Honours Thesis

Location, location, innovation:

The impact of local environmental factors on regional innovation in Australia

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supervised by

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Declaration

Except where appropriately acknowledged this thesis is my own work, has been expressed in my own words and has not previously been submitted for assessment.

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Signature　　　　Date

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In loving memory of my Lolo Abe. I hope you would be proud by what I have achieved.

"As a matter of fact, capitalist economy is not and cannot be stationary. Nor is it merely expanding in a steady manner. It is incessantly being revolutionized from within by new enterprise, i.e., by the intrusion of new commodities or new methods of production or new commercial opportunities into the industrial structure as it exists at any moment." - *Schumpeter, 1942*

"A smart innovation agenda, in short, would be quite different from the one that most rich governments seem to favour. It would be more about freeing markets and less about picking winners; more about creating the right conditions for bright ideas to emerge and less about promises of things like green jobs. But pursuing that kind of policy requires courage and vision and most of the rich economies are not displaying enough of either." - *The Economist, 2010*

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Abstract

This paper investigates the determinants of innovation among Australian regions, focussing on the spatial dimension of innovation and innovative-related activities in creating spillover effects. Through 'exploratory' and 'confirmatory' spatial data analysis we find evidence that innovation activity is spatially dependent, and that there is evidence of spatial clustering of highly innovative regions. Applying spatial econometric techniques, we estimate a Spatial (panel) Durbin Model to control for spatial autocorrelation to analyse the driving forces of innovation throughout regions. We find that the number of university campuses within a region along with university research has a significant and positive effect on local levels of innovation. In terms of spillover effects, we find that population density creates a negative indirect effect; where neighbouring region's population density adversely impacts innovation levels.

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1 Introduction

In an intensely knowledge-driven world, innovation has been widely considered a decisive driver of economic growth and development. The study of knowledge and innovation has been a key area of research, pioneered by the seminal work of Schumpeter (1934, 1942) in what is popularly known as 'creative destruction'. At its simplest, Schumpeter conceptualised how 'innovation' of new methods, products or markets force older ones to become antiquated, requiring the market and competitors to adjust and learn, or face failure. Creative destruction is relevant today more than ever, with anecdotal evidence of disruptive innovation leading to the demise of older business models, markets, and products.[1] From an economic standpoint, in the decades following Schumpeter a wide array of literature has been devoted to understanding the role of innovation. In macroeconomics, the ground-breaking work of Solow (1956) in formalising exogenous growth theory highlighted the role of technological change and progress in driving output growth (an unexplained residual in the model). Following the works of Schumpeter, Romer (1986) and Krugman (1991) develop endogenous growth theory 'endogenising' the Solow residual, a concept built on increasing returns to scale production driving growth[2] rather than exogenous technological change. These theories have been accompanied by a plethora of empirical literature particularly focussed on measuring and understanding the determinants of innovation and technological change.

Innovation in of itself is a concept difficult to pin down and define. In many ways the concept of innovation has been hijacked by the discussion in economic growth circles, commonly considered to simply relate to technological advancement and invention. In actuality innovation encapsulates a vast array of concepts. Schumpeter (1934) defines innovation as the introduction or inception of new *products*, *methods of production*, and *markets*. It also encapsulates the development of new *sources of supply for materials or inputs*, and the creation of new *market structures within industries*. This serves as basis for the contemporary definition of innovation, as highlighted in the Oslo Manual (2005) article 146[3]:

> *"An innovation is the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations."*

The important aspect of this definition is that of 'implementation' and 'novelty', meaning an innovation is something that is practically utilised and is either new, or sufficiently different to older innovations. The importance of innovative activity has recently gained greater attention with the studies of 'spillover effects', or rather externalities from innovation. Arrow (1962) characterised innovation and knowledge a public good, particularly with how knowledge diffusion is non-rivalrous and non-exclusive (yielding positive externalities). This concept of spillovers and externalities is a concept that we are interested in investigating at the regional Australia level. The basis for such a study is grounded in some of the anecdotal evidence we see related to economic geography. This relationship between innovative activity and geography is self-evident in examples like the Silicon Valley (and the wider San Francisco Bay

[1] A key example of this is Uber and the way the company has drastically disrupted traditional taxi industries worldwide.
[2] Romer (1986) suggests growth occurs through knowledge spilling over across economic agents.
[3] The Oslo Manual, produced by the Organisation for Economic Co-operation and Development (OECD), serves the purpose of standardising and providing a framework in approaches to understanding and measuring innovation.

Area) or Route 128 (Boston Area) commonly recognised as high-technological and innovative regions. These are modern examples of geographical innovation, a phenomenon where infrastructure (physical and intellectual) through established firms, new start-ups, universities, and research institutes migrate and congregate towards another regionally, with similar regions again clustering near each other. For instance, Silicon Valley is one region part of a wider subset of regions constituting the San Francisco Bay Area.[4] Regions like Silicon Valley by their very construction attract some of the most successful start ups as firms look to take advantage of the knowledge spillovers nurtured by the region. From a policy perspective, policy makers and economists have quickly sought to identify how and why these regions are so effective at incubating successful innovations and innovative firms where being a 'unicorn' is the norm. The Oslo Manual (2005, article 116) highlights:

> *"identifying the main characteristics and factors that promote innovation activity and the development of specific sectors at regional level can help in understanding innovation processes and be valuable for elaboration of policy."*

Accordingly, new interest has been garnered in quantifying and understanding innovation and its determinants at a regional level in order to replicate the successes of places like Silicon Valley. Applying the broad definition of innovation in the context of 'regions', we look to assess innovative success by the collective performance of the actors within. Such quantification has been addressed in literature regarding 'regional innovation systems'. Based on the concept of 'national systems of innovation' (See: Lundvall (1992); Freeman (1995)), the 'regional innovation system' analyses innovation activity at a sub-national and sub-state level. Cooke et al. (1997) highlight the key role innovation-conducive infrastructure plays; through financial and educational institutions, as well as the development of institutionalised learning and entrepreneurial culture. These system analyses look at firms, knowledge institutions, and the 'state' as "embedded in a system at sectoral, regional and national levels" (Mazzucato, 2013). Importantly, literature in this area has increasingly emphasised universities playing a far greater role in innovation systems (See Etzkowitz and Leydesdorff (2000); Van Looy (2009)). Developing an increasingly entrepreneurial role, universities' strength are characterised in their ability to conduct early stage research, how they are embedded within a system that promotes and facilitates efficient research, and are unconstrained to external shareholders and profit pressures. Audretsch and Stephan (1996) find empirical evidence that firms are attracted to areas with external knowledge sources such as universities. Given this interest in the role of universities, we take a particular interest in how university infrastructure as well as government facilitation of university driven research impacts innovation levels.

With these perspectives in mind, we seek to create a link between regional and national innovation frameworks with empirical work to determine what drives innovation in Australian regions. This formulates the basis of this paper's research questions in investigating what characteristics, conditions, and environmental factors facilitate innovation. With the example of the San Francisco Bay Area in mind we ask, to what extent does location and your neighbours impact on innovation? More specifically we investigate what are the key determinants of innovation in Australia, particularly looking at the role of

[4]Silicon Valley has incubated and attracted the likes of Intel, Apple, and Uber, with institutions such as Stanford University and University of California Berkley situated nearby.

universities. Moreover, we look for evidence of spatial spillovers occurring. In conducting this analysis we utilise spatial econometric tools and techniques, to account for the geographical focus. Tobler (1970) wrote:

> *"Everything is related to everything else, but near things are more related than distant things."*

Although a geographer rather than economist, Tobler's popular "First Law of Geography" inadvertently formalised the idea of spatial dependence (or autocorrelation[5]). There has been increasing popularity in spatial econometrics as greater interest has been in understanding and accounting for the interaction of economic agents where 'social norms', 'neighbourhood effects' and 'other peer group effects' might have an intrinsic impact (Anselin, 2003). LeSage's (2008) review of empirical literature highlights that it is common for regions in space to not be 'independent', rather exhibit qualities of 'spatial dependence'. Papers exploiting spatial econometric tools motivate this study.

The focus of our analysis will be Australian innovation data among SA3 regions (See *Appendix E* for a diagram of SA3 regions) between 2009 and 2015. Motivated by the concepts of regional innovation, economic geography, and spatial spillovers, we investigate the determining factors of innovation in Australia. Our analysis is divided into two major sections: *exploratory spatial data analysis* **(ESDA)**, and *confirmatory spatial data analysis* **(CSDA)**. Through ESDA we test to what extent a region's neighbours impact on local innovation. Controlling for this effect, we then further utilise non-traditional spatial econometric techniques through spatial panel models to investigate the determinants of innovation in Australian regions, particularly emphasising the presence of universities. Through our analysis we are able to conclude that the innovation in neighbouring regions significantly impacts local innovation. There is also evidence that similar innovative-level regions tend to cluster with each other, and that location indeed matters. In accounting for these dependencies, through our spatial regression analysis we conclude that the number of university campuses within a region along with the funding made available to those universities has a significant and positive impact on innovation. We also have the interesting finding of negative spatial spillover effects resulting from population density. Innovation in Australia is particularly relevant today given the National Innovation and Science Agenda. With initiatives such as "business research and innovation", and "new research funding arrangements for universities" (National Science Agenda) at the forefront of the agenda, it is important to understand what facilitates innovation in Australia to allow for accurate policy implementation.

The remainder of this paper is as follows: Section 2 will explore the previous innovation literature in greater detail. Section 3 details the methodology and results of exploratory spatial data analysis. Section 4 presents a theoretical model of knowledge production which forms the foundation of our empirical model. Section 5 highlights our model specification in conducting confirmatory spatial data analysis, with Section 6 detailing the data utilised for estimation. Finally, Section 7 presents the results and discussion, with concluding remarks made in Section 8.

[5]Spatial *dependence* and spatial *autocorrelation* are used interchangeably throughout this paper.

2 Literature Review

2.1 Early approaches and theories of innovation

Schumpeter (1934, 1942) developed innovation theory, providing the conceptual foundation of how the area is studied. Creative destruction is the key concept developed, where economic development is driven by industrial mutation replacing previous methods and products, a concept driven by the formation of temporary monopolies. Creation of such short-term monopolies motivates industrial mutation for firms to remain competitive and survive. Schumpeter's sentiments were echoed by Arrow (1962) who similarly identified the value of knowledge in promoting growth, emphasising spillover externalities occurring from sharing of knowledge.[6] These seminal works gave rise to the field of 'evolutionary economics', pioneered by Nelson and Winter (1982 [2005]). Re-applying Schumpeter's theories in a modern context, Nelson and Winter (1982) conceptualised the idea that selection, continual adaptation, and organisational routines are fundamental to economic growth. In many ways these evolutionary concepts are strongly influenced by evolutionary biology and Universal Darwinism (Witt, 2006). In discussing evolutionary theory, Mazzucato (2013) boils it down to 'adapt or die'/'survival of the fittest' mentality, where firms must co-evolve and innovate in order to not only profit, but survive (Mazzucato, 2013).

2.2 Knowledge and Spatial Spillovers

The combined sentiments of Marshall (1890[2009]), Arrow (1962), and Romer (1986) were formalised by Glaeser et al. (1991) in developing the theory of MAR spillovers or externalities. In our specific context, this relates to how innovation tends to spillover where economic agents are clustered in close proximity. Glaeser and co-authors take some of the key elements from each influential contribution, each of which detail the role of spillovers.[7] Taking into account these formative theories, Glaeser et al. (1991) find that local proximity to similar industries allows for knowledge to spillover. These spillovers are facilitated by employee turnover and transfers to different firms, a "cross-fertilisation" where new ideas are introduced to firms. More generally, the MAR spillover formalises how these knowledge externalities are more conducive to areas where firms are closer in proximity geographically (where cross-fertilisation is better suited). These theories were supported by Krugman (1991) and Feldman (1994) posing similar findings that geography and spatial context are underlying dimensions that need to be accounted in measuring the determinants of innovation. Krugman (1991) develops this idea in more of trade context, however, Feldman (1994) finds empirical evidence that innovative activity is greater in clustered areas. Simply, spillover theories suggest that such agglomeration and clustering allows for spatial diffusion of knowledge, making geography a key consideration. In the context of Silicon Valley, Carlino (2001) identifies how these MAR spillovers have attracted semiconductor firms who seek to take advantage of spatial externalities. Carlino (2001) also highlights how these spillovers can also be informal in nature,

[6] The pair deviated in opinion primarily in which market structure promoted greater growth. Arrow, an advocate for perfect competition driving growth, diverged from Schumpeter's views on the creation of temporary monopolies.

[7] Marshall being the original contributor of knowledge spillover theory; Arrow studying endogenous growth and knowledge; with Romer model similarly specifying knowledge spillover as a mechanism for endogenous growth.

detailing anecdotal accounts of after-work 'bars' facilitating cross-fertilisation through the mingling of employees from different firms.

2.3 Regional linkages and the role of the university

The relationship between innovation and geography is one that is investigated at a variety of levels. Literature regarding "national/regional innovation systems" seeks to understand the characteristics that encourage innovative activity, and unpack the role of state and non-state actors. Established by Lundvall (1992) and Freeman (1995), the concept of systems of national innovation formalise the interrelationships and process driving innovative change at a national level. Lundvall and Freeman's 'system driven approach' focused particularly on how the division of labour plays a key role in the innovative process, emphasising identifying the contributions of each actor in producing knowledge (Fritsch 2002, pg. 87). An expansion of this national system theory was made by Cooke et al. (1997), formalising a similar relationship at a regional level. Cooke and co-authors take an interest in the various dimensions of regional innovation, particularly institutions facilitating autonomous innovation, and the development of systematic entrepreneurial cultures. Both sets of literature highlight the major groups of actors driving innovative activity, namely; private firms, public research institutions (universities), supportive services, and the regional workforce (Fritsch 2002, pg. 87). Rather than supporting the role of individualistic firms, the literature emphasises how innovation is driven by an integrated and broad network of firms within a spatial area (Mazzucato, 2013).

More recent literature focussing on innovation systems have shifted attention towards the role of universities. Seminal work on innovation systems, although not neglecting the role of universities, underemphasise the importance of universities within a regional or national network. Etzkowitz and Leydesdorff (2000) develop the concept of the "Triple Helix Model" of university-industry-government, departing from "Mode 2" which distinctly focused on the government-industry relationship (where innovation activity and facilitation was primarily the responsibility of government and firms). These papers highlight that universities play a central entrepreneurial role as a "quasi firm" (Etzkowitz, 2003), serving a far greater purpose than merely education hubs. Research institutions and universities are identified as effective tools for knowledge and technological transfer, and diffusion. Sampat and Mowery (2004, pg. 210) outline how now "governments seek to use universities as instruments for knowledge-based economic development and change." Van Looy (2009) highlights the continuing shifting role of universities towards one more entrepreneurial. Universities are seen to be capable of a dynamic role, given their ability to conduct both basic and applied research. Moreover, university agendas permit long-term research goals rather than immediate deadlines commanded by private enterprise, and research is publicly disseminated rather than made secret. This is bolstered by potential university-industry collaboration, as well as university research projects leading to commercialisation or spin-off firms. Given the recent focus in the literature focus, we take a particular interest in the role that universities play in inducing innovation in Australian regions.

2.4 Related empirical literature

Investigation of innovation in an empirical context has been largely framed by the 'Griliches-Jaffe' knowledge production function. First developed by Griliches (1979), and subsequently built upon by Jaffe (1989), the knowledge production function looks at knowledge or innovation as a function of knowledge-inputs, often applied with a Cobb-Douglas functional form. The bulk of literature use this framework to estimate the determinants of innovation. Griliches' (1979) major contribution was highlighting how industrial research and development (R&D), along with human capital inputs are drivers of technological change at the firm level. Looking at states and industries rather than firms, Jaffe (1989) finds evidence that knowledge spills over via university funding, controlling for geographic coincidence. Importantly, Jaffe also highlights the key role of university R&D impacting on innovation. Feldman and Florida (1994) also find a strong relationship between industrial R&D, university research, industry presence, and business services at the state level in the United States. More recent papers apply the knowledge production function to a regional system context, with Fritsch (2002) estimating the effects of inputs on patents in European regions utilising a Negbin estimation. This paper confirms the importance of regional R&D. A similar result is in Fritsch and Franke (2004) where R&D expenditure is found to have a positive and significant relationship with innovation. The major differences among papers are largely in the geographical location they measure, level of geographic aggregation (countries, states, counties), and the combination of inputs used to capture knowledge output. These papers primarily focus on the direct and local determinants of innovation rather than accounting for neighbours as we do. Moreover, the models estimated are generally cross-sectional in nature.

In attempting to quantify spillover effects from innovation and innovative inputs, Anselin et al. (1997) examine metropolitan statistical areas (MSA) and states in the US. This is one of the earliest papers incorporating geographical aspects in a meaningful way under the knowledge production function model. The model includes spatial lag variables by incorporating geographical coincidence indices, capturing the effect of industrial R&D and university funding to regions at different distance bands. The authors find that there is strong evidence of spatial externalities at the state level, along with evidence that university research spills over a 50 mile radius from MSAs (the regional level). Anselin et al. (1997) captures the type of analysis we seek to conduct in this paper, however, we incorporate modern spatial econometric techniques to quantify spillovers.

Recently, the use of geocoded data and geographic information systems (GIS) has gained traction in studying economic relationships (Anselin 2003). This has lead to the popularity of spatial econometric methods. These models focus attention on 'specifying, estimating, and testing' spatial interactions, and essentially control the extent spatial relationships impact on particular economic outcomes (Anselin 2001). Importantly these techniques provide a way to determine whether neighbours effect innovation levels, as well as a precise method to determine and measure spatial spillovers. Ó hUallacháin and Leslie (2007) explore spatial relationships using ESDA techniques to identify spatial dependence, however, do not go further in utilising spatial regression models. They find evidence consistent with earlier papers that industrial R&D has a positive and significant effect on innovation, however, fail to find such a positive relationship with university R&D. Although not using spatial techniques, Ó hUallacháin and Leslie's

(2007) is particularly interesting in their 'rethinking' of the knowledge production function, focusing on regional structures as opposed to solely expenditure measures. They employ variables such as industry employment concentration and urbanisation levels to capture regional composition. The most relevant and recent paper synonymous to the type of analysis we conduct is Wang et al. (2015). The authors investigate the space-time dynamics of innovation at the provincial level in China, utilising spatial techniques through ESDA and CSDA. Using the knowledge production framework they utilise a spatial panel model (Spatial Durbin Model; the model we utilise in our analysis) to study the determinants of innovation accounting for spatial relationships. Their analysis finds spatial dependence to exist significantly in coastal regions, and more importantly that R&D expenditure, personnel employed in R&D roles, and GDP per capita to have significant and positive relationships on innovation (proxied by patents). More interestingly, calculating direct and indirect effects they are able to conclude that spatial spillovers exist in the form of R&D expenditure having a significant effect on neighbouring regions. Moreno et al. (2005) conduct a similar analysis utilising data from European regions. They too identify spatial dependence through ESDA, and in their regression analysis find a postive relationship between internal R&D, economic performance indicators, and national institutions, consistent with results in previous literature. Moreover, they determine the presence of spatial spillovers among European countries. Critically, of the empirical literature, studies into Australian regional innovation are absent.

3 Exploratory Spatial Data Analysis

Spatial Diagnostics

A key hypothesis of this paper is that Australian regions[8] exhibit spatial dependence, where neighbouring regions effect local innovation levels. For clarification, we use the term 'local' in the sense of comparing two entities: focusing on region 'A' (who has neighbours 'B' and 'C') – the (neighbour(ing)) effect 'B' and 'C' has on 'A' is referred to as the effect neighbours have 'locally'. In order to determine whether such 'spatial autocorrelation' exists, exploratory spatial data analysis (ESDA)[9] is utilised to quantitatively analyse this phenomenon through 'geographic information systems' (GIS). Anselin (1994) defines ESDA as:

> "the collection of techniques to describe and visualise spatial distributions, identify atypical locations (spatial outliers), discover patterns of spatial association (spatial clusters), and suggest different spatial regimes and other forms of spatial instability or spatial non-stationarity."

Through ESDA we aim to be able to create the link between space and knowledge/innovation, expecting to see some level of spatial association between regions.

3.1 Spatial Weights Matrix

The first step in spatial analysis is the development of a spatial weights matrix. The spatial weights matrix, $\boldsymbol{W}$, is an $n \times n$ non-negative non-stochastic matrix that describes how units of a sample are spatially configured or arranged (Elhorst 2014, pg. 10). In our context, the matrix specifies the relationship and connection between Australian regions over space, where we will have a 326×326 matrix capturing the relationship between SA3 regions. A variety of spatial relationships are commonly used: contiguity (a relationship is defined if regions share a border)[10], inverse distance (where a relationship is specified over distance 'with' or 'without' cut-off), or k^{th} order nearest neighbour (where the number of neighbours for each observation is specified). Generally speaking these matrices are assumed to be symmetric (Elhorst 2014, pg. 10). Formally, the sum of all individual elements or relationships (between i and j) forms the matrix $\tilde{W}$:

$$\sum_{j}^{n} \tilde{w}_{ij} = \tilde{W} \tag{1}$$

Here $\tilde{w}_{ij}$ represents the relationship between the i^{th} and j^{th} observation, or in our case region. Suppose we have a 5×5 matrix, defined on a contiguity relationship where units (regions) are spatially related if their borders touch, denoted by:

$$\tilde{w}_{ij} = \begin{cases} 1, & \text{if contiguous} \\ 0, & \text{otherwise} \end{cases}$$

[8] Details as to how innovation is measured and the nature of the Australian region unit of observation is discussed in depth below in the data description Section 6.1 and 6.2.

[9] Analysis is conducted with ArcGIS and GeoDa, popular GIS programs.

[10] For example, as South Australia and Western Australia share a border, a contiguity relationship would be defined between them.

Accordingly,

$$\tilde{W} = \begin{pmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \end{pmatrix} \rightarrow W = \begin{pmatrix} 0 & 0.5 & 0.5 & 0 & 0 \\ 0.25 & 0 & 0.25 & 0.25 & 0.25 \\ 0.5 & 0.5 & 0 & 0 & 0 \\ 0 & 0.5 & 0 & 0 & 0.5 \\ 0 & 0.5 & 0 & 0.5 & 0 \end{pmatrix} \tag{2}$$

Here each row corresponds with a region; so the first row represents the relationship region 'one' has with the other regions, while the second row represents the relationship region 'two' has with other regions, and so on. From (2) we can extract that region 'one' is neighbours with 'two' and 'three', while region 'two' is neighbours with every other region, or that region 'four' is neighbours only with 'two' and 'five'. Through this matrix a simple contiguous relationship is representable. It is worth noting that all diagonal elements are zero, preventing an observation from being defined as a neighbour of itself (LeSage 2008, pg 19). As is standard practice, matrix $\tilde{W}$ is row-normalised such that row elements sum to one by dividing each row-element by the number of neighbours of that observation (LeSage 2008, pg. 22), giving us our spatial weights matrix ($\tilde{W} \rightarrow W$). Explicitly:

$$w_{ij} = \frac{\tilde{w}_{ij}}{\sum_j \tilde{w}_{ij}} \implies W = \sum_j^n w_{ij} \tag{3}$$

This is done to ensure all weights are equal to or between 0 and 1, effectively allowing for the matrix to act as a weighted average operation, averaging the elements of a given region's neighbours (Elhorst 2014, pg. 12).

Selecting the type of spatial relationship for the available data is not a "mechanical" process, it is largely dependent on the context, namely by looking at the structure and nature of the data and observable unit (Viton 2010, pg. 5). Such selection is also incumbent on ensuring each observation has a neighbour relationship with another observation, but more importantly satisfies at least one of two conditions: (i) that the sum of rows and columns of $\boldsymbol{W}$, $(I_n - \rho W)^{-1}$, and $(I_n - \lambda W)^{-1}$ "before W is row-normalised should be uniformly bounded in absolute value as n goes to infinity" (Kelejian and Prucha; 1998, 1999 [Elhorst 2014, pg. 11]), or (ii) the sum of rows and columns of $\boldsymbol{W}$ prior to row-normalisation should not diverge to infinity at a rate equal to or faster than the rate of the observable unit sample size n (Lee, 2004).[11][12] In deciding the appropriateness of a spatial relationship, the unique composition of the SA3 division and that of Australia poses a challenge. As seen in *Figure 6* of *Appendix E*, rural regions are quite large (in terms of area), while city regions are far smaller but have higher population densities. Using an inverse distance relationship becomes infeasible as the required threshold distance to ensure all regions have a neighbour is in excess of 700km. To put this into perspective, the distance between Adelaide and Melbourne is 726.5km, which is a spatial relationship we do not want to capture. Moreover, given we have no theoretical basis in defining how many neighbours a region should have, k^{th} nearest neighbour principle is unsuitable. As such a contiguity relationship is most appropriate to define regional relationships.

[11] This ρ and λ are spatial autoregressive and autocorrelation coefficients respectively. These are defined in greater detail in Section 5.

[12] Assumption (i) relates more to stationarity conditions of spatial coefficients in spatial regressions.

The spatial relationship utilised for this analysis is characterised as a 'contiguity of p-order 1'. This is to say a relationship is defined if regions share the same border, where only direct neighbouring relationships are captured (not neighbours of neighbours). Overall, the specified relationships are reasonable, where for the most part regions are neighboured quite tightly, particularly in major towns and cities. First order contiguity spatial weights matrices also satisfy both condition (i) and (ii) (Elhorst 2014, pg. 11) such that we do not need to be concerned. The following *Figure 1* displays a connectivity histogram outlining the frequency of number of neighbours, with summary statistics listed below it in *Table 1*. We do not observe any concerning jumps in the data or issues where region have no neighbours.

Figure 1: Neighbour Connectivity Histogram

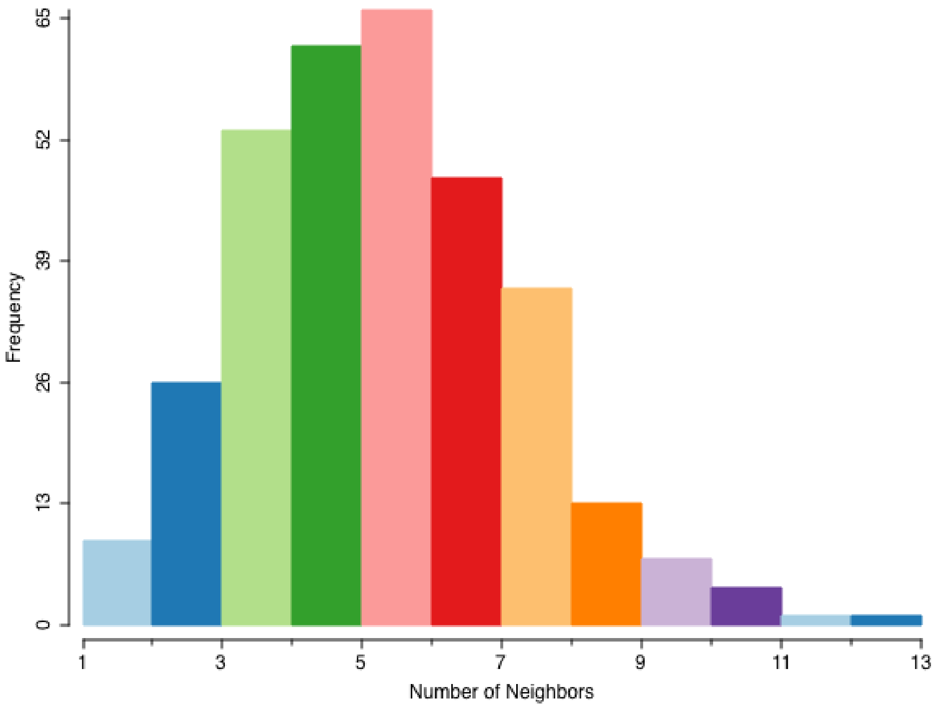


Table 1: Spatial Weights Matrix Summary Statistics

Min	**Max**	**Median**	**Mean**	**Std. Deviation**	**n**
1	12	5	4.810	1.958	326

3.2 Spatial Autocorrelation

Having defined a spatial weights matrix, we study whether our regions and data exhibit spatial dependence/autocorrelation. As touched upon above, spatial autocorrelation follows the idea regions who neighbour each other depend on and impact each other.[13] In the innovation context, this would mean innovation levels in neighbouring regions have effects on each other. Spatial autocorrelation is formally

[13]This diverges from the traditional temporal autocorrelation where the error terms are correlated between years.

defined by Anselin (2003, pg. 312):

$$cov(y_i, y_j) = E(y_i y_j) - E(y_i) - E(y_i) \cdot E(y_j) \neq 0, \text{for } i \neq j \tag{4}$$

Simply, spatial autocorrelation arises where innovation between region i and j are correlated, and co-move. Given the spatial structure of the spatial weights matrix, this spatial covariance becomes meaningful in modelling the idea of innovation spilling over to other regions (Anselin 2003, pg. 312).

The standard specification test for spatial autocorrelation is the ***Moran's I*** test statistic developed by Moran (1948). In contrast to non-spatial econometrics, the Moran's I is comparable to the Durbin-Watson test for serial correlation, which Anselin (2003) notes has a distinct similarity to Moran (1948). Moran's I is relied upon to determine spatial dependence, out performing alternative tests (Anselin and Florax, 1995). The test statistic is defined as:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{(x_i - \bar{x})^2} \tag{5}$$

where $\sum_i \sum_j w_{ij} = S_0$ is a "standardisation factor that corresponds to the sum of the weights for the nonzero cross-products" (Anselin 2003, pg. 323), or simply the aggregate of spatial weights. Here, n is the number of observable units (regions), w_{ij} being the spatial weight between the i^{th} and j^{th} element, x_i and x_j the observation for the variable of interest for i and j (in our case innovation level in the various regions), and $\bar{x}$ the mean of x (mean innovation of the sample). We know that $(x_i - \bar{x})$ and $(x_j - \bar{x})$ denote deviations from the mean. Equation (5) can be re-written in matrix notation:

$$I = \frac{n}{S_0} \cdot \frac{e'We}{e'e} \tag{6}$$

The null hypothesis (H_0) of the Moran's I is of 'no spatial autocorrelation', with expected value:

$$E(I) = \frac{-1}{n-1} = \frac{-1}{326-1} = -0.0031 \tag{7}$$

Values of the test statistic fall between -1 and 1, with 0 test statistics suggesting no spatial autocorrelation (random pattern) meaning no systematic relationship between neighbouring regions, with values > 0 suggesting positive spatial autocorrelation, and values < 0 suggesting negative spatial autocorrelation.

One of the primary issues faced in conducting the Moran's I is the lack of methodology in dealing with panel data. There appears no apparent and widespread method of dealing with both cross section, and temporal elements. Discussion on specification and tests for spatial dependence is noticeably absent in notable spatial panel guides (See: LeSage and Pace 2009; Elhorst 2014). As such a similar approach to Wang et al. (2015) is used, whereby the Moran's I is taken for each observable year (2009-2015). In addition we include statistics by taking the 'within' average of each region over the seven year period in which data was collected. The test statistic is calculated using GIS program *GeoDa*, with p-values obtained running Monte Carlo simulations. The results are presented in *Table 2*. We find conclusive evidence of spatial autocorrelation in each year at the 1% level of significance, with regional within mean also highly significant. The Moran's I in conjunction with the low p-values suggest there is significant and positive spatial dependence, implying that neighbouring regions' innovation levels have a positive relationship locally. This is to say on average, regions characterised with high levels of innovation are also

Table 2: Tests for Spatial Dependence (Autocorrelation): (log) Innovation

	2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**Within Avg.**
Moran's I	0.6025	0.5608	0.5917	0.5814	0.5885	0.5856	0.5913	0.6181
p-value	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
Permutations	999	999	999	999	999	999	999	999

*** 1%, ** 5%, * 10%. Note that p-values reported are *pseudo p-values.*

neighboured by high regions, while low innovative regions are neighboured by similarly low innovation regions.

A graphic representation of the relationship between innovation and innovation in neighbouring regions (spatially weighted) are presented in a Moran's scatter plot. This scatter plot provides a visualisation of the relationship of the level of innovation in a given region in contrast to the weighted average innovation of its neighbours (lagged innovation). This relationship is specified with the x-axis being innovation, and y-axis lagged[14] innovation. *Figure 2* displays the scatter plot using the within averages of each region's innovation levels logged.[15] The scatter plot is augmented to generate a linear regression (represented by the line) denoting the Moran's I slope as well as indicating degree of fit (Anselin, 2003). We note that the plot is divided into four quadrants (LeSage and Pace, 2009), with each specifying a specific relationship as noted in *Table 3.* There is quite a strong positive linear relationship, as observed by the positive trend

Table 3: Quadrant Relationships in Moran's I Scatter Plot

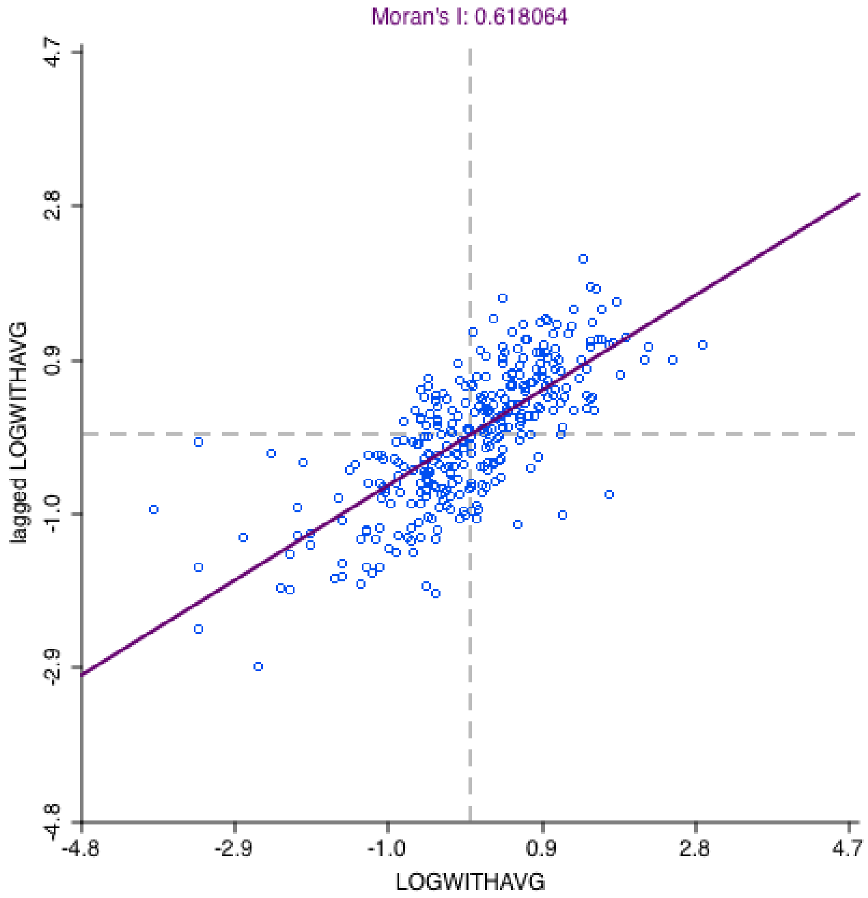
Quadrant I:	Denotes a high-high relationship where regions exhibit above mean level innovation, and the average of neighbouring regions is also above the mean level.
Quadrant II:	Denotes low-high relationships where regions have below average innovation, while its neighbours are above average.
Quadrant III:	Denotes low-low relationships where both regions and its neighbours are below average in innovative output.
Quadrant IV:	Denotes a high-low relationship, where regions are above average in innovation, while neighbours are below average.

line. *Prima facie*, we notice that most observations cluster within high-high and low-low areas, with very little spilling over to either high-low or low-high. This supports the narrative of positive spatial dependence. The scatter suggests that regions with low innovative activity tend to be neighboured by other low innovative regions, while regions characterised with high levels of innovation were neighboured also by highly innovative regions. Anselin's (1995) local indicators of spatial autocorrelation (LISA) map displays this relationship more profoundly. The LISA cluster and significance map decomposes the

[14]Not lag in the traditional sense. Spatially lagged refers to weighted average of a region's neighbours.

[15]Given the similarity in I-statistic and significance, mean is only presented. See *Figure 7* in *Appendix F* for Moran scatter plots for each year.

Figure 2: Moran's I Scatter: Mean (log) Innovation (2009-2015)



Moran's I test (Anselin, 1995), allowing for a visualisation of regions with significant spatial dependent clustering, as well as displaying the nature of such clustering. A LISA map displaying all of Australia is presented in *Figure 3*, with *Appendix H* displaying the level of significance of each region. We observe a distinct pattern where major cities are typified by significant high-high relationships, while remote regions share a low-low relationship (significance at $p < 0.05$).

Figure 4 zooms in to the Eastern states (VIC, NSW, and ACT), to get a better view of the types of relationships. Quite clearly we see high innovative region clustering in the capital cities of Melbourne and Sydney[16] in stark contrast to the low-low relationships in the outer rural areas. Interestingly we have a number of high-low relationships in the outer Canberra regions, as well as low-high relationships on what appears to be the outskirts of Melbourne inner city.

Intuitively what is observed is somewhat expected, supporting the notion that over space, regions tend to cluster around similar innovative regions. This relationship is one that can be explained by rural and urban (major city and remote) differences. Nevertheless, such ESDA is the first step in the story, confirming the idea that regions are spatially dependent.[17] As apparent as the result might appear, this justifies and warrants the use of spatial models to control for spatial autocorrelation.

[16] *Appendix I* shows a zoomed in image of the Melbourne and Metropolitan regions.

[17] Moran's I statistics are also reported for non-log specification on innovation in *Appendix I and K*. We see persistent significant and positive spatial autocorrelation when innovation is not log-transformed.

Figure 3: Local Indicators of Spatial Autocorrelation Map (Australia)

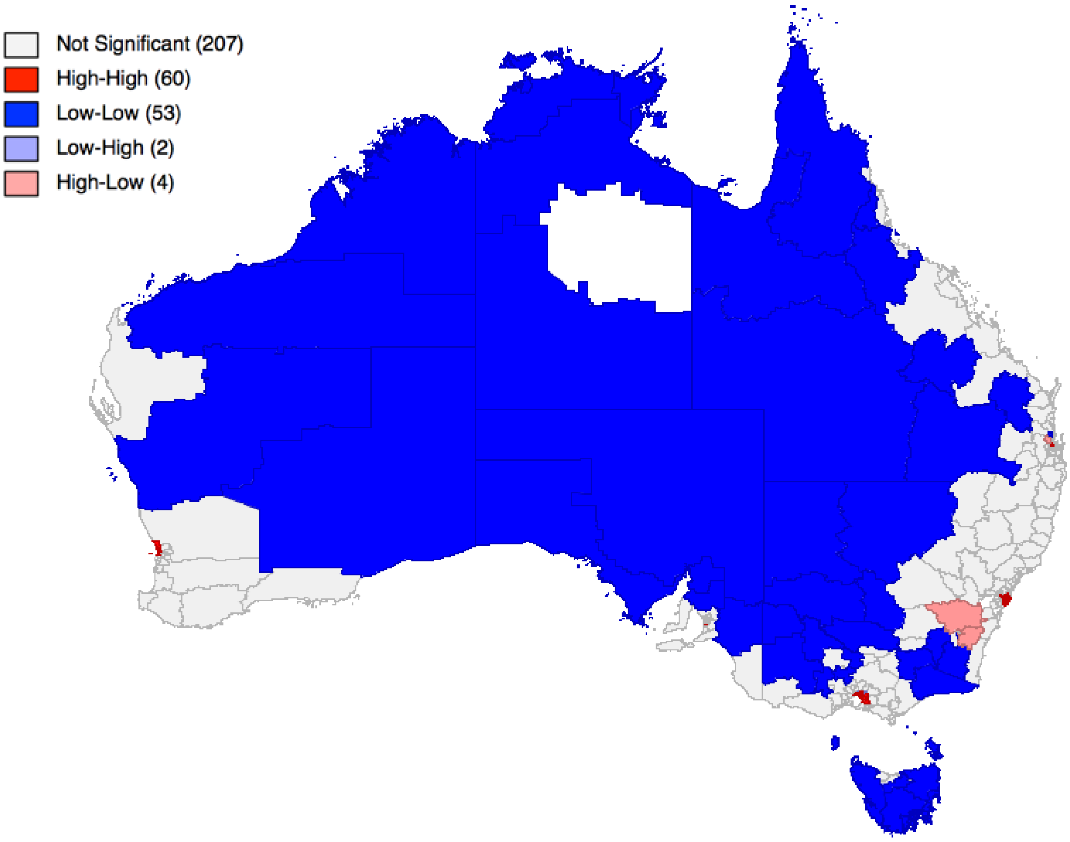
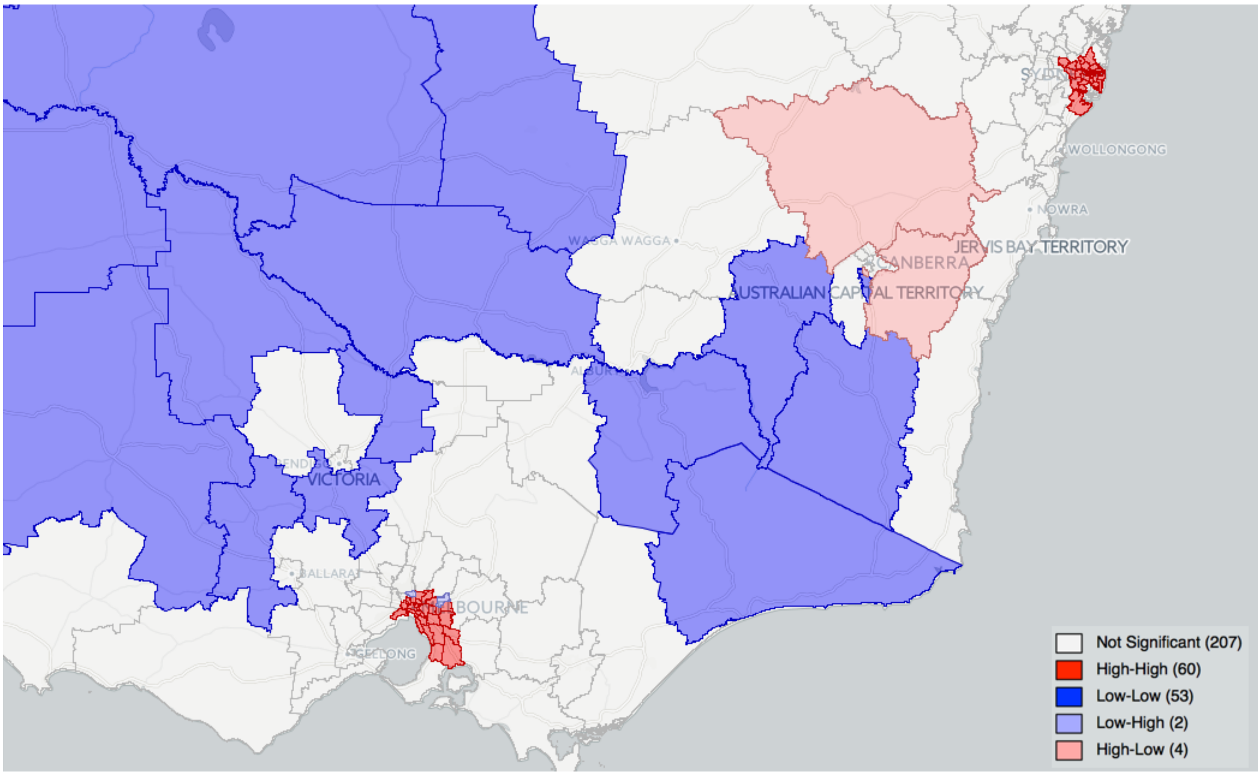


Figure 4: Local Indicators of Spatial Autocorrelation Map (Eastern States)



4 Theoretical Model of Knowledge Production

The "most prevalent model" which serves as a traditional starting point in innovation literature is the 'Griliches-Jaffe knowledge production function' (KPF). The KPF motivates how we think about innovation and modelling it's determinants. The general principle of the KPF is that "the output of innovation is a function of the innovative inputs in that location" (Audretsch and Feldman 2003). Griliches (1979) is widely cited as the principal author in modelling how knowledge is generated by simply treating knowledge as an outcome, or rather 'output', of 'innovative inputs'. At its most basic, Griliches knowledge production boils down to:

$$\begin{aligned} K_i &= f(RD_i, HK_i, \epsilon_i) \\ K_i &= \alpha RD_i^{\beta} \cdot HK_i^{\gamma} \cdot \epsilon_i \end{aligned} \tag{8}$$

Knowledge output is represented by K, with inputs RD and HK being research and development and human capital respectively; the determinants of innovation. Here, ϵ represents unmeasured innovation determinants not captured in the model (Griliches 1979). Importantly, subscript i denotes firm, the unit of observation/anlysis for Griliches.

Griliches work was expanded upon by Jaffe (1989) who tailored the knowledge production function to the context of also capturing spatial and knowledge spillovers. Jaffe refined the production function as:

$$I_{si} = \alpha_i IRD_{si}^{\beta_1} \cdot UR_{si}^{\beta_2} \cdot (UR_{si} \cdot GC_{si}^{\beta_3}) \cdot \epsilon_{si} \tag{9}$$

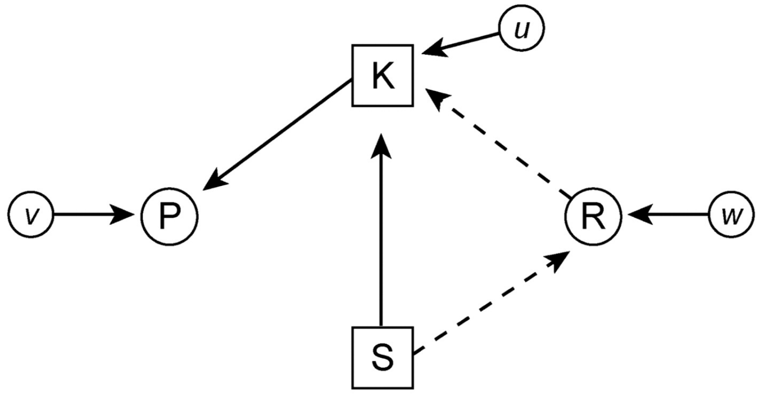
As in Griliches (1979), I represents innovative or knowledge outputs, with IRD (private R&D expenditure) and UR (university R&D spending), being the primary inputs. Additionally Jaffe introduces GC, a 'geographic coincidence' variable, measuring spatial interaction of universities and private business driven research. Here, subscript s denotes US states, and i denotes de-aggregated industry. Notably, a Cobb-Douglas functional form is specified throughout the literature. The benefit of the Cobb-Douglas specification is in the interpretation. Through a log-log transformation, coefficient parameters of the production function are able to be interpreted as 'elasticities'.[18] Moreover, the KPF provides the freedom to allow for a variety of units of observation, from individual firms and states as in Griliches (1979) and Jaffe (1989), to as small as counties or postcodes. Subsequent instances utilising the knowledge production function framework differ primarily in the combinations of inputs, level of regional aggregation and observable unit, focus on industry, and perhaps most usefully, the varieties of measures for innovation and its determinants (See Feldman and Florida (1994), Audretsch and Feldman (1996), Anselin et al (1997)). The suitability and robustness of the knowledge production function as a model for measuring innovation at a geographical level was confirmed by Feldman (1994).

Ó hUallacháin and Leslie (2007) develop a modified "regional production function" which helps us frame our understanding, visually represented in *Figure 5*. Here, R&D spending and regional structures (along with unobserved factors) lead to the accumulation of knowledge which is quantified by patents as an indicator of innovation. This framework serves as the backbone of our analysis, particularly in finding measures that capture funding and structural elements. Previous literature provides guidance by lending

[18] Griliches (1979) production function becomes: $\ln K_i = \alpha + \beta \ln RD_i + \gamma \ln HK_i + \epsilon_i$.

suggestions for useful output and input measures, however, our final model is limited to the availability of data.

Figure 5: Modified regional production function



R	Research and Development expenditures
K	Additions to economically valuable knowledge
P	Patents, a quantitative indication of the number of inventions
S	Regional structure conditions
u,v,w	Other unobserved influences, assumed random and uncorrelated

5 Model Specification and Estimation

Confirmatory Spatial Data Analysis

Confirmatory spatial data analysis (CSDA) is the natural next step having been provided a greater contextual understanding through ESDA. Simply, CSDA is the process of modelling innovation determinants and outcomes through spatial regression analysis[19], and is confirmatory in the sense of confirming the extent to which spatial autocorrelation and spatial spillovers effect innovation (Wang et al. 2015, pg. 116). Accordingly, we model and estimate the determinants of innovation in a Australian regions, controlling for spatial dependence/autocorrelation. The general specification of our model is a spatial panel fixed effects model. The general nesting of spatial panel models is as follows:

$$\begin{aligned} y_{it} &= \tau y_{it-1} + \rho \sum_{j=1}^{n} w_{ij} y_{jt} + x_{it}\beta + \sum_{j=1}^{n} w_{ij} x_{jt}\theta + \mu_i + \gamma_t + u_{it} \\ u_{it} &= \lambda \sum_{j=1}^{n} m_{ij} u_{it} + \epsilon_{it}, \qquad \text{i=1,...,n} \qquad i \neq j \qquad \text{t=1,...,T} \end{aligned} \tag{10}$$

From this general nesting in (10), a variety of potential calibrations are able to be made determining which spatial interactions are included. We identify four spatial models: the spatial Durbin model (SDM), spatial autoregressive (lag) model (SAR), spatial error model (SEM), and the SAC (or Kelejian-Prucha (1998) model). *Table 4* provides a brief specification of each model, with *Appendix L* detailing SAR, SEM and SAC models in greater depth. The model that we are most interested in is the spatial Durbin

Table 4: Spatial Panel Specifications

Model	**Nesting**	**Specification**
SDM	$\lambda = 0$	$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \sum_{k=1}^{K} x_{itk}\beta_k + \sum_{k=1}^{K}\sum_{j=1}^{n} w_{ij} x_{jtk}\theta_k + \mu_i + \gamma_t + \epsilon_{it}$
SAR	λ, $\theta = 0$	$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \sum_{k=1}^{K} x_{itk}\beta_k + \mu_i + \gamma_t + \epsilon_{it}$
SEM	ρ, $\theta = 0$	$y_{it} = \sum_{k=1}^{K} x_{itk}\beta_k + \mu_i + \gamma_t + \lambda \sum_{j=1}^{n} w_{ij} u_{it} + \epsilon_{it}$
SAC	$\theta = 0$	$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \sum_{k=1}^{K} x_{itk}\beta_k + \mu_i + \gamma_t + \lambda \sum_{j=1}^{n} w_{ij} u_{it} + \epsilon_{it}$

We utilise a static specification such that $\tau = 0$

model, which we specify more explicitly as:

$$\begin{aligned} \ln innov_{it} = \rho \sum_{j=1}^{n} w_{ij} \ln innov_{jt} + \beta_1 \ln BRD_{it} + \beta_2 Unis_{it} + \beta_3 Ufunding_{it} + \beta_4 \ln lforce_{it} + \\ \beta_5 \ln popdensity_{it} + \beta_6 \ln busserv_{it} + \beta_7 \ln techserv_{it} + \theta_1 \sum_{j=1}^{n} w_{ij} \ln BRD_{it} + \theta_2 \sum_{j=1}^{n} w_{ij} Unis_{it} \\ + \theta_3 \sum_{j=1}^{n} w_{ij} Ufunding_{it} + \theta_4 \sum_{j=1}^{n} w_{ij} \ln lforce_{it} + \theta_5 \sum_{j=1}^{n} w_{ij} \ln popdensity_{it} + \theta_6 \sum_{j=1}^{n} w_{ij} \ln busserv_{it} + \\ \theta_7 \sum_{j=1}^{n} w_{ij} \ln techserv_{it} + \mu_i + \gamma_t + \epsilon_{it} \end{aligned} \tag{11}$$

We note from the general nesting that $\lambda = 0$, such that we specify two spatial interactions: the spatial effects of neighbouring regions' innovation outcomes (spatially lagged dependent variable, similar to the

[19]Models are estimated using STATA package -*xsmle*- by Belotti, Hughes, and Piano Mortari (2013).

SAR model), as well as the spatial effects of neighbouring regions' inputs/determinants (spatially lagged independent variable). Unlike the SEM the SDM does not spatially interact with the error structure through the composite error term. Our specification is largely inspired by the knowledge production function, as highlighted in Section 4. Much like the general KPF, we use an input-output type model, where our output, is a function of the inputs. This general KPF specification is altered to incorporate spatial elements. Here, the dependent variable we are interested in is innovation, denoted by '$innov_{it}$', with subscripts i and t denoting the unit of observation (Australian regions), and time period/year. This is measured by a proxy comprising of patent, plant breeders rights, and design applications (forms of intellectual property). Our explanatory variables constitute the innovative inputs within a region. The variables selected are largely dictated by previous knowledge production function literature and the availability of data.[20] 'BRD_{it}' captures the average business R&D expenditure in each region, a key driver of innovation from the previous literature. '$Unis_{it}$' captures the number of university campuses in a given region with '$Ufunding_{it}$' the amount of research funding available to universities within the region (in millions), used as a proxy for university R&D expenditure. These two variables capture two elements: the structural/infrastructure element of regional knowledge production, as well as the expenditure/funding element. Variables '$busserv_{it}$' and '$techserv_{it}$' capture local regional infrastructure in terms of support services for innovation; namely access to business services (these might include financial or administrative support services), and access to technical services (these might include training or scientific services) respectively. We also utilise '$popdensity_{it}$', population density, to control for level of urbanisation, and '$lforce_{it}$', labour force, to control for sheer population size and human capital availability. The obvious deviation from traditional models is the prevalence of spatial interaction terms which capture neighbour effects. Recalling from our ESDA, the spatial weights matrix $\sum_{j=1}^{n} w_{ij}$[21], allows for spatial relationships to be captured. As such $\sum_{j=1}^{n} w_{ij} innov_{jt}$ captures the weighted average innovation of neighbouring regions, with coefficient ρ capturing the effect neighbouring innovation has locally. Similarly, $\sum_{j=1}^{n} w_{ij} x_{jt}$ (where x_{jt} is the same vector of explanatory variables listed above but of a region's neighbours) captures the weighted average of neighbouring inputs, with θ capturing the effect neighbouring innovative-input levels impact on local innovation. We choose to spatially lag all independent variables as there is no reason to suggest that the lagged inputs of neighbouring regions would not have an effect on local levels. For instance we might expect that the level of university research funding in a neighbouring region might have a positive effect on local innovation through a spillover mechanism. Where appropriate a log-transformation is specified in order for coefficients to be interpreted as elasticities. However, for instance the number of university campuses remains as a level as interpretation by elasticities is not useful given the nature of the variable (it is not suitable to interpret 'percentage changes' in university campuses).

The specification in equation (11) serves as the basis for our analysis. We compare three models: **(i)**

[20] Greater discussion of variable selection, particularly with respect to previous literature is in the next section, data description.

[21] Recall $\sum_{j=1}^{n} w_{ij} = \mathbf{W}$ is a 326×326 non-negative matrix which is row standardised, capturing the spatial relationship of regions via queen contiguity of order 1. Spatial weights matrix W while produced in GeoDa was imported into STATA using package -*spwmatrix*- by Jeanty (2014).

a general SDM excluding *busserv* and *techserv* ($\beta_6 = \theta_6 = \beta_7 = \theta_7 = 0$), **(ii)** SDM including business and technical services variables, and **(iii)** SDM with primary industry dummies. To test whether certain industries tend to facilitate higher levels of regional innovation, we include 'primary industry dummies' in the model. The primary industry is defined as the industry which has the highest count of businesses within a region. A list of primary industries is listed in *Appendix B*. Specifying these different models serves as a form of robustness check.

5.1 Model Selection

5.1.1 Selection Between Spatial Models

Generally speaking selection of an appropriate model is made on a priori intuition or theory as to the nature of spatial interactions. As mentioned, we infer the SDM is most appropriate as it captures both neighbouring innovation effects, and neighbouring determinant effects, allowing to capture spillover effects (LeSage and Pace 2009). Selecting the correct model is important in ensuring that bias or inconsistency is avoided due to misspecification. Elhorst (2010) specifies a set of formal tests to determine the correct model, taking advantage of the nested nature of spatial models. These tests specify the SDM as the full/unrestricted model, which is compared with restricted models, SAR and SEM, to see if it can be potentially simplified. By testing H_0: $\theta = 0$, if the null fails to be rejected the SDM can be simplified to a SAR model. Similarly by testing H_0: $\theta + \rho\beta = 0$, if the null fails to be rejected the full SDM can be simplified to a SEM. These hypotheses are tested using a Wald test, with results reported along with regression results. Elhorst (2010) suggests caution in relying solely in these tests as such specification tests have yet to receive extensive attention in the literature. As such, irrespective of the results of the test results all the above spatial panel model specifications are presented for comparison. Additionally, a non-spatial static panel fixed effects model is also estimated and presented for a baseline comparison. These panel models follow a similar specification as our spatial models,

$$y_{it} = \alpha + x_{it}\beta + \mu_i + \gamma_t + \epsilon_{it} \tag{12}$$

where α is the constant (intercept), x_{it} is the same vector of local explanatory variables, μ_i is time invariant fixed effects, γ_t are time dummies capturing year specific effects, and ϵ_{it} is the error term.

5.1.2 Model Comparison and Quality

In confirming the validity of the SDM as the appropriate model through relevant testing as seen above, we test the performance of models (i), (ii), and (iii) using the Akaike Information Criterion (AIC) (Akaike, 1974) and Bayesian Information Criterion (BIC) (Schwarz, 1978). AIC (with BIC following a similar process) measures the information loss from a specific model specification. Importantly, AIC and BIC provides a 'relative' comparison as to which model fits the data best, however, does not provide an overall measure of fit like the R^2. The model which yields the lowest AIC/BIC is preferred.

5.2 Fixed Effects Specification

From our specification equation (11), we include μ_i and γ_t to capture unobserved heterogeneity and specific year effects. The general rationale here follows the usual justification of traditional fixed effect specifications, where we assume or expect that there is an inherent time-invariant effect within observations, as well as period effects. It is reasonable to assume that there might be inherent characteristics within regions that might be correlated with the error term. Examples might encompass state or remoteness effects of regions, an inherent innovative or entrepreneurial culture, and generally any underlying feature or composition of a region that might make it more innovative. Moreover, we can control for any period shocks by including time/year dummies.[22] By controlling for such effects, along with controlling for spatial dependencies, we are able to assess the impact of our innovation-determining inputs effectively. We conduct a Hausman test to determine the appropriateness of the fixed effect specification. The results for the Hausman test are listed in each of the estimated model's output table.

5.3 Issues: Bias Correction

An issue identified by Lee and Yu (2010) is the need for bias correction in estimating spatial fixed effects models. Lee and Yu (2010) outline the standard estimation approach in controlling fixed effects fails to estimate parameters consistently. They identify that in models with both individual and time fixed effects that estimates are not properly centred, requiring bias correction. Accordingly, the pair suggest a model transformation using the 'deviation from the time mean operator'. The resulting procedure reduces the number of observation to $n(T-1)$, reducing our number of total observations to 1956 rather than 2282 (nT) (Elhorst 2014, pg. 48). We utilise this "LeeYu transformation approach" to obtain consistent estimates.

5.4 Robustness Checks

We conduct robustness checks to ensure the correct specification of standard errors. Given the nature of our data we expect to observe a level of heteroskedasticity. We would presume that the variance between observations for innovation is not constant, where high-innovative regions will have a higher variance than regions characterised by lower levels of innovation. Similarly as our analysis looks at regions overtime, we expect the potential presence of autocorrelation, as well as the potential effect of within clustering/correlation. Testing for serial autocorrelation[23] we reject the null hypothesis at the 1% level of no autocorrelation, suggesting panel-level serial correlation exists. Testing for heteroskedasticity, however, becomes somewhat difficult given the spatial transformation we conduct, where we are unable to predict the residuals. As such we rely on our inference of the nature of non-constant variance and the results of testing heteroskedasticity in our non-spatial fixed effects model. We test for groupwise heteroskedasticity[24] for an ordinary panel fixed effects model, with the modified Wald test statistic

[22] Control for time effects is in-built into the STATA package used such that no time dummies are reported in the output.

[23] Using STATA command $-xtserial-$.

[24] Using STATA command $-xttest3-$.

reported in *Table 16* of *Appendix N*. Here we reject the null hypothesis of constant variance, suggesting heteroskedasticity needs to be corrected for.

Given the presence of serial correlation and inferred/expected heteroskedasticity, we correct using clustered standard errors (clustering by region). Clustered standard errors are robust to heteroskedasticity and autocorrelation (Hoechle et al. 2007, pg. 4). The use of clustered errors is ideal as it provides this robustness, and supports the natural clustering of our data. As we are looking at observations of regions over time, we expect that these same regions tend to be correlated having inherent similar qualities (within correlation). Therefore we rely on clustered standard errors in our regression analysis.

5.5 Estimation Method

Including spatial terms in a model gives rise to issues of consistency of estimates. For models with a spatial dependence coefficient 'ρ' (in SDM, SAR, and SAC) least squares estimates for local explanatory variables are biased and inconsistent, while models with spatial correlation coefficients interacting with the error 'λ' (in SEM and SAC) are consistent, however are inefficient (LeSage and Pace, 2009). As such to avoid bias and inconsistency, maximum likelihood estimation (MLE) is implemented. LeSage and Pace (2009) discuss how the MLE process works for spatial models, where the concentrated log-likelihood function (concentrated with respect to β, σ^2, and ϵ (Elhorst, 2014)) is maximised with respect to spatial autoregressive coefficient 'ρ'.

6 Data Description

The core data utilised for empirical analysis is sourced from the *Department of Industry, Innovation and Science's* (DIIS) "SA3 Region Innovation data 2009-2015" dataset. The data tracks innovation data points across n=330 Australian regions from the period of 2009 to 2015 (T=7) for a total 2310 observation (N=2310). This dataset is quite unique in that it is collected at a micro-level with direct variable measures, which in the past have been measured by proxies in KPFs. One issue posed is the specificity of data, making it challenging to collect additional data. Supplementary data is collected from *IP Australia* (design and plant breeders rights variables), along with research income data sourced from the "2016-17 Science, Research and Innovation (SRI) Budget Tables" from the DIIS. IP data was matched by converting SA2 codes to SA3 codes, with SRI budget data being matched through a process of converting postcodes to SA3 codes. Descriptive/summary statistics can be found in *Appendix A, B, and C.*

Observations for Barkly, Blue Mountain - South, Lord Howe Island, and Illawara Catchment, are removed due to data not being collected in these regions. This reduces the number of observable units to n=326, reducing total observations to N=2282.

6.1 (Spatial) Unit of Observation

The unit of observation for analysis are the Australian Statistical Area 3 (SA3) regions as defined by the ABS.[25] SA3 captures the 'major' regions as identified by the ABS, with populations within regions ranging from 30,000 and 130,000 (ABS, 2010). Appropriate selection of the observable unit has been of particular emphasis in the literature. There is a general consensus in studying national and regional innovation systems that 'states' are inappropriately large as units of observation (Feldman and Florida, 1994; Varga, 1998), with sub-state units the preferred size, particularly given studies relating to regional innovation systems. Here the SA3 region provides a suitable unit for analysis. *Appendix E* displays the division of Australia under the SA3 regional profile. Omitted regions are denoted by uncoloured (white) areas.

6.2 Dependent Variable

6.2.1 Innovation (Patents, Designs, and Plant Breeders Rights): (Innov)

Measuring innovation in of itself becomes quite a delicate task given the broad reach of concepts it encompasses. Generally there is no 'hard and fast rule' as to how innovation and in fact knowledge is measured within a region, and unhelpfully nor is there a consensus as to the most effective proxy. In the absence of a 'direct' measure, a variety of approaches have been conducted with patent applications being commonly used. Patents are a form of intellectual property that gives the applicant sole rights of a particular invention, but is published publicly to allow for wider social use (Oslo Manual 2005, article 60). In many ways patents are a contentious proxy for innovation, as some patents never precipitate into a final product, nor are all products first patented (Feldman and Florida 1994, pg. 213; Oslo Manual 2005, article 60). This arises as some patents might never come to fruition as they were never practical or unrealistic, while conversely, some inventions might be retained as a trade secret to avoid replication by competitors. Despite controversy, patents are widely employed in literature (More recently: Wang et al., 2015; Ó hUallacháin and Leslie, 2007) as a quantifiable measure. Acs et al. (2002) investigate the suitability of patents as a measure for innovation, which they find to be a "not perfect", but a "fairly reliable measure of innovative activity" (Acs et al. 2002, pg. 1080). As such, patent applications serve as the primary source of innovation measure in our analysis. In addition to patents, this paper also utilises designs and plant breeders rights as measures for innovation (other forms of IP rights). Designs encompass the unique appearance of products (shape, configuration, pattern, ornamentation) (IP Australia, 2016). Plant breeders rights (PBRs) provide commercial exclusivity to newly developed plant varieties (IP Australia, 2016). Together, we combine patents, designs, and PBRs to form a composite measure of innovation.[26]

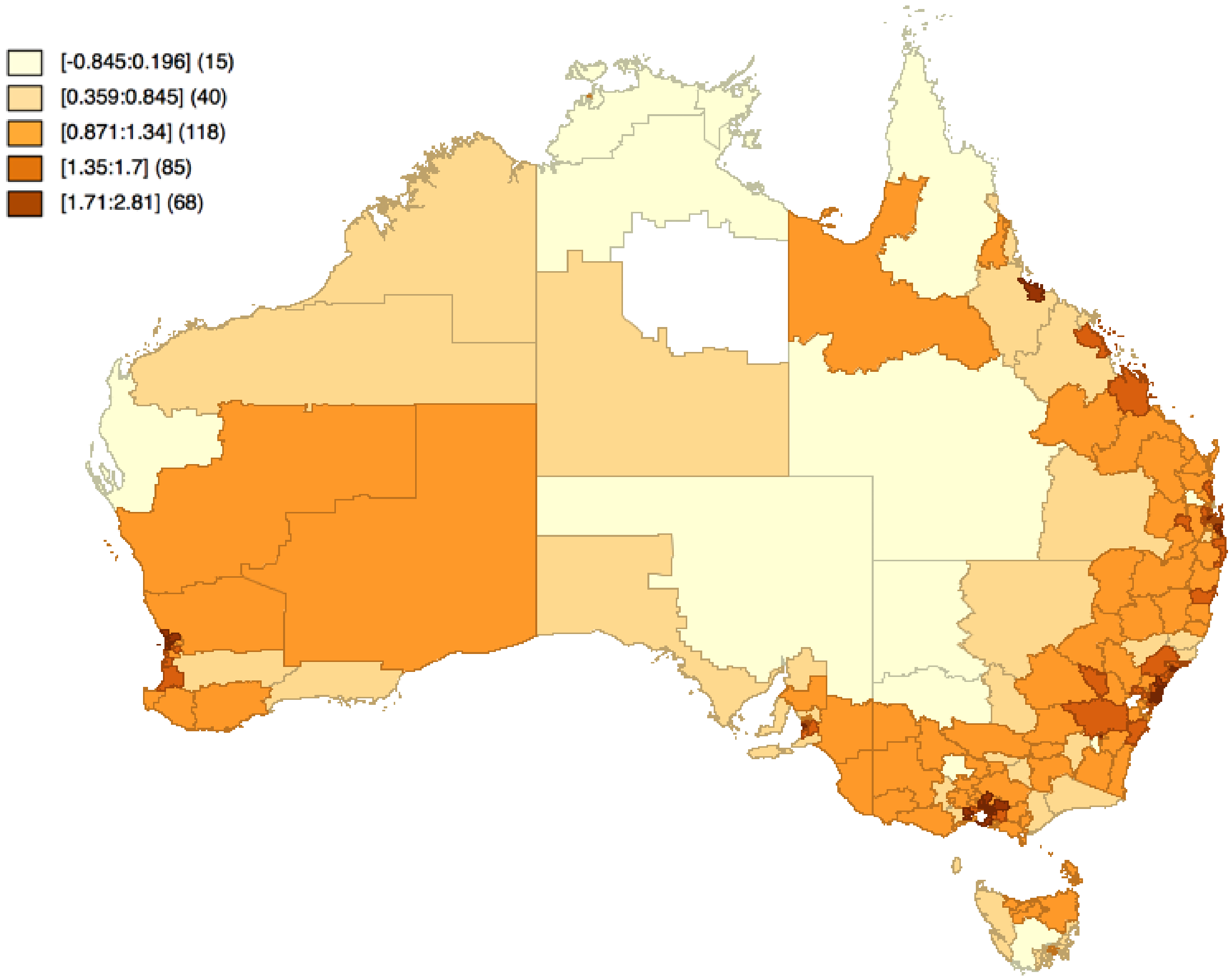
[25] The ABS's development of Australian Statistical Geography Standard provides a framework for geographical analysis, providing a "coherent set of standard regions" capturing the entirety of Australia. For more information see: http://www.abs.gov.au/ausstats/abs@.nsf/mf/1270.0.55.001.

[26] Given the log-transformation of our dependent variable, it is important to note the implications of zero values (given these become missing values). Zero values represent 2.6% of observations. Retaining such a log-transformation is important for not just interpretation, but normalising. Estimating with missing values is not possible given the requirement for strongly balanced panels using $-xsmle-$. As these zero values are 'true zeroes', we allow/transform these variables to true zeroes after log-transformation. With this we are able to retain relative rank. Feldman and Florida (1994) conduct

It is important to make the distinction that data we utilise is for intellectual property applications in the Australian jurisdiction. This is to say we do not capture applications to other international jurisdictions, where designs and PBRs might overlap with Australia IP classifications. Regardless, we assume that any Australian intellectual property that can be protected is done so in all jurisdictions as to ensure widespread protection.

Figure 6 displays a map of the average (log) innovation of each region over the observable time period. Data is divided in five distinct Jenks (natural breaks determined by the underlying data), and provides us a useful guide as to innovation concentrations outside of ESDA.

Figure 6: Australian (logged) Innovation (Natural Breaks/Jenks) Map



6.3 Independent Variables

6.3.1 Business Research and Development Expenditure: (BRD)

Research and development conducted by private firms is widely considered one of the primary sources of economic knowledge generation (Griliches, 1979; Feldman and Florida, 1994; Moreno et al., 2005). The Frascati Manual (2015) defines research and experimental development as any expenditure devoted to

a transformation in their analysis.

increasing the stock of knowledge, with any such activities contributing towards innovation. The relationship between innovative outputs such as patents and R&D is commonly highlighted in the literature (See Griliches (1979), Jaffe (1989), Feldman and Florida (1994), Anselin et al (1997), Wang et al (2016)). The measure available through the DIIS dataset is 'average business research and development expenditure', so a direct monetary measure. Ideally this data would be de-aggregated to specify amounts dedicated to each process (research or development), or even what portion was allocated to university-driven research to measure industry-university collaboration. We note that data for 2015 had yet to be collected at the time of analysis, and as such was linearly extrapolated.[27] Acknowledging the previous literature we expect business R&D to have a positive relationship with innovation.[28]

6.3.2 Number of university campuses: (Unis)

The number of university campuses in the region is one factor relating to knowledge infrastructure referred to by Ó hUallacháin and Leslie (2007) that we consider. Although not featuring heavily in previous literature, university campus counts measure regional access to knowledge resources, and potential for industry-university collaboration. As previously mentioned, Audretsch and Stephan (1996) highlight empirical evidence that firms are attracted to external knowledge sources, with universities attracting innovative firms. In many ways the 'innovation effect' of universities is twofold: they generate innovation themselves, as well as attract other innovative entities. It can also be argued that universities are a source of human capital development. In this sense, universities are quite a dynamic source of innovation, and as such we expect the count of university campuses in a region to have a positive effect.

6.3.3 University Research Funding per Region in $millions: (Ufunding)

University R&D has been a key input in previous literature (See: Ó hUallacháin and Leslie, 2007; Anselin et al 1997; Feldman and Florida, 1994), and was a key feature of the Jaffe (1989) knowledge production function. Feldman and Flordia (1994) highlight how university R&D enhances the stock of knowledge and stimulates technological change, however by no means always guarantees innovation and technology spin-offs. Here we do not have data on the expenditure of R&D by universities, and as such use a proxy in research income received. The specific income measure we use is 'Research Block Grants' (RBGs).[29] RBGs are not the entirety of research funds received by universities, but are a key source of income

[27] Linear extrapolation is suitable given the linear trend and growth over the observed time period.

[28] A similar 'true zero' treatment for 2.7% of observations is used here, as done with the dependent variable.

[29] RBG data is aggregated by university institution, rather than by specific campus or by region. This poses an issue given the amount of research conducted in each region is not necessarily the same. Assigning values proved to be difficult, with potential solutions suggested being weighting by campus size, by enrolments, or by number of research staff employed at each campus. However, these methods required data which was not readily available. The resulting data assigned to each region is total RBG funding received by the universities in that region. This value might seem inflated, however, we propose that universities are highly co-integrated such that campuses do not need to necessarily be assigned varying amounts. Another way of framing the variable is by the amount of research funding readily available to universities within a region. Ideally we would have liked to have data on funding expenditures of the campuses of each region, or be able to deflate values in a non-arbitrary way. However, given the importance of university R&D, we retain the measure in our analysis.

provided by the Australian government. It is reasonable to assume a close one-to-one relationship with research income and expenditure, meaning that research income received in a given year is expected to be expended for research purposes in the same year (given funds are allocated yearly). Unlike the 'number of universities' variable, research captures an expenditure type measure as opposed to physical structure within the region. We expect university R&D to have a positive relationship with regional innovation levels.

6.3.4 Access to Business and Technical Services: (busserv *and* techserv)

Access to business services is a variable that features in Feldman and Florida (1994). Access to support services is important in facilitating innovative activity; for instance access to financial services nearby might be key to acquiring capital in the innovative process. Similarly, access to technical and scientific services might play significant roles in developing new inventions (for instance 3D printing/fabrication services for firm developing delicate components). The DIIS dataset features business counts for certain industries which we use to create these variables. We construct the '**business services**' variable by summing the number of '*administrative and support services*' and '*financial and insurance services*'. Similarly, the **technical services** variable is constructed summing the number of '*education and training services*' with '*professional, scientific and technical services*' within a region. These variables seek to capture the types of regional infrastructure supporting innovation activity, pursuant to Cooke et al. (1997) and Ó hUallacháin and Leslie (2007) who emphasise complementary regional structures. *Appendix C* provides summary statistics of business counts throughout regions from 2009-2015.

6.3.5 Primary Industry Dummy

In determining whether certain industries tend to be more innovative then others we include the primary industry within a region. The primary industry within a region is determined by the industry with the highest count of businesses. A list of industries is listed in *Appendix B* with the number of regions in which each industry is 'primary' for each year.

6.3.6 Control Variables

Population (Density): (popdensity)

Population density within each region is used to control for population size, a region's physical size, and level of urbanisation. Regions with higher population density are expected to be more innovative, indicative of greater urbanisation. Similar to Ó hUallacháin and Leslie (2007) we look to control for metropolitan variation. The density measure we use is *estimated population per square kilometre.*

Labour Force: (lforce)

Although we already have population density, we also want to control for whether the sheer size of a population has significant effect on innovation. Rather than using estimated population, we use labour force to control for population size (given the strong correlation with estimated population, see correlations in *Appendix D*), but also as a measure of access to human capital. Evidently, the labour force statistic does not account for the type of labour (such as labour for innovative roles), however, provides a crude measure for the pool of human capital in a region that is at the disposal of innovative firms.

Random Effect Controls: (State, and Remoteness Dummies)

These variables are included to control for any time invariant effects that might effect innovation. We note that in any fixed effects estimation, as a time-invariant variable this dummy will be dropped for collinearity. As such state controls are reserved for random effects estimations. State/territory dummies are included to control any state or statewide characteristics. Similarly, remoteness dummies control for underlying differences between urban and remote areas. Remoteness is classified by the ABS in different groups: *major cities*, *inner regional*, *outer regional*, *remote*, and *very remote*.

7 Results and Discussion

Table 5: Summary of Results from General Model (i) Estimation

	Models				
	SDM	SAR	SEM	SAC	Non-spatial Panel
Main					
(log) Business R&D	$\circ$	$\circ$	$\circ$	$\circ$	$\circ$
University campuses (count)	+	+	+	+	+
University funding (millions)	+	$\circ$	$\circ$	$\circ$	+
(log) Population density	$\circ$	$\circ$	$\circ$	−	$\circ$
(log) Labour force	$\circ$	$\circ$	$\circ$	$\circ$	$\circ$
[Wx] (log) Business R&D	$\circ$	na	na	na	na
[Wx] Number of universities	$\circ$	na	na	na	na
[Wx] University funding (millions)	$\circ$	na	na	na	na
[Wx] (log) Population density	−	na	na	na	na
[Wx] (log) Labour force	$\circ$	na	na	na	na
Spatial					
ρ	+	+	na	+	na
λ	na	na	+	−	na
Variance					
σ^2	+	+	+	+	na

+ = positive and significant; − = negative and significant; $^\circ$ = not significant; na = not applicable to model
Notes: Clustered Std. Errors – Lee and Yu (2010) transformation – Significance at 10% level

As a first pass, we present the estimation results of our general specification for all spatial panel models in *Table 5* above. Immediately we see a consistent pattern of results where the spatial coefficients are significant in all spatial models. In models with a spatial autoregressive term ρ, the coefficient on lagged innovation is both significant and positive. This significance justifies our use of spatial econometric models and specifications, evidence that traditional non-spatial panel models are not suitable. Moreover, we also observe that the number of university campuses within a region is consistently both significant and positive, with business R&D, and labour force contrastingly consistently insignificant across all models. There are, however, noticeable differences across all models.

Looking at *Table 6*, we see the Wald test statistics in testing for whether our spatial Durbin specification can be simplified to either a SAR or SEM for different SDM specifications. From these test statistics we fail to reject the null hypotheses that the SDM can be simplified to a SAR or SEM under all specifications. Similarly, conducting the Hausman test we reject the null hypothesis that random effects is efficient, justifying the use of our fixed effects specification as consistent. The results of our model selection tests might explain the divergence in results between the different spatial models. The SDM is the only model outside of static panel where university funding is significant. This might simply come down to model misspecification, where omitting lagged independent variables leads to biased estimates. Additionally, in the SAR and SAC models, population density is seen to be significant and negative. This is quite interesting given the result that the SDM finds neighbours population density to be significant and negative. These models tell quite substantially different tales.

7.1 SDM Comparisons

Recalling the three SDMs that we specify for comparison,[30] *Table 6* presents the results for each specification. Immediately we notice that the autoregressive coefficient, ρ, is consistently significant and positive across all model. This suggests that in all instances the innovation in neighbouring regions has a positive effect on local innovation levels. This confirms the finding in ESDA that Australian regions exhibit spatial dependence, but is not evidence of spatial spillovers. A positive and significant ρ provides evidence that there is a tendency for high-innovative regions to be clustered with other high-innovative regions, and low-innovative regions to similarly be clustered with other low-innovative regions. We recall the LISA maps in *Appendices F to H* where we see this type of clustering. Additionally, we find the number of university campuses within a region appears to have a positive and significant effect on local innovation. A similar positive relationship is seen with university funding. When including access to business and technical services in model (ii), we note that university funding no longer is significant. Looking at model (iii) with primary industry dummies, we see that university funding still remains positive and significant, however, lagged population density is no longer significant. Analysing the coefficients on industry dummies, we find that on average that having agriculture as the primary industry has a negative impact on innovation. Although agricultural innovation exists (captured by plant breeders rights), this type of result is somewhat expected; regions focused on agriculture will tend to be in more rural or outer regional areas where innovative activity is not as persistent. For reference we include a summary results for the primary industry for the other models (*Appendix) Table 17*), similarly observing persistent negative relationships with agriculture, along with negative effects by construction industry in SAR, SEM, and non-spatial models.

In evaluating and assessing each model specification, AIC and BIC values are listed at the bottom of the *Table 6* output. To reiterate the comments made earlier, these values measure relative goodness of fit and are not an overall measure of how 'accurate' the model is. The result of these information criterion tests find that model (i), the general specification without business and technical services variables or primary industry dummies, has the lowest AIC and BIC score[31] suggesting it is the most appropriate

[30](i) General SDM (without services or industry variables); (ii) including access to business and technical services variables; and (iii) including primary industry dummies

[31]Model $(i) < (ii) < (iii)$.

Table 6: Spatial Durbin Model (Fixed Effects) Results

	Models		
	SDM (i)	SDM (ii)	SDM (iii)
Main			
ln BRD	-0.010 (0.009)	-0.010 (0.009)	-0.009 (0.010)
unis	0.567*** (0.032)	0.577*** (0.037)	0.527*** (0.072)
Ufunding	0.003* (0.002)	0.003 (0.002)	0.003* (0.002)
ln popdensity	-0.569 0.414	-0.587 (0.420)	-0.584 (0.368)
ln lforce	0.189 (0.345)	0.184 (0.342)	0.277 (0.332)
ln busservices	–	-0.004 (0.017)	–
ln techservices	–	-0.005 (0.016)	–
[Wx]: Lagged Independents			
[Wx] ln BRD	-0.022 (0.016)	-0.020 (0.017)	-0.010 (0.017)
[Wx] unis	-0.427 (0.624)	-0.430 (0.622)	-0.448 (0.622)
[Wx] Ufunding	-0.002 (0.002)	-0.002 (0.003)	-0.002 (0.002)
[Wx] ln popdensity	-1.010* (0.584)	-1.040* (0.596)	-0.798 (0.550)
[Wx] ln lforce	-0.330 (0.525)	-0.323 (0.523)	-0.339 (0.498)
[Wx] ln busservices	–	0.003 (0.031)	–
[Wx] ln techservices	–	0.023 (0.030)	–
Significant Primary Industry Dummies			
Agriculture	–	–	-0.205** (0.087)
Spatial			
ρ	0.118*** (0.026)	0.117*** (0.027)	0.084*** (0.026)
Variance			
σ^2	0.179*** (0.012)	0.179*** (0.012)	0.175*** (0.011)
Test for SAR	19.80***	18.85***	13.22**
Test for SEM	22.55***	21.21***	13.95**
Hausman	122.04***	148.00***	151.49***
AIC	1.226	9.226	35.226
BIC	62.591	92.906	191.428

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$
(.) Clustered Std. Errors – Lee and Yu (2010) Transformed

model.

7.2 Spatial Spillovers: Direct and Indirect Effects

Prior to this point we have failed to provide any formal interpretation of the estimated parameters. Due to the "complicated dependence structure" (LeSage and Pace 2009, pg. 33) exploited by spatial models, greater consideration must be given to interpreting parameter estimates. For instance, it is insufficient to rely on the significance of spatial coefficients ρ and θ to make conclusions on whether spatial spillovers exist (Elhorst 2010). LeSage and Pace (2009, pg. 33) highlight that changes "in a single observation (region) associated with any given explanatory variable will affect the region itself (a direct impact) and potentially affect all other regions indirectly (an indirect impact)." The authors suggest if any meaningful interpretation is to be conducted, direct and indirect effects must be calculated (with indirect effects used as a means for evaluating spillover effects). Direct effects are the effect of a change in the explanatory variable in a given region affecting the region itself, with indirect effect being "the impact of changing a particular element of an exogenous variable on the dependent variable of all other units" (Elhorst 2010, pg. 24). *Table 7* presents how direct and indirect effects are calculated for each specification. For the

Table 7: Direct and spillover effects of different model specifications (Source: Elhorst (2010))

	Direct Effect	**Indirect Effect**
OLS/SEM	β_k	0
SAR/SAC	Diagonal elements of $(I-\rho W)^{-1}\beta_k$	Off diagonal elements of $(I-\rho W)^{-1}\beta_k$
SDM	Diagonal elements of $(I-\rho W)^{-1}(\beta_k+W\theta_k)$	Off diagonal elements of $(I-\rho W)^{-1}(\beta_k+W\theta_k)$

SDM, it becomes apparent that we cannot merely interpret the local (β_k) and lagged (θ_k) coefficients to determine how explanatory variables impact on innovation. We see that the direct effects are not only determined by coefficients on local explanatory variables, but rather lagged explanatory variables as well, and vice versa. Even if β_k and/or θ_k, are significant, this does not mean that the indirect effect of the k^{th} explanatory variable is also significant, or vice versa. The direct and indirect effects are presented in *Table 8*.[32]

7.2.1 Direct Effects

Firstly, looking at direct effects we find that the number of university campuses and university funding received are significant and positive at the 1% and 10% level respectively. More explicitly, these results suggest that an increase in the number of universities within a region by one campus, will on average lead to approximately a 0.6% increase in innovation. In more palatable terms, if the number of universities

[32] STATA package -*xsmle*- computes marginal effect standard errors to calculate effects using a Monte Carlo simulation method.

in a region were increased in a region by five, on average, the level of innovation would increase by 3%. Although the magnitude is quite small, importantly we see a positive relationship with the number of universities within a region and innovation. This supports the idea that knowledge infrastructure facilitates greater levels of innovation. Whether this relationship is born from universities themselves being innovative and patenting more, or these institutions attracting innovative firms as suggested by Audretsch and Stephan (1996), is beyond the scope of our analysis. The low magnitude for these variables might be explained by how multiple campuses within a region from the same university has a redundant effect. For instance if there already existed a campus for University X in a region, and another campus were built, it would be difficult to imagine the additional campus having a significant effect on increasing innovation. This also comes down to the nature of the campus. If the additional campus were a research campus devoted to science, technology, engineering, and mathematics (STEM), this might lead to a more meaningful increase in innovation.

Interpreting the positive significance of university funding (aware of the log-level specification), our result suggests that a one million dollar increase in research funding allocated to a region leads to a 0.3% increase in innovation on average. In more manageable terms, an increase in funding by $10 million will on average lead to a 3% increase in innovation. Similar to the university campus variable, the important result here is not the interpretation of the coefficient, rather the positive and significant relationship with innovation. Thinking about the magnitude qualitatively, this result seems quite reasonable. In reality this might even be understating the effects given the aggregation of the type of research funding. This is to say that not all research funding is allocated to research that is patentable and encompassed by our measure of innovation. For example, university research funding is allocated to economics departments, where useful research might indeed be conducted, but ultimately these will not be quantified into innovation by our metric (patents and other IP). Consequentially, some university research particularly those which are basic, might make a significant contribution (such as a ground-breaking physics theory, or economic model motivating policy), but might only be recognised with citations and publications, rather then patents, designs or plant breeders rights. Perhaps if we utilised research funding dedicated or allocated to STEM research, that might better capture the type of funding that might be directly associated to IP that can be protected. This might be an area of future research and consideration.

7.2.2 Indirect Effects

Population density is the only variable that has a significant indirect effect. Although a control variable, it might be interesting to analyse why such significance arises. At the 10% level of significance, population density on average has an indirect negative impact on innovation. This result suggests that a 1% increase in a regions population density, *ceteris paribus*, on average leads to a 1.2% decrease in innovation in neighbouring regions. Alternatively this can be interpreted as: if for a given region, the average population density of neighbouring regions increases, local innovation in the region will on average decrease. Such a result is surprising. Putting an interpretation to this result is admittedly quite difficult. Given population density is quite static, any increase in population density is made responsible from an increase in population. One way of looking at this might be that as neighbouring regions become

Table 8: Direct and Indirect Effects (SDM (i))

	Coefficient	**(Std. Error)**
Direct Effects		
ln BRD	-0.010	(0.009)
Unis	0.558***	(0.034)
Ufunding	0.003*	(0.002)
ln popdensity	-0.613	(0.406)
ln lforce	0.198	(0.322)
Indirect Effects		
ln BRD	-0.025	(0.018)
Unis	-0.374	(0.676)
Ufunding	-0.002	(0.002)
ln popdensity	-1.173*	(0.612)
ln lforce	-0.349	(0.542)
Total Effects		
ln BRD	-0.036	(0.024)
Unis	0.183	(0.688)
Ufunding	0.001	(0.002)
ln popdensity	-1.785***	(0.565)
ln lforce	-0.151	(0.462)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

(.) Clustered (marginal effects) Std. errors – Lee and Yu (2010) Transformed

more densely populated, this might be associated with greater urbanisation where resources are being re-allocated to the more densely regions. Perhaps, if a region's population density is increasing this might be an indicator that people are migrating away from neighbouring regions. Another interpretation might be localisation effects caused by government policy. Governments tend to develop innovation incubators in more densely populated regions, which might lead to localisation effects by firms and individuals gravitating towards them. These claims are evidently not supported by any kind of evidence, and are at best speculative interpretation, outside the scope of our analysis. Nevertheless, this quite an intriguing result, ultimately indicating that population density causes negative spillover effects. This might be an area of future research and consideration.

7.3 Additional Remarks

In summation, the major results of our CSDA is that neighbouring regions' level of innovation has a significant impact on local innovation levels, confirming our ESDA results. In addition, we find that the number of university campuses and university funding available to a region has a significant and positive direct effect on innovation. We also find that population density has a significant and negative indirect effect. Perhaps the most interesting non-result is the non-significance of business R&D expenditure persistent throughout all fixed effects models. Given the plethora of literature supporting the importance of business expenditures on R&D (Recall: Griliches (1979), Florida and Feldman (1994); Moreno et al., 2005; Wang et al., 2015), we expected to find a significant and positive relationship with innovation. Here this is simply not the case, and one can only speculate the reason for this. In the Australian context business R&D does not appear to be a significant determinant of innovation. From a policy perspective this proves an interesting result, suggesting that private industrial R&D is not a significant driver of innovation. It would be erroneous to imply that business R&D expenditure is an unnecessary factor in innovation with such an assertion beyond the scope of our analysis. Intuitively we propose potential reasons explaining why this is the case. As previously mentioned, the very nature of measuring innovation with proxies using patents and other intellectual property variables is not truly reflecting of all innovations, particularly given some innovations and ideas are not necessarily formally patented. Australian firms may potentially be averse to acquiring intellectual property right protection, opting to retain ideas internally under a veil of secrecy to avoid potential replication. Notwithstanding, our results would indicate policy agendas be focused towards supporting university construction and research funding.

It is also worth mentioning the impact of the Lee and Yu (2010) fixed effects transformation; recalling that we implement the transformation to avoid biased and inconsistent estimates. From *Table 9* we see the results of estimation without Lee and Yu's transformation. Strikingly spatial coefficients are no longer significant in the SDM, SAR, and SEM, but remain in SAC. We also observe persistent significant and positive relationships with university campus counts and university funding. Testing for SAR and SEM using a Wald test, we fail to reject the null hypotheses that the SDM can be simplified to a SAR as well as a SEM; suggesting that the SAC model is most appropriate. This shows that there is quite a major discrepancy between results employing the Lee and Yu (2010) transformation.

8 Conclusion

We conduct a dual analysis in analysing and measuring innovation in Australian regions through exploratory spatial data analysis, and confirmatory spatial data analysis. From ESDA we find that spatial autocorrelation or dependence exists among Australian regions, suggesting that regional innovation is correlated and influenced by neighbouring regions' innovation. In investigating further, a local indicators of spatial autocorrelation map shows high-high innovative and low-low innovative relationships, with persistent high-high clustering in major cities and surrounding areas. Although not surprising, this result justifies the use of spatial econometric techniques in controlling for such effect in effectively identifying the determinants of innovation in these regions. In our CSDA we test a variety of spatial models, ultimately focussing on a general spatial Durbin model for analysis. We find that local innovation is effected by neighbouring regions' innovation, confirming the results from ESDA. In terms of direct effects, the number of universities and university funding has on average a significant and positive effect on local innovation levels (suggesting policy should support universities). Interestingly, business R&D expenditure is insignificant, contrary to past empirical studies. Moreover, in terms of measuring the extent of spatial spillovers, calculating indirect effects we find that only population density causes spillover effects, suggesting that on average if a region's population density increases, neighbouring regions' innovation are negatively effected; an inauspicious spillover effect.

Extensions for this research might include analysis with a dynamic specification, where a temporal and spatially lagged variable are included. Dynamic specifications present issues of endogeneity requiring calculated approaches such as system GMM (Arellano-Bond), which is not yet available for spatial models. Further, research might be to define a set of spatial weights matrices capturing 'organisational contiguity' rather than just spatial relationships, given the increasing role technology is breaking down spatial barriers. Furthermore, we would ideally like to have access to greater de-aggregated data, for instance funding to specific campuses, or research funding or expenditure specifically in STEM research areas. It might also be interesting to incorporate the relationship of citations and publications as a measure of academic contributions. Seeing our indirect effects result, it might also be an interesting case study investigating as to why population density has such an adverse effect.

Table 9: Spatial Panel Fixed Effects Results (without Lee and Yu (2010) Transformation)

	SDM	**SAR**	**SEM**	**SAC**
Main				
ln BRD	-0.00412	-0.00376	-0.00370	-0.00378
	(0.00972)	(0.00963)	(0.00965)	(0.00966)
Unis	0.709***	0.686***	0.688***	0.684***
	(0.0375)	(0.0329)	(0.0331)	(0.0653)
Ufunding	0.00420**	0.00495***	0.00498***	0.00470***
	(0.00176)	(0.00157)	(0.00157)	(0.00142)
ln popdensity	0.00486	-0.0340	-0.0314	0.0319
	(0.265)	(0.253)	(0.253)	(0.251)
ln lforce	0.231	0.317	0.318	0.284
	(0.309)	(0.258)	(0.257)	(0.217)
Wx: lagged independents				
ln BRD	-0.0000189	–	–	–
	(0.0170)			
Unis	0.471	–	–	–
	(0.609)			
Ufuding	0.00399*	–	–	–
	(0.00243)			
ln popdensity	0.283	–	–	–
	(0.496)			
ln lforce	0.276	–	–	–
	(0.480)			
Spatial				
ρ	-0.0180	-0.00662	–	0.341***
	(0.0257)	(0.0259)		(0.0862)
λ	–	–	-0.0136	-0.391***
			(0.0258)	(0.104)
Variance				
σ^2	0.144***	0.145***	0.145***	0.159***
	(0.00946)	(0.00945)	(0.00945)	(0.0101)
Test for SAR	6.98	–	–	–
Test for SEM	6.73	–	–	–
Observations	2282	2282	2282	2282

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
(.) Clustered Std. Errors

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A Summary Statistics

Table 10: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Innovations	36.399	58.569	0	912
Patent applications	28.639	44.775	0	728
Plant Breeder Rights applications	0.574	2.446	0	36
Design applications	7.186	19.154	0	453
Private Business R&D Expenditure	559.663	2618.74	0	32064.332
University Campuses	0.688	1.317	0	13
University Research Funding (millions)	22.308	52.526	0	473.526
New Business Entries	903.447	842.053	6	11778
Business Services	729.316	1036.15	1	14937
Science/Technical Services	771.846	1037.136	1	14021
Population	69709.087	42767.634	467	216248
Population Density	894.872	1256.113	0.032	8424.353
Labour Force	36699.306	23146.329	297	140345

B Primary Industries by Year

Table 11: Count of Primary Industries

Industries	2009	2010	2011	2012	2013	2014	2015	Total
Accommodation and Food	18	16	1	0	0	0	0	35
Administrative and Support	19	19	0	1	0	0	0	39
Agriculture, Forestry, and Fishing	19	19	90	88	91	91	91	489
Arts and Recreation	14	14	0	0	0	0	0	28
Construction	13	13	172	173	171	168	171	881
Education and Training	13	13	0	0	0	0	0	26
Utilities	20	21	0	0	0	0	0	41
Financial and Insurance	21	21	3	2	2	2	2	53
Health Care and Social Assistance	11	11	0	0	0	0	0	22
Information Media and Telecomms	22	21	0	0	0	0	0	43
Manufacturing	13	13	0	0	0	0	0	26
Mining	24	26	0	0	0	0	0	50
Professional, Scientific, Technical	12	13	48	51	48	47	48	267
Public Admin and Safety	20	22	0	0	0	0	0	42
Rental, Hiring, and Real Estate	14	12	10	9	12	15	13	85
Retail Trade	18	19	1	1	0	0	0	39
Transport, Postal, and Warehousing	35	35	1	1	2	3	1	78
Wholesale Trade	20	18	0	0	0	0	0	38

C Industry Counts

Table 12: Summary of Industries within a region

Variable	Mean	Std. Dev.	Min.	Max.
Accommodation	266.53	347.346	0	6081
Administrative	269.364	350.959	0	4573
Agriculture	482.862	680.534	0	4110
Arts	141.858	231.452	0	2433
Construction	828.109	749.398	0	4014
Education	133.496	260.438	0	3855
Utilities	102.053	295.449	0	3691
Financial	459.952	818.015	0	11683
Health	303.522	336.601	0	2593
Information Media	130.648	305.509	0	3816
Manufacturing	248.336	249.907	0	2964
Mining	115.397	364.675	0	6327
Professional	638.349	958.341	0	13112
Public Admin	112.308	349.538	0	5636
Real estate	572.287	692.899	0	9171
Retail	379.759	358.405	0	3742
Transport	415.556	656.515	0	11721
Wholesale	260.731	321.488	0	3823

N=2282

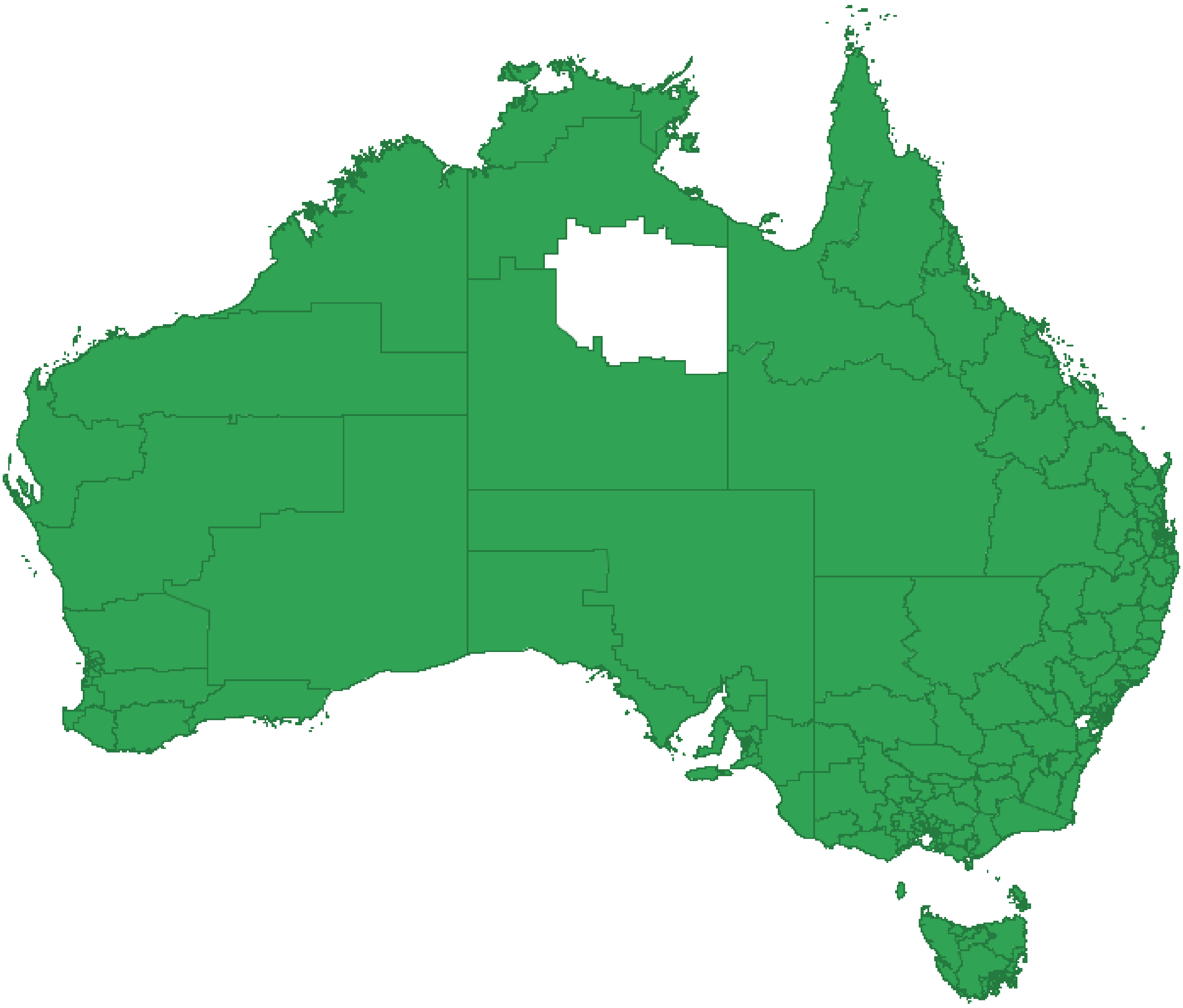
D Correlations

Table 13: Correlation Table

Variables	innov	BRD	Unis	lUfund	lbusserv	ltechserv	lpopdens	llforce	lpop
innov	1.000								
BRD	0.620	1.000							
Unis	0.229	0.206	1.000						
lUfund	0.304	0.194	0.720	1.000					
lbusserv	0.581	0.430	0.193	0.226	1.000				
ltechserv	0.585	0.414	0.184	0.229	0.645	1.000			
lpopdens	0.704	0.501	0.070	0.166	0.483	0.511	1.000		
llforce	0.721	0.538	0.177	0.185	0.580	0.559	0.563	1.000	
lpop	0.688	0.525	0.153	0.159	0.557	0.524	0.524	0.988	1.000

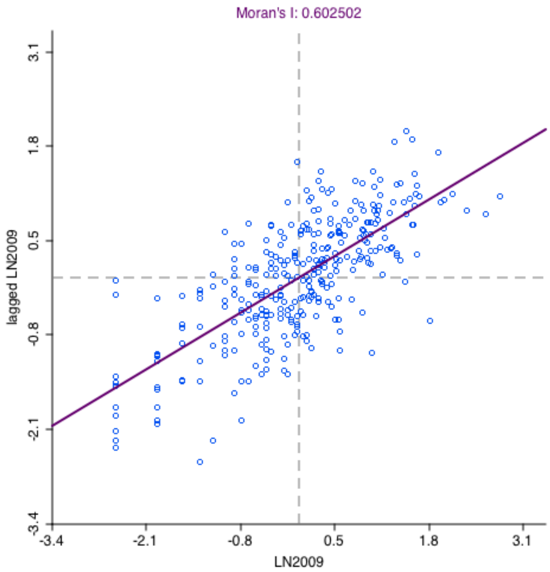
E Unit of Observation

Figure 7: Statistical Area 3: Australian Regional Division

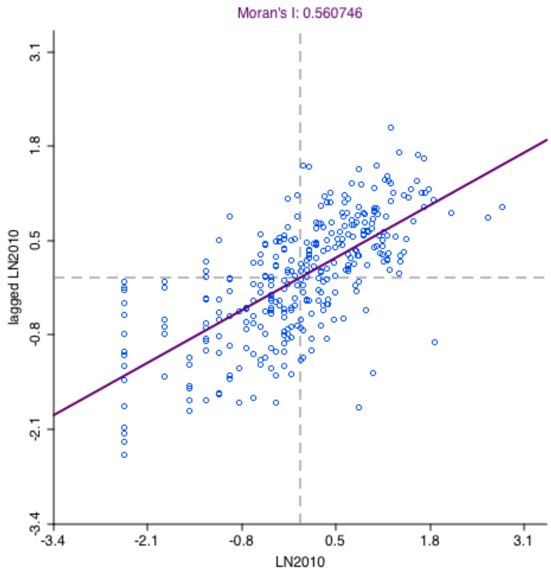


F Moran's I Scatter (Innovation log-transformed)

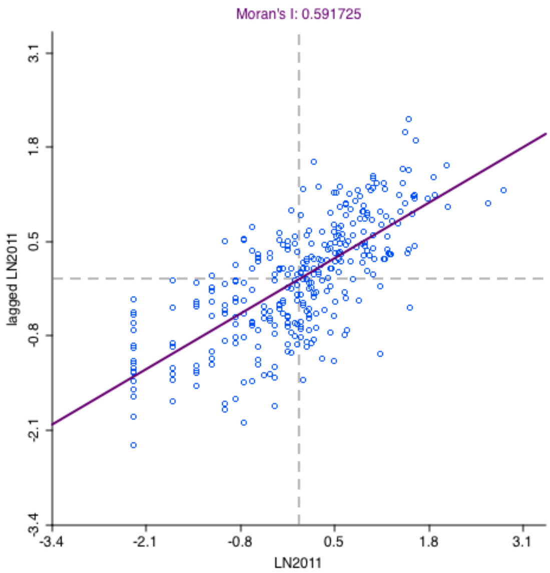
Figure 8: Moran's I Scatter Plots



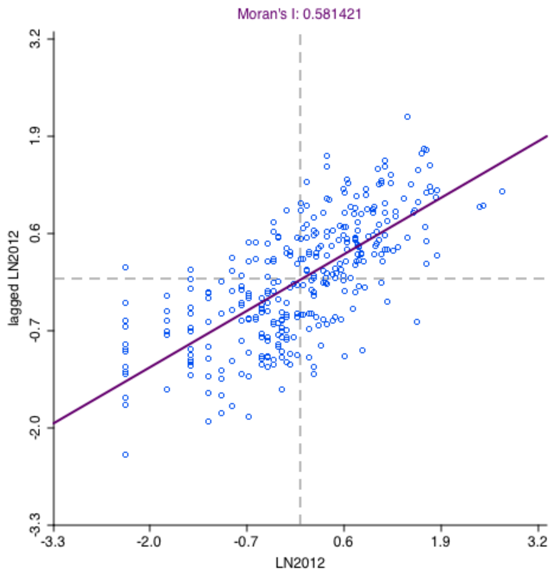
(i) 2009



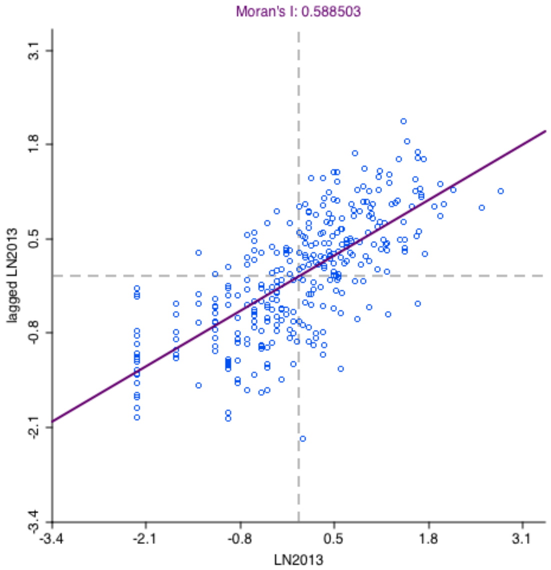
(ii) 2010



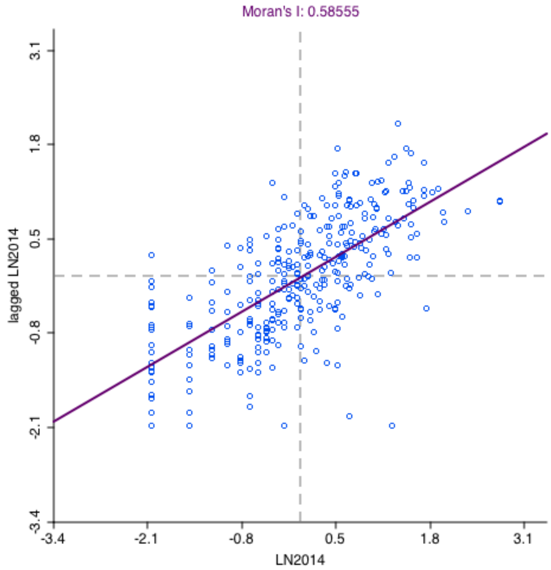
(iii) 2011



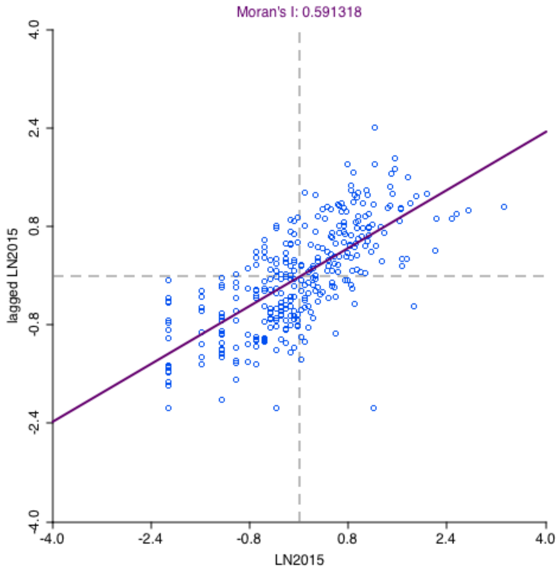
(iv) 2012



(v) 2013

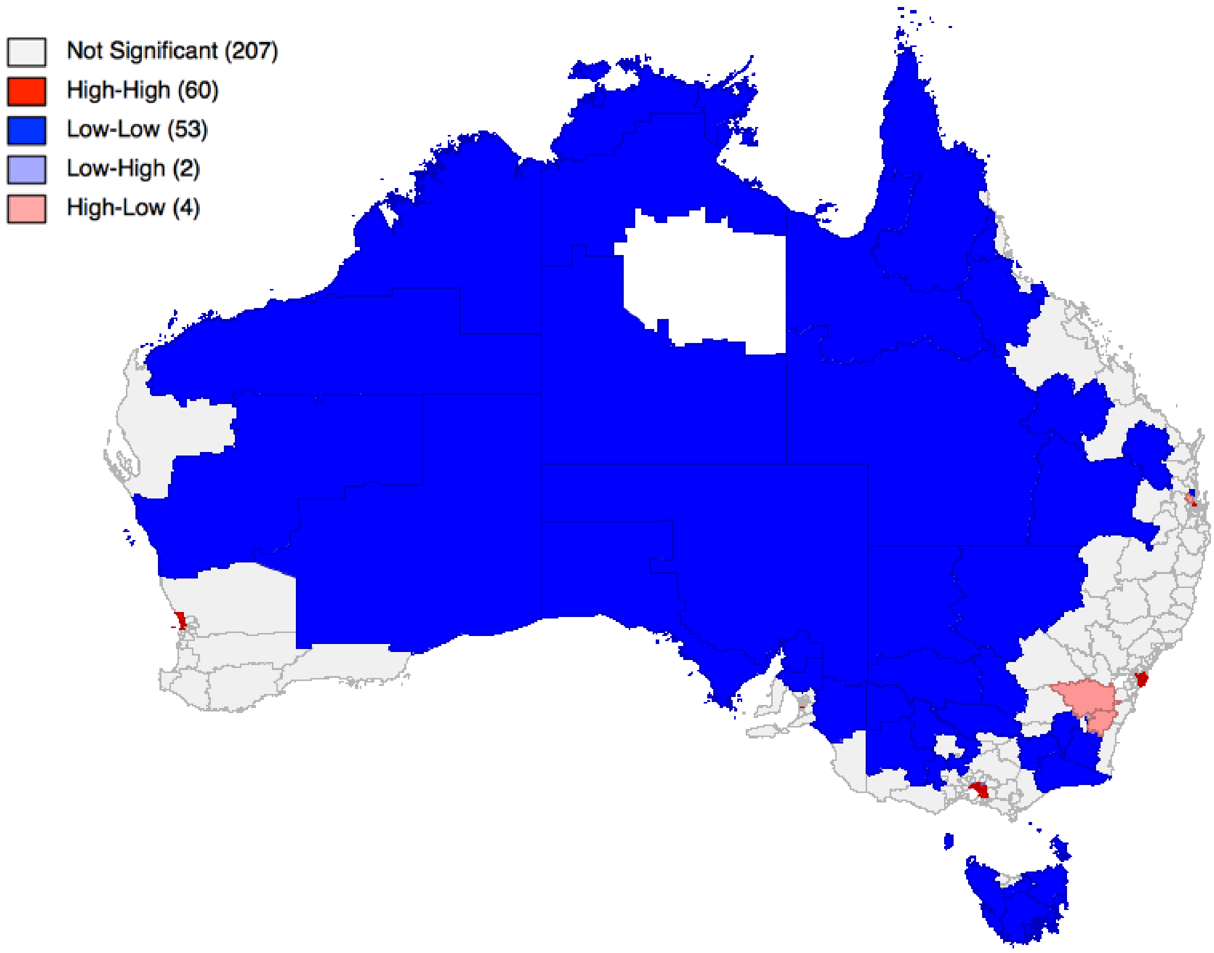


(vi) 2014

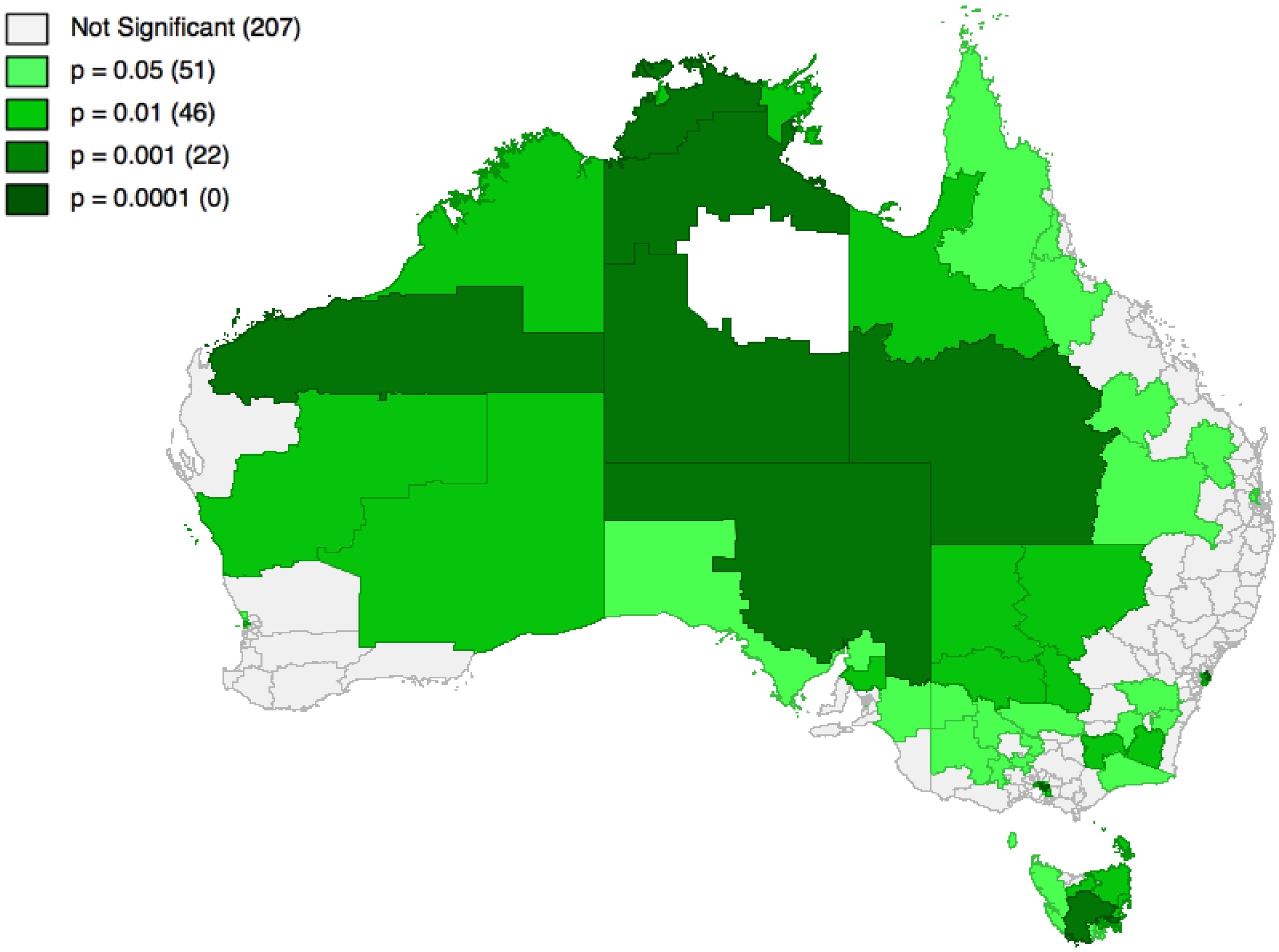


(vii) 2015

G LISA Map (Australia)

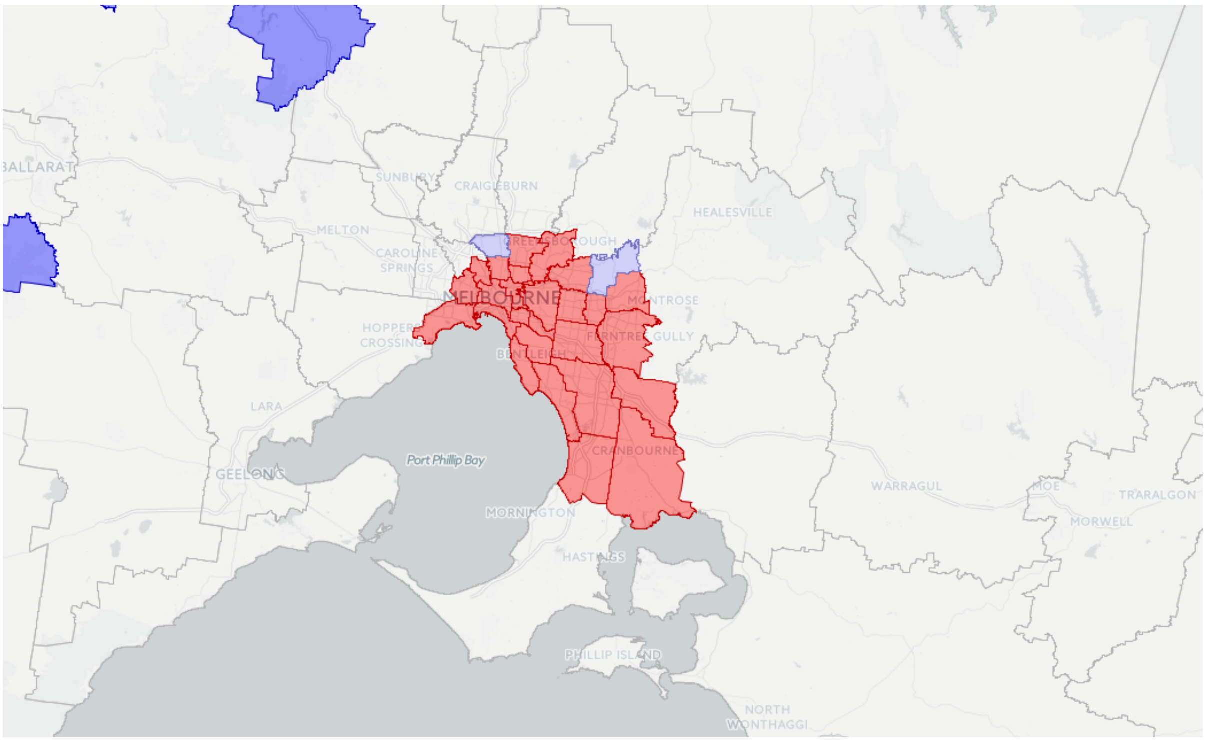


H LISA Significance Map (Australia)

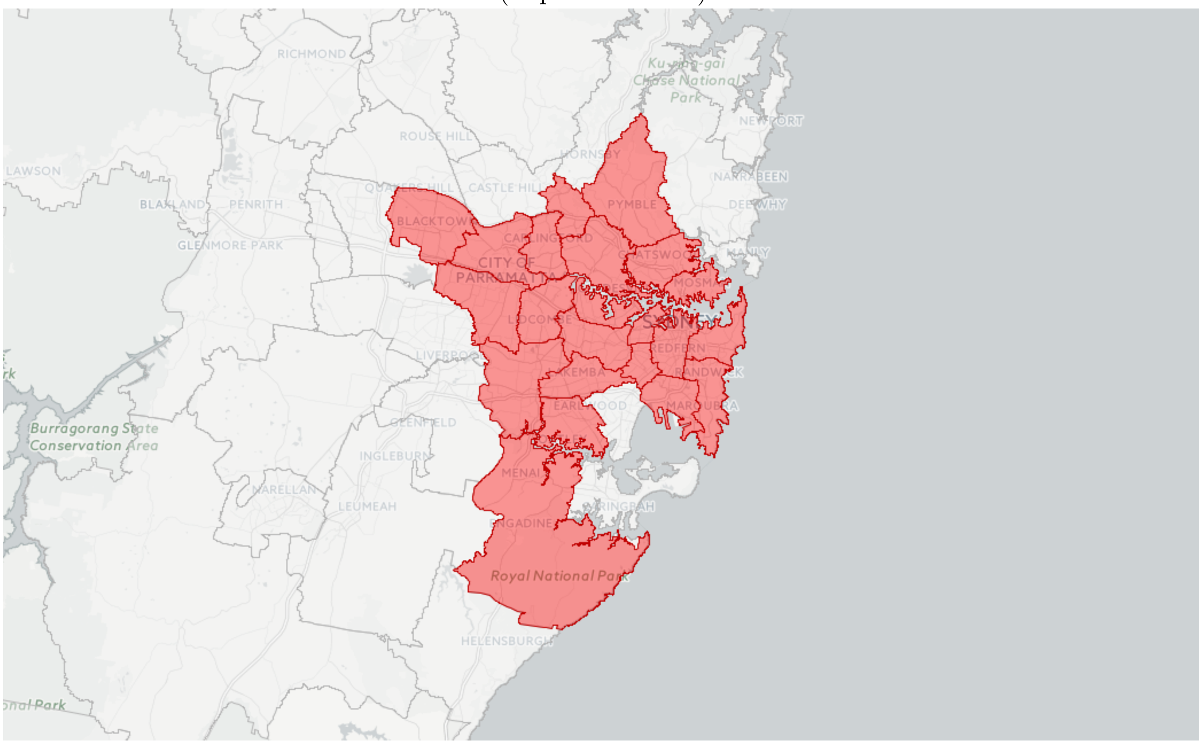


I LISA Map (Melbourne and Sydney)

Figure 9: Moran's I Scatter Plots



(Top: Melbourne)



(Bottom: Sydney)

J Moran's I (not logged)

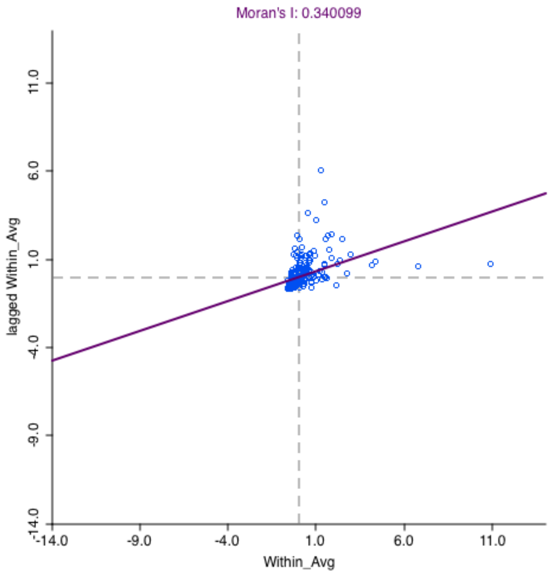
Table 14: Tests for Spatial Dependence/Autocorrelation (for innovation not log-transformed)

	2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**Within Mean**
Moran's I	0.3596	0.3128	0.3699	0.3777	0.3502	0.2809	0.1948	0.3400
p-value	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
Permutations	999	999	999	999	999	999	999	999

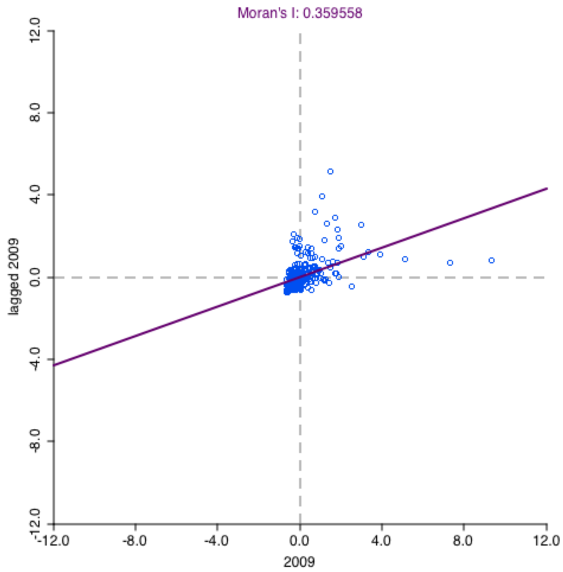
*** 1%, ** 5%, * 10%. Note that p-values reported are *pseudo p-values*.

K Moran's I scatter (not logged)

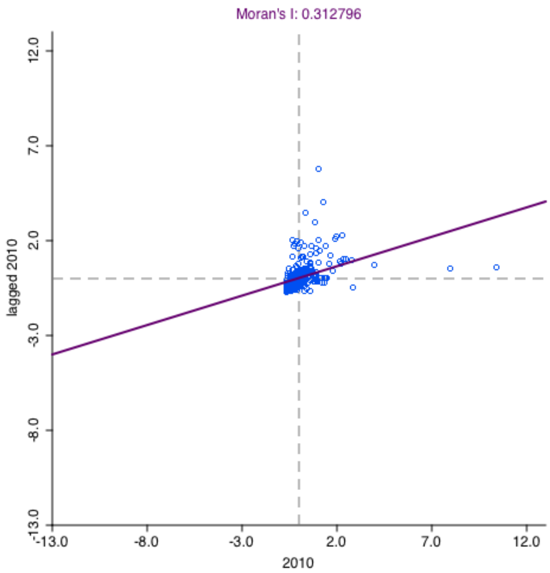
Figure 10: Moran's I Scatter Plots (no log transformation)



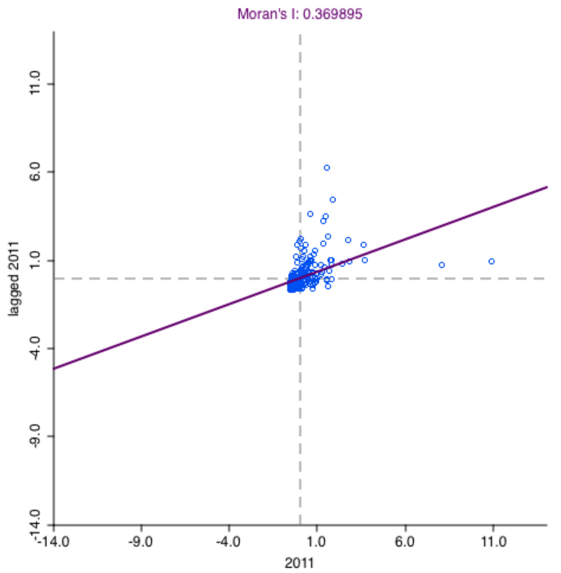
(i) Within Average



(ii) 2009

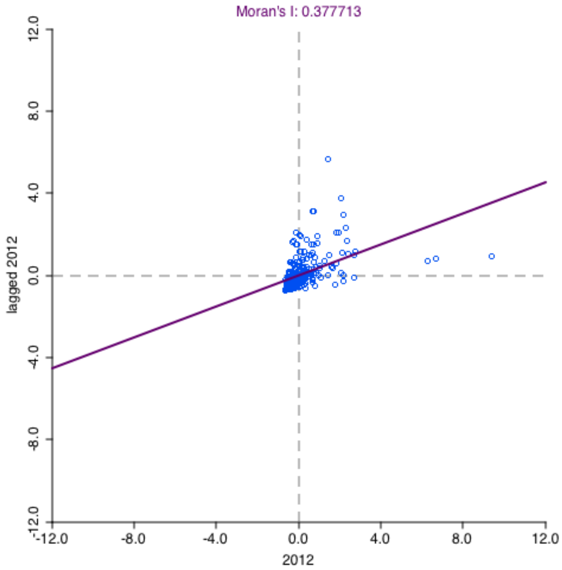


(iii) 2010

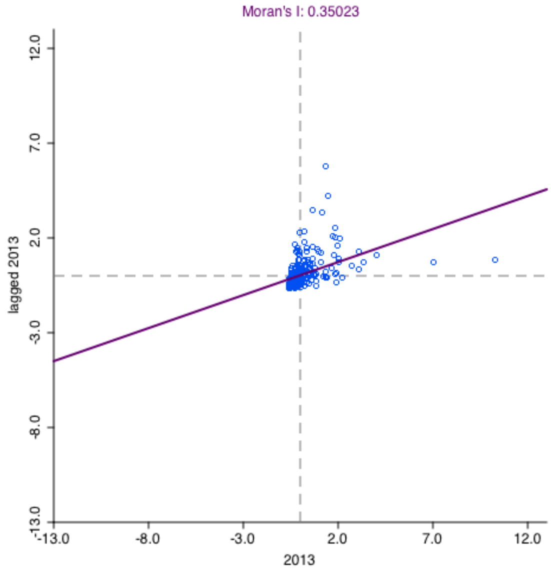


(iv) 2011

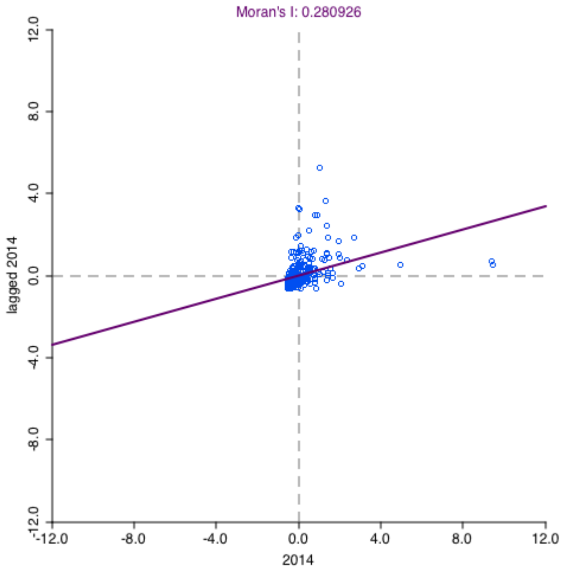
[!]



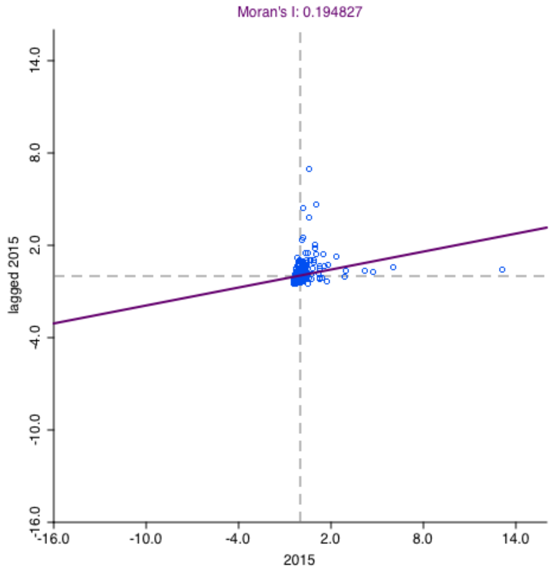
(v) 2012



(vi) 2013



(vii) 2014



(viii) 2015

L Spatial Panel Model Specifications

L.1 SAR Model

Specifications for the spatial autoregressive, or lag, model from the general nesting are where λ and $\theta = 0$. More explicitly we specify the model as:

$$\ln innov_{it} = \rho \sum_{j=1}^{N} w_{ij} \ln innov_{jt} + \beta_1 \ln BRD_{it} + \beta_2 Unis_{it} + \beta_3 Ufunding_{it} + \beta_4 \ln lforce_{it} + \\ \beta_5 \ln popdensity_{it} + \mu_i + \gamma_t + \epsilon_{it} \quad (13)$$

The spatial lag model proposes that the dependent variable (innovation), depends upon the dependent of neighbouring observations (regions), and is common throughout the literature (Anselin et al. 2006, p. 6). In our context, the SAR model suggests that innovation within a region is expected to be partly determined or correlated by innovation in neighbouring regions (suggested in ESDA). Year dummies are not included as estimation allows for both fixed effects to be automatically controlled.

L.2 SEM Model

The spatial error model is specified where ρ and $\theta = 0$:

$$\ln innov_{it} = \beta_1 \ln BRD_{it} + \beta_2 Unis_{it} + \beta_3 Ufunding_{it} + \beta_4 \ln lforce_{it} + \beta_5 \ln popdensity_{it} + \\ \mu_i + \gamma_t + \lambda \sum_{j=1}^{N} w_{ij} u_{it} + \epsilon_{it} \quad (14)$$

Unlike the SAR or SDM models, spatially lagged dependent and explanatory variables are not included, with local inputs being the primary determinant of innovation. Here the spatial interaction occurs in the composite error term. SEM models have no requirement on formal theory or intuition, and are appropriate where omitted variables entered into the error component follow some spatial pattern (Elhorst, 2010).

L.3 SAC Model

The SAC model combines both the SAR and SEM to have spatial coefficients on both the dependent variable and error term ($\theta = 0$):

$$\ln innov_{it} = \rho \sum_{j=1}^{N} w_{ij} \ln innov_{jt} + \beta_1 \ln BRD_{it} + \beta_2 Unis_{it} + \beta_3 Ufunding_{it} + \beta_4 \ln lforce_{it} + \\ \beta_5 \ln popdensity_{it} + \mu_i + \gamma_t + \lambda \sum_{j=1}^{N} w_{ij} u_{it} + \epsilon_{it} \quad (15)$$

The SAC model is the closest to a full/general nested model combining three spatial interactions. Intuitively it might be tempting to include all types of spatial interactions, however, Elhorst (2010) that one interaction effect needs to be omitted in order for the model to be identified.

M Results form SAR, SEM, and SAC Fixed Effects Estimation

Table 15: Spatial Panel Estimation Results

	SAR	**SEM**	**SAC**
Main			
ln BRD	-0.0130	-0.0121	-0.0116
	(0.00958)	(0.00942)	(0.00878)
Unis	0.604***	0.615***	0.483***
	(0.0383)	(0.0490)	(0.133)
Ufunding	0.000299	0.000303	0.000790
	(0.00169)	(0.00171)	(0.00124)
ln popdensity	-0.846	-0.804	-0.657*
	(0.566)	(0.586)	(0.337)
ln lforce	0.0122	0.0194	0.0510
	(0.291)	(0.308)	(0.197)
Spatial			
ρ	0.154***	–	0.610***
	(0.0275)		(0.0420)
λ	–	0.141***	-0.631***
		(0.0340)	(0.0627)
Variance			
σ^2	0.182***	0.182***	0.148***
	(0.0117)	(0.0117)	(0.0109)
Hausman	238.82***	$-^{\dagger}$	$-^{+}$
Observations	1956	1956	1956

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(.) Clustered Std. Errors – Lee and Yu (2010) Transformed

† Hessian not negative semidefinite; + SAC only used with FE

N Results from non-spatial panel model (FE and RE)

Table 16: Results from non-spatial Fixed and Random Effects Panel Model

	Fixed Effects	**Random Effects**
ln BRD	-0.00382	0.0170*
	(0.0104)	(0.00888)
Unis	0.685***	0.0572
	(0.0355)	(0.0418)
Ufunding	0.00494***	0.00309***
	(0.00170)	(0.000874)
ln popdensity	-0.0336	0.126***
	(0.274)	(0.0225)
ln lforce	0.315	0.629***
	(0.279)	(0.0761)
d09	0.408***	0.443***
	(0.0412)	(0.0337)
d10	0.361***	0.395***
	(0.0415)	(0.0359)
d11	0.282***	0.309***
	(0.0388)	(0.0347)
d12	0.298***	0.322***
	(0.0411)	(0.0368)
d13	0.220***	0.236***
	(0.0346)	(0.0314)
d14	0.0389	0.0489
	(0.0333)	(0.0309)
Constant	-0.957	-5.423***
	(2.113)	(0.727)
Modified Wald Test	33471.8***	–
Observations	2282	2282

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(.) Clustered Std. Errors

NOTE: Random effects (time-invariant) controls are omitted from output.

O Results for Primary Industry differences

Table 17: Summary of Industry Differences (all spatial models)

	Models				
	SDM	SAR	SEM	SAC	Static Panel
Main					
(log) Business R&D	∘	∘	∘	∘	∘
University campuses (count)	+	+	+	+	+
University funding (millions)	+	∘	∘	∘	∘
(log) Labour force	∘	∘	∘	∘	∘
(log) Population density	∘	∘	∘	∘	∘
Primary Industries					
Information and Media	∘	∘	∘	∘	∘
Accommodation Services	∘	∘	∘	∘	∘
Admin and Support Services	∘	∘	∘	∘	∘
Agriculture	–	–	–	–	–
Arts	∘	∘	∘	∘	∘
Construction	∘	–	–	∘	–
Education and Training	∘	∘	∘	∘	∘
Utilities	∘	∘	∘	∘	∘
Financial Services	∘	∘	∘	∘	∘
Health	∘	∘	∘	∘	∘
Manufacturing	∘	∘	∘	∘	∘
Mining	∘	∘	∘	∘	∘
Professional and Scientific Services	∘	∘	∘	∘	∘
Public Admin and Safety Services	∘	∘	∘	∘	∘
Real Estate	∘	∘	∘	∘	∘
Retail	∘	∘	∘	∘	∘
Transport	∘	∘	∘	∘	∘
Spatial					
ρ	+	+	na	+	na
λ	na	na	+	−	na
Variance					
σ^2	+	+	+	+	na

+ = positive and significant; − = negative and significant; ∘ = not significant
(Significance at 10% level)

P Spatial Panel Random Effects Results

Table 18: Spatial Panel Results: Random Effects

	SDM	**SAR**
Main		
ln BRD	0.0152*	0.0152*
	(0.00901)	(0.00896)
Unis	0.0704	0.0593
	(0.0447)	(0.0419)
Ufunding	0.00239**	0.00300***
	(0.000939)	(0.000869)
ln popdensity	0.00363	0.115***
	(0.0326)	(0.0228)
Constant	-6.301***	-5.576***
	(1.036)	(0.713)
Wx: lagged independents		
ln BRD	0.0118	–
	(0.0151)	
Unis	-0.00746	–
	(0.0509)	
Ufunding	0.00149	–
	(0.00118)	
ln popdensity	0.164***	–
	(0.0386)	
ln lforce	-0.0632	–
	(0.107)	
Spatial		
ρ	0.0232	0.0642***
	(0.0231)	(0.0236)
Variance		
σ^2	0.171***	0.171***
	(0.0111)	(0.0112)
Observations	2282	2282

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(.) Clustered Std. Errors – Lee and Yu (2010) Transformed

Notes: **(i)** Time dummies and time invariant controls are omitted from the output

(ii) RE results for SEM are not listed as estimation does not produce negative semidefinite Hessian.

(iii) SAC is not listed as only appropriate for FE specifications.