0847^{***}	-0.0528^{**}
					(0.02281)	(0.02310)
log_traffic_mac						0.0894^{***}
						(0.02887)
log_transit_mac						0.0467^{*}
						(0.02401)
R^2	0.85726	0.85863	0.86423	0.85762	0.85791	0.85920
Adj. R^2	0.85694	0.85824	0.86379	0.85734	0.85759	0.85885
Num. obs.	8073	8073	8073	8073	8073	8073
RMSE	0.39092	0.38913	0.38145	0.39037	0.39003	0.38830

Notes: Standard errors in parenthesis. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

APPENDIX E

Part 1: Valuations data robustness tests

E.1 Log-level linear regression model results

Results from the linear model in table E.1 show that increasing distance and travel time from the CBD decreases land values. This is a non-linear relationship as predicted by the AMM model, with the effect diminishing as accessibility worsens.

Table E.1: Linear regression results ($lsqmvalue$)

	Distance (% change)			Travel time (% change)		
	S	S+P	S+P+M	S	S+P	S+P+M
Syd. distance	-4.9557^{***}	-6.1374^{***}	-7.8701^{***}			
	(0.09935)	(0.11330)	(0.14498)			
Syd. distance^2	0.0319^{***}	0.0143^{***}	0.0509^{***}			
	(0.00112)	(0.00315)	(0.00421)			
Par. distance		2.0197^{***}	-0.7295^{***}			
		(0.09636)	(0.12763)			
Par. distance^2		0.0082^{***}	0.0220^{***}			
		(0.00270)	(0.00265)			
Mac. distance			4.7138^{***}			
			(0.14644)			
Mac. distance^2			-0.0549^{***}			
			(0.00288)			
Syd. drive time				-1.3767^{***}	-1.4978^{***}	-1.4665^{***}
				(0.10925)	(0.10775)	(0.10853)
Syd. drive time^2				0.0059^{***}	0.0084^{***}	0.0073^{***}
				(0.00087)	(0.00087)	(0.00087)
Syd. transit time				-1.1098^{***}	-0.8395^{***}	-1.0321^{***}
				(0.06131)	(0.06913)	(0.06728)
Syd. transit time^2				0.0026^{***}	0.0032^{***}	0.0033^{***}
				(0.00027)	(0.00033)	(0.00032)
Par. drive time					1.7867^{***}	0.2240^{*}
					(0.13014)	(0.13352)
Par. drive time^2					-0.0193^{***}	-0.0069^{***}
					(0.00123)	(0.00123)
Par. transit time					-0.6105^{***}	-0.4377^{***}
					(0.07200)	(0.06881)
Par. transit time^2					0.0013^{***}	0.00042
					(0.00036)	(0.00034)
Mac. drive time						0.6749^{***}
						(0.12446)
Mac. drive time^2						-0.0097^{***}
						(0.00111)

	Distance (% change)			Travel time (% change)		
	S	S+P	S+P+M	S	S+P	S+P+M
Mac. transit time						0.8187***
						(0.05925)
Mac. transit time^2						−0.0011***
						(0.00028)
Coast distance	−1.4933***	1.3209***	0.7556***	−2.3911***	−3.6984***	−3.4340***
	(0.08891)	(0.18735)	(0.17873)	(0.09099)	(0.11946)	(0.12055)
Coast distance^2	0.0251***	−0.00042	−0.0048**	0.0277***	0.0377***	0.0314***
	(0.00169)	(0.00205)	(0.00206)	(0.00174)	(0.00191)	(0.00190)
Neighbourhood controls	Yes	Yes	Yes	Yes	Yes	Yes
Zoning controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.81461	0.82281	0.84082	0.79297	0.80144	0.82298
Adj. R^2	0.81433	0.82251	0.84052	0.79262	0.80103	0.82254
Num. obs.	10000	10000	10000	10000	10000	10000

Notes: Standard errors in parenthesis. Coefficients transformed to percentages. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

E.2 Level-level spatial error model

As a robustness check, I also estimate the models with a level-level specification using land values per square metre for each property ($sqmvalue$) as the dependent variable under three specifications: Sydney only (S), Sydney and Parramatta (S+P), and Sydney, Parramatta and Macquarie Park (S+P+M).

Table E.2: SEM regression results ($sqmvalue$)

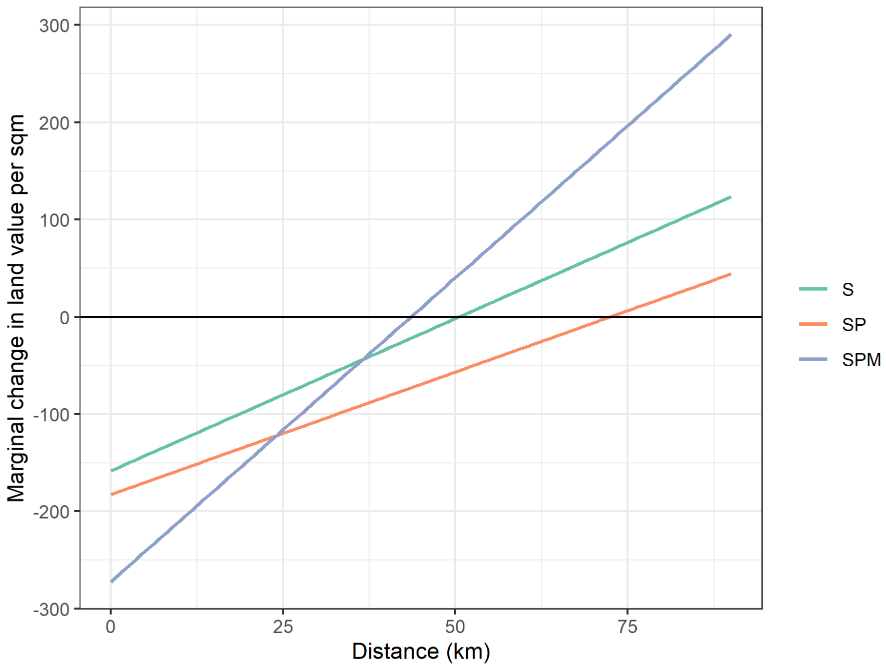
	Distance			Travel time		
	S	S+P	S+P+M	S	S+P	S+P+M
Syd. distance	−158.26***	−182.67***	−272.30***			
	(4.679)	(5.098)	(5.290)			
Syd. distance^2	1.56***	1.26***	3.12***			
	(0.067)	(0.129)	(0.143)			
Par. distance		57.91***	−21.91***			
		(4.225)	(4.453)			
Par. distance^2		−0.108	0.62***			
		(0.117)	(0.113)			
Mac. distance			190.34***			
			(5.181)			
Mac. distance^2			−3.04***			
			(0.148)			
Syd. drive time				−41.64***	−39.86***	−45.72***
				(2.647)	(2.642)	(2.653)
Syd. drive time^2				0.29***	0.28***	0.31***
				(0.022)	(0.021)	(0.021)
Syd. transit time				−20.25***	−14.77***	−24.30***
				(1.569)	(1.666)	(1.685)
Syd. transit time^2				0.07***	0.07***	0.10***
				(0.007)	(0.008)	(0.008)
Par. drive time					16.69***	5.63*

	Distance			Travel time		
	S	S+P	S+P+M	S	S+P	S+P+M
					(3.331)	(3.341)
Par. drive time^2					-0.14^{***}	-0.07^{**}
					(0.031)	(0.031)
Par. transit time					-14.78^{***}	-13.48^{***}
					(1.698)	(1.665)
Par. transit time^2					0.02^{**}	0.02^{**}
					(0.009)	(0.009)
Mac. drive time						10.44^{***}
						(2.833)
Mac. drive time^2						-0.15^{***}
						(0.026)
Mac. transit time						23.06^{***}
						(1.513)
Mac. transit time^2						-0.08^{***}
						(0.008)
Coast distance	-41.40^{***}	26.29^{***}	41.57^{***}	-62.21^{***}	-85.28^{***}	-65.72^{***}
	(4.606)	(7.359)	(6.746)	(4.606)	(5.153)	(5.004)
Coast distance^2	1.04^{***}	0.19^{*}	-0.49^{***}	0.96^{***}	1.24^{***}	0.89^{***}
	(0.098)	(0.112)	(0.103)	(0.096)	(0.101)	(0.097)
λ	0.92^{***}	0.91^{***}	0.88^{***}	0.91^{***}	0.91^{***}	0.88^{***}
	(0.006)	(0.007)	(0.009)	(0.006)	(0.007)	(0.008)
Neighbourhood controls	Yes	Yes	Yes	Yes	Yes	Yes
Zoning controls	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	10000	10000	10000	10000	10000	10000
Parameters	18	20	22	20	24	28
Log Likelihood	−79216.546	−79119.235	−78482.250	−79487.190	−79363.133	−79118.393
AIC (Linear model)	161967.909	160818.565	158574.348	161820.662	161254.360	159831.754
AIC (Spatial model)	158469.092	158278.469	157008.500	159014.380	158774.266	158292.786
LR test: statistic	3500.817	2542.096	1567.848	2808.282	2482.094	1540.968
LR test: p-value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

E.2.1 Distance specifications

Figure E.1: Marginal effect of Sydney distance on land values per m^2



E.2.2 Travel time specifications

Figure E.2: Marginal effect of Sydney drive time on land values per m^2

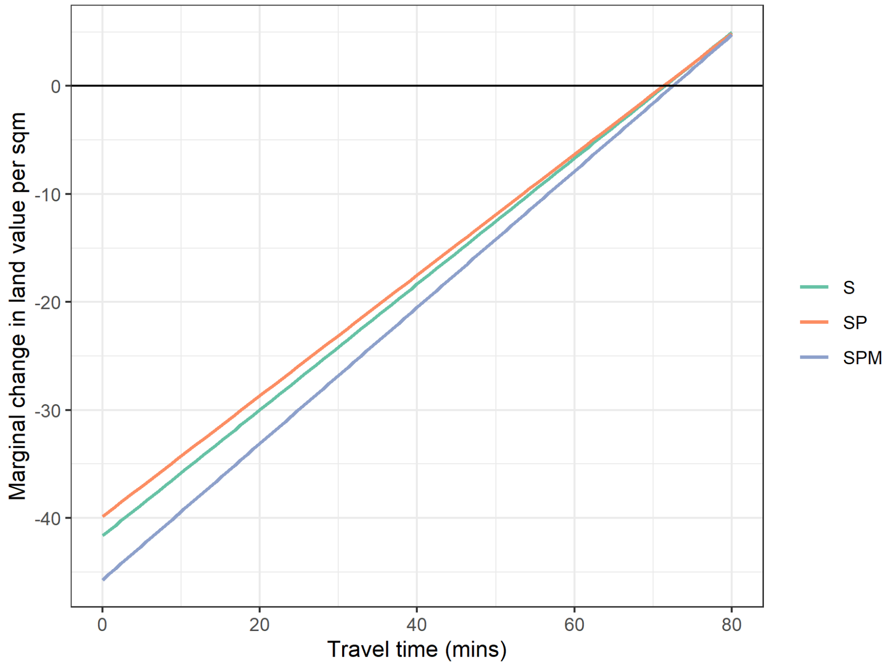
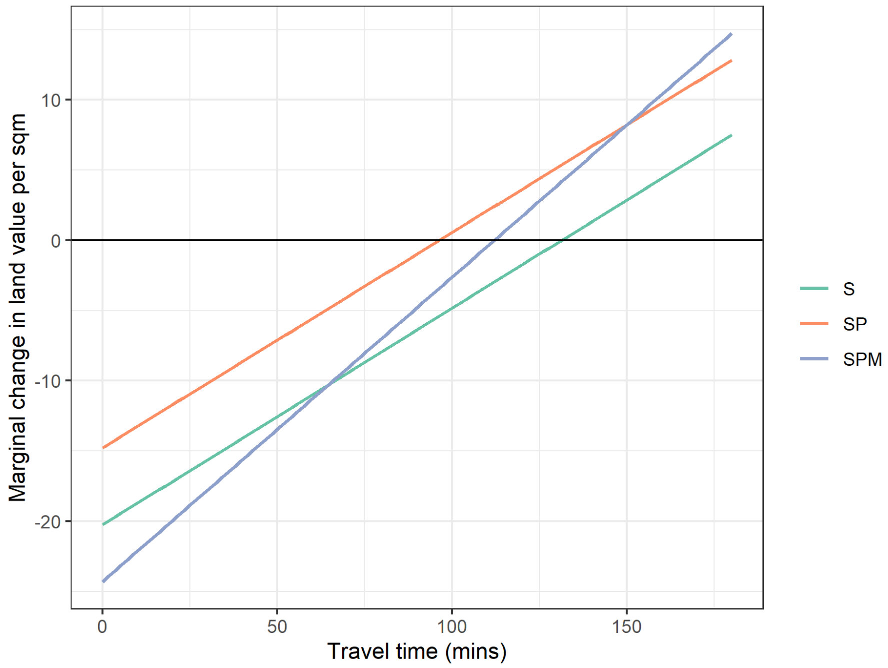


Figure E.3: Marginal effect of Sydney transit time on land values per m^2



E.3 Log-level spatial autoregressive models

Table E.3: SARM regression results ($lsqmvalue$)

	Distance (% change)			Travel time (% change)		
	S	S+P	S+P+M	S	S+P	S+P+M
Syd. distance	-1.1167^{***}	-1.8044^{***}	-3.6432^{***}			
	(0.10379)	(0.12323)	(0.16159)			
Syd. distance^2	0.0121^{***}	0.0089^{***}	0.0466^{***}			
	(0.00106)	(0.00198)	(0.00402)			
Par. distance		0.9974^{***}	-0.9915^{***}			
		(0.08939)	(0.12200)			
Par. distance^2		-0.00055	0.0090^{***}			
		(0.00152)	(0.00255)			
Mac. distance			3.8260^{***}			
			(0.14016)			
Mac. distance^2			-0.0506^{***}			
			(0.00274)			
Syd. drive time				-0.8617^{***}	-0.8994^{***}	-1.1097^{***}
				(0.09310)	(0.09191)	(0.09836)
Syd. drive time^2				0.0066^{***}	0.0072^{***}	0.0080^{***}
				(0.00074)	(0.00074)	(0.00079)
Syd. transit time				-0.4658^{***}	-0.3776^{***}	-0.5094^{***}
				(0.05279)	(0.05891)	(0.05353)
Syd. transit time^2				0.0021^{***}	0.0023^{***}	0.0025^{***}
				(0.00023)	(0.00028)	(0.00024)
Par. drive time					0.5127^{***}	-0.4082^{***}
					(0.11479)	(0.08924)
Par. drive time^2					-0.0035^{***}	0.0029^{***}
					(0.00109)	(0.00084)
Par. transit time					-0.3446^{***}	-0.2525^{***}
					(0.06229)	(0.01277)
Par. transit time^2					0.00037	0.00006
					(0.00031)	
Mac. drive time						0.5633^{***}
						(0.11277)
Mac. drive time^2						-0.0054^{***}
						(0.00101)
Mac. transit time						0.5507^{***}
						(0.05373)
Mac. transit time^2						-0.0014^{***}
						(0.00026)
Coast distance	-0.4414^{***}	0.7033^{***}	0.3271^{*}	-0.2664^{***}	-0.6499^{***}	-0.3864^{***}
	(0.08268)	(0.14286)	(0.17116)	(0.07832)	(0.10791)	(0.11938)
Coast distance^2	0.0083^{***}	-0.0037^{*}	-0.0092^{***}	0.0060^{***}	0.0087^{***}	0.0031^{*}
	(0.00157)	(0.00190)	(0.00197)	(0.00145)	(0.00170)	(0.00181)
ρ	0.8399^{***}	0.8197^{***}	0.7784^{***}	0.8667^{***}	0.8618^{***}	0.8273^{***}
	(0.01098)	(0.01248)	(0.01539)	(0.00872)	(0.00915)	(0.01126)
Neighbourhood controls	Yes	Yes	Yes	Yes	Yes	Yes
Zoning controls	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	10000	10000	10000	10000	10000	10000
Parameters	18	20	22	20	24	28
Log Likelihood	−1722.71156	−1662.68535	−1291.31876	−1646.24864	−1586.36892	−1344.71440
AIC (Linear model)	5090.28271	4641.75601	3573.88262	6198.07007	5788.20127	4648.04811
AIC (Spatial model)	3481.42313	3365.37070	2626.63751	3332.49729	3220.73784	2745.42879
LR test: statistic	1610.85959	1278.38531	949.24510	2867.57279	2569.46343	1904.61932
LR test: p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

	Distance (% change)			Travel time (% change)		
	S	S+P	S+P+M	S	S+P	S+P+M

Notes: Standard errors in parenthesis. Coefficients transformed to percentages. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table E.4: SARM total impact distance estimates (% points) ($lsqmvalue$)

	S		S+P		S+P+M	
Variable	Direct	Total	Direct	Total	Direct	Total
Syd_dist	−1.12	−6.98	−1.81	−10.01	−3.66	−16.44
Syd_dist^2	0.01	0.08	0.01	0.05	0.05	0.21
coast_dist	−0.44	−2.76	0.71	3.90	0.33	1.48
coast_dist^2	0.01	0.05	−0.00	−0.02	−0.01	−0.04
Par_dist			1.00	5.53	−1.00	−4.48
Par_dist^2			−0.00	−0.00	0.01	0.04
MP_dist					3.84	17.27
MP_dist^2					−0.05	−0.23

Table E.5: SARM total impact travel time estimates (% points) ($lsqmvalue$)

	S		S+P		S+P+M	
Variable	Direct	Total	Direct	Total	Direct	Total
S_time_traffic	−0.87	−6.47	−0.91	−6.51	−1.12	−6.43
S_time_traffic^2	0.01	0.05	0.01	0.05	0.01	0.05
S_transit_time	−0.47	−3.50	−0.38	−2.73	−0.51	−2.95
S_transit_time^2	0.00	0.02	0.00	0.02	0.00	0.02
coast_dist	−0.27	−2.00	−0.65	−4.70	−0.39	−2.24
coast_dist^2	0.01	0.05	0.01	0.06	0.00	0.02
P_time_traffic			0.52	3.71	−0.41	−2.37
P_time_traffic^2			−0.00	−0.03	0.00	0.02
P_transit_time			−0.35	−2.49	−0.25	−1.46
P_transit_time^2			0.00	0.00	0.00	0.00
M_time_traffic					0.57	3.26
M_time_traffic^2					−0.01	−0.03
M_transit_time					0.55	3.19
M_transit_time^2					−0.00	−0.01

E.4 Level-level spatial autoregressive models

Table E.6: SARM regression results ($sqmvalue$)

	Distance			Travel time		
	S	S+P	S+P+M	S	S+P	S+P+M
Syd. distance	-27.02^{***}	-50.10^{***}	-120.87^{***}			
	(2.145)	(2.687)	(3.566)			
Syd. distance^2	0.34^{***}	0.237	1.88^{***}			
	(0.023)		(0.091)			
Par. distance		34.98^{***}	-24.94^{***}			
		(2.176)	(2.774)			
Par. distance^2		−0.028	0.20^{***}			
			(0.057)			
Mac. distance			132.30^{***}			
			(3.209)			

	Distance			Travel time		
	S	S+P	S+P+M	S	S+P	S+P+M
Mac. distance^2			-2.01^{***}			
			(0.063)			
Syd. drive time				-32.37^{***}	-33.40^{***}	-41.71^{***}
				(2.227)	(2.233)	(2.292)
Syd. drive time^2				0.26^{***}	0.27^{***}	0.32^{***}
				(0.018)	(0.018)	(0.018)
Syd. transit time				-13.75^{***}	-10.54^{***}	-15.73^{***}
				(1.247)	(1.718)	(1.397)
Syd. transit time^2				0.05^{***}	0.06^{***}	0.08^{***}
				(0.005)	(0.008)	(0.007)
Par. drive time					30.81^{***}	5.69^{***}
					(2.708)	(2.200)
Par. drive time^2					-0.20^{***}	-0.027
					(0.027)	(0.020)
Par. transit time					-16.18^{***}	-13.03^{***}
					(1.614)	(1.320)
Par. transit time^2					0.02^{***}	0.02^{***}
					(0.008)	(0.007)
Mac. drive time						11.10^{***}
						(2.605)
Mac. drive time^2						-0.10^{***}
						(0.023)
Mac. transit time						20.95^{***}
						(1.233)
Mac. transit time^2						-0.07^{***}
						(0.006)
Coast distance	7.42^{***}	47.40^{***}	37.58^{***}	13.23^{***}	3.834	17.32^{***}
	(0.796)	(2.482)	(3.892)	(1.870)	(5.529)	(2.535)
Coast distance^2	0.012	-0.41^{***}	-0.70^{***}	-0.053	-0.028	-0.25^{***}
	(0.007)	(0.045)	(0.045)	(0.035)	(0.093)	(0.040)
ρ	0.90^{***}	0.88^{***}	0.83^{***}	0.89^{***}	0.89^{***}	0.86^{***}
	(0.007)	(0.009)	(0.011)	(0.007)	(0.008)	(0.009)
Neighbourhood controls	Yes	Yes	Yes	Yes	Yes	Yes
Zoning controls	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	10000	10000	10000	10000	10000	10000
Parameters	18	20	22	20	24	28
Log Likelihood	−79565.339	−79436.630	−78641.974	−79387.909	−79203.800	−78847.964
AIC (Linear model)	161967.909	160818.565	158574.348	161820.662	161254.360	159831.754
AIC (Spatial model)	159166.678	158913.260	157327.948	158815.817	158455.601	157751.929
LR test: statistic	2803.231	1907.305	1248.400	3006.845	2800.760	2081.826
LR test: p-value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

The SAR model incorporates a spatially autocorrelated dependent variable, which addresses spatial non-stationarity in the dependent variable (land values), but not in the unobservables (in constrast with the SEM). In the presence of a spatially autocorrelated dependent variable, the coefficients when estimated by OLS are biased and inconsistent. Using the SAR model addresses this problem, but adds additional difficulties in interpreting the model results, as the coefficients no longer represent the full impact of a change in the covariates due to the presence of indirect spillover effects. The structure of the SAR model is shown in equation E.1.

$$y = \rho \mathbf{W} y + \mathbf{X}\beta + \epsilon \tag{E.1}$$

$$\mathbf{W} y = \sum_{j=1}^{n} w_{ij} y_j, \quad i = 1, \ldots, n \tag{E.2}$$

$$\epsilon \sim N(0, \sigma^2 I_n) \tag{E.3}$$

The total impact tables from the SAR model in table E.7 and E.8 incorporate the direct and indirect effects on the dependent variable. The total effect of a change in an explanatory variable is the sum of the direct effect and indirect effect. The direct effect is the average effect of a change in one observation's explanatory variable (travel time) on that observation's dependent variable (land value). The indirect effect is the average effect on that observation's dependent variable from a change in an explanatory variable in another observation. This indirect effect can be captured courtesy of the spatial weights matrix which allows for spillovers across observations as a function of their distance from each other (Golgher & Voss, 2015). Including the direct and indirect effects is important from a policy perspective, as changes in travel times may be driven by transport infrastructure projects, which would affect the travel times of a number of properties and hence the effects on neighbouring properties must be considered. The total effects of changes in travel time to the Sydney CBD are higher when indirect effects are considered.

Table E.7: SARM total impact distance estimates ($sqmvalue$)

	S		S+P		S+P+M	
Variable	Direct	Total	Direct	Total	Direct	Total
Syd_dist	−27.225	−276.522	−50.442	−416.397	−121.541	−748.158
Syd_dist^2	0.343	3.482	0.239	1.972	1.894	11.659
coast_dist	7.483	76.000	47.720	393.924	37.794	232.643
coast_dist^2	0.012	0.118	−0.416	−3.431	−0.711	−4.378
Par_dist			35.219	290.734	−25.083	−154.403
Par_dist^2			−0.028	−0.233	0.205	1.259
MP_dist					133.033	818.900
MP_dist^2					−2.026	−12.473

Table E.8: SARM total impact travel time estimates ($sqmvalue$)

	S		S+P		S+P+M	
Variable	Direct	Total	Direct	Total	Direct	Total
S_time_traffic	−32.610	−320.484	−33.641	−312.543	−41.973	−313.749
S_time_traffic^2	0.267	2.621	0.279	2.595	0.329	2.457
S_transit_time	−13.861	−136.221	−10.623	−98.692	−15.832	−118.344
S_transit_time^2	0.058	0.573	0.070	0.649	0.085	0.632
coast_dist	13.333	131.029	3.861	35.873	17.431	130.299
coast_dist^2	−0.054	−0.527	−0.028	−0.263	−0.252	−1.881
P_time_traffic			31.036	288.342	5.727	42.813
P_time_traffic^2			−0.202	−1.880	−0.027	−0.203
P_transit_time			−16.298	−151.417	−13.117	−98.051
P_transit_time^2			0.026	0.245	0.022	0.166
M_time_traffic					11.169	83.490
M_time_traffic^2					−0.107	−0.802
M_transit_time					21.083	157.597
M_transit_time^2					−0.077	−0.577

E.5 Land value dependent variable regressions

I also conduct robustness tests by specifying the dependent variable as land values instead of land values per square metre. I add a level and squared area variable to control for variation in land sizes to the regression.

Table E.9: Linear regression results (Land value)

	Distance			Travel time		
	S	S+P	S+P+M	S	S+P	S+P+M
Land size	397.49***	407.22***	412.43***	391.32***	392.25***	401.65***
	(7.732)	(7.716)	(7.888)	(7.862)	(7.892)	(7.886)
Land size^2	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Syd. distance	−25171.07***	−31268.62***	−30881.73***			
	(913.332)	(1060.883)	(1452.440)			
Syd. distance^2	169.32***	31.633	−17.442			
	(10.304)	(29.298)	(41.358)			
Par. distance		10415.32***	4927.15***			
		(898.465)	(1249.240)			
Par. distance^2		85.85***	128.94***			
		(25.139)	(26.006)			
Mac. distance			5617.05***			
			(1465.777)			
Mac. distance^2			5.676			
			(28.690)			
Syd. drive time				−5603.03***	−5948.38***	−3643.01***
				(962.029)	(967.828)	(1017.571)
Syd. drive time^2				16.94**	23.80***	2.573
				(7.648)	(7.822)	(8.182)
Syd. transit time				−3051.59***	−2468.81***	−2722.01***
				(539.217)	(619.895)	(630.271)
Syd. transit time^2				2.189	1.842	−1.176
				(2.370)	(2.928)	(2.972)
Par. drive time					257.941	−5195.61***
					(1168.949)	(1247.920)
Par. drive time^2					−14.604	34.93***
					(11.025)	(11.503)

	Distance			Travel time		
	S	S+P	S+P+M	S	S+P	S+P+M
Par. transit time					-508.928	-94.183
					(645.715)	(643.223)
Par. transit time^2					0.794	-5.067
					(3.230)	(3.206)
Mac. drive time						1877.744
						(1163.070)
Mac. drive time^2						-44.32^{***}
						(10.381)
Mac. transit time						1051.28^{*}
						(558.679)
Mac. transit time^2						11.33^{***}
						(2.667)
Coast distance	-15150.47^{***}	1417.585	229.057	-22229.24^{***}	-25340.60^{***}	-27421.38^{***}
	(813.557)	(1745.094)	(1751.267)	(799.616)	(1071.584)	(1126.748)
Coast distance^2	235.51^{***}	102.66^{***}	121.90^{***}	284.28^{***}	317.37^{***}	333.27^{***}
	(15.497)	(19.002)	(20.236)	(15.313)	(17.163)	(17.760)
Neighbourhood controls	Yes	Yes	Yes	Yes	Yes	Yes
Zoning controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.714	0.719	0.720	0.706	0.707	0.715
Adj. R^2	0.714	0.718	0.719	0.705	0.706	0.715
Num. obs.	10000	10000	10000	10000	10000	10000

Notes: Standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

E.6 Log-log comparison models estimated by OLS

Table E.10: Log-level and Log-log model comparisons ($lsqmvalue$)

	S	S+P	S+P+M	S	S+P	S+P+M
(Intercept)	8.9782^{***}	8.6540^{***}	8.2139^{***}	11.0271^{***}	11.1842^{***}	10.3956^{***}
	(0.03134)	(0.03210)	(0.03190)	(0.03623)	(0.03817)	(0.03905)
zonecodeR2	-0.3271^{***}	-0.3228^{***}	-0.2642^{***}	-0.2939^{***}	-0.3036^{***}	-0.2449^{***}
	(0.00720)	(0.00705)	(0.00675)	(0.00705)	(0.00707)	(0.00685)
zonecodeR3	-0.2061^{***}	-0.2105^{***}	-0.1748^{***}	-0.1800^{***}	-0.1860^{***}	-0.1531^{***}
	(0.00877)	(0.00856)	(0.00813)	(0.00864)	(0.00863)	(0.00829)
zonecodeR4	-0.1683^{***}	-0.1618^{***}	-0.1188^{***}	-0.1378^{***}	-0.1490^{***}	-0.1091^{***}
	(0.01464)	(0.01430)	(0.01356)	(0.01450)	(0.01448)	(0.01390)
zonecodeR5	-1.4194^{***}	-1.4188^{***}	-1.4536^{***}	-1.4210^{***}	-1.4041^{***}	-1.4400^{***}
	(0.03026)	(0.02973)	(0.02839)	(0.03002)	(0.02998)	(0.02873)
SEIFA_disadv	0.0000^{**}	0.0002^{***}	0.0001^{***}	0.0002^{***}	0.0003^{***}	0.0002^{***}
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
FracAustAncestry	-0.0110^{***}	-0.0095^{***}	-0.0078^{***}	-0.0107^{***}	-0.0108^{***}	-0.0097^{***}
	(0.00054)	(0.00053)	(0.00050)	(0.00053)	(0.00053)	(0.00051)
FracBachAbove	-0.0084^{***}	-0.0046^{***}	0.0061^{***}	-0.0078^{***}	-0.0085^{***}	0.0012^{**}
	(0.00053)	(0.00053)	(0.00053)	(0.00052)	(0.00052)	(0.00053)
FracUnemp	-0.0185^{***}	-0.0160^{***}	-0.0139^{***}	-0.0192^{***}	-0.0193^{***}	-0.0185^{***}
	(0.00149)	(0.00146)	(0.00139)	(0.00148)	(0.00148)	(0.00142)
FracHighInc	0.0203^{***}	0.0185^{***}	0.0137^{***}	0.0190^{***}	0.0211^{***}	0.0166^{***}
	(0.00076)	(0.00077)	(0.00075)	(0.00076)	(0.00078)	(0.00076)
FracEngSpoken	-0.0030^{***}	-0.0015^{***}	0.0005^{**}	-0.0035^{***}	-0.0029^{***}	-0.0014^{***}

	S	S+P	S+P+M	S	S+P	S+P+M
	(0.00022)	(0.00022)	(0.00021)	(0.00021)	(0.00022)	(0.00021)
FracOccProf	0.0287***	0.0215***	0.0145***	0.0250***	0.0246***	0.0180***
	(0.00088)	(0.00088)	(0.00084)	(0.00088)	(0.00088)	(0.00085)
S_time_traffic	−0.0135***	−0.0150***	−0.0150***			
	(0.00056)	(0.00055)	(0.00056)			
S_time_traffic^2	0.0000***	0.0000***	0.0000***			
	(0.00000)	(0.00000)	(0.00000)			
S_transit_time	−0.0106***	−0.0071***	−0.0089***			
	(0.00032)	(0.00036)	(0.00035)			
S_transit_time^2	0.0000***	0.0000***	0.0000***			
	(0.00000)	(0.00000)	(0.00000)			
coast_dist	−0.0252***	−0.0403***	−0.0379***	−0.0239***	−0.0275***	−0.0247***
	(0.00047)	(0.00062)	(0.00063)	(0.00041)	(0.00048)	(0.00048)
coast_dist^2	0.0003***	0.0004***	0.0003***	0.0002***	0.0003***	0.0002***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
P_time_traffic		0.0199***	0.0035***			
		(0.00068)	(0.00070)			
P_time_traffic^2		−0.0002***	−0.0000***			
		(0.00001)	(0.00001)			
P_transit_time		−0.0067***	−0.0048***			
		(0.00038)	(0.00036)			
P_transit_time^2		0.0000***	0.0000***			
		(0.00000)	(0.00000)			
M_time_traffic			0.0087***			
			(0.00067)			
M_time_traffic^2			−0.0001***			
			(0.00001)			
M_transit_time			0.0073***			
			(0.00032)			
M_transit_time^2			−0.0000***			
			(0.00000)			
log_traffic_syd				−0.3161***	−0.3016***	−0.3488***
				(0.00813)	(0.00826)	(0.00837)
log_transit_syd				−0.5075***	−0.4670***	−0.5193***
				(0.00775)	(0.00836)	(0.00820)
log_traffic_par					−0.00472	−0.1796***
					(0.00991)	(0.01017)
log_transit_par					−0.0934***	−0.0716***
					(0.01027)	(0.00988)
log_traffic_mac						−0.0276***
						(0.00884)
log_transit_mac						0.3703***
						(0.00817)
R^2	0.78968	0.79967	0.82023	0.79187	0.79312	0.81004
Adj. R^2	0.78958	0.79956	0.82012	0.79179	0.79303	0.80995
Num. obs.	38514	38514	38514	38514	38514	38514

Notes: Standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Appendix F

Part 1: Full tables for sales regressions

F.1 Log-level models

Table F.1: Linear regression results ($lsqmvalue$)

	S	S+P	S+P+M	S	S+P	S+P+M
(Intercept)	7.9890***	7.7101***	7.5641***	8.4823***	8.3174***	8.1750***
	(0.09486)	(0.09572)	(0.09538)	(0.09566)	(0.09777)	(0.09949)
PropertyTypeOther	0.5292***	0.5517***	0.5301***	0.5277***	0.5213***	0.5120***
	(0.04264)	(0.04158)	(0.04115)	(0.04208)	(0.04190)	(0.04112)
PropertyTypeUnit	0.8287***	0.8023***	0.7933***	0.8032***	0.8003***	0.7760***
	(0.01632)	(0.01598)	(0.01583)	(0.01624)	(0.01620)	(0.01597)
Bedrooms	−0.0256***	−0.0314***	−0.0300***	−0.0345***	−0.0351***	−0.0370***
	(0.00730)	(0.00713)	(0.00705)	(0.00721)	(0.00720)	(0.00707)
Baths	0.0706***	0.0843***	0.0885***	0.0847***	0.0888***	0.0953***
	(0.00860)	(0.00841)	(0.00832)	(0.00852)	(0.00850)	(0.00834)
Parking	−0.0915***	−0.0879***	−0.0846***	−0.0893***	−0.0881***	−0.0839***
	(0.00509)	(0.00498)	(0.00492)	(0.00503)	(0.00502)	(0.00494)
SEIFA_disadv	0.0004***	0.0003***	0.0004***	0.0008***	0.0008***	0.0007***
	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)
FracAustAncestry	−1.3689***	−1.1574***	−0.9902***	−1.5589***	−1.4469***	−1.1105***
	(0.15677)	(0.15360)	(0.15266)	(0.15375)	(0.15405)	(0.15275)
FracBachAbove	−1.1816***	−1.0386***	−0.6540***	−1.7822***	−1.6402***	−1.1166***
	(0.12826)	(0.12522)	(0.12873)	(0.12685)	(0.12964)	(0.13167)
FracUnemp	5.1403***	3.8593***	3.8577***	3.3414***	3.4536***	3.6551***
	(0.33143)	(0.32898)	(0.32947)	(0.33514)	(0.33499)	(0.33265)
FracHighInc	2.9802***	3.0511***	3.0858***	2.9985***	3.0503***	3.0147***
	(0.18368)	(0.17909)	(0.17707)	(0.17896)	(0.18383)	(0.18374)
FracEngSpoken	0.1321**	−0.1883***	−0.1829***	−0.1261**	−0.1187**	−0.1545**
	(0.05968)	(0.06024)	(0.06070)	(0.05923)	(0.06026)	(0.06006)
FracOccProf	1.3879***	1.4469***	1.1038***	1.8655***	1.7495***	1.2797***
	(0.19099)	(0.18678)	(0.18722)	(0.18751)	(0.19106)	(0.18948)
dist_syd	−0.0341***	−0.0426***	−0.0562***			
	(0.00136)	(0.00138)	(0.00174)			
dist_syd^2	0.0002***	−0.0001***	0.0003***			
	(0.00002)	(0.00004)	(0.00006)			
coast_dist	−0.0075***	0.0252***	0.0195***	−0.0129***	−0.0170***	−0.0186***
	(0.00121)	(0.00244)	(0.00245)	(0.00109)	(0.00171)	(0.00186)
coast_dist^2	0.00003	−0.0001***	−0.0002***	0.0000***	0.0000***	0.0000***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
dist_par		0.0245***	0.0119***			
		(0.00126)	(0.00171)			
dist_par^2		0.0001***	0.0001***			
		(0.00004)	(0.00004)			
dist_mac			0.0264***			

	S	S+P	S+P+M	S	S+P	S+P+M
			(0.00188)			
dist_mac^2			-0.0004^{***}			
			(0.00004)			
time_traffic_syd				-0.0204^{***}	-0.0197^{***}	-0.0197^{***}
				(0.00137)	(0.00142)	(0.00158)
time_traffic_syd^2				0.0001^{***}	0.0001^{***}	0.0001^{***}
				(0.00001)	(0.00001)	(0.00001)
time_transit_syd				-0.0065^{***}	-0.0065^{***}	-0.0090^{***}
				(0.00088)	(0.00100)	(0.00101)
time_transit_syd^2				0.0000^{**}	0.0000^{***}	0.0000^{***}
				(0.00000)	(0.00000)	(0.00000)
time_traffic_par					0.0066^{***}	-0.0092^{***}
					(0.00192)	(0.00213)
time_traffic_par^2					-0.0000^{***}	0.0001^{***}
					(0.00002)	(0.00002)
time_transit_par					-0.00027	0.0041^{***}
					(0.00095)	(0.00098)
time_transit_par^2					-0.0000^{***}	-0.0000^{***}
					(0.00000)	(0.00001)
time_traffic_mac						0.0208^{***}
						(0.00224)
time_traffic_mac^2						-0.0003^{***}
						(0.00002)
time_transit_mac						-0.00086
						(0.00083)
time_transit_mac^2						0.0000^{***}
						(0.00000)
R^2	0.85324	0.86060	0.86404	0.85726	0.85863	0.86423
Adj. R^2	0.85295	0.86029	0.86370	0.85694	0.85824	0.86379
Num. obs.	8073	8073	8073	8073	8073	8073

Notes: Standard errors in parenthesis. Coefficients transformed to percentages. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table F.2: SEM regression results ($lsqmvalue$)

	S	S+P	S+P+M	S	S+P	S+P+M
(Intercept)	8.7291^{***}	8.4414^{***}	8.2359^{***}	8.8652^{***}	9.0865^{***}	8.9126^{***}
	(0.11059)	(0.11688)	(0.11632)	(0.10998)	(0.11712)	(0.12096)
PropertyTypeOther	0.5133^{***}	0.5196^{***}	0.5144^{***}	0.4960^{***}	0.4894^{***}	0.4900^{***}
	(0.03782)	(0.03778)	(0.03759)	(0.03798)	(0.03765)	(0.03750)
PropertyTypeUnit	0.7579^{***}	0.7585^{***}	0.7535^{***}	0.7409^{***}	0.7285^{***}	0.7265^{***}
	(0.01509)	(0.01507)	(0.01501)	(0.01525)	(0.01519)	(0.01513)
Bedrooms	-0.0302^{***}	-0.0319^{***}	-0.0315^{***}	-0.0346^{***}	-0.0328^{***}	-0.0326^{***}
	(0.00651)	(0.00651)	(0.00647)	(0.00655)	(0.00649)	(0.00647)
Baths	0.0822^{***}	0.0841^{***}	0.0853^{***}	0.0867^{***}	0.0864^{***}	0.0869^{***}
	(0.00765)	(0.00765)	(0.00761)	(0.00770)	(0.00764)	(0.00761)
Parking	-0.0739^{***}	-0.0735^{***}	-0.0720^{***}	-0.0721^{***}	-0.0704^{***}	-0.0697^{***}
	(0.00453)	(0.00453)	(0.00450)	(0.00456)	(0.00453)	(0.00451)
SEIFA_disadv	0.0001^{*}	0.00015	0.0002^{**}	0.0002^{**}	0.0003^{***}	0.0003^{***}
	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)
FracAustAncestry	-1.0815^{***}	-1.0250^{***}	-0.9220^{***}	-1.2318^{***}	-1.1966^{***}	-1.0692^{***}
	(0.15159)	(0.15162)	(0.15130)	(0.15171)	(0.15072)	(0.15081)
FracBachAbove	-0.6787^{***}	-0.6907^{***}	-0.4772^{***}	-1.0273^{***}	-0.9233^{***}	-0.8289^{***}

	S	S+P	S+P+M	S	S+P	S+P+M
	(0.12601)	(0.12578)	(0.12743)	(0.12794)	(0.12816)	(0.12943)
FracUnemp	3.8815***	3.7401***	3.6627***	3.5969***	3.7530***	3.8453***
	(0.31375)	(0.31546)	(0.31433)	(0.31657)	(0.31428)	(0.31482)
FracHighInc	2.3767***	2.4482***	2.3918***	2.6162***	2.6131***	2.5538***
	(0.18519)	(0.18499)	(0.18423)	(0.18418)	(0.18573)	(0.18706)
FracEngSpoken	−0.1124*	−0.1814***	−0.1724***	−0.2141***	−0.1426**	−0.1512**
	(0.05985)	(0.06106)	(0.06096)	(0.06028)	(0.06054)	(0.06048)
FracOccProf	1.2716***	1.3158***	1.1117***	1.6897***	1.4055***	1.2960***
	(0.18475)	(0.18485)	(0.18543)	(0.18444)	(0.18600)	(0.18646)
dist_syd	−0.0457***	−0.0468***	−0.0599***			
	(0.00238)	(0.00246)	(0.00277)			
dist_syd^2	0.0002***	0.00001	0.0004***			
	(0.00004)	(0.00007)	(0.00009)			
coast_dist	−0.0271***	−0.0070*	−0.00575	−0.0331***	−0.0454***	−0.0451***
	(0.00251)	(0.00402)	(0.00401)	(0.00234)	(0.00308)	(0.00318)
coast_dist^2	0.0003***	0.0002***	0.0001**	0.0002***	0.0004***	0.0004***
	(0.00005)	(0.00006)	(0.00006)	(0.00005)	(0.00005)	(0.00005)
λ	0.9012***	0.8930***	0.8860***	0.8833***	0.8913***	0.8875***
	(0.00823)	(0.00926)	(0.00979)	(0.00927)	(0.00871)	(0.00911)
dist_par		0.0096***	−0.00252			
		(0.00244)	(0.00273)			
dist_par^2		0.0002***	0.0004***			
		(0.00007)	(0.00008)			
dist_mac			0.0313***			
			(0.00309)			
dist_mac^2			−0.0007***			
			(0.00010)			
time_traffic_syd				−0.0191***	−0.0170***	−0.0194***
				(0.00155)	(0.00157)	(0.00172)
time_traffic_syd^2				0.0001***	0.0001***	0.0001***
				(0.00001)	(0.00001)	(0.00002)
time_transit_syd				−0.0055***	−0.0057***	−0.0065***
				(0.00097)	(0.00108)	(0.00111)
time_transit_syd^2				0.00001	0.0000***	0.0000***
				(0.00000)	(0.00001)	(0.00001)
time_traffic_par					−0.0123***	−0.0173***
					(0.00242)	(0.00253)
time_traffic_par^2					0.0000***	0.0001***
					(0.00003)	(0.00003)
time_transit_par					0.00164	0.0029***
					(0.00100)	(0.00103)
time_transit_par^2					−0.0000***	−0.0000***
					(0.00000)	(0.00001)
time_traffic_mac						0.0167***
						(0.00256)
time_traffic_mac^2						−0.0002***
						(0.00003)
time_transit_mac						−0.00121
						(0.00095)
time_transit_mac^2						0.00001
						(0.00000)
Num. obs.	8073	8073	8073	8073	8073	8073
Parameters	19	21	23	21	25	29
Log Likelihood	−3042.03841	−3023.22642	−2972.21888	−3059.67300	−2994.02729	−2954.82218
AIC (Linear model)	7985.79392	7574.62365	7377.23656	7766.01901	7696.05379	7377.83767
AIC (Spatial model)	6122.07682	6088.45284	5990.43777	6161.34600	6038.05458	5967.64436
LR test: statistic	1865.71710	1488.17081	1388.79880	1606.67300	1659.99920	1412.19331

	S	S+P	S+P+M	S	S+P	S+P+M
LR test: p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Notes: Standard errors in parenthesis. Coefficients transformed to percentages. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table F.3: SARM regression results ($lsqmvalue$)

	S	S+P	S+P+M	S	S+P	S+P+M
(Intercept)	1.0750***	1.0349***	0.8229***	2.4522***	1.6478***	1.6642***
	(0.20306)	(0.21168)	(0.20472)	(0.21413)	(0.20317)	(0.21435)
PropertyTypeOther	0.4728***	0.4900***	0.4790***	0.4847***	0.4833***	0.4851***
	(0.04066)	(0.03980)	(0.03929)	(0.03999)	(0.03948)	(0.03904)
PropertyTypeUnit	0.7597***	0.7341***	0.7303***	0.7523***	0.7410***	0.7308***
	(0.01566)	(0.01539)	(0.01520)	(0.01551)	(0.01535)	(0.01517)
Bedrooms	−0.0291***	−0.0323***	−0.0299***	−0.0308***	−0.0355***	−0.0373***
	(0.00695)	(0.00682)	(0.00671)	(0.00685)	(0.00678)	(0.00667)
Baths	0.0725***	0.0837***	0.0866***	0.0827***	0.0892***	0.0929***
	(0.00819)	(0.00804)	(0.00793)	(0.00809)	(0.00800)	(0.00790)
Parking	−0.0820***	−0.0804***	−0.0781***	−0.0811***	−0.0787***	−0.0764***
	(0.00486)	(0.00476)	(0.00470)	(0.00479)	(0.00474)	(0.00469)
SEIFA_disadv	0.0004***	0.0003***	0.0004***	0.0006***	0.0006***	0.0006***
	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00010)	(0.00009)
FracAustAncestry	−1.4264***	−1.2944***	−1.0744***	−1.1915***	−1.1751***	−0.8838***
	(0.14912)	(0.15231)	(0.14648)	(0.14655)	(0.14363)	(0.08984)
FracBachAbove	−0.9755***	−0.8476***	−0.6061***	−1.0762***	−1.1303***	−0.8787***
	(0.12210)	(0.12096)	(0.12313)	(0.12278)	(0.12222)	(0.11478)
FracUnemp	6.3407***	5.1946***	4.9285***	4.8805***	4.9018***	4.6986***
	(0.31712)	(0.31720)	(0.31644)	(0.32241)	(0.31815)	(0.31519)
FracHighInc	2.7815***	2.8590***	2.8487***	2.0660***	2.5067***	2.4138***
	(0.17387)	(0.17428)	(0.16943)	(0.17264)	(0.17291)	(0.15542)
FracEngSpoken	0.2408***	−0.04913	−0.1050*	0.1674***	0.0937*	0.00558
	(0.05642)	(0.06171)	(0.05832)	(0.05698)	(0.05566)	
FracOccProf	1.0218***	1.1472***	0.9296***	0.9151***	1.0230***	0.8201***
	(0.18167)	(0.18002)	(0.17898)	(0.18093)	(0.18015)	(0.16314)
dist_syd	0.00103	−0.0071***	−0.0219***			
	(0.00146)	(0.00167)	(0.00190)			
dist_syd^2	0.0000***	−0.0000*	0.0004***			
	(0.00001)	(0.00004)	(0.00006)			
coast_dist	0.00081	0.0227***	0.0170***	0.0065***	0.0166***	0.0156***
	(0.00107)	(0.00236)	(0.00235)	(0.00121)	(0.00185)	(0.00195)
coast_dist^2	−0.0000**	−0.0002***	−0.0002***	−0.0001***	−0.0002***	−0.0002***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
ρ	0.7360***	0.7245***	0.7368***	0.6319***	0.7013***	0.6822***
	(0.01935)	(0.02075)	(0.01997)	(0.02031)	(0.01905)	(0.02033)
dist_par		0.0233***	0.0154***			
		(0.00121)	(0.00163)			
dist_par^2		−0.00003	−0.0000**			
		(0.00004)	(0.00004)			
dist_mac			0.0231***			
			(0.00180)			
dist_mac^2			−0.0005***			
			(0.00004)			
time_traffic_syd				−0.0187***	−0.0159***	−0.0171***
				(0.00130)	(0.00134)	(0.00148)
time_traffic_syd^2				0.0001***	0.0001***	0.0001***

	S	S+P	S+P+M	S	S+P	S+P+M
				(0.00001)	(0.00001)	(0.00001)
time_transit_syd				-0.0026^{***}	-0.0035^{***}	-0.0063^{***}
				(0.00084)	(0.00094)	(0.00096)
time_transit_syd^2				0.0000^{***}	0.0000^{***}	0.0000^{***}
				(0.00000)	(0.00000)	(0.00000)
time_traffic_par					0.0042^{**}	-0.0035^{*}
					(0.00178)	(0.00211)
time_traffic_par^2					0.0000^{***}	0.0001^{***}
					(0.00002)	(0.00002)
time_transit_par					−0.00117	0.00137
					(0.00087)	(0.00097)
time_transit_par^2					-0.0000^{***}	-0.0000^{***}
					(0.00000)	(0.00000)
time_traffic_mac						0.0139^{***}
						(0.00183)
time_traffic_mac^2						-0.0002^{***}
						(0.00002)
time_transit_mac						0.0011^{***}
						(0.00037)
time_transit_mac^2						0.0000^{**}
						(0.00000)
Num. obs.	8073	8073	8073	8073	8073	8073
Parameters	19	21	23	21	25	29
Log Likelihood	−3635.86441	−3451.54166	−3339.16507	−3480.31021	−3383.25030	−3285.29233
AIC (Linear model)	7985.79392	7574.62365	7377.23656	7766.01901	7696.05379	7377.83767
AIC (Spatial model)	7309.72882	6945.08332	6724.33013	7002.62041	6816.50060	6628.58466
LR test: statistic	678.06510	631.54033	654.90643	765.39860	881.55319	751.25301
LR test: p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Notes: Standard errors in parenthesis. Coefficients transformed to percentages. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

F.2 Level-level models

Table F.4: Linear regression results ($sqmvalue$)

	S	S+P	S+P+M	S	S+P	S+P+M
(Intercept)	4881.27^{***}	4007.67^{***}	3050.87^{***}	11201.11^{***}	9470.67^{***}	8985.07^{***}
	(529.273)	(511.860)	(497.361)	(486.370)	(491.983)	(498.909)
PropertyTypeOther	1309.87^{***}	1446.30^{***}	1341.62^{***}	1241.64^{***}	1206.24^{***}	1138.72^{***}
	(237.917)	(222.379)	(214.577)	(213.923)	(210.823)	(206.190)
PropertyTypeUnit	3175.91^{***}	2903.80^{***}	2872.56^{***}	2929.55^{***}	2886.82^{***}	2771.19^{***}
	(91.054)	(85.445)	(82.564)	(82.562)	(81.537)	(80.077)
Bedrooms	-143.49^{***}	-164.34^{***}	-142.98^{***}	-216.43^{***}	-230.97^{***}	-257.23^{***}
	(40.729)	(38.137)	(36.752)	(36.678)	(36.214)	(35.474)
Baths	68.767	170.65^{***}	199.15^{***}	198.96^{***}	239.07^{***}	273.53^{***}
	(48.003)	(44.995)	(43.377)	(43.304)	(42.759)	(41.823)
Parking	-255.78^{***}	-247.84^{***}	-226.05^{***}	-237.13^{***}	-240.22^{***}	-224.32^{***}
	(28.407)	(26.612)	(25.670)	(25.596)	(25.272)	(24.753)
SEIFA_disadv	2.02^{***}	0.218	1.28^{**}	4.00^{***}	3.60^{***}	3.21^{***}
	(0.570)	(0.537)	(0.519)	(0.512)	(0.518)	(0.508)
FracAustAncestry	-7239.60^{***}	-6299.10^{***}	-4326.82^{***}	-6270.21^{***}	-5501.95^{***}	-3824.16^{***}
	(874.706)	(821.389)	(796.069)	(781.720)	(775.149)	(765.995)

	S	S+P	S+P+M	S	S+P	S+P+M
FracBachAbove	-7997.25^{***}	-6724.38^{***}	-4374.34^{***}	-11395.03^{***}	-10271.40^{***}	-7540.48^{***}
	(715.609)	(669.613)	(671.296)	(644.914)	(652.325)	(660.277)
FracUnemp	54693.19^{***}	44003.61^{***}	41688.91^{***}	37295.96^{***}	37202.55^{***}	37401.72^{***}
	(1849.208)	(1759.282)	(1718.049)	(1703.925)	(1685.606)	(1668.106)
FracHighInc	28139.24^{***}	28910.13^{***}	28894.11^{***}	24371.49^{***}	25033.68^{***}	23637.37^{***}
	(1024.847)	(957.730)	(923.353)	(909.871)	(925.004)	(921.360)
FracEngSpoken	2349.12^{***}	-417.847	-878.53^{***}	606.91^{**}	439.432	435.775
	(332.985)	(322.149)	(316.542)	(301.130)	(303.227)	(301.191)
FracOccProf	3912.03^{***}	5418.41^{***}	3322.09^{***}	5567.65^{***}	5384.21^{***}	2990.60^{***}
	(1065.655)	(998.830)	(976.265)	(953.361)	(961.370)	(950.140)
dist_syd	-288.89^{***}	-362.44^{***}	-501.46^{***}			
	(7.562)	(7.404)	(9.066)			
dist_syd^2	2.87^{***}	2.46^{***}	7.36^{***}			
	(0.090)	(0.218)	(0.301)			
coast_dist	0.226	172.28^{***}	120.47^{***}	-5.718	-32.79^{***}	-58.21^{***}
	(6.753)	(13.069)	(12.763)	(5.551)	(8.596)	(9.316)
coast_dist^2	-0.034	-1.83^{***}	-2.36^{***}	0.068	0.144	0.43^{***}
	(0.109)	(0.116)	(0.115)	(0.088)	(0.105)	(0.112)
dist_par		230.15^{***}	152.50^{***}			
		(6.723)	(8.894)			
dist_par^2		-1.21^{***}	-1.64^{***}			
		(0.196)	(0.198)			
dist_mac			215.60^{***}			
			(9.814)			
dist_mac^2			-4.72^{***}			
			(0.193)			
time_traffic_syd				-227.37^{***}	-228.72^{***}	-203.44^{***}
				(6.978)	(7.160)	(7.908)
$\text{time\_traffic\_syd}^2$				1.68^{***}	1.72^{***}	1.67^{***}
				(0.062)	(0.068)	(0.073)
time_transit_syd				-89.47^{***}	-77.65^{***}	-95.11^{***}
				(4.480)	(5.008)	(5.086)
$\text{time\_transit\_syd}^2$				0.33^{***}	0.37^{***}	0.42^{***}
				(0.021)	(0.024)	(0.024)
time_traffic_par					120.26^{***}	53.36^{***}
					(9.648)	(10.704)
$\text{time\_traffic\_par}^2$					-1.03^{***}	-0.21^{*}
					(0.104)	(0.116)
time_transit_par					-28.60^{***}	-11.51^{**}
					(4.783)	(4.891)
$\text{time\_transit\_par}^2$					0.035	-0.11^{***}
					(0.023)	(0.025)
time_traffic_mac						42.51^{***}
						(11.211)
$\text{time\_traffic\_mac}^2$						-1.13^{***}
						(0.122)
time_transit_mac						12.94^{***}
						(4.176)
$\text{time\_transit\_mac}^2$						0.06^{***}
						(0.020)
R^2	0.781	0.809	0.823	0.823	0.829	0.837
Adj. R^2	0.781	0.809	0.823	0.823	0.828	0.836
Num. obs.	8073	8073	8073	8073	8073	8073

Notes: Standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table F.5: SEM regression results ($sqmvalue$)

	S	S+P	S+P+M	S	S+P	S+P+M
(Intercept)	12028.78***	9668.26***	7313.71***	13802.07***	13337.09***	12646.88***
	(671.630)	(656.587)	(628.241)	(570.751)	(603.550)	(614.503)
PropertyTypeOther	1328.56***	1366.25***	1325.22***	1169.93***	1151.36***	1121.69***
	(202.446)	(201.800)	(197.912)	(198.978)	(197.327)	(196.347)
PropertyTypeUnit	2725.47***	2755.25***	2711.93***	2629.79***	2562.06***	2559.56***
	(80.897)	(80.558)	(79.046)	(79.843)	(79.549)	(79.130)
Bedrooms	−180.57***	−183.61***	−179.82***	−219.81***	−210.04***	−224.17***
	(34.861)	(34.770)	(34.087)	(34.290)	(34.038)	(33.906)
Baths	202.69***	215.94***	226.47***	242.65***	252.51***	266.00***
	(40.974)	(40.866)	(40.068)	(40.315)	(40.035)	(39.856)
Parking	−216.67***	−218.53***	−203.39***	−209.45***	−209.98***	−209.10***
	(24.244)	(24.169)	(23.710)	(23.887)	(23.720)	(23.628)
SEIFA_disadv	1.83***	1.34**	1.96***	2.36***	3.00***	2.85***
	(0.551)	(0.549)	(0.539)	(0.541)	(0.543)	(0.540)
FracAustAncestry	−5272.48***	−4925.86***	−3859.39***	−5825.48***	−5409.03***	−4997.98***
	(813.885)	(811.319)	(797.460)	(794.242)	(789.216)	(788.169)
FracBachAbove	−6082.76***	−6017.19***	−4025.56***	−9028.38***	−8272.12***	−7364.34***
	(676.997)	(673.356)	(671.725)	(669.603)	(670.914)	(676.434)
FracUnemp	38800.82***	37133.53***	36380.87***	36656.16***	37058.62***	36792.57***
	(1685.091)	(1687.664)	(1656.319)	(1657.682)	(1646.225)	(1646.390)
FracHighInc	22042.21***	22564.64***	22013.91***	22411.54***	21923.76***	20959.27***
	(996.956)	(991.648)	(972.291)	(963.679)	(971.899)	(976.323)
FracEngSpoken	−418.545	−987.59***	−947.09***	−585.45*	−190.348	−53.032
	(321.911)	(327.030)	(321.463)	(315.458)	(316.885)	(315.791)
FracOccProf	1996.56**	2817.40***	980.539	4768.86***	3344.25***	2625.61***
	(992.221)	(989.322)	(977.457)	(965.482)	(973.886)	(974.350)
dist_syd	−475.59***	−508.18***	−631.12***			
	(13.145)	(13.384)	(14.747)			
dist_syd^2	4.90***	6.15***	10.48***			
	(0.212)	(0.398)	(0.472)			
coast_dist	−160.94***	−70.53***	−53.34**	−151.42***	−229.36***	−220.75***
	(14.178)	(22.071)	(21.465)	(12.090)	(15.835)	(16.038)
coast_dist^2	2.69***	0.83**	0.057	2.09***	2.90***	2.63***
	(0.327)	(0.337)	(0.323)	(0.236)	(0.268)	(0.265)
λ	0.93***	0.91***	0.90***	0.87***	0.88***	0.86***
	(0.006)	(0.007)	(0.008)	(0.010)	(0.010)	(0.012)
dist_par		154.70***	36.73**			
		(13.459)	(14.609)			
dist_par^2		−2.70***	−0.370			
		(0.393)	(0.411)			
dist_mac			314.05***			
			(16.506)			
dist_mac^2			−7.94***			
			(0.525)			
time_traffic_syd				−194.00***	−193.12***	−176.84***
				(8.091)	(8.191)	(8.939)
time_traffic_syd^2				1.43***	1.51***	1.49***
				(0.075)	(0.077)	(0.081)
time_transit_syd				−98.00***	−84.08***	−90.35***
				(5.061)	(5.642)	(5.785)
time_transit_syd^2				0.40***	0.42***	0.42***
				(0.025)	(0.028)	(0.028)
time_traffic_par					49.12***	45.71***
					(12.612)	(13.093)

	S	S+P	S+P+M	S	S+P	S+P+M
time_traffic_par^2					-0.65^{***}	-0.44^{***}
					(0.137)	(0.145)
time_transit_par					-23.13^{***}	-20.21^{***}
					(5.232)	(5.384)
time_transit_par^2					0.004	-0.06^{**}
					(0.025)	(0.028)
time_traffic_mac						-7.896
						(13.289)
time_traffic_mac^2						-0.44^{***}
						(0.154)
time_transit_mac						9.29^{*}
						(4.946)
time_transit_mac^2						0.06^{**}
						(0.025)
Num. obs.	8073	8073	8073	8073	8073	8073
Parameters	19	21	23	21	25	29
Log Likelihood	−72402.189	−72340.289	−72161.860	−72189.425	−72123.879	−72068.369
AIC (Linear model)	147275.067	146178.635	145574.417	145554.367	145317.087	144943.411
AIC (Spatial model)	144842.378	144722.579	144369.719	144420.850	144297.757	144194.738
LR test: statistic	2434.689	1458.056	1206.698	1135.516	1021.330	750.673
LR test: p-value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table F.6: SARM regression results ($sqmvalue$)

	S	S+P	S+P+M	S	S+P	S+P+M
(Intercept)	-2612.40^{***}	824.563	486.801	7041.39^{***}	5201.38^{***}	6617.47^{***}
	(590.489)	(883.344)	(499.948)	(624.773)	(639.259)	(616.262)
PropertyTypeOther	1122.76^{***}	1339.05^{***}	1266.95^{***}	1181.34^{***}	1157.02^{***}	1124.52^{***}
	(232.057)	(237.778)	(212.601)	(211.460)	(210.019)	(204.395)
PropertyTypeUnit	2859.45^{***}	2784.88^{***}	2781.25^{***}	2819.21^{***}	2763.13^{***}	2719.64^{***}
	(89.382)	(86.170)	(83.192)	(82.422)	(81.424)	(80.290)
Bedrooms	-170.88^{***}	-171.55^{***}	-148.40^{***}	-205.34^{***}	-223.89^{***}	-253.06^{***}
	(39.395)	(38.694)	(36.353)	(35.993)	(35.404)	(35.115)
Baths	129.19^{***}	185.16^{***}	209.21^{***}	210.23^{***}	252.30^{***}	276.80^{***}
	(47.141)	(45.272)	(42.949)	(42.341)	(41.652)	(41.342)
Parking	-238.70^{***}	-243.31^{***}	-223.78^{***}	-232.62^{***}	-235.03^{***}	-223.99^{***}
	(27.715)	(26.589)	(25.409)	(25.316)	(25.020)	(24.568)
SEIFA_disadv	2.70^{***}	0.668	1.65^{***}	4.07^{***}	3.84^{***}	3.43^{***}
	(0.554)	(1.114)	(0.458)	(0.510)	(0.512)	(0.502)
FracAustAncestry	-7521.95^{***}	-6625.74^{***}	-4586.77^{***}	-5985.07^{***}	-5389.68^{***}	-3846.40^{***}
	(860.352)	(2145.167)	(783.346)	(783.323)	(759.901)	(765.168)
FracBachAbove	-7749.46^{***}	-6751.02^{***}	-4595.82^{***}	-10251.44^{***}	-9479.05^{***}	-7470.24^{***}
	(734.127)	(1322.905)	(670.911)	(656.581)	(644.679)	(646.205)
FracUnemp	57623.23^{***}	46597.02^{***}	43600.01^{***}	40606.99^{***}	40313.55^{***}	38666.55^{***}
	(1803.957)	(1725.438)	(1682.857)	(1715.868)	(1700.912)	(1689.985)
FracHighInc	25494.51^{***}	27625.26^{***}	27790.03^{***}	22118.63^{***}	23350.36^{***}	22599.43^{***}
	(1014.828)	(1838.773)	(926.866)	(933.184)	(924.260)	(940.027)
FracEngSpoken	2052.97^{***}	-240.273	-784.81^{**}	974.76^{***}	715.74^{**}	544.15^{*}
	(335.509)	(1206.290)	(307.866)	(307.215)	(292.157)	(304.396)
FracOccProf	2612.75^{**}	4753.42^{***}	2949.89^{***}	3733.80^{***}	3766.23^{***}	2435.30^{***}
	(1111.622)	(1628.087)	(943.648)	(979.511)	(959.300)	(910.581)

	S	S+P	S+P+M	S	S+P	S+P+M
dist_syd	-99.80^{***}	-267.38^{***}	-421.46^{***}			
	(10.436)	(14.224)	(14.700)			
dist_syd^2	1.45^{***}	2.10^{***}	7.08^{***}			
	(0.104)	(0.246)	(0.300)			
coast_dist	29.71^{***}	154.94^{***}	107.38^{***}	34.94^{***}	23.74^{**}	-25.47^{***}
	(6.968)	(13.246)	(12.778)	(6.792)	(9.902)	(7.085)
coast_dist^2	-0.37^{***}	-1.79^{***}	-2.33^{***}	-0.40^{***}	-0.46^{***}	0.084
	(0.112)	(0.142)	(0.114)	(0.099)	(0.117)	(0.079)
ρ	0.66^{***}	0.30^{***}	0.25^{***}	0.29^{***}	0.31^{***}	0.17^{***}
	(0.026)	(0.039)	(0.037)	(0.029)	(0.030)	(0.028)
dist_par		205.92^{***}	138.99^{***}			
		(8.740)	(9.014)			
dist_par^2		-1.33^{***}	-1.79^{***}			
		(0.205)	(0.197)			
dist_mac			207.42^{***}			
			(9.854)			
dist_mac^2			-4.69^{***}			
			(0.192)			
time_traffic_syd				-201.85^{***}	-200.87^{***}	-188.67^{***}
				(7.341)	(7.571)	(8.282)
time_traffic_syd^2				1.58^{***}	1.56^{***}	1.60^{***}
				(0.063)	(0.069)	(0.074)
time_transit_syd				-76.61^{***}	-64.66^{***}	-87.83^{***}
				(4.610)	(5.120)	(5.108)
time_transit_syd^2				0.31^{***}	0.33^{***}	0.40^{***}
				(0.021)	(0.024)	(0.024)
time_traffic_par					114.23^{***}	61.47^{***}
					(9.670)	(9.734)
time_traffic_par^2					-0.84^{***}	-0.24^{**}
					(0.103)	(0.102)
time_transit_par					-32.77^{***}	-16.66^{***}
					(4.870)	(4.643)
time_transit_par^2					0.04^{**}	-0.08^{***}
					(0.024)	(0.024)
time_traffic_mac						31.29^{***}
						(10.867)
time_traffic_mac^2						-1.00^{***}
						(0.118)
time_transit_mac						15.23^{***}
						(4.176)
time_transit_mac^2						0.04^{**}
						(0.020)
Num. obs.	8073	8073	8073	8073	8073	8073
Parameters	19	21	23	21	25	29
Log Likelihood	−73430.914	−73042.461	−72746.352	−72703.396	−72579.541	−72429.156
AIC (Linear model)	147275.067	146178.635	145574.417	145554.367	145317.087	144943.411
AIC (Spatial model)	146899.828	146126.921	145538.705	145448.793	145209.083	144916.312
LR test: statistic	377.238	53.714	37.712	107.574	110.004	29.099
LR test: p-value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

APPENDIX G

Part 1: Full tables for land values regressions

G.1 Log-level models

Table G.1: Linear regression results ($lsqmvalue$)

	S	S+P	S+P+M	S	S+P	S+P+M
(Intercept)	8.3669***	7.9602***	7.7073***	9.0540***	8.7643***	8.3237***
	(0.05534)	(0.05863)	(0.05610)	(0.06045)	(0.06207)	(0.06141)
zonecodeR2	−0.3375***	−0.2939***	−0.2377***	−0.3307***	−0.3271***	−0.2693***
	(0.01329)	(0.01319)	(0.01263)	(0.01421)	(0.01396)	(0.01331)
zonecodeR3	−0.1954***	−0.1680***	−0.1445***	−0.2092***	−0.2127***	−0.1781***
	(0.01612)	(0.01582)	(0.01501)	(0.01717)	(0.01683)	(0.01593)
zonecodeR4	−0.1276***	−0.0792***	−0.0409*	−0.1446***	−0.1420***	−0.1049***
	(0.02662)	(0.02612)	(0.02481)	(0.02827)	(0.02772)	(0.02620)
zonecodeR5	−1.3708***	−1.3783***	−1.2978***	−1.3018***	−1.3018***	−1.3345***
	(0.05093)	(0.04996)	(0.04749)	(0.05406)	(0.05325)	(0.05086)
SEIFA_disadv	0.00001	0.0001*	0.0001**	0.00002	0.0001**	0.00005
	(0.00006)	(0.00006)	(0.00006)	(0.00007)	(0.00007)	(0.00006)
FracAustAncestry	−0.0077***	−0.0066***	−0.0062***	−0.0122***	−0.0106***	−0.0093***
	(0.00100)	(0.00098)	(0.00093)	(0.00106)	(0.00104)	(0.00098)
FracBachAbove	−0.00036	0.00014	0.0102***	−0.0066***	−0.0037***	0.0069***
	(0.00094)	(0.00093)	(0.00093)	(0.00102)	(0.00102)	(0.00102)
FracUnemp	−0.0073***	−0.0086***	−0.0118***	−0.0209***	−0.0190***	−0.0169***
	(0.00274)	(0.00268)	(0.00254)	(0.00287)	(0.00282)	(0.00267)
FracHighInc	0.0053***	0.00202	0.0065***	0.0171***	0.0161***	0.0109***
	(0.00142)	(0.00140)	(0.00133)	(0.00149)	(0.00151)	(0.00147)
FracEngSpoken	0.0012***	−0.00038	0.0015***	−0.0023***	−0.0011***	0.0010**
	(0.00040)	(0.00040)	(0.00039)	(0.00042)	(0.00043)	(0.00041)
FracOccProf	0.0186***	0.0175***	0.0079***	0.0269***	0.0204***	0.0141***
	(0.00163)	(0.00160)	(0.00154)	(0.00171)	(0.00171)	(0.00163)
Syd_dist	−0.0495***	−0.0613***	−0.0787***			
	(0.00099)	(0.00113)	(0.00145)			
Syd_dist^2	0.0003***	0.0001***	0.0005***			
	(0.00001)	(0.00003)	(0.00004)			
coast_dist	−0.0149***	0.0132***	0.0075***	−0.0239***	−0.0369***	−0.0343***
	(0.00089)	(0.00187)	(0.00179)	(0.00091)	(0.00119)	(0.00121)
coast_dist^2	0.0002***	−0.00000	−0.0000**	0.0002***	0.0003***	0.0003***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Par_dist		0.0202***	−0.0073***			
		(0.00096)	(0.00128)			
Par_dist^2		0.0000***	0.0002***			
		(0.00003)	(0.00003)			
MP_dist			0.0471***			
			(0.00146)			
MP_dist^2			−0.0005***			

	S	S+P	S+P+M	S	S+P	S+P+M
			(0.00003)			
S_time_traffic				-0.0137^{***}	-0.0149^{***}	-0.0146^{***}
				(0.00109)	(0.00108)	(0.00109)
S_time_traffic^2				0.0000^{***}	0.0000^{***}	0.0000^{***}
				(0.00001)	(0.00001)	(0.00001)
S_transit_time				-0.0111^{***}	-0.0084^{***}	-0.0103^{***}
				(0.00061)	(0.00069)	(0.00067)
S_transit_time^2				0.0000^{***}	0.0000^{***}	0.0000^{***}
				(0.00000)	(0.00000)	(0.00000)
P_time_traffic					0.0178^{***}	0.0022^{*}
					(0.00130)	(0.00134)
P_time_traffic^2					-0.0001^{***}	-0.0000^{***}
					(0.00001)	(0.00001)
P_transit_time					-0.0061^{***}	-0.0043^{***}
					(0.00072)	(0.00069)
P_transit_time^2					0.0000^{***}	0.00000
					(0.00000)	(0.00000)
M_time_traffic						0.0067^{***}
						(0.00124)
M_time_traffic^2						-0.0001^{***}
						(0.00001)
M_transit_time						0.0081^{***}
						(0.00059)
M_transit_time^2						-0.0000^{***}
						(0.00000)
R^2	0.81461	0.82281	0.84082	0.79297	0.80144	0.82298
Adj. R^2	0.81433	0.82251	0.84052	0.79262	0.80103	0.82254
Num. obs.	10000	10000	10000	10000	10000	10000

Notes: Standard errors in parenthesis. Coefficients transformed to percentages. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table G.2: SEM regression results ($lsqmvalue$)

	S	S+P	S+P+M	S	S+P	S+P+M
(Intercept)	8.4100^{***}	8.1919^{***}	7.9738^{***}	8.3966^{***}	8.5884^{***}	8.3298^{***}
	(0.06543)	(0.07319)	(0.06967)	(0.07632)	(0.07892)	(0.07765)
zonecodeR2	-0.2499^{***}	-0.2468^{***}	-0.2075^{***}	-0.2730^{***}	-0.2737^{***}	-0.2526^{***}
	(0.01385)	(0.01388)	(0.01362)	(0.01420)	(0.01408)	(0.01398)
zonecodeR3	-0.1631^{***}	-0.1605^{***}	-0.1358^{***}	-0.1938^{***}	-0.1942^{***}	-0.1794^{***}
	(0.01623)	(0.01621)	(0.01582)	(0.01664)	(0.01649)	(0.01632)
zonecodeR4	-0.0543^{**}	-0.0469^{*}	-0.01858	-0.1008^{***}	-0.1065^{***}	-0.0902^{***}
	(0.02497)	(0.02497)	(0.02439)	(0.02557)	(0.02536)	(0.02511)
zonecodeR5	-1.3426^{***}	-1.3370^{***}	-1.2969^{***}	-1.3981^{***}	-1.3707^{***}	-1.3486^{***}
	(0.04771)	(0.04764)	(0.04653)	(0.04942)	(0.04917)	(0.04878)
SEIFA_disadv	-0.00001	0.00001	0.00005	-0.0001^{***}	-0.00009	-0.00009
	(0.00006)	(0.00006)	(0.00006)	(0.00006)	(0.00006)	(0.00006)
FracAustAncestry	-0.0065^{***}	-0.0062^{***}	-0.0057^{***}	-0.0083^{***}	-0.0082^{***}	-0.0076^{***}
	(0.00094)	(0.00094)	(0.00092)	(0.00096)	(0.00095)	(0.00094)
FracBachAbove	0.0058^{***}	0.0054^{***}	0.0102^{***}	0.0057^{***}	0.0057^{***}	0.0085^{***}
	(0.00093)	(0.00093)	(0.00093)	(0.00099)	(0.00098)	(0.00099)
FracUnemp	-0.0060^{**}	-0.0063^{**}	-0.0079^{***}	-0.0080^{***}	-0.0077^{***}	-0.0085^{***}
	(0.00249)	(0.00249)	(0.00243)	(0.00256)	(0.00254)	(0.00251)
FracHighInc	0.0031^{**}	0.0027^{*}	0.0042^{***}	0.0081^{***}	0.0100^{***}	0.0084^{***}

	S	S+P	S+P+M	S	S+P	S+P+M
	(0.00144)	(0.00144)	(0.00140)	(0.00148)	(0.00149)	(0.00148)
FracEngSpoken	0.00051	0.00017	0.0008^{**}	-0.00039	0.00028	0.0007^{*}
	(0.00040)	(0.00040)	(0.00039)	(0.00041)	(0.00041)	(0.00041)
FracOccProf	0.0120^{***}	0.0121^{***}	0.0073^{***}	0.0148^{***}	0.0132^{***}	0.0120^{***}
	(0.00155)	(0.00155)	(0.00152)	(0.00158)	(0.00158)	(0.00157)
Syd_dist	-0.0496^{***}	-0.0530^{***}	-0.0770^{***}			
	(0.00189)	(0.00210)	(0.00228)			
Syd_dist^2	0.0003^{***}	0.0001^{***}	0.0006^{***}			
	(0.00003)	(0.00005)	(0.00006)			
coast_dist	-0.0274^{***}	-0.0122^{***}	-0.0083^{***}	-0.0360^{***}	-0.0480^{***}	-0.0432^{***}
	(0.00184)	(0.00303)	(0.00290)	(0.00194)	(0.00218)	(0.00217)
coast_dist^2	0.0004^{***}	0.0002^{***}	0.0001^{**}	0.0003^{***}	0.0004^{***}	0.0004^{***}
	(0.00004)	(0.00005)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
λ	0.8905^{***}	0.8858^{***}	0.8602^{***}	0.9228^{***}	0.9189^{***}	0.9051^{***}
	(0.00790)	(0.00845)	(0.01038)	(0.00538)	(0.00571)	(0.00677)
Par_dist		0.0092^{***}	-0.0126^{***}			
		(0.00174)	(0.00192)			
Par_dist^2		0.0000^{*}	0.0002^{***}			
		(0.00005)	(0.00005)			
MP_dist			0.0497^{***}			
			(0.00224)			
MP_dist^2			-0.0006^{***}			
			(0.00006)			
S_time_traffic				-0.0099^{***}	-0.0089^{***}	-0.0102^{***}
				(0.00111)	(0.00111)	(0.00113)
S_time_traffic^2				0.0000^{***}	0.0000^{***}	0.0000^{***}
				(0.00001)	(0.00001)	(0.00001)
S_transit_time				-0.0062^{***}	-0.0042^{***}	-0.0068^{***}
				(0.00066)	(0.00070)	(0.00072)
S_transit_time^2				0.0000^{***}	0.0000^{***}	0.0000^{***}
				(0.00000)	(0.00000)	(0.00000)
P_time_traffic					-0.0029^{**}	-0.0064^{***}
					(0.00140)	(0.00142)
P_time_traffic^2					0.00001	0.0000^{**}
					(0.00001)	(0.00001)
P_transit_time					-0.0032^{***}	-0.0026^{***}
					(0.00071)	(0.00071)
P_transit_time^2					0.00000	0.00000
					(0.00000)	(0.00000)
M_time_traffic						0.0054^{***}
						(0.00120)
M_time_traffic^2						-0.0000^{***}
						(0.00001)
M_transit_time						0.0055^{***}
						(0.00064)
M_transit_time^2						-0.0000^{***}
						(0.00000)
Num. obs.	10000	10000	10000	10000	10000	10000
Parameters	18	20	22	20	24	28
Log Likelihood	-1414.13214	-1393.65904	-1138.12037	-1704.05107	-1609.20425	-1484.68042
AIC (Linear model)	5090.28271	4641.75601	3573.88262	6198.07007	5788.20127	4648.04811
AIC (Spatial model)	2864.26428	2827.31807	2320.24075	3448.10214	3266.40850	3025.36083
LR test: statistic	2228.01844	1816.43793	1255.64187	2751.96794	2523.79277	1624.68728
LR test: p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Notes: Standard errors in parenthesis. Coefficients transformed to percentages. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table G.3: SARM regression results ($lsqmvalue$)

	S	S+P	S+P+M	S	S+P	S+P+M
(Intercept)	1.6525***	1.6412***	1.7568***	1.6829***	1.6433***	1.6289***
	(0.10133)	(0.11028)	(0.12944)	(0.09115)	(0.08433)	(0.10544)
zonecodeR2	−0.3017***	−0.2802***	−0.2345***	−0.2865***	−0.2848***	−0.2500***
	(0.01218)	(0.01224)	(0.01200)	(0.01218)	(0.01196)	(0.01207)
zonecodeR3	−0.1976***	−0.1844***	−0.1644***	−0.1856***	−0.1853***	−0.1658***
	(0.01476)	(0.01472)	(0.01425)	(0.01472)	(0.01455)	(0.01441)
zonecodeR4	−0.1110***	−0.0887***	−0.0554**	−0.0930***	−0.0918***	−0.0738***
	(0.02440)	(0.02438)	(0.02365)	(0.02424)	(0.02402)	(0.02362)
zonecodeR5	−1.3415***	−1.3525***	−1.2821***	−1.3562***	−1.3202***	−1.3133***
	(0.04661)	(0.04639)	(0.04505)	(0.04635)	(0.04622)	(0.04590)
SEIFA_disadv	−0.0002***	−0.0001***	−0.0001**	−0.0000*	0.00002	−0.00003
	(0.00006)	(0.00006)	(0.00006)	(0.00006)		(0.00004)
FracAustAncestry	−0.0069***	−0.0065***	−0.0060***	−0.0070***	−0.0065***	−0.0060***
	(0.00092)	(0.00068)	(0.00089)	(0.00057)	(0.00089)	(0.00089)
FracBachAbove	0.0023***	0.0026***	0.0102***	0.00052	0.00078	0.0074***
	(0.00086)	(0.00086)	(0.00088)	(0.00080)	(0.00083)	(0.00091)
FracUnemp	−0.00336	−0.00384	−0.0068***	−0.0053**	−0.0056**	−0.0058***
	(0.00253)	(0.00250)	(0.00242)	(0.00247)	(0.00226)	(0.00223)
FracHighInc	0.0027**	0.00123	0.0046***	0.0035***	0.0057***	0.0043***
	(0.00128)	(0.00116)	(0.00127)	(0.00127)	(0.00133)	(0.00133)
FracEngSpoken	0.0007*	−0.00010	0.0012***	−0.00005	0.00019	0.0013***
	(0.00037)	(0.00020)	(0.00038)	(0.00012)	(0.00037)	(0.00037)
FracOccProf	0.0163***	0.0157***	0.0081***	0.0158***	0.0134***	0.0097***
	(0.00150)	(0.00147)	(0.00147)	(0.00138)	(0.00157)	(0.00147)
Syd_dist	−0.0111***	−0.0180***	−0.0364***			
	(0.00104)	(0.00123)	(0.00162)			
Syd_dist^2	0.0001***	0.0000***	0.0004***			
	(0.00001)	(0.00002)	(0.00004)			
coast_dist	−0.0044***	0.0070***	0.0032*	−0.0026***	−0.0065***	−0.0038***
	(0.00083)	(0.00143)	(0.00171)	(0.00078)	(0.00108)	(0.00119)
coast_dist^2	0.0000***	−0.0000*	−0.0000***	0.0000***	0.0000***	0.0000*
	(0.00002)	(0.00002)	(0.00002)	(0.00001)	(0.00002)	(0.00002)
ρ	0.8399***	0.8197***	0.7784***	0.8667***	0.8618***	0.8273***
	(0.01098)	(0.01248)	(0.01539)	(0.00872)	(0.00915)	(0.01126)
Par_dist		0.0099***	−0.0099***			
		(0.00089)	(0.00122)			
Par_dist^2		−0.00001	0.0000***			
		(0.00002)	(0.00003)			
MP_dist			0.0382***			
			(0.00140)			
MP_dist^2			−0.0005***			
			(0.00003)			
S_time_traffic				−0.0086***	−0.0089***	−0.0111***
				(0.00093)	(0.00092)	(0.00098)
S_time_traffic^2				0.0000***	0.0000***	0.0000***
				(0.00001)	(0.00001)	(0.00001)
S_transit_time				−0.0046***	−0.0037***	−0.0050***
				(0.00053)	(0.00059)	(0.00054)
S_transit_time^2				0.0000***	0.0000***	0.0000***
				(0.00000)	(0.00000)	(0.00000)
P_time_traffic					0.0051***	−0.0040***
					(0.00115)	(0.00089)
P_time_traffic^2					−0.0000***	0.0000***
					(0.00001)	(0.00001)

	S	S+P	S+P+M	S	S+P	S+P+M
P_transit_time					-0.0034^{***}	-0.0025^{***}
					(0.00062)	(0.00013)
P_transit_time^2					0.00000	0.00000
					(0.00000)	
M_time_traffic						0.0056^{***}
						(0.00113)
M_time_traffic^2						-0.0000^{***}
						(0.00001)
M_transit_time						0.0055^{***}
						(0.00054)
M_transit_time^2						-0.0000^{***}
						(0.00000)
Num. obs.	10000	10000	10000	10000	10000	10000
Parameters	18	20	22	20	24	28
Log Likelihood	−1722.71156	−1662.68535	−1291.31876	−1646.24864	−1586.36892	−1344.71440
AIC (Linear model)	5090.28271	4641.75601	3573.88262	6198.07007	5788.20127	4648.04811
AIC (Spatial model)	3481.42313	3365.37070	2626.63751	3332.49729	3220.73784	2745.42879
LR test: statistic	1610.85959	1278.38531	949.24510	2867.57279	2569.46343	1904.61932
LR test: p-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Notes: Standard errors in parenthesis. Coefficients transformed to percentages. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

G.2 Level-level models

Table G.4: Linear regression results ($sqmvalue$)

	S	S+P	S+P+M	S	S+P	S+P+M
(Intercept)	6646.89^{***}	5072.88^{***}	4182.27^{***}	8647.17^{***}	7725.95^{***}	6336.14^{***}
	(141.133)	(144.366)	(130.251)	(144.783)	(147.492)	(143.890)
zonecodeR2	-1121.84^{***}	-943.65^{***}	-733.99^{***}	-1062.44^{***}	-1023.48^{***}	-867.39^{***}
	(33.898)	(32.475)	(29.331)	(34.026)	(33.182)	(31.191)
zonecodeR3	-853.83^{***}	-744.21^{***}	-658.24^{***}	-833.50^{***}	-829.37^{***}	-744.27^{***}
	(41.119)	(38.946)	(34.851)	(41.124)	(39.982)	(37.319)
zonecodeR4	-860.73^{***}	-667.97^{***}	-513.11^{***}	-811.27^{***}	-784.23^{***}	-681.04^{***}
	(67.881)	(64.326)	(57.591)	(67.714)	(65.861)	(61.395)
zonecodeR5	-1256.84^{***}	-1303.77^{***}	-953.71^{***}	-1113.40^{***}	-1022.69^{***}	-932.93^{***}
	(129.876)	(123.013)	(110.263)	(129.471)	(126.530)	(119.165)
SEIFA_disadv	-3.19^{***}	-2.80^{***}	-2.59^{***}	-2.67^{***}	-2.28^{***}	-2.46^{***}
	(0.157)	(0.149)	(0.134)	(0.159)	(0.157)	(0.147)
FracAustAncestry	-19.47^{***}	-15.40^{***}	-12.54^{***}	-24.70^{***}	-20.83^{***}	-16.78^{***}
	(2.559)	(2.421)	(2.167)	(2.530)	(2.468)	(2.305)
FracBachAbove	-5.90^{**}	−3.526	28.46^{***}	-22.99^{***}	-17.13^{***}	11.73^{***}
	(2.403)	(2.280)	(2.158)	(2.442)	(2.417)	(2.390)
FracUnemp	−1.557	−6.023	-19.01^{***}	-24.04^{***}	-25.24^{***}	-24.15^{***}
	(6.977)	(6.595)	(5.901)	(6.882)	(6.704)	(6.258)
FracHighInc	28.38^{***}	15.04^{***}	28.85^{***}	41.61^{***}	48.41^{***}	33.98^{***}
	(3.617)	(3.437)	(3.089)	(3.564)	(3.586)	(3.433)
FracEngSpoken	12.55^{***}	5.79^{***}	10.50^{***}	4.79^{***}	5.06^{***}	10.09^{***}
	(1.032)	(0.994)	(0.910)	(1.013)	(1.013)	(0.960)
FracOccProf	83.66^{***}	79.03^{***}	45.20^{***}	92.88^{***}	78.30^{***}	62.53^{***}
	(4.159)	(3.930)	(3.577)	(4.102)	(4.066)	(3.825)
Syd_dist	-114.33^{***}	-162.38^{***}	-244.99^{***}			

	S	S+P	S+P+M	S	S+P	S+P+M
	(2.534)	(2.790)	(3.366)			
Syd_dist^2	0.99^{***}	0.40^{***}	2.45^{***}			
	(0.029)	(0.078)	(0.098)			
coast_dist	-18.37^{***}	89.82^{***}	74.18^{***}	-30.91^{***}	-47.61^{***}	-32.09^{***}
	(2.267)	(4.613)	(4.150)	(2.179)	(2.839)	(2.824)
coast_dist^2	0.49^{***}	-0.53^{***}	-0.89^{***}	0.53^{***}	0.58^{***}	0.30^{***}
	(0.043)	(0.050)	(0.048)	(0.042)	(0.045)	(0.045)
Par_dist		81.61^{***}	0.016			
		(2.373)	(2.963)			
Par_dist^2		0.21^{***}	0.51^{***}			
		(0.066)	(0.062)			
MP_dist			170.43^{***}			
			(3.400)			
MP_dist^2			-2.54^{***}			
			(0.067)			
S_time_traffic				-66.87^{***}	-68.16^{***}	-72.44^{***}
				(2.617)	(2.560)	(2.543)
S_time_traffic^2				0.45^{***}	0.48^{***}	0.49^{***}
				(0.021)	(0.021)	(0.020)
S_transit_time				-27.94^{***}	-22.89^{***}	-30.55^{***}
				(1.468)	(1.643)	(1.576)
S_transit_time^2				0.08^{***}	0.10^{***}	0.12^{***}
				(0.006)	(0.008)	(0.007)
P_time_traffic					58.25^{***}	16.56^{***}
					(3.093)	(3.128)
P_time_traffic^2					-0.46^{***}	-0.14^{***}
					(0.029)	(0.029)
P_transit_time					-22.74^{***}	-17.25^{***}
					(1.711)	(1.612)
P_transit_time^2					0.04^{***}	0.02^{***}
					(0.009)	(0.008)
M_time_traffic						14.59^{***}
						(2.916)
M_time_traffic^2						-0.21^{***}
						(0.026)
M_transit_time						30.71^{***}
						(1.388)
M_transit_time^2						-0.09^{***}
						(0.007)
R^2	0.709	0.741	0.793	0.713	0.729	0.765
Adj. R^2	0.709	0.740	0.792	0.713	0.729	0.765
Num. obs.	10000	10000	10000	10000	10000	10000

Notes: Standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table G.5: SEM regression results ($sqmvalue$)

	S	S+P	S+P+M	S	S+P	S+P+M
(Intercept)	6488.83^{***}	5440.00^{***}	4574.14^{***}	6846.86^{***}	6837.42^{***}	5958.92^{***}
	(173.503)	(184.043)	(163.392)	(178.628)	(184.049)	(177.186)
zonecodeR2	-840.70^{***}	-815.12^{***}	-669.07^{***}	-925.43^{***}	-913.56^{***}	-845.95^{***}
	(33.180)	(32.993)	(31.182)	(33.912)	(33.538)	(32.867)
zonecodeR3	-718.96^{***}	-700.59^{***}	-611.22^{***}	-811.67^{***}	-804.46^{***}	-759.32^{***}

	S	S+P	S+P+M	S	S+P	S+P+M
	(38.827)	(38.516)	(36.202)	(39.748)	(39.277)	(38.399)
zonecodeR4	-558.32^{***}	-516.17^{***}	-411.82^{***}	-689.06^{***}	-691.76^{***}	-642.36^{***}
	(59.594)	(59.192)	(55.729)	(61.107)	(60.433)	(59.135)
zonecodeR5	-1217.24^{***}	-1196.57^{***}	-1039.61^{***}	-1281.18^{***}	-1180.72^{***}	-1082.68^{***}
	(113.814)	(112.899)	(106.279)	(118.100)	(117.179)	(114.907)
SEIFA_disadv	-2.21^{***}	-2.12^{***}	-1.97^{***}	-2.55^{***}	-2.21^{***}	-2.22^{***}
	(0.146)	(0.145)	(0.136)	(0.151)	(0.151)	(0.147)
FracAustAncestry	-13.55^{***}	-12.17^{***}	-9.84^{***}	-18.04^{***}	-17.20^{***}	-15.43^{***}
	(2.236)	(2.220)	(2.091)	(2.294)	(2.270)	(2.223)
FracBachAbove	10.44^{***}	8.78^{***}	25.71^{***}	6.25^{***}	6.64^{***}	15.88^{***}
	(2.230)	(2.216)	(2.135)	(2.355)	(2.332)	(2.332)
FracUnemp	-10.04^{*}	-11.09^{*}	-16.70^{***}	-15.99^{***}	-16.66^{***}	-19.29^{***}
	(5.943)	(5.897)	(5.553)	(6.119)	(6.049)	(5.918)
FracHighInc	19.64^{***}	16.91^{***}	21.81^{***}	31.74^{***}	38.08^{***}	32.18^{***}
	(3.436)	(3.412)	(3.206)	(3.526)	(3.540)	(3.494)
FracEngSpoken	7.84^{***}	5.85^{***}	7.90^{***}	5.88^{***}	6.99^{***}	8.52^{***}
	(0.954)	(0.957)	(0.902)	(0.978)	(0.976)	(0.957)
FracOccProf	52.60^{***}	52.53^{***}	35.45^{***}	61.06^{***}	55.47^{***}	51.83^{***}
	(3.689)	(3.663)	(3.477)	(3.781)	(3.759)	(3.688)
Syd_dist	-158.26^{***}	-182.67^{***}	-272.30^{***}			
	(4.679)	(5.098)	(5.290)			
Syd_dist^2	1.56^{***}	1.26^{***}	3.12^{***}			
	(0.067)	(0.129)	(0.143)			
coast_dist	-41.40^{***}	26.29^{***}	41.57^{***}	-62.21^{***}	-85.28^{***}	-65.72^{***}
	(4.606)	(7.359)	(6.746)	(4.606)	(5.153)	(5.004)
coast_dist^2	1.04^{***}	0.19^{*}	-0.49^{***}	0.96^{***}	1.24^{***}	0.89^{***}
	(0.098)	(0.112)	(0.103)	(0.096)	(0.101)	(0.097)
λ	0.92^{***}	0.91^{***}	0.88^{***}	0.91^{***}	0.91^{***}	0.88^{***}
	(0.006)	(0.007)	(0.009)	(0.006)	(0.007)	(0.008)
Par_dist		57.91^{***}	-21.91^{***}			
		(4.225)	(4.453)			
Par_dist^2		-0.108	0.62^{***}			
		(0.117)	(0.113)			
MP_dist			190.34^{***}			
			(5.181)			
MP_dist^2			-3.04^{***}			
			(0.148)			
S_time_traffic				-41.64^{***}	-39.86^{***}	-45.72^{***}
				(2.647)	(2.642)	(2.653)
S_time_traffic^2				0.29^{***}	0.28^{***}	0.31^{***}
				(0.022)	(0.021)	(0.021)
S_transit_time				-20.25^{***}	-14.77^{***}	-24.30^{***}
				(1.569)	(1.666)	(1.685)
S_transit_time^2				0.07^{***}	0.07^{***}	0.10^{***}
				(0.007)	(0.008)	(0.008)
P_time_traffic					16.69^{***}	5.63^{*}
					(3.331)	(3.341)
P_time_traffic^2					-0.14^{***}	-0.07^{**}
					(0.031)	(0.031)
P_transit_time					-14.78^{***}	-13.48^{***}
					(1.698)	(1.665)
P_transit_time^2					0.02^{**}	0.02^{**}
					(0.009)	(0.009)
M_time_traffic						10.44^{***}
						(2.833)
M_time_traffic^2						-0.15^{***}
						(0.026)

	S	S+P	S+P+M	S	S+P	S+P+M
M_transit_time						23.06^{***}
						(1.513)
M_transit_time^2						-0.08^{***}
						(0.008)
Num. obs.	10000	10000	10000	10000	10000	10000
Parameters	18	20	22	20	24	28
Log Likelihood	−79216.546	−79119.235	−78482.250	−79487.190	−79363.133	−79118.393
AIC (Linear model)	161967.909	160818.565	158574.348	161820.662	161254.360	159831.754
AIC (Spatial model)	158469.092	158278.469	157008.500	159014.380	158774.266	158292.786
LR test: statistic	3500.817	2542.096	1567.848	2808.282	2482.094	1540.968
LR test: p-value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table G.6: SARM regression results ($sqmvalue$)

	S	S+P	S+P+M	S	S+P	S+P+M
(Intercept)	3052.63^{***}	2540.56^{***}	1969.51^{***}	3838.06^{***}	3395.15^{***}	2588.49^{***}
	(105.506)	(107.003)	(124.709)	(121.367)	(100.426)	(133.141)
zonecodeR2	-941.19^{***}	-867.16^{***}	-707.54^{***}	-892.13^{***}	-871.44^{***}	-777.27^{***}
	(29.060)	(28.990)	(27.317)	(28.923)	(29.045)	(27.826)
zonecodeR3	-775.78^{***}	-731.89^{***}	-665.66^{***}	-733.97^{***}	-729.64^{***}	-681.85^{***}
	(35.184)	(34.915)	(32.474)	(34.903)	(34.903)	(33.277)
zonecodeR4	-684.90^{***}	-609.98^{***}	-491.34^{***}	-616.93^{***}	-603.62^{***}	-550.70^{***}
	(57.649)	(57.206)	(53.585)	(57.696)	(57.356)	(54.792)
zonecodeR5	-1238.47^{***}	-1276.25^{***}	-1001.73^{***}	-1257.19^{***}	-1131.83^{***}	-1003.03^{***}
	(111.456)	(110.209)	(102.736)	(109.807)	(109.175)	(106.222)
SEIFA_disadv	-2.78^{***}	-2.64^{***}	-2.48^{***}	-2.28^{***}	-1.92^{***}	-2.02^{***}
	(0.121)	(0.121)	(0.124)	(0.132)	(0.081)	(0.130)
FracAustAncestry	-15.75^{***}	-14.31^{***}	-12.04^{***}	-15.40^{***}	-13.23^{***}	-11.19^{***}
	(2.166)	(2.144)	(2.010)	(2.177)	(2.194)	(2.041)
FracBachAbove	−0.160	1.08^{***}	25.39^{***}	-6.88^{***}	-5.19^{***}	12.94^{***}
		(0.200)	(2.005)	(2.107)	(1.276)	(2.093)
FracUnemp	0.895	−0.485	-10.90^{**}	−3.103	−5.624	−7.746
			(5.526)	(4.671)		(5.501)
FracHighInc	17.85^{***}	12.66^{***}	23.32^{***}	16.87^{***}	26.07^{***}	20.74^{***}
	(2.887)	(2.814)	(2.882)	(3.034)	(3.057)	(3.038)
FracEngSpoken	7.51^{***}	4.75^{***}	8.29^{***}	5.67^{***}	5.65^{***}	8.49^{***}
	(0.837)	(0.878)	(0.845)	(0.871)	(0.930)	(0.847)
FracOccProf	68.41^{***}	66.65^{***}	41.04^{***}	65.26^{***}	56.66^{***}	47.26^{***}
	(2.339)	(2.262)	(3.328)	(3.529)	(3.234)	(3.387)
Syd_dist	-27.02^{***}	-50.10^{***}	-120.87^{***}			
	(2.145)	(2.687)	(3.566)			
Syd_dist^2	0.34^{***}	0.237	1.88^{***}			
	(0.023)		(0.091)			
coast_dist	7.42^{***}	47.40^{***}	37.58^{***}	13.23^{***}	3.834	17.32^{***}
	(0.796)	(2.482)	(3.892)	(1.870)	(5.529)	(2.535)
coast_dist^2	0.012	-0.41^{***}	-0.70^{***}	−0.053	−0.028	-0.25^{***}
	(0.007)	(0.045)	(0.045)	(0.035)	(0.093)	(0.040)
ρ	0.90^{***}	0.88^{***}	0.83^{***}	0.89^{***}	0.89^{***}	0.86^{***}
	(0.007)	(0.009)	(0.011)	(0.007)	(0.008)	(0.009)
Par_dist		34.98^{***}	-24.94^{***}			
		(2.176)	(2.774)			

	S	S+P	S+P+M	S	S+P	S+P+M
Par_dist^2		-0.028	0.20^{***}			
			(0.057)			
MP_dist			132.30^{***}			
			(3.209)			
MP_dist^2			-2.01^{***}			
			(0.063)			
S_time_traffic				-32.37^{***}	-33.40^{***}	-41.71^{***}
				(2.227)	(2.233)	(2.292)
S_time_traffic^2				0.26^{***}	0.27^{***}	0.32^{***}
				(0.018)	(0.018)	(0.018)
S_transit_time				-13.75^{***}	-10.54^{***}	-15.73^{***}
				(1.247)	(1.718)	(1.397)
S_transit_time^2				0.05^{***}	0.06^{***}	0.08^{***}
				(0.005)	(0.008)	(0.007)
P_time_traffic					30.81^{***}	5.69^{***}
					(2.708)	(2.200)
P_time_traffic^2					-0.20^{***}	-0.027
					(0.027)	(0.020)
P_transit_time					-16.18^{***}	-13.03^{***}
					(1.614)	(1.320)
P_transit_time^2					0.02^{***}	0.02^{***}
					(0.008)	(0.007)
M_time_traffic						11.10^{***}
						(2.605)
M_time_traffic^2						-0.10^{***}
						(0.023)
M_transit_time						20.95^{***}
						(1.233)
M_transit_time^2						-0.07^{***}
						(0.006)
Num. obs.	10000	10000	10000	10000	10000	10000
Parameters	18	20	22	20	24	28
Log Likelihood	−79565.339	−79436.630	−78641.974	−79387.909	−79203.800	−78847.964
AIC (Linear model)	161967.909	160818.565	158574.348	161820.662	161254.360	159831.754
AIC (Spatial model)	159166.678	158913.260	157327.948	158815.817	158455.601	157751.929
LR test: statistic	2803.231	1907.305	1248.400	3006.845	2800.760	2081.826
LR test: p-value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

G.3 Congestion model

Table G.7: Marginal value of congestion estimates

	sqmvalue		*lsqmvalue*	
	SUM	SEM	SUM	SEM
(Intercept)	6106.3920^{***}	5923.3251^{***}	6172.6403^{***}	8.2723^{***}
	(180.79654)	(216.77054)	(179.87341)	(0.08047)
zonecodeR2	-857.8342^{***}	-965.0045^{***}	-1001.1622^{***}	-0.2612^{***}
	(36.35448)	(39.18906)	(36.70585)	(0.01451)
zonecodeR3	-767.0457^{***}	-877.0884^{***}	-891.1958^{***}	-0.1933^{***}

	sqmvalue		*lsqmvalue*	
	SUM	SEM	SUM	SEM
	(44.35229)	(46.67354)	(45.11278)	(0.01728)
zonecodeR4	-953.0006^{***}	-1030.6410^{***}	-1119.0020^{***}	-0.1936^{***}
	(71.54034)	(71.10834)	(72.86535)	(0.02632)
zonecodeR5	-873.4663^{***}	-1195.2240^{***}	-1022.0505^{***}	-1.5288^{***}
	(160.56649)	(159.84082)	(164.04765)	(0.05916)
SEIFA_disadv	-2.8318^{***}	-2.5305^{***}	-3.1179^{***}	-0.00005
	(0.17773)	(0.18221)	(0.18004)	(0.00007)
FracAustAncestry	-16.8436^{***}	-18.4528^{***}	-21.4672^{***}	-0.0060^{***}
	(2.76651)	(2.74375)	(2.83282)	(0.00102)
FracBachAbove	18.7872^{***}	16.9723^{***}	11.9176^{***}	0.0082^{***}
	(2.92483)	(2.91296)	(2.97089)	(0.00108)
FracUnemp	-14.0944^{*}	-7.01077	-11.12117	-0.00427
	(7.56165)	(7.36275)	(7.76371)	(0.00273)
FracHighInc	56.3736^{***}	54.1849^{***}	65.3996^{***}	0.0151^{***}
	(3.95459)	(4.11003)	(4.00845)	(0.00152)
FracEngSpoken	10.4158^{***}	8.4044^{***}	10.5387^{***}	-0.00001
	(1.13848)	(1.17250)	(1.16749)	(0.00043)
FracOccProf	61.4724^{***}	57.8467^{***}	74.3273^{***}	0.0120^{***}
	(4.59915)	(4.52930)	(4.67615)	(0.00168)
S_time_notraffic	-129.5462^{***}	-21.1144^{***}	-32.6940^{***}	-0.0070^{***}
	(5.35448)	(1.97135)	(1.80562)	(0.00073)
S_time_notraffic^2	1.2031^{***}			
	(0.05992)			
S_time_traffic - S_time_notraffic	-23.0037^{***}	-7.8012^{***}	-12.4752^{***}	-0.0025^{***}
	(2.80875)	(1.12250)	(1.16971)	(0.00042)
(S_time_traffic - S_time_notraffic)^2	0.4062^{***}			
	(0.07071)			
S_transit_time	-21.6307^{***}	-28.3981^{***}	-37.8625^{***}	-0.0066^{***}
	(2.03930)	(2.03474)	(1.88010)	(0.00075)
S_transit_time^2	0.0803^{***}	0.1368^{***}	0.1683^{***}	0.0000^{***}
	(0.00988)	(0.00974)	(0.00883)	(0.00000)
P_time_notraffic	24.1686^{***}	8.0023^{***}	17.3675^{***}	-0.0040^{***}
	(5.10475)	(2.22715)	(1.84886)	(0.00083)
P_time_notraffic^2	-0.1602^{***}			
	(0.05681)			
P_time_traffic - P_time_notraffic	-7.98586	-3.42105	1.09557	-0.0017^{**}
	(6.34837)	(2.22893)	(2.29837)	(0.00083)
(P_time_traffic - P_time_notraffic)^2	0.5210^{*}			
	(0.29927)			
P_transit_time	-22.6804^{***}	-16.2245^{***}	-19.5680^{***}	-0.0037^{***}
	(2.07814)	(1.81533)	(1.60810)	(0.00067)
P_transit_time^2	0.0498^{***}	0.01308	0.0172^{**}	-0.00000
	(0.01066)	(0.00985)	(0.00844)	(0.00000)
M_time_notraffic	122.8226^{***}	5.9923^{**}	6.7430^{***}	0.0029^{***}
	(6.62234)	(2.51946)	(2.21267)	(0.00093)
M_time_notraffic^2	-1.5316^{***}			
	(0.07965)			
M_time_traffic - M_time_notraffic	-7.9127^{**}	-8.8142^{***}	-15.2427^{***}	-0.0022^{***}
	(3.95312)	(1.44609)	(1.48887)	(0.00054)
(M_time_traffic - M_time_notraffic)^2	-0.10190			
	(0.14179)			
M_transit_time	6.7051^{***}	23.9757^{***}	33.2361^{***}	0.0060^{***}
	(2.18466)	(1.84777)	(1.53194)	(0.00068)
M_transit_time^2	0.0234^{**}	-0.0868^{***}	-0.1002^{***}	-0.0000^{***}
	(0.01041)	(0.00952)	(0.00741)	(0.00000)
coast_dist	-16.9754^{***}	-69.6713^{***}	-23.0098^{***}	-0.0472^{***}

	sqmvalue		*lsqmvalue*	
	SUM	SEM	SUM	SEM
	(3.66702)	(6.28338)	(3.40606)	(0.00233)
coast_dist^2	0.1191**	1.0696***	0.2957***	0.0005***
	(0.05807)	(0.12190)	(0.05501)	(0.00005)
λ		0.8795***		0.8816***
		(0.00877)		(0.00841)
R^2	0.73778		0.72305	
Adj. R^2	0.73697		0.72236	
Num. obs.	10000	10000	10000	10000
RMSE	866.82883		890.57421	
Parameters		28		28
Log Likelihood		−81365.19870		−2349.86049
AIC (Linear model)		164244.06558		6001.76012
AIC (Spatial model)		162786.39740		4755.72098
LR test: statistic		1459.66818		1248.03915
LR test: p-value		0.00000		0.00000

Notes: Standard errors in parenthesis. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Appendix H

Part 2: DiD identification tests

H.1 Treatment and baseline outcomes regression

Table H.1: Treatment and baseline outcomes regression

	(1)	(2)	(3)
Change in travel time	2.072***	0.800	0.790
	(3.478)	(1.467)	(1.454)
SA1 % with Australian ancestry		−2.958***	−2.984***
		(−5.821)	(−5.708)
SA1 % with Bachelor's degree or above		−1.760**	−1.768**
		(−2.460)	(−2.483)
SA1 % unemployed		−1.766	−1.596
		(−0.933)	(−0.842)
SA1 % with high income		8.130***	7.981***
		(10.930)	(8.271)
SA1 % speaking English at home		−4.742***	−4.736***
		(−17.160)	(−16.901)
SA1 % working in a professional occupation		−5.839***	−5.897***
		(−5.142)	(−5.172)
SEIFA Index of Disadvantage			0.031
			(0.303)
Adj. R^2	0.002	0.133	0.133
N	7,007	7,007	7,007

t statistics in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Heteroskedasticity-robust standard errors. The dependent variable is land values in July 2012 (baseline outcome).
Change in travel time refers to the change in public transport travel times to the Sydney CBD during the morning peak in minutes from before and after the Metro opens.

H.2 Parallel trends assumption graphs

Figure H.1: Parallel trends assumption checks (travel time treatment)

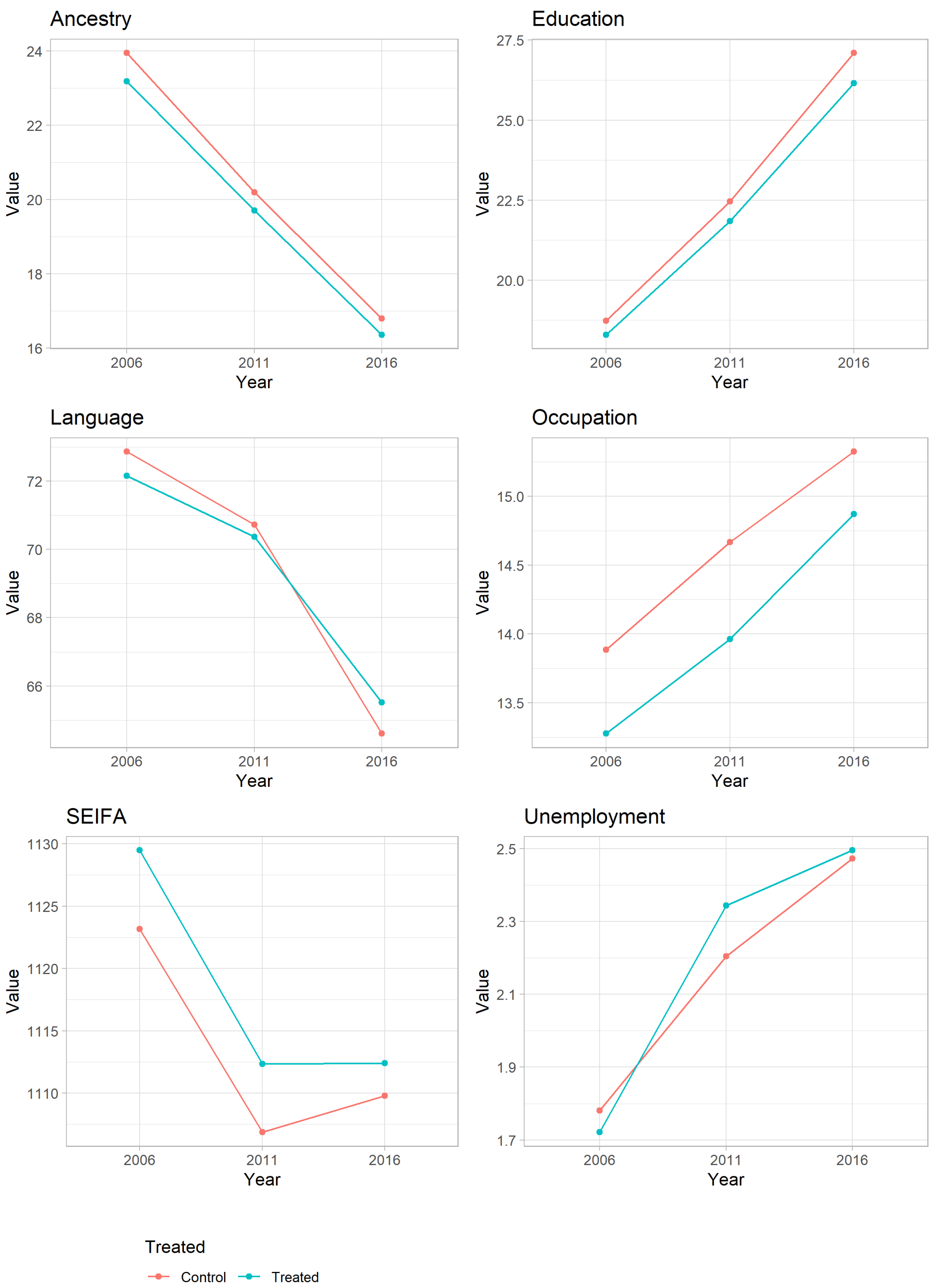
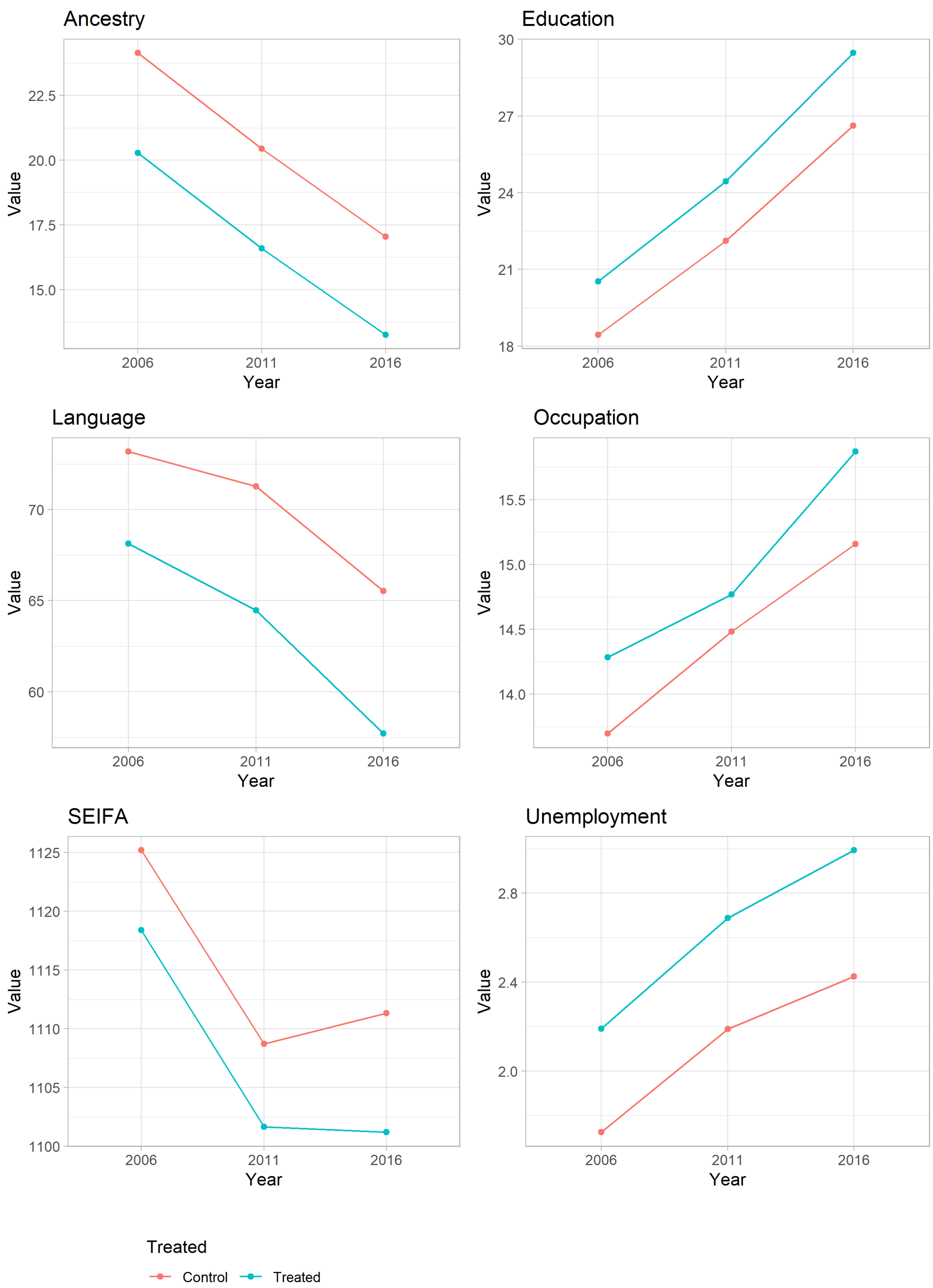


Figure H.2: Parallel trends assumption checks (distance-based treatment)



APPENDIX I

Part 2: Full regression tables

I.1 Main DiD regression

Table I.1: Difference in differences regression estimates

	(1) Land value ($)	(2) Land value/sqm ($)	(3) ln(Land value)
Post-Metro=1	756,605.758***	748.698***	0.9686***
	(20.303)	(47.717)	(86.8326)
ΔPT travel time (mins)	−15,045.319***	−9.739***	−0.0050***
	(−3.267)	(−7.184)	(−4.5268)
Post-Metro=1 × ΔPT travel time (mins)	−2,754.159***	−3.810***	−0.0036***
	(−4.196)	(−22.968)	(−19.9391)
SA1 % with Australian ancestry	2,159.907	1.219*	0.0014***
	(1.605)	(1.949)	(2.9755)
SA1 % with Bachelor's degree or above	−3,798.220	6.801***	0.0009
	(−1.161)	(7.244)	(1.1796)
SA1 % unemployed	−12,488.851**	−11.006***	−0.0073***
	(−2.401)	(−6.983)	(−6.0084)
SA1 % with high income	18,224.753***	−7.032***	0.0061***
	(4.075)	(−4.893)	(5.1093)
SA1 % speaking English at home	1,182.414	−4.666***	−0.0022***
	(0.718)	(−10.954)	(−7.5125)
SA1 % working in a professional occupation	−6,724.554	−0.980	−0.0089***
	(−1.180)	(−0.850)	(−10.9335)
SEIFA Index of Disadvantage	−298.504	−0.951***	−0.0003***
	(−0.723)	(−6.933)	(−3.5904)
Property FE	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes
Adj. R^2	0.576	0.884	0.9558
Adj. within R^2	0.422	0.914	0.9651
N	14,014	14,014	14,014

ΔPT travel time: Change in public transport travel time to Sydney CBD in minutes.
Heteroskedasticity-robust standard errors clustered at property level.
t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I.2 Alternate DiD regressions

Table I.2: Difference in differences regression alternative specification estimates

	Binary		Distance		Distance cutoffs	
	(1) $/sqm	(2) ln(·)	(3) $/sqm	(4) ln(·)	(5) $/sqm	(6) ln(·)
Post-Metro=1	486.230***	0.725***	631.894***	0.734***	489.968***	0.717***
	(49.713)	(78.220)	(46.949)	(71.404)	(55.739)	(78.838)
Post-Metro=1 × Treatment=1	22.266***	−0.024***				
	(3.086)	(−4.323)				
SA1 % with Australian ancestry	1.740***	0.002***	1.170*	0.002***	1.172*	0.002***
	(2.622)	(3.768)	(1.843)	(3.721)	(1.960)	(3.611)
SA1 % with Bachelor's degree or above	7.430***	0.001*	4.552***	0.001	5.346***	0.001
	(7.600)	(1.858)	(4.683)	(1.572)	(5.856)	(0.674)
SA1 % unemployed	−9.370***	−0.006***	−9.277***	−0.005***	−9.742***	−0.006***
	(−5.922)	(−4.821)	(−5.969)	(−4.391)	(−6.442)	(−4.315)
SA1 % with high income	−7.512***	0.006***	−0.271	0.006***	−5.776***	0.006***
	(−5.035)	(4.870)	(−0.173)	(5.520)	(−4.172)	(5.491)
SA1 % speaking English at home	−6.580***	−0.004***	−7.355***	−0.004***	−5.500***	−0.004***
	(−14.952)	(−12.051)	(−17.067)	(−12.466)	(−14.216)	(−11.666)
SA1 % working in a professional occupation	−4.401***	−0.012***	−4.332***	−0.012***	−5.821***	−0.013***
	(−3.670)	(−13.715)	(−3.820)	(−14.579)	(−5.413)	(−16.058)
SEIFA Index of Disadvantage	−0.963***	−0.000***	−0.959***	−0.000***	−0.560***	−0.000
	(−6.696)	(−3.947)	(−6.741)	(−3.429)	(−4.063)	(−1.144)
Post-Metro=1 × Station dist. (km)			−49.116***	−0.005**		
			(−17.841)	(−2.490)		
Post-Metro=1 × Dist. cutoff=2					28.209***	−0.003
					(4.871)	(−0.685)
Post-Metro=1 × Dist. cutoff=3					433.817***	0.196**
					(3.897)	(2.339)
Post-Metro=1 × Dist. cutoff=4					352.384***	0.154***
					(6.931)	(4.249)
Post-Metro=1 × Dist. cutoff=5					401.380***	0.222***
					(8.225)	(6.980)
Post-Metro=1 × Dist. cutoff=6					250.789***	0.147***
					(8.222)	(6.538)
Post-Metro=1 × Dist. cutoff=7					207.739***	0.110***
					(8.788)	(6.887)
Post-Metro=1 × Dist. cutoff=8					181.393***	0.099***
					(9.489)	(6.510)
Property FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.874	0.950	0.883	0.950	0.894	0.954
Adj. within R^2	0.906	0.961	0.912	0.961	0.921	0.964
N	14,014	14,014	14,014	14,014	14,014	14,014

PT travel time: Public transport travel time to Sydney CBD in minutes.
Heteroskedasticity-robust standard errors clustered at property level.
t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX J

Part 2: Additional robustness checks

Table J.1: DiD regression: No neighbourhood controls

	(1) Land value ($)	(2) Land value/sqm ($)	(3) ln(Land value)
Post-Metro=1	625,125.870***	855.443***	0.9643***
	(13.939)	(74.692)	(79.7240)
ΔPT travel time (mins)	−15,302.051***	−9.624***	−0.0049***
	(−3.137)	(−7.034)	(−4.3574)
Post-Metro=1 × ΔPT travel time (mins)	−2,685.209***	−4.184***	−0.0039***
	(−3.907)	(−25.088)	(−20.7562)
Neighbourhood controls	No	No	No
Property FE	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes
Adj. R^2	0.574	0.880	0.9542
Adj. within R^2	0.419	0.910	0.9638
N	14,014	14,014	14,014

PT travel time: Public transport travel time to Sydney CBD in minutes.
Heteroskedasticity-robust standard errors clustered at property level.
t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table J.2: DiD regression: No fixed effects

	(1) Land value ($)	(2) Land value/sqm ($)	(3) ln(Land value)
Post-Metro=1	745,496.912***	762.738***	1.0992***
	(12.606)	(38.364)	(38.1765)
ΔPT travel time (mins)	736.607**	3.175***	−0.0006**
	(2.006)	(18.738)	(−2.1532)
Post-Metro=1 × ΔPT travel time (mins)	−2,251.867**	−3.082***	−0.0040***
	(−2.380)	(−11.219)	(−8.6709)
Constant	4,259,771.559***	1,554.699***	15.2973***
	(7.348)	(12.237)	(68.3665)
Neighbourhood controls	Yes	Yes	Yes
Property FE	No	No	No
Clustered SE	No	No	No
Adj. R^2	0.174	0.662	0.6792
N	14,014	14,014	14,014

PT travel time: Public transport travel time to Sydney CBD in minutes.
Heteroskedasticity-robust standard errors.
t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table J.3: DiD regression: No clustered standard errors

	(1) Land value ($)	(2) Land value/sqm ($)	(3) ln(Land value)
Post-Metro=1	756,605.758***	748.698***	0.9686***
	(20.297)	(47.704)	(86.8078)
ΔPT travel time (mins)	−15,045.319***	−9.739***	−0.0050***
	(−3.266)	(−7.181)	(−4.5255)
Post-Metro=1 × ΔPT travel time (mins)	−2,754.159***	−3.810***	−0.0036***
	(−4.195)	(−22.962)	(−19.9334)
Constant	1,697,342.445***	2,558.168***	13.8119***
	(3.027)	(14.372)	(112.8898)
Neighbourhood controls	Yes	Yes	Yes
Property FE	Yes	Yes	Yes
Clustered SE	No	No	No
Adj. R^2	0.576	0.884	0.9558
Adj. within R^2	0.422	0.914	0.9651
N	14,014	14,014	14,014

PT travel time: Public transport travel time to Sydney CBD in minutes.
Heteroskedasticity-robust standard errors.
t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX K

Willingness to pay calculations

Table K.1: List of assumptions

Variable	Assumption
Working weeks in a year	48
Median age	36
Retirement age	67
Years of work remaining	31
Discount rate	5.0%

Methodology:

1. Using assumptions on travel time saving and working weeks per year, calculate annual time savings.

2. Using assumed discount rates, discount annual time savings to their present values.

3. Divide the value uplift (which represents the present $ value of time saved) by the sum of the present value of minutes saved and convert this to a $ per hour measure.

K.1 Part 1 WTP estimates

Table K.2: Sensitivity tests for sales price drive time WTP estimates

	Working weeks per year										
Discount rate	32	34	36	38	40	42	44	46	**48**	50	52
2.5%	$29.76	$28.01	$26.45	$25.06	$23.81	$22.68	$21.64	$20.70	$19.84	$19.05	$18.31
3.0%	$31.84	$29.96	$28.30	$26.81	$25.47	$24.26	$23.15	$22.15	$21.22	$20.38	$19.59
3.5%	$33.98	$31.99	$30.21	$28.62	$27.19	$25.89	$24.72	$23.64	$22.66	$21.75	$20.91
4.0%	$36.20	$34.07	$32.18	$30.49	$28.96	$27.58	$26.33	$25.18	$24.14	$23.17	$22.28
4.5%	$38.49	$36.22	$34.21	$32.41	$30.79	$29.32	$27.99	$26.77	$25.66	$24.63	$23.68
5.0%	$40.84	$38.43	$36.30	$34.39	$32.67	$31.11	$29.70	$28.41	$27.22	$26.14	$25.13
5.5%	$43.25	$40.70	$38.44	$36.42	$34.60	$32.95	$31.45	$30.08	$28.83	$27.68	$26.61
6.0%	$45.71	$43.02	$40.63	$38.50	$36.57	$34.83	$33.25	$31.80	$30.48	$29.26	$28.13
6.5%	$48.24	$45.40	$42.88	$40.62	$38.59	$36.75	$35.08	$33.56	$32.16	$30.87	$29.68
7.0%	$50.81	$47.82	$45.17	$42.79	$40.65	$38.71	$36.95	$35.35	$33.87	$32.52	$31.27

Table K.3: Sensitivity tests for sales price transit time WTP estimates

	Working weeks per year										
Discount rate	32	34	36	38	40	42	44	46	**48**	50	52
2.5%	$36.28	$34.15	$32.25	$30.55	$29.02	$27.64	$26.39	$25.24	$24.19	$23.22	$22.33
3.0%	$38.81	$36.53	$34.50	$32.68	$31.05	$29.57	$28.23	$27.00	$25.87	$24.84	$23.88
3.5%	$41.43	$38.99	$36.83	$34.89	$33.14	$31.57	$30.13	$28.82	$27.62	$26.52	$25.50
4.0%	$44.13	$41.54	$39.23	$37.17	$35.31	$33.63	$32.10	$30.70	$29.42	$28.25	$27.16
4.5%	$46.92	$44.16	$41.71	$39.51	$37.54	$35.75	$34.12	$32.64	$31.28	$30.03	$28.87
5.0%	$49.78	$46.85	$44.25	$41.92	$39.83	$37.93	$36.21	$34.63	$33.19	$31.86	$30.64
5.5%	$52.72	$49.62	$46.86	$44.40	$42.18	$40.17	$38.34	$36.67	$35.15	$33.74	$32.44
6.0%	$55.73	$52.45	$49.54	$46.93	$44.58	$42.46	$40.53	$38.77	$37.15	$35.67	$34.29
6.5%	$58.80	$55.34	$52.27	$49.52	$47.04	$44.80	$42.77	$40.91	$39.20	$37.63	$36.19
7.0%	$61.94	$58.30	$55.06	$52.16	$49.55	$47.19	$45.05	$43.09	$41.29	$39.64	$38.12

Table K.4: Sensitivity tests for land valuations drive time WTP estimates

	Working weeks per year										
Discount rate	32	34	36	38	40	42	44	46	**48**	50	52
2.5%	$30.49	$28.69	$27.10	$25.67	$24.39	$23.23	$22.17	$21.21	$20.33	$19.51	$18.76
3.0%	$32.61	$30.70	$28.99	$27.47	$26.09	$24.85	$23.72	$22.69	$21.74	$20.87	$20.07
3.5%	$34.82	$32.77	$30.95	$29.32	$27.85	$26.53	$25.32	$24.22	$23.21	$22.28	$21.42
4.0%	$37.09	$34.91	$32.97	$31.23	$29.67	$28.26	$26.97	$25.80	$24.72	$23.74	$22.82
4.5%	$39.43	$37.11	$35.05	$33.20	$31.54	$30.04	$28.67	$27.43	$26.29	$25.23	$24.26
5.0%	$41.83	$39.37	$37.19	$35.23	$33.47	$31.87	$30.42	$29.10	$27.89	$26.77	$25.74
5.5%	$44.30	$41.70	$39.38	$37.31	$35.44	$33.75	$32.22	$30.82	$29.54	$28.35	$27.26
6.0%	$46.83	$44.08	$41.63	$39.44	$37.46	$35.68	$34.06	$32.58	$31.22	$29.97	$28.82
6.5%	$49.42	$46.51	$43.92	$41.61	$39.53	$37.65	$35.94	$34.38	$32.94	$31.63	$30.41
7.0%	$52.05	$48.99	$46.27	$43.83	$41.64	$39.66	$37.86	$36.21	$34.70	$33.31	$32.03

Table K.5: Sensitivity tests for land valuations transit time WTP estimates

	Working weeks per year										
Discount rate	32	34	36	38	40	42	44	46	**48**	50	52
2.5%	$18.92	$17.81	$16.82	$15.93	$15.14	$14.42	$13.76	$13.16	$12.61	$12.11	$11.64
3.0%	$20.24	$19.05	$17.99	$17.04	$16.19	$15.42	$14.72	$14.08	$13.49	$12.95	$12.46
3.5%	$21.61	$20.33	$19.21	$18.19	$17.28	$16.46	$15.71	$15.03	$14.40	$13.83	$13.30
4.0%	$23.02	$21.66	$20.46	$19.38	$18.41	$17.54	$16.74	$16.01	$15.34	$14.73	$14.16
4.5%	$24.47	$23.03	$21.75	$20.60	$19.57	$18.64	$17.80	$17.02	$16.31	$15.66	$15.06
5.0%	$25.96	$24.43	$23.08	$21.86	$20.77	$19.78	$18.88	$18.06	$17.31	$16.62	$15.98
5.5%	$27.49	$25.88	$24.44	$23.15	$21.99	$20.95	$20.00	$19.13	$18.33	$17.60	$16.92
6.0%	$29.06	$27.35	$25.83	$24.47	$23.25	$22.14	$21.14	$20.22	$19.37	$18.60	$17.88
6.5%	$30.67	$28.86	$27.26	$25.82	$24.53	$23.36	$22.30	$21.33	$20.44	$19.63	$18.87
7.0%	$32.30	$30.40	$28.71	$27.20	$25.84	$24.61	$23.49	$22.47	$21.54	$20.67	$19.88

K.2 Part 2 WTP estimates

Table K.6: Sensitivity tests for DiD travel time WTP estimates

		Working weeks per year										
		32	34	36	38	40	42	44	46	**48**	50	52
Discount rate	2.5%	\$27.96	\$26.31	\$24.85	\$23.54	\$22.36	\$21.30	\$20.33	\$19.45	\$18.64	\$17.89	\$17.20
	3.0%	\$29.91	\$28.15	\$26.58	\$25.18	\$23.92	\$22.79	\$21.75	\$20.80	\$19.94	\$19.14	\$18.40
	3.5%	\$31.92	\$30.05	\$28.38	\$26.88	\$25.54	\$24.32	\$23.22	\$22.21	\$21.28	\$20.43	\$19.65
	4.0%	\$34.01	\$32.01	\$30.23	\$28.64	\$27.21	\$25.91	\$24.73	\$23.66	\$22.67	\$21.76	\$20.93
	4.5%	\$36.15	\$34.03	\$32.14	\$30.44	\$28.92	\$27.54	\$26.29	\$25.15	\$24.10	\$23.14	\$22.25
	5.0%	\$38.36	\$36.10	\$34.10	\$32.30	\$30.69	\$29.23	\$27.90	\$26.68	\$25.57	\$24.55	\$23.61
	5.5%	\$40.62	\$38.23	\$36.11	\$34.21	\$32.50	\$30.95	\$29.54	\$28.26	\$27.08	\$26.00	\$25.00
	6.0%	\$42.94	\$40.41	\$38.17	\$36.16	\$34.35	\$32.72	\$31.23	\$29.87	\$28.63	\$27.48	\$26.43
	6.5%	\$45.31	\$42.65	\$40.28	\$38.16	\$36.25	\$34.52	\$32.95	\$31.52	\$30.21	\$29.00	\$27.88
	7.0%	\$47.73	\$44.92	\$42.43	\$40.19	\$38.18	\$36.36	\$34.71	\$33.20	\$31.82	\$30.55	\$29.37