Accounting for Natural Capital in Productivity Analysis

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Khanh Vy Hoang

Abstract

This thesis addresses several fundamental measurement issues in valuing natural capital services for the explicit inclusion of natural resources in measures of productivity. By addressing these measurement issues, this thesis considers the economy and the environment as a whole, ensuring the connection of traditional measures of productivity and natural capital are more prominently recognised. The thesis consists of two sections. The first section (Chapter 2) focuses on the effect of including subsoil assets in mining sector productivity estimates. Three different methods for estimating natural capital user cost values are considered. Productivity measures, which include the service flow of natural capital, require user cost values for natural capital to be the same as the current standard methodology for producing capital service aggregates (Organisation for Economic Co-operation and Development [OECD] 2001). The results show that while the different methods yield different multifactor productivity (MFP) estimates, the most influential adjustment to traditional productivity measures is the inclusion of natural capital. This generated substantial productivity gains for the Australian mining sector, where natural capital added at least 1.0 percentage point growth to annual productivity from 1995–1996 to 2015–2016. The second section comprises Chapter 3 and Chapter 4. The focus here is on enhancing the agricultural sector's productivity estimates by accounting for changes in the quality of agricultural land. Chapter 3 utilises a novel Australian administrative dataset of land sales to construct constant-quality land-price indexes. This chapter considers four hedonic spatial pricing models for valuing agricultural land, and two different approaches to creating constant-quality price indexes. Chapter 4 provides adjusted productivity estimates of the agriculture sector. Accounting for the quality of agricultural land reduces annual productivity growth by 1.3 percentage points each year between 1995–1996 and 2017–2018. The connecting link between all the chapters is that they were motivated by the need to enhance productivity estimates through the explicit inclusion of natural capital. The results from this thesis inform trade-offs of natural resources against environmental effects, and that, in turn, support sustainable development that fully considers intergenerational equity and income distribution resulting from the use of natural capital.

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Abbreviations

2008 SNA	2008 System of National Accounts
ABS	Australian Bureau of Statistics
ABARES	Australian Bureau of Agricultural and Resource Economics and Sciences
AIC	akaike information criterion
ASGS	Australian Statistical Geography Standard
AWAP	Australian Water Availability Project
BIC	bayesian information criterion
CPI	consumer price index
EEA	Experimental Ecosystem Accounting
EU	European Union
FAO	Food and Agriculture Organisation
GAM	generalised additive model
GCV	generalised cross-validation
GDP	gross domestic product
GOS	gross operating surplus
GVA	gross value added
KLEMS	capital labour energy materials services
IMF	International Monetary Fund
MFP	multifactor productivity
NPV	net present value
NCS	natural capital stock
NSW	New South Wales
OECD	Organisation for Economic Co-operation and Development
PKS	productive capital stock
PIM	perpetual inventory method
R&D	research and development
RBA	Reserve Bank of Australia
REML	restricted maximum likelihood
SA	South Australia
SA3/SA4	Statistical Area Level 3/4
SEEA CF	System of Environmental-Economic Accounting Central Framework
TFP	total factor productivity
UBRE	unbiased risk estimator
UN	United Nations
US	United States
VG	Valuer-General
WA	Western Australia

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Chapter 1

Introduction

1.1 Background and Importance of Research

Traditional measures of economic growth typically do not fully consider the role of the environment in the productive process. Although a country's income is generated through the depletion of natural capital (for example, subsoil assets) in the value of gross domestic product (GDP), the role of natural capital as an input in growth measures of traditional multifactor productivity (MFP) is frequently ignored. While the indivisibility between the economy and natural capital has been recognised internationally, progress in ensuring this connection in traditional measures of productivity has lagged. If these links are not soon recognised and accounted for, economic development will likely continue at the expense of the quality and quantity of the world's natural capital. The effects of this degradation will, in time, show on each nation's balance sheet as well as in lowered productive capacity over time.

The enduring gap of not including natural capital in productivity measures raises important research questions: *How to account for natural capital depletion? Will a failure to account for this depletion be a risk to the future wellbeing (increase in material standards of living)?* To answer these questions, this thesis explicitly values natural capital and its service flows in the context of productivity analysis. The secondary research questions are: *What are the economic consequences of the extraction and depletion of subsoil assets on potential productivity growth for the mining sector? What are the effects on productivity of the agricultural sector over time from accounting for land quality?* These research questions all query how to include natural capital in economic measures of productivity.

The importance of the research agenda has not been lost on international organisation. According to the World Bank (2011), a resource-rich country is highly dependent on natural capital as it is the source of many ecosystem services. These services are often undervalued or renewable only under restricted management regimes. Therefore, there is a growing interest in whether economic and other human activity leads to the degradation of ecosystems. Thus, it reduces the capacity for ecosystems to provide the services on which people depend.[1]

MFP is an indicator of innovation, as it captures increases in productivity from utilising a given set of resources more efficiently (World Bank 2011). Typically, MFP represents technology change and other factors not traditionally included in standard labour inputs and produced capital. Therefore, estimated MFP growth is likely to include effects from the quantity and quality of natural capital used by production processes, as they are typically excluded as inputs from the calculations. For example, changes to quality of land has the potential to the measure of agricultural productivity. In Australia, official productivity statistics do not yet explicitly include the services provided by natural capital both at the national and regional levels. This deficiency is because the measurement of environmental inputs contains numerous unresolved issues in current economic-environment accounting frameworks (UN et al. 2014a and UN et al. 2014b).

Despite its importance, measurement of the value of natural capital by official government agencies is still in its infancy (Schreyer & Obst 2015). Estimates on the stock of produced assets (such as machinery, equipment and buildings) and information on land value vary between countries. Only a few nations release balance sheets that include natural capital, and even fewer include estimates of environmental assets (Schreyer & Obst 2015). As a result, established national datasets have not supported the analysis of the connections between the sustainability of economic growth, wealth and, more generally, wellbeing (OECD 2011). This is supported by a recent study by Freeman, Inkaar and Diewert (2021). The authors found that cross-country productivity comparisons when including

[1] The issue of sustainability of ecosystems is acknowledged in several global policy forums, most notably the outcomes following Rio+ G20 and United Nations Convention on Biological Diversity. Over the past 15 years, the World Bank has played a prominent role in advancing broad measures of national wealth (World Bank 2011) with global initiatives such as the Bank's Wealth Accounting projects and the Economics of Ecosystems and Biodiversity (TEEB) and Valuation of Ecosystem Services (WAVES).

natural capital are challenging due to the assumption that all countries use the same set of natural resources. This assumption does not hold because countries do not extract all the same resources. By assigning 'missing natural resources' a reservation price[2] equal to the world resource price, the authors found a substantial impact on relative productivity levels for countries heavily reliant on natural resources.

In the case of ecosystem service, the application to productivity measurement is even more challenging. As terrestrial and marine ecosystems are complex and dynamic, the estimation of a simple measure of depletion based on the approach used for non-renewable and renewable resources, may potentially understate ecosystem degradation. The effect may distort people's expectations of ecosystem prices and, therefore, the asset-inflation rate. For example, agricultural land prices may not reflect the total cost of land management practices. However, when soil quality is reduced, production yield and productivity tends to also fall (Azad & Ancev 2020). In this context, being able to link capital accounting theory and ecosystem accounting provides the platform to improve estimates of productivity.

Statistical offices, such as the Australian Bureau of Statistics (ABS), do not record the complete set of environmental assets defined in the 2008 System of National Accounts (2008 SNA) (UN et al. 2009) in the national balance sheets.[3] The ABS only measures land area (the 'space' attribute of land) with no adjustment made for quality. Consequently, it does not account for soil degradation due to land management choices or exogenous factors. Thus, the role of soil quality as a factor of production is ignored. This measure also ignores the productive limits of agricultural land and other critical environmental inputs such as the management of soil resources.

Natural capital depletion is similarly omitted in mining productivity derivations (Syed et al. 2015). A recent study by Brandt et al. (2017) showed that the direction of the change to productivity growth relies on the rate of change of labour and capital and natural capital extraction. Thus, excluding natural capital could lead to productivity being underestimated during resource booms, where other factors of production such as

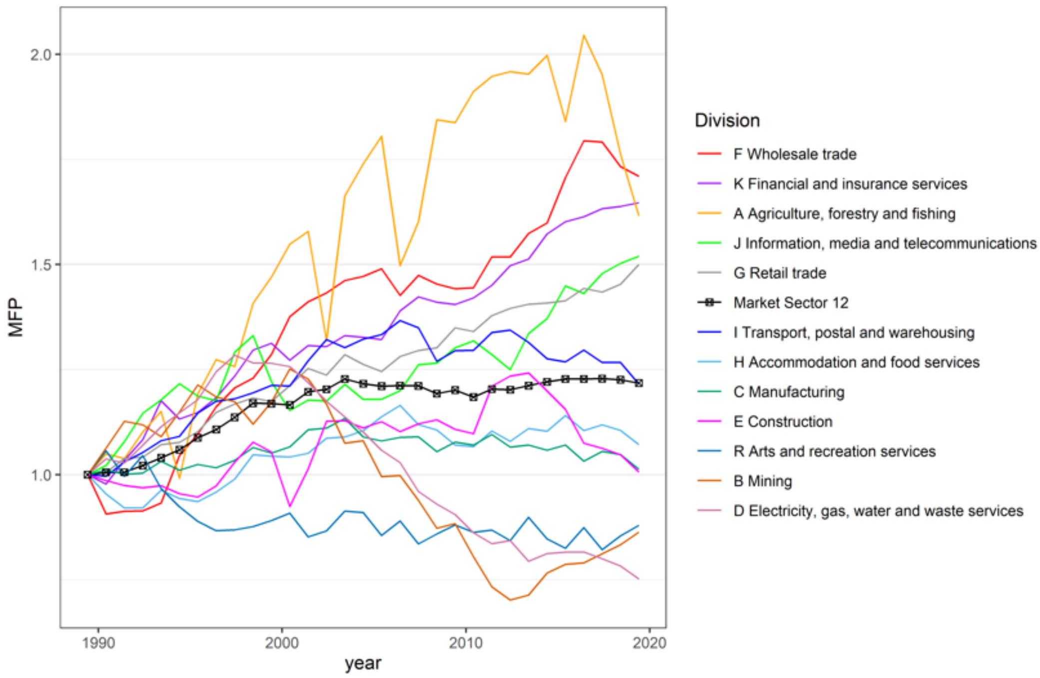
[2]The reservation prices refer to the price of an input that is not used in production, that is, a price sufficient enough for demand to be zero as defined by Hicks (1940)

[3]The Australian national balance sheets include environmental assets such as land, subsoil assets and native standing timber. Water and fish stocks have not been incorporated due to valuation difficulties and a lack of available data.

produced capital increase quicker than natural resource inputs. Therefore, a failure to account for changes in natural capital distorts one's view of productivity performance and, importantly, the extent to which gains in productivity are sustainable.

To illustrate the vital role of natural resources in productivity measurement, Figure 1.1 shows Australia's official MFP statistics produced by the ABS for the 12 core market sectors. Notably, the ABS-defined sector 'Agriculture, forestry and fishing' has the strongest productivity gains, notwithstanding significant declines in productivity during drought periods. In this sector, from 1989–1990 to 2015–2016, productivity improved by almost 90 per cent, in contrast to the market sector productivity growth, which increased by only 18 per cent. Further, mining sector productivity over the same period recorded the weakest productivity gains. The overall view of Australia's productivity performance would be different without the significant productivity performance of the Agriculture, forestry, and fishing sector and significant productivity adjustment of the mining sector.

Figure 1.1 – **MFP estimates across 12 selected industries using quality adjusted labour (1989–1999 to 2019–2020)**



Source: ABS Estimates of Industry Multifactor Productivity (ABS 2020)

One straightforward strategy to help ensure natural capital is used efficiently over time is to include its contribution to productivity. This is because when making choices about policy, decision-makers are using flawed economic measures - flawed because they do not (for the most part) account for effects of production activity on the natural environment.

The OECD has shown increasing interest in measuring forms of productivity that are more inclusive of natural capital, but these efforts have so far had limited (if any) application in decision-making processes.

This thesis contributes to enhancing measures of productivity by highlighting the potential mismeasurements in official MFP statistics due to failing to account for natural capital and providing solutions to integrate natural capital into existing measures. First, the results show that official MFP statistics provided by the ABS overstate the growth of capital input by excluding subsoil assets. Second, the thesis provides empirical evidence that the simple mean or median land price index rises more rapidly than constant-quality price indexes, implying a rise in the quality of agricultural land. This conclusion is strengthened by the outcome that different hedonic models imply similar constant-quality price changes compared to the mean and median land price index. Third, it shows the ABS method, which fails to recognise changes in land quality, understates the growth of agricultural capital input and thus overstates MFP growth. Therefore, this thesis responds to several fundamental measurement issues that have not received adequate attention in the literature, highlighting the role of natural capital in economic growth.

1.2 Natural Capital

> Natural capital can be defined as the world's stocks of natural assets which include geology, soil, air, water and all living things. It is from this natural capital that humans derive a wide range of services, often called ecosystem services, which make human life possible.
> - World Forum on Natural capital (2020, para. 1)

Natural capital is recognised as an essential economic asset[4] that has the potential for

[4]In economic theory, viewing natural resources as capital goes back over 200 years to classical economists such as Faustmann and Ricardo (Gaffney 2008), with the modern treatment pioneered by Hotelling (1931). Since the 1970s, work by Weitzman (1976), Hartwick (1990), Heal (1998), Arrow et al. (2004), Nordhaus (2006) and Arrow et al. (2012) has resulted in the development of a robust conceptual framework for treating natural stocks as capital. Despite this strong theoretical support, often the value of natural capital into national balance sheets has lagged for many critical stocks such as biodiversity, wetlands and forests (UN 2014a).

long-term use in terms of productivity and welfare. A long history exists to integrate natural capital to include the stocks and flows of natural resources present in a country (such as timber, fish, water, mineral and energy resources, land and soil) into the national accounts (see Harrison 1993; Vanoli 1995). To date, however, no definitive method has been arrived at to account for natural capital in national accounts. Ayres and Kneese (1969) and Meadows et al. (1972) all highlighted the importance of the environment for economic development, providing impetus for economists to analyse these issues by including non-renewable resources in macro-economic models. Weitzman (1976) later established a welfare measure of GDP in which national income equals the return to wealth. Collectively, these studies began the 'green accounting literature', which analyses the relationship between concepts such as income, wealth and welfare in macro-economic models, including the role of natural resources (Heal & Kriström 2005).

While the green accounting literature offered a promising way forward, the approach did not lead to integrate natural capital into national accounts measures.This is because it was established at a very high level of abstraction without searching any longer for any relationship to actual national accounting measurements'(Vanoli 2005). Consequently, national statistical agencies followed a more empirical approach, initially attempting to integrate environmental and natural resources into the national accounts. This was conducted during the 1970s and 1980s in France (Interministerial Commission for Natural Heritage Accounts et al. 1986) and Norway (Alfsen et al. 1987).

The methods used to evaluate ecosystems and the concepts of value and approached to valuation for national accounting purposes are not the same as those typically applied by economists. There are several differences in the concept in comparison to the welfare theoretic approach, specifically between exchange values and shadow prices.[5] This issue arises both in the measurement of wealth (Arrow et al. 2003; World Bank 2011) and when deriving the change in surpluses of individual economic agents. Some sections of the economics community are critical of environmental-economic accounting because national accounts exclude the valuation of consumer surplus (Heal Kriström 2005)

[5]In national accounting, exchange values is considered the value at which goods and services and assets, are sold regardless of the prevailing market conditions. This implies that externalities are not market transactions and as such are excluded. In contrast, the concept of shadow prices used in wealth accounting incorporate the effects of externalities to reflect the marginal contributions of assets to well-being (Dasgupta 2009)

In 1993, the UN Statistical Commission released the *Handbook of National Accounting: Integrated Environmental and Economic Accounting*. The most prominent subsequent extension to national accounting literature is a framework known as the System of Environmental-Economic Accounting (SEEA) (UN et al. 2014a). The Commission's adoption in 2012 of the SEEA Central Framework (CF) highlights the importance of environmental assets and the measurement of natural resources.

The SEEA Experimental Ecosystem Accounting (EEA) (UN et al. 2014b) considers the interactions between individual resources to measure the broad set of benefits that arise from ecosystems. The principle of ecosystem accounting is to value the material and non-material benefits derived from ecosystems. While the SEEA CF and SEEA EEA provide a landmark framework, some challenges remain in measuring ecosystem assets and their services and in integrating them into the national accounts system, noting that the SEEA EEA applied many core accounting concepts developed in the 2008 SNA. For example, the boundary of economic activity, the types of accounts and principles of valuation, and the definitions and classifications of economic units are all aligned with the two frameworks.

1.3 Structure of the Thesis

The first section (Chapter 2) of the thesis focuses on the effect of including subsoil assets in mining sector productivity estimates, and the second section (Chapter 3 and Chapter 4) focuses on enhancing agricultural sector productivity estimates by accounting for changes in the quality of agricultural land. This entails using frameworks that are coherent with the existing 2008 SNA framework used by the national statistics system to compile indicators of economic growth. This consistency with SNA means that productivity measures can be integrated into 'official' indicators that are widely used in policy formulation.

How to measure contributions of natural capital to productivity change is an emerging area of research, as more environmental datasets have been recently made publicly available. Despite theoretical developments in this area, it is unresolved as to which user cost method best characterises contributions of natural capital. **Chapter 2** provides a concise explanation of the mechanics underlying different user cost of natural capital methods.

Three user cost of natural capital approaches are used to test the robustness of the results to select methods of measurement. More conclusive findings of the contribution of subsoil assets to the mining sector's productivity growth can also be drawn from the analysis. The first method is the unit resource rent method suggested by Brandt et al. (2017) and adopted by the World Bank (Lange et al. 2018); the second method is the residual value method recommended by the UN SEEA 2012 (UN et al. 2014a; UN et al. 2014b); and the third method, proposed by Diewert and Fox (2016a), is a variant of the traditional user cost. The contribution of this chapter is twofold: An empirical comparison of different approaches to the user cost of natural capital has never been undertaken until this thesis; and the results implies that the most influential adjustment to traditional productivity measures is the inclusion itself of natural capital. Based on the comparison of the methods, the study shows that user cost values derived from the unit resource rent method are rarely negative, are less volatile and provide a more realistic representation of production functions over time. The study confirms that accounting for changes in subsoil assets appears to have been a significant driver of productivity change during the Australian mining boom from 2010 to 2015.

Due to the focus of environmental accounting frameworks on spatial areas, a unique opportunity exists to utilise emerging geospatial datasets. **Chapter 3** examines the importance of factors that contribute to land value growth at the national level and for the six main agricultural states of Australia. First, the chapter examines the roles of location-type factors and environmental-type factors on land values; this is achieved through the comparison of different spatial hedonic models. This study demonstrates that land quality is positively correlated with land price, which is essential for decision-makers considering a pricing instrument. Second, comparison of two distinct index-construction methods shows that estimates of agricultural land adjusted for quality are reasonably insensitive to both the hedonic models and whether time-dummy or double-imputation indexes are employed. The contribution of this chapter is to provide the first portrait of the relationship between Australia's agricultural land values and land quality over the past 40 years at both national and state levels. In doing so, the chapter utilises a unique Australian administrative spatial dataset developed by the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES). This study also provides the first empirical comparison of time-dummy and double imputation hedonic price indexes in this context, and highlights that agricultural land prices may not reflect land management practices that by reducing soil quality, reduces the production yield. In this context, linking capital accounting theory and environmental accounting provide a platform to improve the estimates of agricultural productivity.

The emerging challenges of climate change and environmental degradation facing the agriculture sector highlight the importance of better understanding the determinants of farm productivity, including the contribution of land quality dimension. In this context, **Chapter 4** applies constant-quality land price indexes to enhance measures of agriculture productivity and outlines the relationship between productivity and land quality. These constant-quality price indexes aims to reflect the evolution of the prices of agricultural land with the level of quality being fixed. In doing so, this chapter provides an example of how measures of natural capital can be enhanced through the use of extensive administrative data. The novelty of Chapter 4 is in the use of constant-quality price indexes in the derivation of agricultural MFP. The results show that the agriculture sector MFP is overstated when land quality is ignored, so that quality change appears as a change in quantity.

The thesis concludes with **Chapter 5** summarises the main goals and research questions asked and highlights the contributions of the thesis. This concluding chapter highlights some future research directions as well as the limitations of this work.

Chapter 2

Accounting for Natural Capital in Mining Multifactor Productivity: A Comparison of User Costs for Non-renewable Resources

2.1 Introduction and Related Literature

The growth in national productivity interests economists and policymakers alike because increases in productivity levels imply that an economy can produce more output with limited inputs - hence, improve the material state of the economy. The typical production function assumed when constructing multifactor productivity (MFP) measures includes labour and produced capital as input factors. MFP is considered to represent elements such as more efficient management and technological change not directly embodied in capital stocks. The traditional approach to deriving MFP excludes the contribution of natural capital, despite it being a major input for some industries (for example, mining) and its extraction may constitute a non-trivial share of GDP in some countries. For example, subsoil assets[1] have played a vital role in the Australian economy, most notably

[1] According to the 2008 System of National Accounts (2008 SNA), 'subsoil assets are... those proven subsoil resources of coal, oil and natural gas, metallic minerals or non-metallic minerals that are economically exploitable given current technology and relative prices.' (UN et al. 2009, para. 12.17). In the Australian case, the scope is broader than proven resources, since it includes proven and probable resources (Australian Bureau of Statistics [ABS] 2016b).

over the last century. They are crucial inputs in the mining sector and are the fourth most significant non-financial asset on the Australian balance sheet[2], being around 10 per cent of total non-financial assets in 2015–2016. The value of subsoil assets stock has tripled compared to a decade ago, primarily due to significant increase in world prices of key minerals in the 2000s.

The implications of excluding natural capital in MFP measures particularly for the mining sector — can be considerable because of its significance to the economy. In 2015–2016, mining represented about 11 per cent of Australian gross domestic product (GDP) in nominal value-added terms (approximately A$160 billion). From 1989–1990 to 2015–2016, the output of the mining sector in current price terms surged by 8.4 per cent a year, while in real output terms its growth was more modest (3.0 per cent annually).

Based on ABS estimates, Australia's mining MFP fell 31 per cent between 1989 and 2007. The weakness in productivity growth in the mining sector over the past 2 decades is not unique to Australia. Canada's annual average growth in mining MFP between 1989 and 2000 was 1.9 per cent a year, while the United States (US) recorded 0.6 per cent annual growth over the same period. From 2000 to 2007, the corresponding numbers for Canada and the US were -1.1 per cent and -1.7 per cent a year, respectively (Bradley & Sharpe 2009).

The omission of natural capital has been shown in several studies to significantly influence the pattern of productivity growth in Australian mining. Topp et al. (2008) assessed mining MFP to grow by only 0.01 per cent a year on average over a 30-year time horizon (1974–1975 to 2006–2007). They attributed the stagnated MFP to resource depletion and to output growth lagging behind capital investments. Topp et al. (2008) also found that production lags were the main cause of mining productivity declines between 2004–2005 and 2006–2007; whereas prior to 2004–2005, the more significant factor is a decline in yield. They concluded that that mining MFP was lower when adjusted for production lags and falls in yield.

Loughton (2011) applied extraction of natural resources as a quality indicator. The author concluded that accounting for quality of natural resources added approximately 2 per cent

[2] A country's balance sheet shows the values of assets owned and of the liabilities owed by the country at a particular point in time (ABS 2016b).

growth to mining MFP between 1985–1986 and 2009–2010. The size of the adjustment sharply increased between 2005–2006 and 2011–2012, owing to a general increase in commodity prices. Overall, Loughton (2011) found that the contribution of natural capital to productivity growth was moderate compared to other production factors.

Later, the Bureau of Resources and Energy Economics (2013) assessed the Australian mining sector's productivity growth at the regional level. Their report found that the MFP growth rate increased on average from -0.7 per cent to 2.5 per cent annually between 1985–1986 and 2009–2010, after accounting for the effect of depletion in production lags as well as deposit quality.

In another study, Syed et al. (2015) adjusted mining MFP growth to factor in lags in input–output and the effects of depletion using an indicator of energy productivity. They found the unadjusted average annual MFP rate of growth of -0.65 per cent rose to 2.5 per cent from 1985–1986 to 2009–2010. For the coal mining and oil and gas extraction subsector, MFP growth also rose after depletion and production lags were considered. Similarly, at the state level, the adjusted mining MFP also exhibited stronger growth. Syed et al. (2015) concluded that resource depletion and input–output lags could explain much of the fall in mining productivity, as measured by the ABS.

Overall, these studies highlight the importance of using adjusted measures of MFP to consider the depletion of natural capital. Comprehensive productivity analysis, which includes all three input factors (labour, produced capital and natural capital), provides more accurate estimates and, thus, new insights into economic growth. The magnitude and direction of the adjustment of MFP depend on the growth of the natural capital input relative to other input factors. Failure to account for natural capital may send misleading signals about a country's economic progress, and may lead to an overestimation of economic growth in countries heavily reliant on natural resource depletion.

One of the reasons for excluding natural capital in productivity analysis is that there remain some unresolved issues with the measurement of natural inputs in environmental accounting frameworks (UN et al. 2014a). The progress by national statistical agencies in measuring quantities of natural stocks and the value of natural capital is still in its infancy, and is generally disconnected from valuation approaches for other assets (Schreyer & Obst 2015). Even statistical offices such as the ABS do not record the full set of environmental assets within the 2008 SNA economic asset boundary in the national balance sheets. The environmental assets on the Australian national balance sheets are land, subsoil assets and native standing timber. Water and fish stocks are excluded due to difficulties in valuing them, as well as a lack of available data. Further, some statistical agencies, like the ABS, have not yet explicitly included natural resources in official measures of productivity due to unresolved issues (mainly around ownership principles and recognition of an asset) in these accounting frameworks.[3]

The aim of this chapter is to address one of these anomalies. Notably, this chapter considers the issues in valuating natural capital for the purpose of explicitly including natural resources in productivity analysis. There are different methods for valuation, and each involves the choice of many parameters, such as returns on natural capital and estimation of asset life. The extent of choices that feed into the valuation model highlights the lingering fundamental measurement issues, even with the valuation of basic natural capital.

Productivity measures that include the service flow of non-renewable natural capital require user cost values (depletion rents) of natural capital in order to be consistent with the current standard methodology for constructing capital service aggregates (OECD 2001). When the natural capital 'delivers' services to its owner(s), usually no market transaction has occurred. The valuation of these implicit transactions — where the services (quantities) are drawn from the natural capital stock and where prices are the user costs (or shadow prices) of natural capital - is one of the measurement challenges in productivity analysis.

Broadly, there are two approaches for deriving service flows of natural capital. The first is the resource rents approach, which is the most common approach for valuing natural capital service flow. While there are several methods within this approach, this chapter

[3]There are estimates of mining productivity that incorporate subsoil mineral assets in ABS (2018, Table 24) data, but these are still labelled as experimental and are not included in the official set of productivity estimates. The ABS (2014, para. 15) noted that 'to treat the services obtained by miners from mineral and energy resources consistent with the treatment for capital services requires the creation of a non-produced asset owned by miners that is separate from the resources themselves'. The System of Environmental-Economic Accounting (SEEA) 2012 (UN et al. 2014a; UN et al. 2014b) illustrates some examples of recording depletion against the extractor, while in the national accounts it is recorded against the government sector. Thus, the ABS experimental mining productivity estimates are based on a production function that includes natural capital, but without satisfying the ownership principle.

considers two specific methods: the unit resource rent method suggested by Brandt et al. (2017) and adopted by the World Bank (Lange et al. 2018)[4]; and the residual value method, which was recommended by SEEA 2012 (UN et al. 2014;UN et al. 2014). The second approach for the valuation of natural capital services is the traditional user cost approach. Diewert and Fox (2016a) provide a method for calculating user cost values within this approach.

The three aforementioned methods are derived using data taken from the Australian national accounts to construct aggregate capital services and MFP growth estimates for the mining sector, accounting for the 27 subsoil minerals recorded on the national balance sheets. It is the first study to compare the application of the three methods for valuing natural capital services in the context of productivity analysis, thus, providing insight into the plausibility of each method and the issues involved in their implementation. Comparison of the results may assist other countries facing different natural capital data availability (for example, when data on the cost of extraction is not available) to make informed decisions on the most appropriate method best suited to the available data.

This chapter is organised as follows: Section 2.2 describes the theoretical model providing the framework to account for natural capital in a productivity analysis. Section 2.3 presents the three different methods for natural capital valuation. Section 2.4 discusses how output and aggregate input growth rates were constructed (data sources and calculations) under each of these three methods. Section 2.5 examines and compares the aggregate capital services and MFP growth estimates for the Australian mining sector, derived by employing the three different methods for natural capital valuation. Section 2.6 concludes the chapter.

[4] Brandt et al. (2017) applied their method to various subsoil assets using the World Bank (2011) estimates of unit rents for these assets.

2.2 Accounting for Natural Capital in Productivity Measurement

We followed the framework in Brandt et al. (2017) to construct a model of production that is inclusive of natural capital. The production function that accounts for natural capital is given in Eq. 2.1.

$$Y_t = A_t F(K_t, N_t, L_t) \tag{2.1}$$

where $Y_t = (Y_{1,t}, .., Y_{z,t}, .., Y_{Z,t})$ is a quantity vector of outputs produced in period t, A_t represents technological change which changes over time,[5] and F is the production function. $K_t = (K_{1,t}, .., K_{j,t}, .., K_{J,t})$ and $N_t = (N_{1,t}, .., N_{m,t}, .., N_{M,t})$ are quantity vectors of produced and natural capital inputs used in production in period t and represent the flow of produced and natural capital services, respectively. The quantity vector $L_t = (L_{1,t}, .., L_{h,t}, .., L_{H,t})$ represents labour inputs used in production in period t. Within this framework, natural capital represents a separate input in the production process. The set of inputs is simply extended to include N_t and in doing so, the contribution of natural capital in production is isolated and treated as a distinct factor of production similar to labour and produced capital.

Productivity growth is commonly measured as growth in outputs relative to the growth of factor inputs. Generally, growth in outputs can be attained either by supplying more inputs or by efficiency increases of how inputs are transformed into outputs. In a measurement framework that includes only a subset of inputs, 'multifactor productivity' is often used.[6] In the context of the above model, A_t is period t MFP and the growth rate of A_t represents MFP growth. Thus, the measure of MFP growth in period t, within the above framework, is given in Eq. 2.2.[7]

[5] A_t is also known as the Hicks-neutral (or disembodied) technological change.

[6] Although commonly used synonymously, the term 'total factor productivity' should refer to the case in which all inputs used in the production process are considered. Hence, here, following ABS practices, we use the term 'multifactor productivity' (MFP).

[7] This measure extends the ABS index number measure which is based on Solow's (1957) growth accounting framework.

$$MFP_{t,t-1} = \frac{Y_{t,t-1}}{I_{t,t-1}} \tag{2.2}$$

where $Y_{t,t-1}$ is (1 plus) the growth rate of outputs and $I_{t,t-1}$ denotes the growth rate of aggregate inputs, consisting of produced capital, natural capital and labour. That is, $I_{t,t-1}$ is a weighted combination of the growth rate of aggregate productive capital services ($K_{t,t-1}$), the growth rate of aggregate natural capital services ($N_{t,t-1}$), and the growth rate of aggregate labour ($L_{t,t-1}$).

Another justification for including natural capital as a separate variable in the production function and in the measurement of MFP growth stems from the fact that natural capital inputs are treated differently from produced capital input.

> While it is relatively easy to measure the flow of natural capital services as the volume of natural capital extraction, the services of produced capital, such as machines and buildings, are more difficult to observe and their service flow is assumed to be proportional to the produced capital stock. This implies that the rate of change of capital services equals the rate of change of the capital stock (Brandt et al. 2017, p. 4).

The growth rate of produced capital services for all assets ($K_{t,t-1}$) is calculated as the growth rate of the *stock* of different produced asset types weighted by their user cost shares. Conversely, the rate of natural capital services growth for all assets ($N_{t,t-1}$) is calculated as a *flow* measure, based on extraction of each natural asset annually.[8] Therefore, it is neither practicable nor desirable to mix natural capital in the aggregation of produced capital services.

To construct the aggregate inputs growth measure ($I_{t,t-1}$), the growth rate of different inputs has to be weighted appropriately. According to production theory, the weights are factor income (or cost) shares. The factor income (or cost) shares are derived using the total input costs. In particular, the total input costs at time t (X_t) are given by Eq. 2.3,

$$X_t = u_t^K \cdot K_t + u_t^N \cdot N_t + w_t \cdot L_t \tag{2.3}$$

[8] See section 2.4 for a detailed discussion on the construction of $K_{t,t-1}$ and $N_{t,t-1}$.

where $u_t^K = (u_{1,t}^K, .., u_{j,t}^K, .., u_{J,t}^K)$ denotes the user costs of produced capital, $u_t^N = (u_{1,t}^N, .., u_{m,t}^N, .., u_{M,t}^N)$ denotes the user costs of natural capital, and $w_t = (w_{1,t}, .., w_{h,t}, .., w_{H,t})$ denotes the wage rates of different types of workers. Note that the prices of capital inputs (produced and natural) are represented by user costs,[9] and the cost of inputs is obtained by multiplying the price vectors (u_t^K, u_t^N, w_t) with the corresponding quantity vectors (K_t, N_t, L_t). Thus, the corresponding factor income (or cost) shares are defined in Eq. 2.4.

$$\begin{aligned} S_t^K &\equiv u_t^K \cdot \frac{K_t}{X_t} \\ S_t^N &\equiv u_t^N \cdot \frac{N_t}{X_t} \\ S_t^L &\equiv w_t \cdot \frac{L_t}{X_t} \end{aligned} \tag{2.4}$$

Section 2.3 presents the three different methods considered for deriving user costs values of natural capital.

It should be noted that within the extended framework with natural capital, it is not necessary to hold the typical assumption regarding returns to scale or degree of competitive markets to derive MFP growth. These assumptions are necessary when costs are considered equal to nominal gross value added (GVA), and the weights of factor inputs are their income shares in GVA, that is, the income share attached to each input factor are the output elasticities for each factor (OECD 2001). In this framework, total input costs, X_t, are considered to be more significant than in the traditional framework to account for the costs of services from natural capital. In the extended framework, the input costs X_t do not necessarily equal nominal GVA, as there are unmeasured inputs, such as the natural capital stock.

For every period, income (or cost) shares are derived and incorporated with the (one plus) growth rates of factor inputs to obtain an index growth for the aggregate inputs. Specifically, $I_{t,t-1}$ is computed in the form of a Törnqvist index using Eq. 2.5,

[9] User costs capture the marginal productivity of each type of capital service. Given that under cost minimisation the marginal productivity of each input factor equals its real input price, user costs can be used as prices of capital inputs.

$$I_{t,t-1} = (K_{t,t-1})^{\bar{S}_t^K} (N_{t,t-1})^{\bar{S}_t^N} (L_{t,t-1})^{\bar{S}_t^L} \tag{2.5}$$

where $\bar{S}_t^K$, $\bar{S}_t^N$ and $\bar{S}_t^L$ are the corresponding average of the factor income (or cost) shares in period t and $t-1$ of produced capital, natural capital and labour, respectively; and $K_{t,t-1}$, $N_{t,t-1}$ and $L_{t,t-1}$ are (one plus) the growth rates of aggregate productive capital services, aggregate natural capital services and aggregate labour, respectively.[10]

By taking the natural log of Eq. 2.2, and with rearrangement, the contribution of MFP to output growth components that are additive can be shown to be measured by Eq. 2.6.

$$\begin{aligned} ln(Y_{t,t-1}) &= ln(MFP_{t,t-1}) + ln(I_{t,t-1}) \\ &= ln(MFP_{t,t-1}) + \bar{S}_t^K ln(K_{t,t-1}) + \bar{S}_t^N ln(N_{t,t-1}) + \bar{S}_t^L ln(L_{t,t-1}) \end{aligned} \tag{2.6}$$

The growth accounting framework shown in Eq. 2.6 is used to derive the contribution of input factors to output growth, and to indirectly estimate the rate of MFP growth. The growth rate of output is equivalent to the growth rate of MFP plus a weighted average of capital growth, natural capital and labour growth. The additive nature of this framework enables the contribution of all inputs and MFP to be quantified in terms of their contribution to an industry's output growth. Further, this approach supports analysis of the compositional change of the inputs over time due to changes between natural and produced capital and labour inputs.

2.3 Alternative Methods for the Valuation of Natural Capital Inputs

A variety of approaches can be used to value annual service flows of natural capital. One challenge of measuring service flows of natural capital is the availability of data in different countries. For example, data on the cost of extraction of subsoil assets is not

[10]Brandt et al. (2017) have shown that the difference between the growth of the traditional input index (comprising of labour and capital only) and the growth in natural capital inputs determines whether traditional MFP growth is adjusted upwards or downwards.

readily available. The comparison of different methods provide insight into the plausibility of each method and the issues involved in their implementation which will help countries make more informed decision on which is the best method given data constraints. This chapter considers three methods for calculating natural capital services. These are, the unit resource rent method (World Bank 2011/ Brandt et al. 2017) and the residual value method (UN et al. 2014a). In addition, Diewert and Fox (2016a) provide a method for calculating user cost values within this approach, which is the third method considered. Subsections 2.3.1 to 2.3.3 present the three methods for calculating the user cost of natural capital.

2.3.1 Unit resource rent method

We begin by introducing some notation and definitions. As presented in Section 2.2, we denote the number of asset types of natural capital used in the production model (Eq. 2.1) by M (indexed $m = 1...M$). We further let $V_{m,t-1}$ and $V_{m,t}$ denote the market value of asset type m at the beginning and end of period t. Also, let $P^N_{m,t}$ denote the ex-ante expected price of one unit of asset type m at the beginning of period t and $NCS_{m,t}$ the corresponding stock of asset type m to produce Eq. 2.7. Thus, it is assumed that market values can be decomposed into price and quantity components in every period.

$$V_{m,t} = P^N_{m,t} NCS_{m,t} \tag{2.7}$$

Let $R_{m,t}$ denote the net revenue (resource rent) of natural asset type m during period t. If we assume that expectations about the value of revenues during period t and expectations about the price of the natural asset at the end of period t are realised, then the relationship between V$_{m,t-1}, V_{m,t} and R_{m,t} in Eq. 2.8 should hold.$[11]

$$V_{m,t-1} = (1+r)^{-1} R_{m,t} + (1+r)^{-1} V_{m,t} \tag{2.8}$$

[11]See Diewert and Fox (2016b) for a discussion on the problems associated with accounting for sunk cost assets.

In Eq. 2.8, r is the opportunity cost of capital (rate of return) at the beginning of period t. It should be noted that Eq. 2.8 represents the net present value (NPV) approach.

As discussed in Section 2.2, the flow of natural capital services of asset type m in period t ($N_{m,t}$) is equivalent to the net revenue (resource rent), $R_{m,t}$. Following Brandt et al. (2017), $R_{m,t}$, generated by mining or extracting $D_{m,t}$ units of asset type m during period t is defined in Eq. 2.9,

$$\begin{aligned} R_{m,t} &\equiv (p_{m,t} \cdot \alpha_m - c_{m,t} \cdot \beta_m) D_{m,t} \\ &= u^N_{m,t} D_{m,t} \end{aligned} \tag{2.9}$$

where α_m is a positive vector of asset type m final products quantities generated by extracting one unit of asset type m, $p_{m,t}$ is the corresponding period t market output price vector, β_m is a positive vector of input requirements for extracting (mining) one unit of asset type m and $c_{m,t}$ is the corresponding period t market input price vector. Thus, $u^N_{m,t} \equiv p_{m,t} \cdot \alpha_m - c_{m,t} \cdot \beta_m > 0$ is the 'unit resource rent', that is, the user cost of extracting one unit of asset type m during period t. In this method, the unit resource rent, which is the market price net of extraction costs, is taken as the user cost of capital based on the assumption of inter-temporally optimal depletion of natural capital. Applying these to the definition at the end of period t user cost value of asset type m, $UCV^N_{m,t}$, (given in Diewert and Fox 2016a), yields Eq. 2.10.

$$UCV^N_{m,t} \equiv V_{m,t-1}(1 + r) - V_{m,t} = R_{m,t} = u^N_{m,t} D_{m,t} \tag{2.10}$$

Note that the net revenue (resource rent) from the physical extraction of a natural capital asset equals the user cost value of the natural capital asset for each period. As a result, the unit resource rent mirrors the value of a natural resource based on the quality of deposits and scarcity.

In this method, the resource rent (user cost value) is derived by estimating unit resource rent for each type of asset and multiplying it by the corresponding extracted amount. Brandt et al. (2017) estimated the resource rent of natural capital using average extraction costs across countries.[12] Similar studies have used the Brandt et al. (2017) method due to lack of available data.

The unit resource rent of an asset, in concept, removes the value-added (or gross operating surplus), accrued to the asset from its marketed output. In other words, it could be considered the surplus value accrued to the extractor of the natural capital derived after considering all costs and normal returns.

2.3.2 Residual value method

The unit resource rent method provides one way of estimating the resource rent (user cost value) of natural capital. SEEA (UN et al. 2014a) provides three alternative methods for estimating resource rent.[13]

> The resource rent and the net return to environmental assets can be derived within the national accounts framework through a focus on the operating surplus of extracting enterprises. In this context, the operating surplus earned by an enterprise is considered to comprise a return for the investment in produced assets and return on the environmental assets used in production (UN et al. 2014a, para. 5.117).

The residual value method provides a way to isolate the resource rent from the gross annual return of the natural capital extractor. Under this method, the residual return (resource rent) arising from the natural capital asset can be separated from gross operating surplus (GOS) after accounting for subsidies and taxes, and deducting costs of production and return on produced assets. Broadly, resource rent is equivalent to GOS minus user costs of produced assets (consumption of fixed capital plus return to produced assets), as shown in Eq. 2.11. An assumption for the return to produced assets, defined as r^K, is required in this calculation, which ideally should be industry specific. Here an endogenous

[12] The unit user cost of natural capital equals the marginal resource rent (that is, the market price net of marginal extraction cost). Hence, the marginal extraction costs would be the relevant estimates in the estimation of unit rents. However, these are not readily available, and average extraction costs are used as an approximation for marginal extraction costs.

[13] The three main methods of estimating resource rent described in the SEEA (UN et al. 2014a, paras 5.121-5.131) comprise the residual value method, the appropriate method and the access pricing method. As the country's institutional arrangements profoundly influence both the appropriate and access price methods, the residual value method is the recommended way for estimating resource rent.

r^K is derived which represents the internal rate of return for the mining industry. The endogenous rate is derived by equating all GOS to capital services and solving for r^K.[14]

$$UCV_{m,t}^{N} \equiv GOS_t - \sum_j u_{j,t}^{K} K_{j,t} \tag{2.11}$$

This method has been discussed in Coremberg (2004) and OECD (2009), and subsequently applied by Adams and Wang (2016) to the Canadian productivity estimates of the mining and oil and gas sectors. In this case, as resource rent is derived residually using the GOS (as obtained in the national accounts), the income share of labour does not change. This method partitions an amount of GOS which in traditional measures of MFP is allocated entirely to the user costs of produced capital to natural capital. By comparison to the unit resource rent method, which derives estimates of resource rent at the asset-type level, in this method estimates of resource rent for a given industry/sector are derived already at the aggregate level.[15] One difficulty that is worth noting in estimating resource rents using this method is that the measure of GOS for the mining sector, as captured by the Australian national accounts, will include some downstream processing, refinement and other value-added activity undertaken by this sector.

Further, use of the residual method may result in insignificant or negative resource rents. Obst et al. (2015) state that 'resource rent type approaches are inappropriate in cases where market structures do not permit the observed market price to incorporate a reasonable exchange value for the relevant ecosystem service' (p.17). The traditional user cost method provides an alternative if the residual value method produces implausible estimates for natural capital and the services they provide.

2.3.3 Traditional user cost method

Both the unit resource rent method and the residual value method require Eq. 2.8 to hold (the NPV approach). That is, their derived user cost values (Eq. 2.10) are valid *if* expectations about $R_{m,t}$ and $V_{m,t}$ formed at the beginning of period t are realised at

[14] The derivation of an endogenous rate of return is shown in Appendix A1.

[15] See Section 2.4 for a detailed discussion on the implementation of the two methods to derive $N_{t,t-1}$ and $\bar{S}_t^N$ for a given industry/sector.

the end of period t. However, there is an alternative way to derive user cost values of natural capital. In particular, Diewert and Fox (2016a) show how traditional user cost techniques can be used to derive them. Continuing the same notation as above, let the period t expected inflation rate for the price of a unit of asset type m (denoted as $i^N_{m,t}$) be defined as $1 + i^N_{m,t} \equiv \frac{P^N_{m,t}}{P^N_{m,t-1}}$ and the period t depletion rate of asset type m. Substituting these definitions in the user cost value definition in Eq. 2.10 yields the user cost value in Eq. 2.12,

$$
\begin{aligned}
UCV^N_{m,t} &\equiv V_{m,t-1}(1+r) - V_{m,t} \\
&= P^N_{m,t-1}NCS_{m,t-1}(1+r) - P^N_{m,t}NCS_{m,t} \\
&= P^N_{m,t-1}NCS_{m,t-1}(1+r) - P^N_{m,t-1}(1+i^N_{m,t})(1-\delta^N_{m,t})NCS_{m,t-1} \\
&= P^N_{m,t-1}[r - i^N_{m,t} + (1+i^N_{m,t})\delta^N_{m,t}]NCS_{m,t-1}
\end{aligned}
\tag{2.12}
$$

where $P^N_{m,t-1}[r - i^N_{m,t} + (1+i^N_{m,t})\delta^N_{m,t}]$ has the form of the traditional user cost of capital, only if $\delta^N_{m,t}$ is the depletion rate rather than the usual 'wear and tear' depreciation rate.

Diewert and Fox (2016a) show that under the assumption that expectations formed at the beginning of period t are realised at the end of period t, the derived user cost values in Eq. 2.10 and Eq. 2.12 are equal.

As pointed out by Diewert and Fox (2016a), one advantage of the traditional user cost method is that, as opposed to the previous two methods, it does not require Eq. 2.8 to hold for the derived user cost value (the last equality in Eq. 2.12) to be valid. One would expect that it is improbable that Eq. 2.8 will hold because anticipated price changes are, in general, not equal to actual ex-post price changes. This is because it is not likely that producers foresee all the random noise intrinsic in predicting ex-post asset prices changes. As the traditional user cost method does not require Eq. 2.8 to hold, it would suggest that the traditional user cost method is a more reasonable way of valuing non-renewable natural capital for productivity.

Another advantage of the traditional user cost method to estimate natural capital services is that it follows the same method typically used for estimates of produced capital services and that its user cost value (the last equality in Eq. 2.12) can be decomposed into the sum of waiting services ($rP^N_{m,t-1}NCS_{m,t-1}$), revaluation ($-i^N_{m,t}P^N_{m,t-1}NCS_{m,t-1}$), and depletion

$(\delta^N_{m,t}P^N_{m,t}NCS_{m,t-1})$ terms.[16]

The user cost value derived within the traditional user cost method can be re-written in terms of capital gains. Specifically, the last equality in Eq. 2.12 can be re-written as Eq. 2.13.

$$(rP^N_{m,t-1} + \delta^N_{m,t}P^N_{m,t} - i^N_{m,t}P^N_{m,t-1})NCS_{m,t-1} \tag{2.13}$$

Note that the re-valuation term $i^N_{m,t}P^N_{m,t-1}$ represents the capital gains of asset type m, denoted by $\tau^N_{m,t}$. That is, $\tau^N_{m,t} \equiv P^N_{m,t} - P^N_{m,t-1} = i^N_{m,t}P^N_{m,t-1}$. Thus, the last equality in Eq. 2.12 becomes $(rP^N_{m,t-1} + \delta^N_{m,t}P^N_{m,t} - \tau^N_{m,t})NCS_{m,t-1}$.

However, the traditional user cost method in this context exhibits the same challenges as those faced when determining the user cost of produced capital (for example, how to form the expected values for $\delta^N_{m,t}$ and $i^N_{m,t}$ in an unambiguous manner and the sensitivity of the user cost estimates to the choices of these parameters).[17] A study by Inklaar (2010) found that different choices and assumptions in estimating the user cost of capital matter only a little. The consequential choice is the rate of return.

2.4 Data Construction

This section describes how the volume measures of output and inputs (that is, produced capital, natural capital, labour and their respective weights) are derived for each reported model in Section 2.5. The ABS (2017a) national accounts, ABS (2018) productivity data and ABS supply-use data are the main sources of data on output, labour and produced capital. Also discussed in this section are the challenges of various measurement problems associated with determining a rate of return for the user cost of capital.

[16]See Diewert and Fox (2016a) for the application of this decomposition in deriving income measures in the green accounting context.

[17]This is especially important when user cost estimates become negative.

2.4.1 Output

GVA is used as the output measure and is equal to the value of gross outputs at basic prices detracted by total intermediate inputs at purchasers' prices.[18] The volume of real GVA is derived from ABS supply-use tables based on a double-deflation procedure. This procedure involves deflating separately the nominal value of output and the nominal value of intermediate inputs to obtain the volume measures. An industry's total output, under the double-deflation approach, is deflated by the price of all its outputs (primary and secondary), while each individual intermediate input is deflated by its own price index (UN 2018).

Adopting the ABS approach, the volume index of real GVA, Y_t, are indexes of the Laspeyres form,[19] as shown in Eq. 2.14.

$$Y_t = \frac{\sum p_{t-1}q_t}{\sum p_{t-1}q_{t-1}} = \frac{\sum p_{t-1}q_t}{Y_{t-1}} \tag{2.14}$$

where p is prices and q denotes quantities. From Eq. 2.14, $Y_{t,t-1}$ can be calculated as $\sum p_{t-1}q_t$ which is equivalent to the supply-use tables in prices of the previous year. Thus, the double-deflation procedure enables the volume measure of value added to be derived by subtracting a previous year's price value of intermediate inputs from a previous year's price value of gross output. This is only feasible with Laspeyres quantity indexes.

2.4.2 Labour input

The labour input for the mining industry is calculated using H_t, the indexes of hours worked at time t. This index is derived using total hours worked in the mining industry based on data from the ABS Labour Force Survey, as given by $L_{t,t-1} = \frac{H_t}{H_{t-1}}$. The survey derives hours worked as the product of employment and average hours worked. Applying an index of hours worked provides a better measure of labour input than using

[18] Basic price is the amount a producer receives from the sale of a good or service (minus taxes plus subsidies), whereas the purchaser's price is the amount paid by a purchaser to obtain a good or service.

[19] The ABS (2016b) use a Laspeyres output volume index in MFP estimates to maintain consistency with the output estimates published in its annual national accounts.

employment, due to the fact that hours worked captures changes in the proportion of part-time employees, standard weekly hours, leave taken and paid and unpaid overtime worked. The ABS official MFP estimates apply a labour volume series based on hours worked, adjusted for labour quality. This adjustment accounts for changes to quality of the aggregate series for different skill levels. For simplicity and to facilitate comparison with productivity statistics of other countries, the unadjusted labour volume series is used.

2.4.3 Capital input

The user cost value of capital, as measured here, is composed of two parts - the user cost value of produced capital and the user cost value of natural capital: $u_t^{'} K_t^{'} = u_t^K \cdot K_t + u_t^N \cdot N_t$. Before discussing the volume measures of capital (produced and natural), the options for the rates of return, r, need to be explained, as these will be used in calculating the volume measures.

Rates of return

There are various methods for selecting r described in literature. Broadly, these can be categorised into two groups. The first group consists methods which use exogenous estimates, while the second group consists of methods which derived the rates of return endogenously. The second approach generally constrain the value of inputs used during the period (including capital services) to be equivalent to the value of outputs produced during the same period.

Most commonly, government bond interest rates are selected as exogenous rates of return. The use of an exogenous rate likely leads to the calculated capital rent being different to capital income. Capital income is the sum of GOS and the component of return on the owner's capital in gross mixed income, and thus, it is different from capital rent. This approach could be considered an ex-ante view to determining the rate of return because it essentially is the expected return on an investment decision. The ex-ante approach could result in negative rental prices (user costs) in periods where significant changes in capital gains and losses occur. As rental prices (user costs) are used to form weights in the estimation of capital services indexes, negative weights will cause problems in creating an aggregate index.

The second way to select rates of return is by deriving an endogenous rate of return. This represents the internal rate of return for a given industry. The endogenous rate is derived by equating all non-labour income to capital services (produced and natural) and solving for the rate of return (Hall and Jorgenson, 1967; see Appendix A.1). It imposes these implicit assumptions: the underlying production function exhibits constant returns to scale; markets are competitive; and the expected return is the same as the realised return (OECD 2001).

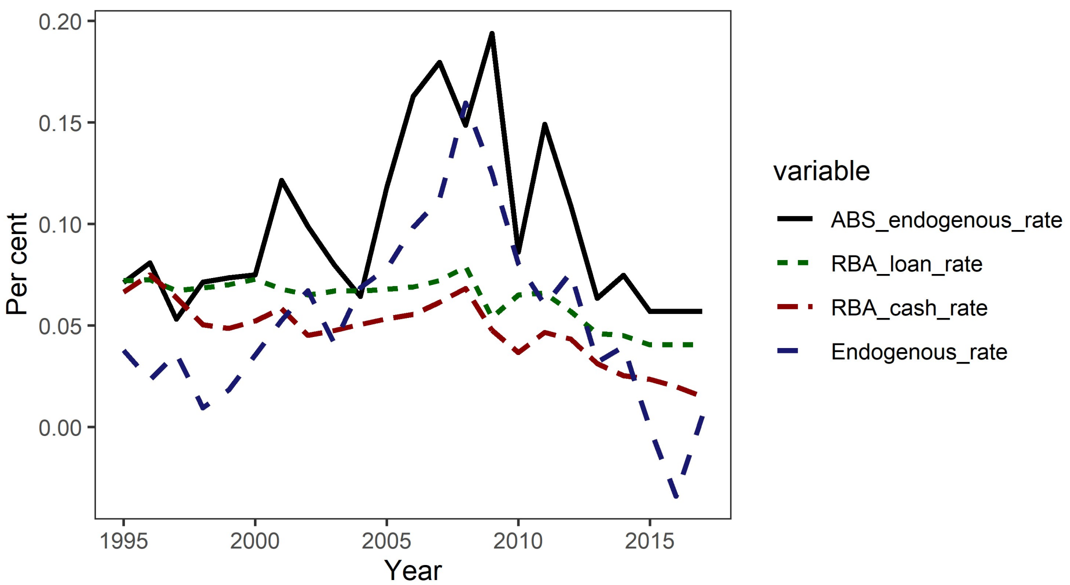
An endogenous approach is an ex-post rate of return because it applies the rate of return after the results of investment decisions are known. A common issue with using an endogenous rate of return is that when income from capital is insignificant, the corresponding internal rate of return will also be insignificant.

Criticisms of the endogenous approach revolve around the fact that this approach assumes all of GOS (after deducting labour income) is attributable to the capital in the scope of the productivity analysis. The OECD (2009) notes that there are a number of reasons to argue that GOS should be attributed to other unobserved capital assets (such as intangibles). This distinction, while minor in appearance, questions the assumptions on the representation of GOS[20] routinely made in productivity analyses. For example, capital assets that can be included are natural resources. Hence, if an endogenous rate is computed based on only fixed assets currently measured in the national accounts, in addition to, unmeasured assets that provide capital services, then 'the resulting rate may be liable to bias' (OECD 2009, p. 68). Inklaar (2010) found that estimates of an endogenous rate of return are difficult to reconcile with the cost of capital in financial markets or with industry specific risks. Karabarbounis and Neiman (2019) provides a different perspective on endogenous and exogenous returns on capital, associating the residual after accounting for the labour and capital share of income as 'factorless income'. Both studies emphasise that an endogenous rate of return will only be a useful economic concept if all the relevant capital assets are correctly accounted for.

[20]Namely, that GOS exactly represents the remuneration of the fixed assets recognised in the 2008 System of National Accounts (UN 2009) or the value of the services of these assets.

Figure 2.1 plots four rates of return over the period 1995–1996 to 2015–2016. Evidently, the average exogenous and endogenous rates of return can vary substantially over time. The endogenous approach makes the assumption of perfect competition and that capital and rental markets are operating in a way that the marginal cost of the assets is equal to their marginal product and revenue. Schreyer (2005) discusses examples in which 'mark-ups'[21] could exist. It is assumed that mark-ups would be positive in the long run, because a negative result over a period of time would imply sustained losses, which is not economically plausible. Situations in which positive mark-ups could exist include where output markets are not sufficiently competitive so that monopoly rents exist; where mark-ups provide incentives for entrepreneurial activity under Schumpeterian growth patterns; where long gestation periods of investment are common within industries; and where time-varying capacity utilisation exists. These situations are prevalent in the mining sector in which significant capital investment usually occurs before full-capacity utilisation is possible. As a result, negative returns is some years to be quite common in the mining industry.

Figure 2.1 – **Rates of return**



Note: 'Endogenous rate' refers to the endogenous rate of return that includes both produced and natural capital, derived by the author from unpublished Australian Bureau of Statistics (ABS) national accounts data.
Source: Reserve Bank of Australia for the business loan rate (RBA 2020a, Table F5) and the cash rate (Table F1.1).

A consequence of using an endogenously determined rate of return can be that industry

[21]Mark-ups is the degree that an endogenous rate of return would be greater than an exogenous rate.

rates of return can appear economically implausible (or negative for some years). As with the endogenous approach, there are some practical issues associated with using an ex-ante or exogenous rate of return. Another approach, suggested by Oulton (2007), is where an ex-post endogenous rate is initially derived, followed by the selection of an ex-ante rate as the trend of the ex-post rate of return. This method avoids the issue of choosing an exogenous rate of return while preserving the nature of the ex-ante calculation (OECD 2009). One advantage of using a hybrid approach is that it enables an empirically calculated industry-specific rate of return that includes (among other things) missing capital assets (such as land, research and development [R&D], and other intellectual property assets).

Most importantly, regardless of which rate of return is applied, economically meaningless negative user costs could occur due to the expected nominal return including depreciation/depletion that is less than the expected nominal asset-inflation rate in some years. Economic theory suggests that rental prices (user costs) should be positive over the long term.[22] Thus, following the ABS method to resolve this issue, any negative user costs are set to a tiny positive number (0.001). In this way, the weights of the capital stock for that asset become positive, and subsequently, adjust the weights of the remaining assets. The actual choices (that is, which rate of return is used) is provided in what follows (different considerations depending on how and which natural capital valuation method is used).

Produced capital input

Following the ABS (2016b), the produced capital inputs are compiled at the asset-type level, denoted by j, where $j = 1...16$.[23] The service flow of each type of produced

[22] The user cost of capital is used to weight the volumes of capital services provided together with the stocks of capital within each industry. One can interpret this as the marginal cost of the capital services being provided and, thus, making negative user costs economically implausible. Given that there are no significant changes to the production function, the weight of each asset capital service would remain relatively stable over the short to medium terms.

[23] The estimates of produced capital are based on the following 16 asset types: machinery and equipment; computers and computer peripherals; electronic and electrical machinery and communications equipment; industrial machinery and equipment; road vehicles and other transport equipment; non-dwelling construction; ownership transfer costs of non-dwelling construction; intellectual property products; computer software; research and development; mineral and petroleum exploration; artistic originals (film and television, music and literature); orchards, plantations and vineyards; and livestock.

asset ($K_{j,t}$) is assumed to be proportional to the produced capital stock, that is, $K_{j,t} = \gamma_t PKS_{j,t}$, where γ_t is the capacity utilisation rate and $PKS_{j,t}$ is the productive capital stock. The capacity utilisation rate is presumed to be constant over time. This implies that, for each type of asset, the growth rate of produced capital services equals the growth rate of produced capital stock. Thus, the growth rate of produced capital services for all assets ($K_{t,t-1}$) is calculated as the growth rate of the stock for different produced asset types weighted by their user cost shares. Specifically, $K_{t,t-1}$ is computed using a Törnqvist index, as in Eq. 2.15,

$$K_{t,t-1} = \prod_{j=1}^{16} \left(\frac{K_{j,t}}{K_{j,t-1}} \right)^{\bar{s}_{j,t}^K} = \prod_{j=1}^{16} \left(\frac{PKS_{j,t}}{PKS_{j,t-1}} \right)^{\bar{s}_{j,t}^K} \tag{2.15}$$

where $\bar{s}_{j,t}^K = \frac{1}{2}\left(\frac{u_{j,t}^K K_{j,t}}{\sum_{j=1}^{16} u_{j,t}^K K_{j,t}} + \frac{u_{j,t-1}^K K_{j,t-1}}{\sum_{j=1}^{16} u_{j,t-1}^K K_{j,t-1}} \right)$ are weights calculated as the two-period average value share of each type of capital services. $PKS_{j,t}$ is estimated by applying a perpetual inventory method (PIM) to volume estimates of gross fixed capital formation (investment) at the asset type level, in conjunction with age-efficiency profiles. In sum, the PIM is used to transform all capital assets of different vintages into equivalent efficiency units and then add them up into an estimate of the productive capital stock.[24]

The user cost of produced capital, $u_{j,t}^K$, is derived using the end of period traditional user cost approach, which in its most basic form is comprised of three components - a rate of return reflecting financing costs ($r^K P_{j,t-1}^K$); depreciation of the asset ($\delta_{m,t}^K P_{j,t}^K$); and a capital gain/loss component ($\tau_{j,t}^K$); see Section 3.3.[25]

For r^K, a mix of endogenous (ex-post) and exogenous (ex-ante) rates of return is applied in ABS official productivity estimates. The ABS (2016b) applies an endogenous rate set a 'floor' of 4 per cent, plus the consumer price index (CPI). This method prevents the nominal rate of return from falling below 0 when income is low in some years. Consequently, this approach avoids the occurrence of negative user costs while simultaneously preserving the industry-specific rates of return derived from the endogenous rate of return. One advantage of this method is that the floor retains the

[24] For a full description of the method used to derive the capital stock measures see ABS (2016b, chapter 14).

[25] Similar to the ABS, the user cost of produced capital includes a corporate income tax component, tax depreciation allowances, investment credits and indirect taxes.

long-term ex-ante nature of investment decision-making, and enables the manifestation of higher rates of return in the case of missing assets. The fact that this method is not symmetric (that is, it imposes a floor to the rate of return, but does not impose a corresponding 'ceiling') is a deficiency. In the case where a 'pure' endogenous rate of return is used (with no floor), the income share of capital inputs is attributed to income (or cost) of produced capital, and hence, there is no allowance for the income share to attribute to unmeasured inputs.

In the unit resource rent and residual value methods, an exogenous r^K is used to allocate a share of non-labour income to natural capital services.[26] In Section 2.4.3, two exogenous rates of return were considered. The first was the Reserve Bank of Australia (RBA) cash rate, and the second was the RBA business loan rate. In choosing the exogenous rate of return, several factors were considered. First, using an exogenous rate of return may lead to volatility in the user costs and, in some cases, even negative user costs. Second, determining a variable rate from the options in the financial market data to reflect industry-specific longer-run expectations is challenging, particularly because short-run financial market fluctuations may not correspond to long-run expectations. The RBA cash rate compared to the RBA business loan rate proved to be less volatile over the long run. Thus, the r^K selected is the RBA cash rate. This rate is conservative relative to those expected in some subsoil minerals markets such as oil and gas extraction, and as a consequence may overstate the resulting resource rent estimates.

One interpretation that fits this framework is that the difference between the calculated capital services and capital income (defined in the national accounts as GOS) may be attributed to returns to other assets such as natural capital or intangibles. These missing assets would contribute to the GOS used to derive endogenous rates of return. Another factor to consider is that GOS is an ex-post indicator of the return to capital. The extent to which inconsistencies in average rates of return will exist depends on the difference between expected and realised returns. For the traditional user cost method, the choice of r^K depends on r^N, as discussed in Section 2.4.5.

[26]Noting that in the traditional MFP the endogenous rate is derived by equating all non-labour income to produced capital services and solving for the rate of return.

2.4.4 Natural capital input

Similar to produced capital inputs, natural capital inputs are compiled at the asset-type level, denoted by m, where $m = 1...27$. Australia has a comprehensive set of data on subsoil minerals compared to most countries. Australia's dataset for natural capital input construction consists of annual data on 27 minerals included on the Australian national balance sheet, based on Geoscience Australia's annual *Australia's Identified Mineral Resources* report. These include antimony, bauxite, black coal, brown coal, cadmium, cobalt, copper, diamonds, gold, iron ore, lead, lithium, magnesite, mineral sands (ilmenite, rutile, zircon and nickel), petroleum products (crude oil, condensate, natural gas and LPG), platinum, rare earths, silver, tin, uranium and zinc.

The flow of natural capital inputs, N_t, is the vector of quantities of natural capital inputs, $N_t = (N_{1t}, ..., N_{it}, ..., N_{Mt})$. As discussed in Section 2.3, three methods for valuing natural capital inputs were calculated. Natural capital enters the productivity estimates directly as a flow measure. Under the unit resource rent method, the measure of the flow of natural capital services is the extraction amount of natural capital. Monetary valuation presents a common metric in which individual subsoil assets can be aggregated and compared. Thus, to build an aggregate natural capital input growth measure, it is necessary to have a price for natural capital inputs. N_t is then an aggregate of different types of subsoil assets, m, with the associated user costs, $u_{m,t}$, that is, $N_{m,t} = UCV_{m,t}$. The capital services growth for natural capital is constructed as a Törnqvist index shown in Eq. 2.16,

$$N_{t,t-1} = \prod_{j=1}^{27} \left(\frac{N_{m,t}}{N_{m,t-1}} \right)^{\bar{s}^N_{m,t}} \tag{2.16}$$

where $\bar{s}^N_{m,t} = \frac{1}{2}\left(\frac{u^N_{m,t} N_{m,t}}{\sum_{m=1}^{27} u^N_{m,t} N_{m,t}} + \frac{u^N_{m,t-1} N_{m,t-1}}{\sum_{m=1}^{27} u^N_{m,t-1} N_{m,t-1}} \right)$ are weights calculated as the two-period average value share of each type of subsoil asset. N_t is constructed in the same manner under the residual method and the traditional user cost method. An additional complexity of the traditional user cost method is deriving the volume of natural capital stock, NCS_t, which is discussed next.

Valuation of natural capital stock

As there are limited transactions in subsoil mineral resources in situ, the valuation of stock of these natural capital assets, V_t, is measured using the NPV approach, which is the standard approach for pricing capital.[27] As the ABS (2015) reported, the NPV is determined as the expected economic benefits that are attributed to a natural asset. The calculations should be at the individual resource type level, ideally for specific resource type and quality, and then aggregated to derive a total value of subsoil mineral resources (UN 2014a). Use of the NPV approach to value mineral subsoil resources requires an estimate of the discounted sum of the value of resource rents generated over the lifetime of the asset.

Thus, the value of natural capital V_t is derived using Eq. 2.17,

$$V_{m,t} = \sum_{e=1}^{E} \frac{R_{m,t}}{(1+r)^e} \tag{2.17}$$

where $R_{m,t}$ is the resource rent of asset m in the year t. The real discount rate, which includes a premium for mining risks (assumed to be a constant 7.5 per cent) is denoted by r, and E is the natural resource asset life. Note that, in comparison, the discount rate, which is assumed to be the risk-free rate, applied by the ABS to the value of the produced capital stock is lower, at 4 per cent. The World Bank (Lange et al. 2018) also used a 4 per cent discount rate.[28] The asset life, denoted by E, is derived by the economic demonstrated resource (EDR) of the natural resource divided by the rate of extraction. In Australia, these resources include both measured and indicated resources. Measured resources are those where the volume is computed from a detailed sampling so that the geological character of the deposit is well established. Indicated resources are those for which the geological nature is calculated from similar information to that used for measured resources. Subsoil assets are counted as being economical when they have a high geological assurance, and at current market price the extraction is expected to be

[27]Provided the right assumptions are made about cash flow, discount rates and the life of the asset, the written-down replacement cost or the discounted value of future returns should yield the same result, see Dixit and Pindyck (1994).

[28]For coherence with the official valuation estimate of subsoil minerals asset produced by the ABS in the Australian balance sheet, the ABS valuation model was adopted.

profitable.

The resource rent, $R_{m,t}$, in the year t is calculated as revenue less production cost (including a 'normal' rate of return on fixed capital) multiplied by the quantity $D_{m,t}$ of the resource extracted. As prices of subsoil minerals are volatile, a five year moving average of annual prices is used to smooth prices and reduce the volatility in estimates of revenue. One interpretation of this method is that it represents what mining businesses would consider longer-term prices when assessing the value of mineral deposits (ABS 2016b). Further, the smooth prices result in more plausible NPV.[29]

Change in the monetary value of subsoil assets between t and $t-1$ can include new discoveries or holding gains and losses. Thus, NCS_t is derived using the same NPV formula but replaces the unit resource rent used for year t with the unit rent used for a base year. This results in a time series of constant price stock values for subsoil assets. The volume of subsoil asset then only shows changes in the stock values caused by changes in the future extraction path and change to the physical stocks. The price that was actually paid to acquire the natural asset (acquisition price), P^N, were calculated as V_t/NCS_t.

2.4.5 Choice of traditional user cost models

Given the possible choices of parameters, four traditional user costs of capital models were selected for comparison against the unit resource rent and the residual value methods. Initially, 16 variations were tested for the sensitivity of choice of asset prices and the rates of return on the aggregate of capital services and corresponding rates of MFP growth. These variants are shown in Table A.1 in Appendix A.2, together with the results of the sensitivity analysis. The following subsection will describe the four selected models and the construction of the choices for i^N, r^N, r^K and τ^N under these models, along with explanations for why they were chosen for comparison. The parameters of the four

[29] Ideally, prices should be the price of the mineral as extracted from a mine site without further processing. In practice, a range of prices reflecting various degrees of transformation through simple or more complex manufacturing processes is used to compile the resource rent. While some manufacturing processes are undertaken at a mine site, such as coal washing or iron ore crushing (to produce fines for export), more elaborate processes such as metal smelting and refining are often undertaken offsite. For example, commodities such as black coal are semi-processed by washing to extract non-coal material before sale. Other mineral products are commonly valued in more elaborately transformed states. Prices for metals such as copper, lead, zinc, nickel and gold are for the refined product and are usually based on London Metal Exchange prices.

traditional user cost models are summarised in Table 2.1.

Table 2.1 – **Traditional user cost models**

	Natural capital			**Produced capital**
Model	r^N	$i^N_{m,t}$	$\tau^N_{m,t}$	r^K
Exogenous	RBA cash rate	price deflater	Yes	RBA cash rate
Jorgenson	endo. rate[a]	price deflater	Yes	endo. rate
Diewert and Fox	endo. rate	geometric smoothing[b]	Yes	endo. rate
No capital gains	endo. rate	price deflater	No	endo. rate

Note: [a] Refers to the endogenous rate of return including both produced and natural capital. [b] Based on Diewert and Fox's (2016a, p. 20) method.
Source: Australian System of National Accounts (ABS 2017a), RBA (2020a, Table F5).

Model 1:'Exogenous'

As discussed in Section 2.4.3 several issues need to be considered in the choice of the rate of return (opportunity cost of capital, produced or natural) in the user cost formula. In this model, an exogenous rate of return is used for both produced and natural capital because the rate should reflect industry specific long-run risk, rather than asset specific risk. The r^K and r^N selected is the RBA cash rate as this rate is less volatile compared with those expected in some markets for subsoil minerals such as oil and gas extraction. See Section 2.4.3 for a comparison of different rates of return.

Model 2:'Jorgenson'

Christensen and Jorgenson (1969) developed the traditional user cost method for the geometric model of depreciation, which plays an important role in Diewert and Fox's (2016a) user cost of natural capital method. There are two main approaches to the user cost formula: an ex-post approach that utilises the actual beginning and end-of-period constant-quality asset prices; and an ex-ante approach, which utilises the actual beginning of period constant-quality asset price, as well as an anticipated price for the asset at the end of the period. Christensen and Jorgenson (1969) advocated for ex-post inflation rates and for the cost of capital in this model to be endogenously determined.

Model 2 is referred to as 'Jorgenson' as it used ex-post inflation rates in the user cost formula, where i^e_t is defined as $\frac{P^N_{t+1}}{P^N_t} - 1$ and where P^N_t and P^N_{t+1} are the actual beginning and end of period asset acquisition prices. The cost of capital is determined based on solving Eq. A.6 for r_t. From a national accounting view, this approach has the benefit of preserving coherence with the 2008 SNA (UN et al. 2009). The user cost values derived are the sum of GOS recorded in the income account. Moreover, this method can be considered as a decomposition of GOS into more granular components.

Method 3: 'Diewert and Fox'

Diewert (1980, 2005) and Hill and Hill (2003) advocate the ex-ante user costs for most purposes, as they tend to be smoother than their ex-post counterparts. Further, they will generally be more closely aligned to a rental or leasing price for the asset. The Diewert and Fox method overcomes one major issue of using Jorgensonian user costs, which is in their volatility and their propensity to become negative, particularly when asset-inflation rates are high for assets such as subsoil assets.

In this approach, predicted asset inflation rates, i_t^p, are applied in the user cost formula, as set out by Diewert and Fox (2018). They suggested a straightforward geometric moving average method for forming predicted asset-inflation rates to reducing volatility and thus, producing smoother user costs. To calculate the predicted asset-inflation rates, i_t^p is defined as $\left(\frac{P_{t-5}^N}{P_t^N}\right)^{\frac{1}{5}} - 1$.

Method 4: 'No capital gains'

Besides the challenges around choice of rate of return (as discussed in Section 2.4.3), the choice of asset price is another component of the user cost that is subjective. Generally, the ex-post, constant-quality asset-specific price changes are used in estimating holding gains, noting that in some instances, this has led to negative rental prices because of volatile fluctuations in subsoil mineral prices. There is the possible problem of market bubbles in commodity prices during mining booms. Use of the CPI was the solution to market bubbles suggested by the OECD (2009) with the idea that a general measure of inflation helps keep real purchasing power neutral. This solution may be equally applicable to mineral resources, given that significant increase in world prices of key minerals during the mining boom make the ex-post user cost model impractical.[30] Nevertheless, the assumption that mining businesses base their expectations of holding gains on the CPI is mainly unsupported in the literature.

Model 4 differs from the other three models in that it is the only one that excludes the capital gains term, τ, from the user cost of capital formula to remove the effect of holding gains. This is particularly relevant for subsoil minerals that are subject to volatile fluctuations in commodity prices. MacGibbon (2010) found that this approach provides more plausible asset weights in the New Zealand context, which displayed markedly less volatility and tracked better with rental prices (where observable).

2.5 Results

This section compares estimates of capital services growth and MFP growth that include natural capital for the Australian mining sector under the different user cost values methods. It further assesses their fit in producing appropriate weights for the aggregation of natural capital services in particular, and for the aggregation of all inputs in general. To determine which method is best for estimating natural capital user cost values, one should first make a decision about the criteria against which each model should be examined. Parameters that are used to assess (but not necessarily determine) the suitability of user cost values include their plausibility, their volatility and their relationship with directly observed rental prices (where available) (MacGibbon 2010).

2.5.1 Natural capital stock and natural capital services

The plots in the left column of Figure 2.2 present estimated unit rents and level of discovery for selected subsoil minerals (crude oil, iron ore and black coal) for the period spanning 1995–1996 and 2015–2016. The patterns of the resource rent and the subsoil minerals stock are similar to each other: both stayed low and stagnant before 2005–2006 and then grew sharply after that.

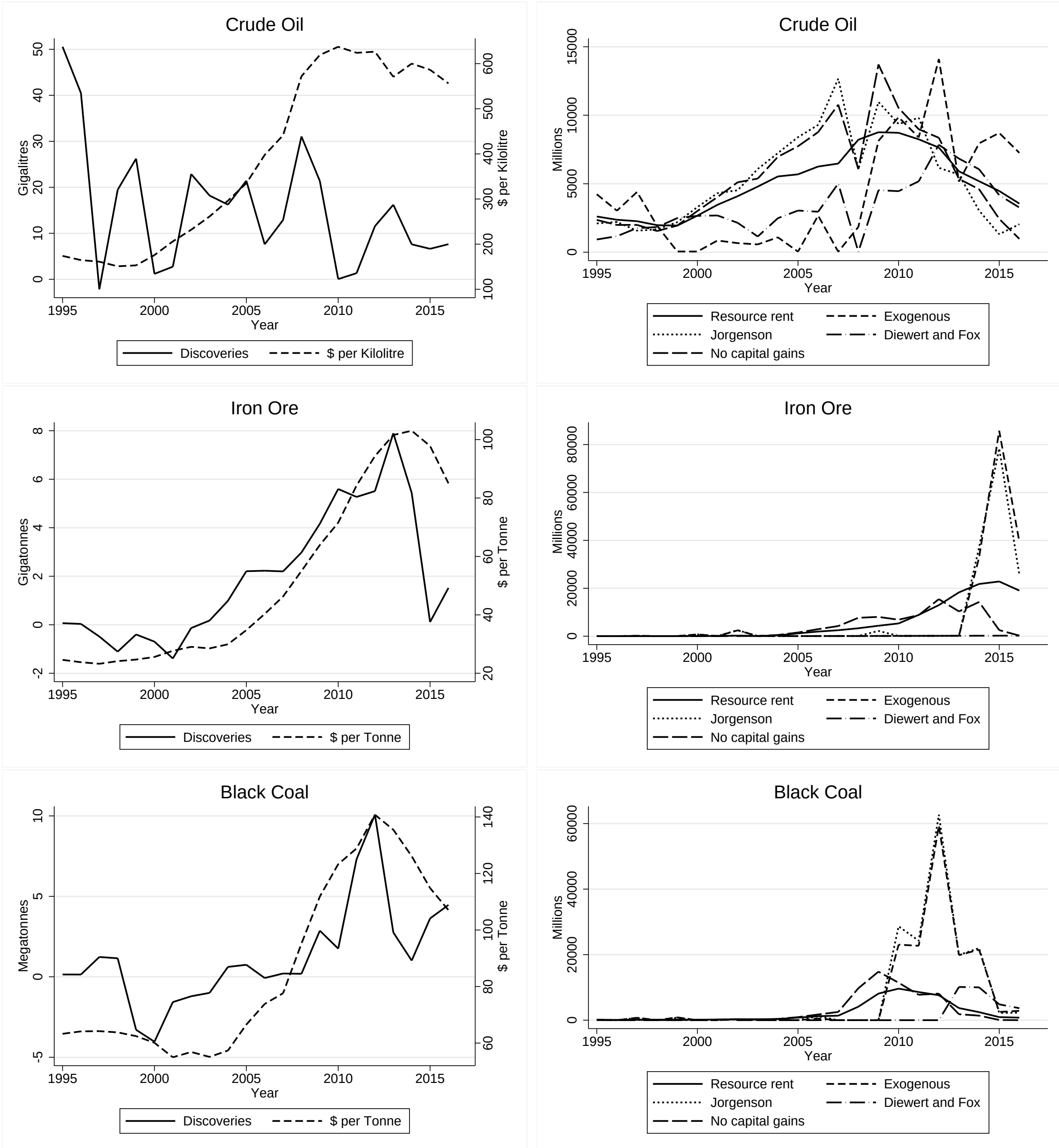
[30] There would be some capital assets, such as computers, where expected price changes would likely differ to the general inflation and asset-specific prices may be required.

Over the whole period, the implicit price of the subsoil mineral resources increased by over five times, especially during the period from 2005–2006 to 2012–2013. During this period of steady price increases, discoveries also increased by around three times. The resource rent is mostly positive; however, it does become negative in some periods for iron ore and black coal.

Since the early 2000s, a structural shift has occurred in the Australian mining sector, as prices for essential subsoil mineral resource exports rose significantly, in line with a rise in demand in emerging economies. The higher resource prices provided significant rents for companies with existing mines (Grafton 2012). In response, the value of subsoil mineral resources rose until 2011, increasing threefold compared to 1995. The rise in the value of subsoil minerals might not be intuitive since extraction depletes these stocks. However, subsoil minerals are only included in the balance sheet when they are economically proven and probable. The World Bank (Lange et al. 2018) also found that the value of natural capital assets doubled in the decade between 1995 and 2014, with the majority of the growth in non-renewable assets (308 per cent) due to changes in prices and in volumes.

The plots in the right column of Figure 2.2 present user cost values of selected subsoil minerals estimated by the unit resource rent and the traditional user cost methods. It shows that the estimated user cost values of the traditional user cost models are volatile compared to those estimated by the unit resource rent method. Intuitively, this phenomenon could be explained by the capability to quickly change the production capacity of mines to meet demand during the commodity price boom. A study by Parham (2013) postulates that during a commodity price boom firms incur higher short-term costs to accommodate rising demand, as the opportunity cost (for example, failure to ship a tonne of coal) at the peak of the commodity boom is substantial. This factor, along with potential over investment in infrastructure and declining resource grades and quality, may account for the pattern of the user costs values of produced capital.

Figure 2.2 – **Trends in Australian subsoil mineral resources, 1989-1999 to 2015-2016**

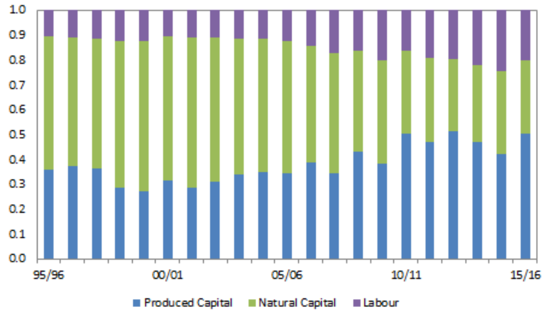


Note: The figures on the left hand side compare the price of the subsoil minerals with the level of new discoveries. The figures on the right-hand side compare the user cost values of selected subsoil minerals under the unit resource rent method and four traditional user cost models. The residual value method is not included because its natural capital services are not estimated for each subsoil mineral.
Source: ABS Australian System of National Accounts (ABS 2017a).

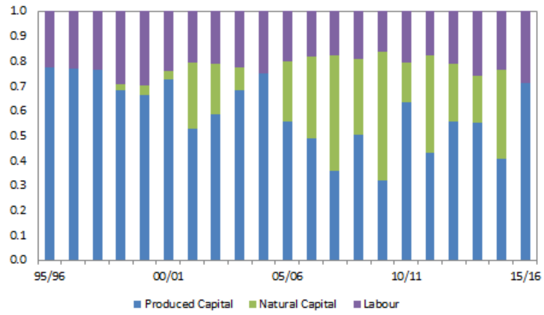
2.5.2 Factor cost shares

Factor income (or costs) shares refer to the share of output allocated to capital (natural and produced) and labour. As described in Eq. 2.3, the factor cost shares are the sum of the user costs of the input factors. The method for constructing the factor income cost shares is the same for all six models. Figure 2.3 reports estimated cost shares using the different user cost value methods.

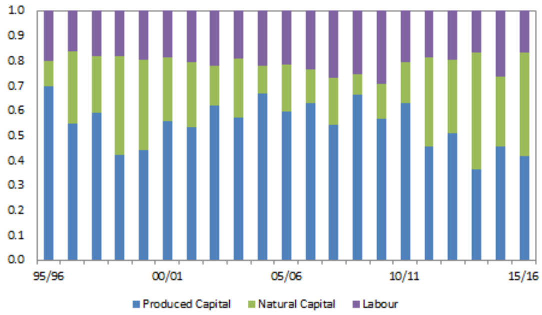
Figure 2.3 – **Cost shares**



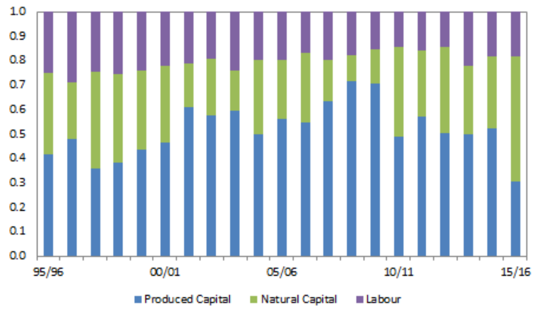
(a) **Resource rent**



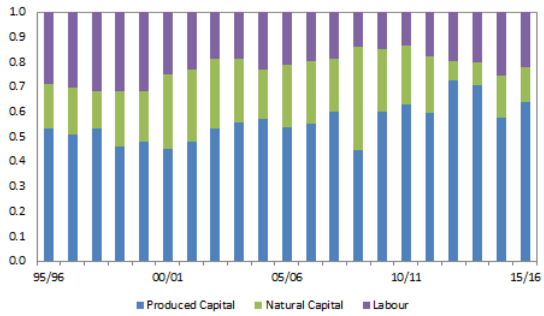
(b) **Residual method**



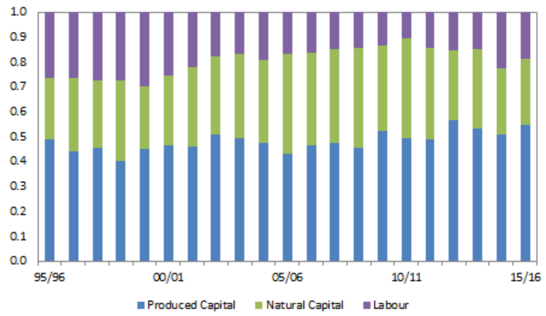
(c) **Exogenous**



(d) **Jorgenson**



(e) **Diewert and Fox**



(f) **No capital gains**

The estimated cost shares allocated to produced capital, natural capital and labour are affected by which user cost values method is applied. Some substantial differences in the pattern of the allocation between produced and natural capital are most noticeable when comparing the residual value method and the traditional user costs models with the unit resource rent method. The natural capital share in the residual value method often sits at 0 due to GOS being exhausted in that period entirely by produced capital. This results in often implausible capital services weights, as it implies zero contribution of natural capital to productivity. The unit resource rent method generally allocates the largest weight to natural capital, and its estimated cost shares are much less volatile.

The estimated cost shares vary across the different traditional user costs models. The effect of different variables and parameter choices on both the user cost values estimates (weights) for aggregating natural capital and the cost shares estimates (weights) for aggregating all inputs across the three different methods (for parameters choice) is pronounced. The price index for capital services of subsoil minerals is volatile, particularly from the 2000s onwards. These subsoil mineral rental prices have significant implications on the cost share of subsoil minerals, including negative values for some periods.[31]

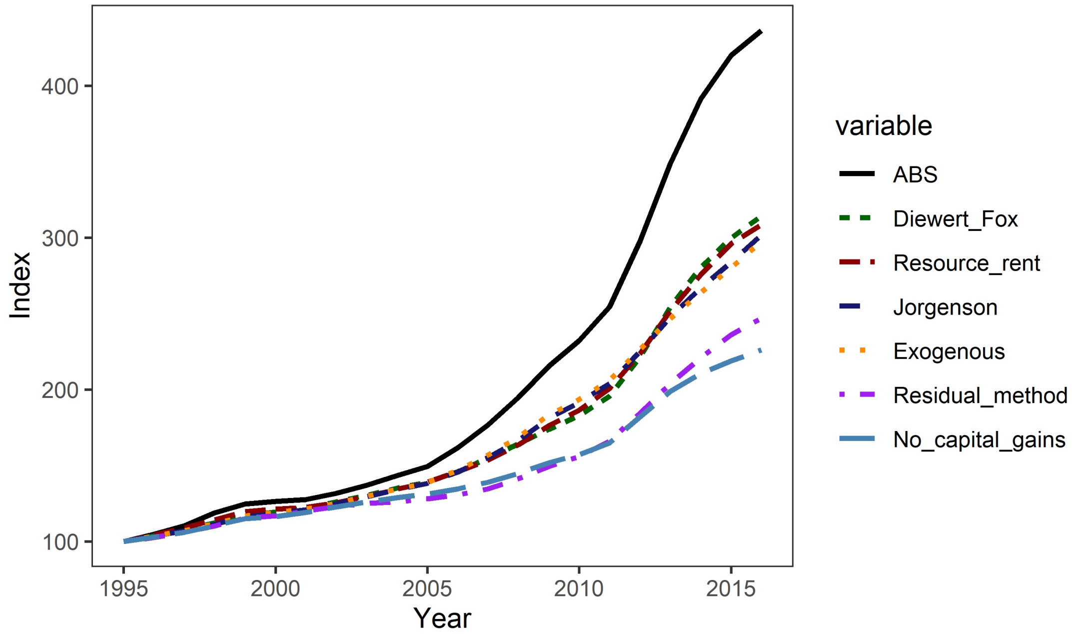
2.5.3 Mining capital services and multifactor productivity

Drivers of MFP are typically factors that generate efficiency in use of inputs (for example, capacity utilisation, economies of scale, changes in the quality of inputs, and technological change). Productivity measures in the Australian mining sector are released annually by the ABS. The most recent ABS (2018) data suggests that mining sector MFP has declined significantly in the past decade. Such decreases in mining MFP contributed materially to a productivity slowdown of the market sector, as it contributes around 8 per cent of its total GVA. The special features of the mining sector imply that traditional measures of productivity warrant careful interpretation. As mining activity is heavily reliant on the availability and quality of the natural capital stock, ignoring the role of natural capital may bias estimates of productivity. For example, when ore grades decline as deposits deplete, more inputs are needed to produce a unit of saleable output, causing the measured productivity of mining to fall. This factor is captured by the resource rent factor share shown in 2.3, where the share of natural capital declines over time. Figure

[31] Alston (2018) made a similar observation regarding the United States (US) Department of Agriculture's Economic Research Service price index for services from land. He noted the volatility of the index was remarkable. The land rental price fluctuations have significant (and perhaps implausible) implications for both the predicted and observed cost share of land.

2.4 plots the latest ABS capital services index and the adjusted capital services indexes that account for natural capital. An upward trend in the capital services indexes, that include natural capital, is observed.

Figure 2.4 – **Mining capital services**



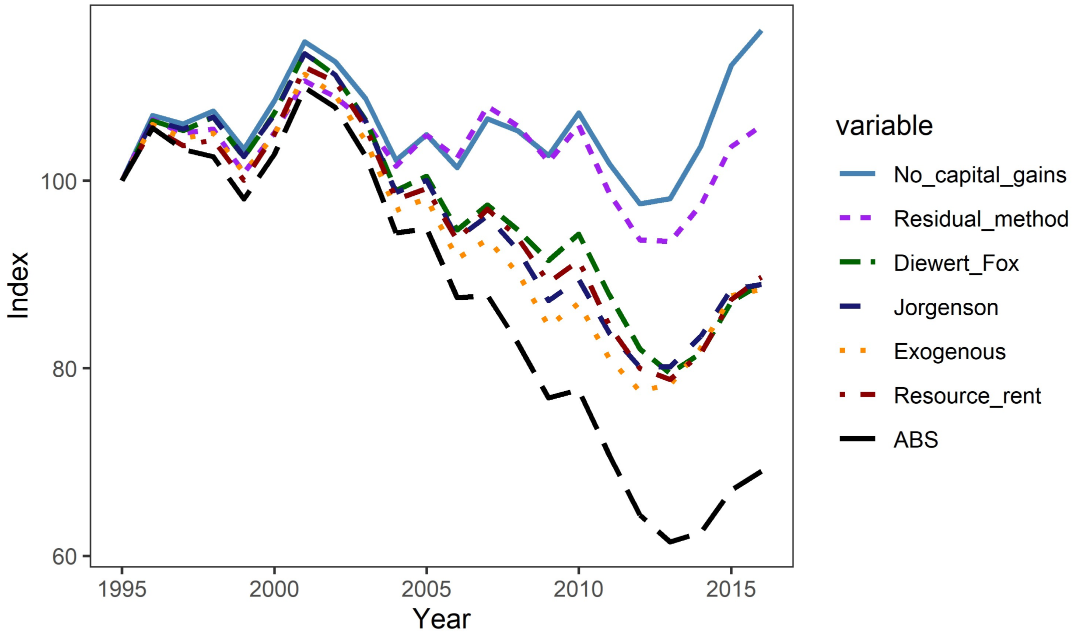
Source: Estimates of Industry Multifactor Productivity (ABS 2018) and author's estimates

Figure 2.5 shows the various mining MFP estimates that include natural capital against the ABS unadjusted mining MFP estimate. The inclusion of natural capital has a positive effect on MFP, noting that it is not the case that MFP growth is an overestimation of productivity growth during a mining resources boom. This is because during the mining boom not only was there natural capital growth, but also growth in the other factor inputs. Further a resources boom comes hand in hand with an investment boom, originating from the mining industry, but this will spillover into other sectors of the economy.

Table 2.2 compares the estimates of MFP growth for the mining sector with and without natural capital, using the growth-accounting framework. This framework determines how the rate of observed change in an industry's output can be explained by the rate of change of all the inputs. This framework considers the residual as MFP growth, and the contribution of adding natural capital as an input of production on MFP growth depends on the relative rate of growth of produced to natural capital.

Importantly, adding natural capital has no effect on output (value-added) growth in

Figure 2.5 – **Mining multifactor productivity**



Source: Estimates of Industry Multifactor Productivity (ABS 2018) and author's estimates

this framework. However, the contribution of labour[32] and produced capital inputs to productivity has changed to include the contribution of natural capital. Growth accounting with natural capital can be used to examine the changing contribution of natural capital over time. MFP growth rises when natural capital growth is slower than that for produced capital, and vice versa. As shown in Table 2.2, even though subsoil minerals grow very fast during the resources boom, other inputs grow even faster, and MFP that includes natural capital of the mining sector is adjusted upwards. From 2004–2005 onwards, the growth contribution of natural capital was relatively significant in Australia. After that, it stagnated, as commodity prices started to fall.

Looking at the averages over the selected periods, including natural capital as a factor of production raises the rate of MFP growth in all periods for all user costs of natural capital methods. In general, the inclusion of natural resources results in moderate increases in the measured growth rate of MFP for the mining sector. On average, during the period 1995–1996 to 2015–2016, the growth rate of natural capital was between -0.1 per cent and 0.8 per cent, while the growth rate of produced capital was between 2.7 per cent and 3.9 per cent.

[32]Except for the residual value method because the cost share of labour remained the same, while the cost share of capital is proportioned across produced and natural capital.

Table 2.2 – **Mining MFP growth decomposition (average growth rates (%))**

Period	Output growth	Produced capital	Natural capital	Labour input	MFP growth	Adjust. effect[a]
Resource rent						
1995/96 - 2000/01	4.35	1.07	1.62	-0.03	1.69	0.01
2001/02 - 2005-06	1.04	1.52	0.02	1.14	-1.54	2.86
2006/07 - 2010/11	4.89	3.70	0.31	1.78	-0.76	3.33
2011/12 - 2015/16	7.84	5.09	1.14	0.29	1.41	1.72
1995/96 - 2015/16	4.52	2.76	0.81	0.75	0.27	1.89
Residual method						
Period	Output growth	Produced capital	Natural capital	Labour input	MFP growth	Adjust. effect
1995/96 - 2000/01	4.35	2.37	0.15	-0.07	1.91	0.22
2001/02 - 2005-06	1.04	2.56	0.18	1.83	-3.60	0.80
2006/07 - 2010/11	4.89	3.84	1.28	1.68	-2.06	2.03
2011/12 - 2015/16	7.84	5.94	0.59	0.11	1.2	1.51
1995/96 - 2015/16	4.52	3.62	0.53	0.84	-0.52	1.10
Traditional user costs - Exogenous						
Period	Output growth	Produced capital	Natural capital	Labour input	MFP growth	Adjust. effect
1996/97 - 2000/01	4.35	1.68	0.87	-0.05	1.80	-0.11
2001/02 - 2005-06	1.04	2.66	0.35	1.95	-3.89	0.51
2006/07 - 2010/11	4.89	4.95	-0.06	2.31	-2.48	1.61
2011/12 - 2015/16	7.84	4.57	1.40	0.33	1.74	2.05
1996/97 - 2015/16	4.52	3.38	0.65	1.08	-0.59	1.03
Traditional user costs - Jorgenson						
Period	Output growth	Produced capital	Natural capital	Labour input	MFP growth	Adjust. effect
1995/96 - 2000/01	4.35	1.38	0.91	-0.08	2.12	0.44
2001/02 - 2005-06	1.04	2.57	0.36	1.92	-3.80	0.60
2006/07 - 2010/11	4.89	5.40	-0.02	1.61	-2.29	1.80
2011/12 - 2015/16	7.84	5.21	1.40	0.22	1.21	1.52
1995/96 - 2015/16	4.52	3.53	0.67	0.87	-0.56	1.06
Traditional user costs - Diewert and Fox						
Period	Output growth	Produced capital	Natural capital	Labour input	MFP growth	Adjust. effect
1995/96 - 2000/01	4.35	1.63	0.69	-0.08	2.13	0.45
2001/02 - 2005-06	1.04	2.37	0.50	1.79	-3.63	0.77
2006/07 - 2010/11	4.89	4.98	0.02	1.56	-1.52	2.57
2011/12 - 2015/16	7.84	7.07	-0.38	0.24	0.27	0.58
1995/96 - 2015/16	4.52	3.90	0.40	0.83	-0.55	1.06
Traditional user costs - No capital gains						
Period	Output growth	Produced capital	Natural capital	Labour input	MFP growth	Adjust. effect
1995/96 - 2000/01	4.35	1.46	0.67	-0.07	2.31	0.62
2001/02 - 2005-06	1.04	2.04	-0.03	1.51	-2.49	1.91
2006/07 - 2010/11	4.89	4.25	-0.72	1.33	0.08	4.17
2011/12 - 2015/16	7.84	5.76	-0.51	0.12	2.62	2.93
1995/96 - 2015/16	4.52	3.29	-0.11	0.68	0.71	2.23

Note: [a] 'Adjust. effect' indicates the growth difference (in percentage points) between the mining sector MFP estimates adjusted for natural capital and the ABS MFP estimates for the same sector.
Source: Estimates of Industry Multifactor Productivity (ABS 2018) and author's estimates

The contribution of natural capital input is higher under the unit resource rent method (1.9 percentage points) compared to the residual value method (1.1 percentage points) and the traditional user cost method (1.0 to 2.2 percentage points). This result arises because the income share of natural capital under the unit resource rent method (as shown in Figure 2.3) is the largest compared to the other user costs methods.

This chapter indicates that failing to include subsoil minerals as a capital input in productivity analysis may account for a substantial proportion of the mining productivity slowdown over the past 10 years. Nevertheless, it does not explain all of the productivity declines in the sector. Overall, the unadjusted MFP growth over the past 20 years is substantially lower than the MFP growth adjusted for natural capital by at least 1.0 percentage point each year.

2.6 Conclusion

This chapter used Australian data from the mining sector to compare methods for modelling natural capital as a capital input into the production process. It showed that while different methods of user cost values yield different MFP estimates, the most influential adjustment to traditional mining MFP is the inclusion itself of subsoil minerals (natural capital). Including natural capital in productivity measurement generates substantial measured productivity gains for the Australian mining sector. In general, natural capital contributed positively to MFP growth. Overall, natural capital added at least 1.0 percentage points growth on average to annual productivity growth between 1995–1996 and 2015–2016, noting that the effect of adding natural capital does change over time.

The size and direction of the productivity growth adjustment principally depend on the rate of natural capital growth relative to the rate of growth of produced capital and labour. We find that failing to account for natural capital has led to an underestimation of productivity during the mining boom when produced capital was growing faster than natural capital. Nevertheless, recognising natural capital as a factor of production does not explain the entire decline in MFP, as other factors may have also contributed to the decline.

The subsoil asset user costs derived from the unit resource rent method are rarely negative, and the subsoil asset weights display markedly less volatility, providing a more realistic representation of the production functions over time. Hence, this method is considered to be a superior choice to determine user costs of natural capital. The residual value method produces implausible weights for natural capital, which often sits at zero when GOS in that period is entirely exhausted by produced capital.

An analysis of the various traditional user cost models indicated that the choice of parameters profoundly influences the resulting estimates. Regardless of which model is used, none completely resolve the issue of negative user cost values for some subsoil minerals in some periods. Indeed there is little difference in the resulting estimates of mining MFP growth using the Jorgenson and Diewert and Fox models, even though there are substantial differences in the way user cost values are estimated. The results presented here confirm that from the explored traditional user cost models the preferred option is the Diewert and Fox model. The subsoil asset weights that are derived from this model are less volatile, and occurrences of negative predicted user costs are minimal.

In conclusion, the measurement of natural capital does not receive sufficient attention from national statistical agencies, most likely because accounting for the contribution of natural capital to economic growth is associated with significant uncertainties, such as lack of appropriate data, difficulties in setting the price and accounting for quality change. Thus, there remains work to be done to resolve the debate over how best to measure and account for the price and quantity of natural capital in productivity analysis. An important step contributed by this chapter is a comparison of the empirical implications of different user cost values and its impacts on mining productivity measurement. We hope our methodologies could be applied to study natural capital in natural resource rich economies to enhance our understanding of global changes in natural resources stock and how it affects productivity.

Chapter 3

Environmental Attributes and the Value of Agricultural Land - A Hedonic Analysis

3.1 Introduction

Agricultural land is a vital asset of any farm. In Australia, agricultural land accounts for over 60 per cent of the capital stock in the agricultural industry. Commonly, many rural properties are valued based on past sales in their local areas and on general expectations, such as local market conditions, using appraisal approaches. One aspect of the agricultural valuation market - unlike commercial and residential property investment that generally has a relatively liquid market - is the relatively low number of sales from which to determine value. Further, the land appraisal approach has the problem of subjectivity and may be systematically biased (Berry & Bednarz 1975). The emerging challenges of climate change and environmental degradation mean that a better understanding of the determinants of agricultural land productivity and, hence, its value is more important than ever.

Factors affecting agricultural land values are divided into two categories: income from economic goods produced by the use of the land, and possibilities of an alternative use for the property (Rutkauskas et al. 2018). In the income category, land value is estimated using a discounted cashflow method. The assessed value should also be influenced by general economic conditions (for example, inflation and interest rates). In the alternative use category, land value is determined by income from non-agricultural activities such as residential or commercial buildings and multiple methods can be used to estimate land price (Rutkauskas et al. 2018).

Information about agricultural land value is not readily. The Department of Agriculture, Water and the Environment (ABARES) produces price indexes of broadacre farmlands. However, these price indexes have limitations, for example, they fail to account for and quantify the determinants of land values such as location and land use. The Australian Bureau of Statistics (ABS) estimates the value of agricultural land stock as a component of the non-produced asset in the national balance sheet but there is no adjustment made for quality. The ABS measure ignores soil degradation due to land management choices or exogenous factors such as climate and rainfall. Therefore, a source of bias in the measurement of agricultural land values is the inability to property incorporate quality changes. On way to minimise such bias is by quality-adjusted price indexes, which measure the price change of 'like with like'.

This thesis uses a unique administrative dataset, containing a census of farm-level transactions sales records in Australia spanning more than 40 years. Further, geographic information systems mapping has been used to integrate spatial data of individual farms to an extensive range of characteristics. This rich dataset allows, for the first time, the construction of quality-adjusted price indexes of Australian agricultural land at the national and regional levels. To the best of our knowledge, this chapter is the first empirical comparison of different spatial hedonic models performed on the Australian agricultural land market. In this chapter the classic hedonic model is extended by adding location-specific variables as well as a type-specific land-use variable. Hedonic regression models can be helpful for shedding light on the following questions: *How might agricultural land be valued in the absence of a robust real estate market? How do non-physical land characteristics such as proximity to a nearest town, affect price? How should agricultural land be valued in non-revenue generating periods (such as during a prolonged drought)?*

The hedonic pricing method calculates the implicit marginal price of the various characteristics of land from its sale price. As every farm is unique, the use of hedonic regression models for estimating its value is justified. Hedonic methods usually model the conditional expectation of lagged agricultural land prices given a bundle of characteristics. Here, the hedonic pricing model is extended to factor in the spatial dimension due to spatial dependence and spatial autocorrelation between land values and spatial variables such as rainfall and temperature.[1]

While there are minimal studies on the hedonic analysis of agricultural land, particularly in Australia, the literature on valuing a residential property is large. For example, Hill and Scholz (2017) and Hill (2011) used variations of hedonic price valuation that employ longitude and latitude as a way of controlling for locational dependence. They found that the use of geospatial splines is superior to postcode (regional) dummies to adjust for omitted locational characteristics.

In this chapter, a spatial hedonic pricing model is constructed that includes a locational dummy variable. The method used by Hill and Scholz (2017) which directly employs spatial coordinate information in the model is applied. Both these models are estimated over time and at both national and regional levels. Overall, over a dozen variables were used to capture the environmental attributes of the agricultural land, including land use, soil acidity, average minimum and maximum temperature, average rainfall, water availability, population accessibility and distance to infrastructure.

In real estate markets where farms are rarely sold in consecutive periods, the ability to price unmatched farms is essential. Two distinct approaches to constructing price indexes that deals with this problem are considered: the time-dummy hedonic method and the hedonic imputation method. Both methods remove the effects of quality changes on the price and allow the indexes to incorporate unmatched farms between consecutive periods. The two hedonic index methods appear similar, however, Diewert et al. (2007) have shown that they can provide quite different results, even in the case where comparable functional forms are used to compare results over time periods. The time-dummy method constrains the regression parameters to be constant over time, while the hedonic imputation method allows for quality adjustment parameters to vary in each period. Inherently, the hedonic imputation method is more flexible, as it allows for shadow prices of characteristics to

[1] Anselin (1988) considered two spatial models—the spatial lag model and the spatial error model. Recent spatial hedonic models of real estate prices are based on these econometric developments. More sophisticated hedonic models that utilise spatial variables include the semi-parametric model, lattice model and the geostatistical model. Each of these hedonic models applies spatial weights using alternative criteria defined on the interaction between spatial units.

evolve.

This chapter makes two contributions to the measurement of agricultural land values. First, it quantifies the link between environmental attributes of agricultural land and agricultural land values over time in Australia. Second, this chapter assesses the suitability of different spatial hedonic pricing models in the construction of agricultural land price indexes that account for quality change at the national and regional levels. These constant-quality price indexes could potentially enhance national accounts and productivity measurement.

This chapter is organised as follows: Section 3.2 provides an overview of previous applications of hedonic pricing methods to value agricultural land, with the data then described in Section 3.3. Sections 3.4 and 3.5 develop a theoretical model providing the mechanism through which locational variables enter the hedonic model. Empirical results are given in Section 3.6, and Section 3.7 concludes the chapter.

3.2 Application of Hedonic Methods to Value Agricultural Land

Table 3.1 provides a collation of variables used in previous studies of hedonic models. To the best of my knowledge, King and Sinden (1988) published the most seminal study to date on the use of a hedonic approach to estimate Australian agricultural land values. Their survey of the Manilla Shire in New South Wales (NSW) determined the extent to which changes in land condition affect land prices, and whether land improvements are justified. Their model included production characteristics (for example, size, slope, river frontage and wheat yield), consumption characteristics (for example, house and the age of residence), location, and both buyer and seller characteristics (for example, investment skill, age and a ranking of sale pressure). They found that markets recognised land quality, with higher-quality land selling for more—a reflection of anticipated crop yields. They also identified that the market factored in the unpriced costs of improving lower-quality land. Much like mineral deposits are natural capital inputs to the mining industry, soil quality is a natural capital input to farming.

Dent and Ward (2015) assessed whether the cost of investing in irrigation infrastructure leads to increases in agricultural land values. Their model controlled for climate and a number of geographic and soil variables, including distance to coast, distance to primary roads, soil texture and soil nutrients. They concluded that the cost to irrigate per hectare would outweigh the average increase of agricultural land value.

Sheng et al. (2018) examined the relationship between access to public infrastructure and agricultural land prices using hedonic regression analysis. They performed the analysis on the NSW farm-level data between 2009 and 2011 and showed that superior access to road and rail transport has a positive effect on agricultural land values, particularly for large and cropping farms. The authors concluded that there is a spillover effect generated by the public infrastructure to farms, which may affect agricultural productivity.

Other non-Australian research includes the study by Mendelsohn et al. (1994), which provided an analysis of the effect of climate on land values using a Ricardian approach. They found that higher temperatures reduced average agricultural land values. The control variables used in this study included income per capita, soil salinity, flood risk, erosion, land slope, soil type (sand/clay) and soil moisture.[2]

Earlier, Palmquist and Danielson (1989) considered whether soil erosion (among other factors) helped to determine farm prices for North Carolina. They concluded that draining wet soils could improve agricultural land values by up to 34 per cent and that increased soil erosion is likely to be detrimental to values. Huang et al. (2006) later found that agricultural land values tended to decline with increased 'ruralness' (that is, distance from urbanised areas), population density, per capita income and soil productivity.

Pyykkoñen (2006) presented a comprehensive analysis of factors affecting land prices between different regions in Finland. He included a range of farm and non-farm factors in his hedonic pricing model, including parcel size, land features, land quality, cropping yield, climate variables, population density, government support, unemployment and infrastructure availability. This study supports the view that numerous factors affect agricultural land prices besides pure agricultural income. Pyykkoñen (2006) also stressed the importance of accounting for spatial differences, emphasising it is a necessity to achieve

[2]Mendelsohn et al. (1994) used geophysical and economic data for close to 3,000 counties in the US. Using monthly climate variables in both normal and quadratic forms, the effect of long-term global warming on agricultural land values was the focus of their study.

Table 3.1 – **Examples of variables used to explain land values**

Variable	Reference
Agricultural returns - Monetary variables	- Market revenues (Barnard et al. 1997; Carlberg 2002) - Returns to land (Goodwin et al. 2010; Weerahewa et al. 2008) - Net income (Devadoss & Manchu 2007) - Producer price of wheat (Goodwin & Ortalo-Magne 1992)
Agricultural returns – Non-monetary variables	- Yield (Devadoss & Manchu 2007; King & Sinden 1988) - Soil quality, temperature and precipitation, irrigation and slope (King & Sinden 1988; Mendelsohn et al. 1994) - Fraction of cropland (Gardner 2002) - Proximity of a port and access to infrastructure (Folland & Hough 1991; Huanget al. 2006; Sheng et al. 2018) - Irrigation (Dent & Ward 2015)
Government payments	- Total government payments (Devadoss & Manchu 2007; Henderson & Gloy 2008) - One or multiple categories of government support (Goodwin et al. 2003; Pyykkonen 2006)
Variables describing the market	- Pig density (Duvivier et al. 2005) - Manure, farm density and average farm size (Pyykkonen 2006) - Size of the agricultural land market (Duvivier et al. 2005)
Macroeconomic factors	- Property tax rate and interest rate (Devadoss & Manchu 2007; Weerahewa et al. 2008) - Inflation rate (Alston 1986) - Multifactor productivity (MFP) growth (Gardner 2002) - Debt-to-asset ratio, credit availability (Devadoss & Manchu 2007) - Unemployment rate (Pyykkonen 2006)
Urban pressure indicators	- Total population (Devadoss & Manchu 2007) - Population growth, rurality (Gardner 2002) - Ratio of population to farm hectares and urbanisation categories (Goodwin et al. 2011) - Dummy variables for city areas (Henderson & Gloy 2008) - Proportion of the labour employed in agriculture (Pyykkonen 2006)

Source: Feichtinger & Salhofer (2011) and author's own compilation.

accurate estimates. In a separate study, Drescher et al. (2001) controlled for several external factors such as economic and government influences, expectations about the future and market participant characteristics, to assess land values.

3.3 Data Source and Variable Definition

This section discusses the key features of the data. The dataset utilised is unique and was created using three main sources. The primary data source is the database from

CoreLogic, containing individual sales of Australian agricultural land for over 40 years. Also included is the address of the property, the total land area traded, the sale price of the parcel, and the contract and settlement dates. A more detailed description of CoreLogic variables is provided in Appendix B1.

The CoreLogic data was geocoded using a combination of the physical address and spatial coordinates of the property. The geocoded data allowed for linking to spatial datasets such as the Australian Standard Geographic Classification at the Statistical Areas Level 1 topography data from Geoscience Australia (2020a, 2020b), the Bureau of Meteorology (2020a, 2020b) and the CSIRO National Landcare Program. As a result of this linking, the dataset contains over 50 variables including environmental attributes of the property, such as soil and climate.[3]

3.3.1 Data cleaning

The data recorded transactions of individual sales collated by CoreLogic, that may contain errors such as:

1. human error in data entry;
2. insufficient or missing detail in free-text fields; and
3. duplicate records or multi-sale purchases.

Duplicate records occur when one property is recorded at the contract date, and then on the exchange date. Another reason is when a land parcel is subdivided and sold to multiple buyers at the same price. Thus, before analysis could start, several data cleaning processes were undertaken. First, all incomplete sales records, duplicates and multi-sale purchases, non-agricultural properties (for example, land-use purposes such as mining, abattoirs, urban corridors, hobby farms and residential properties), and transactions that occurred before 1975 and after 2018 were removed. The raw dataset contained 700,424 property transactions (for 349,217 unique properties) between 1900 and 2018. After removing duplicate records, 583,576 transactions remained. When we removed observations labelled as 'non-farm', sold before 1974 and after 2018, and where the contract price and year equalled 0, only 307,784 transactions remained.

[3]The full list of variables available is described in Chancellor et al. (2019).

The data also included transactions in which the sale price per hectare was unrealistically low. These sales were suspected to be between family members. The prevalence of hobby farms was another challenge, as they are often situated on small land parcels located close to urban areas and usually include large buildings or homesteads. These factors can result in hobby farms having extremely high sale price per hectare. As the market price in these transactions generally does not reflect the average value of agricultural land. Hence, property with land size smaller than two hectares were removed to exclude potential residential properties. Additionally, land sold for less than AU$50 per hectare and where the price exceeded AU$40,000 per hectare were also excluded. Another issue is 'multi sale' transactions, where several land parcels are grouped for sale, but often, only a single contract price is recorded. These 'multi sale' transactions distort the relationship between contract price and land area. In this study, multi sale transactions are excluded. When these records are removed the number of transactions that remained was 196,599.

The final component of data cleaning involved making statistical edits to extreme outliers based on the assumption of a normally distributed dataset. The Tukey method was used to identify sales prices per hectare that were above or below 1.5 times the inter-quartile range (IQR) by year at the state level, that is, $Q1 - 1.5(IQR), Q3 + 1.5(IQR)$ (Tukey 1947). A number of simple regression models were also run to identify additional outliers using Cook's distance method. After this cleaning process, 147,812 transactions remained in the scope. Overall, around 65 per cent of records were removed due to data cleaning, plus an additional 10 per cent due to statistical edits.

Figures 3.1 to 3.3 show average land price per hectare, average total sale price and average hectares within each of the ABS Australian Statistical Geography Standard (ASGS) Statistical Area Level 3 (SA3) regions[4] over time, respectively.

More expensive land parcels are usually clustered closer to residential areas (which potentially indicates that there could be a hobby farm effect). Farms located in SA3 regions further from the coast tend to record a lower average land price per hectare. Land parcels also tend to be more abundant in areas further away from the Australian coastline. Nevertheless, in terms of the average sale price, the pattern is mixed.

[4]SA3 is one of the spatial units defined under the ABS Australian Statistical Geography Standard (ASGS). SA3s represent the area serviced by regional cities based on a population of between 30,000 and 130,000 people. See ABS (2013) for a more detailed description of SA3 groupings.

Generally, land productivity (yield) depends on various factors, including (but not limited to) agronomic variables as well as environmental variables. Agricultural land that is nutrient rich will be of higher value than land that has eroded or does not have the qualities that produce high yield of crops. Land located near the coastline experienced higher average rainfall, which supports more reliable crop or livestock production. It would seem that, high rainfall properties are likely to attract higher prices per hectare than agricultural land in more arid areas of inland Australia. As with rainfall, variations in temperature can affect agricultural production and possibly the value of agricultural land. The regions that experience hotter temperatures for protracted periods may be less desirable for some farming activities (and may attract lower land prices, in turn). When observed alongside rainfall, average maximum temperature may indicate drought-prone properties, which would be negatively related to the agricultural land values.

Figure 3.1 – **Average price per hectare by SA3 (1974-1975 to 2017-2018)**

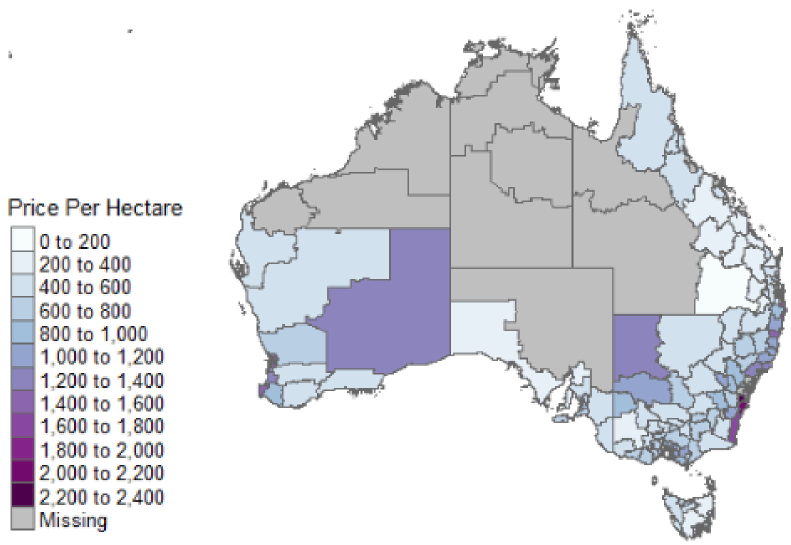


Figure 3.3 – **Average hectare by SA3 (1974-1975 to 2017-2018)**

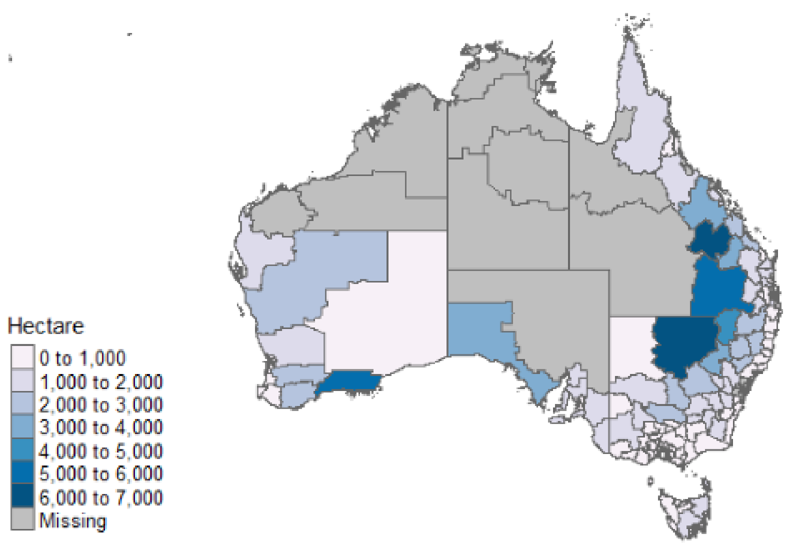
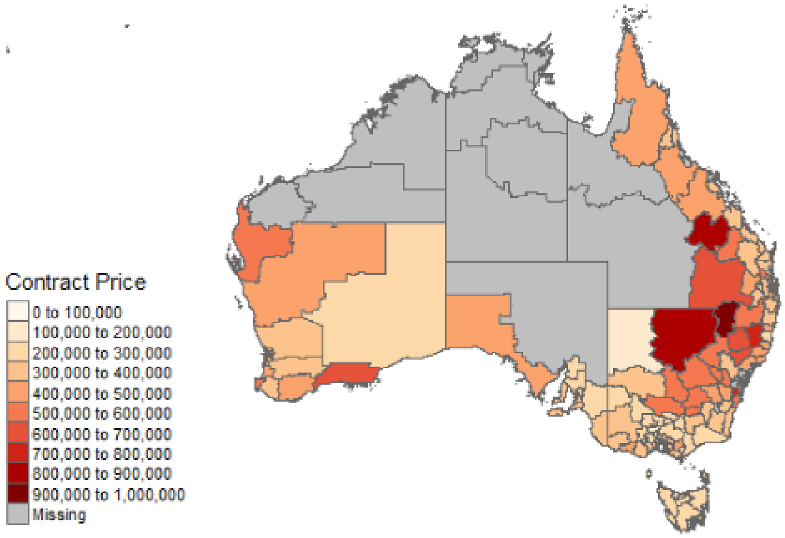


Figure 3.2 – **Average contract price by SA3 (1974-1975 to 2017-2018)**



3.4 Hedonic Price Indexes

3.4.1 An overview

When the quality of a product changes, the price index of that product should be accordingly adjusted. Hedonic price method is the preferred method for carrying out the quality adjustment (ILO et al. 2004). The hedonic price method consists of analysing the price of a good based on its characteristics. Rosen (1974) formalised the hedonic price method, which consists of quantifying the implicit prices of various attributes of heterogeneous goods, extending the works of Houthakker (1952), Muth (1966), and Lancaster (1966).[5] Thus, the hedonic price method implies that agricultural land is a heterogeneous good comprising a set of characteristics $X = (x_1, ..., x_b, ..., x_B)$ and is distinguished through a set of both intrinsic and extrinsic characteristics.

The hedonic price method calculates the implicit marginal price of a set of characteristics from the price, $P(X)$, of agricultural land. It regresses the price of a product on a set of characteristics, noting that it may not be possible to independently observe the prices of each characteristic. At equilibrium, each implicit marginal price, p_b, equals

[5] Rosen's model applies a nonlinear relationship to describe the price of goods and their inherent attributes. The implicit price is a function of the quantity of the attribute being bought and of the quantities of other attributes associated with the good (based on the functional form of the model). Thus, it is not constant.

the marginal willingness to pay for this characteristic. Therefore, the calculation of the different marginal implicit prices requires the derivation of the hedonic price function. This is done by regressing prices of agricultural land on their inherent attributes. Eq. 3.1 describes a classical hedonic equation, where Y is the price of the agricultural land, P is property-related attributes, L is locational variables, E is environmental conditions, and t is an indicator of time.

$$Y = f(P, L, E, t) \tag{3.1}$$

In the context of the agricultural sector, hedonic regression analysis has been used to determine the relationship of the price of agricultural land on the unpriced characteristics of the land, such as climate conditions and soil conditions (Mendelsohn et al. 1994; Palmquist & Danielson 1989). The hedonic regression equation can have a linear, semi-logarithmic or logarithmic–logarithmic functional form. The most common form of a property-valuation hedonic model is the semi-logarithmic form. Its results are easy to interpret because the coefficient estimates are direct proportions of the price that are attributable to each characteristic. A conventional hedonic pricing regression model has agricultural land market defined by price or price per hectare regressed against determinant characteristics.[6] In practice, the variables are determined based on the author's study or data availability.[7]

In this chapter, we compare two methods, the time-dummy method and the double-imputation method. These are discussed in Sections 3.4.2 to 3.4.4.

3.4.2 Time-dummy methods

The time-dummy method is the original hedonic method commonly in the form of the semi-logarithm function.[8] Eq. 3.2 is the standard semi-log formulation.

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[6]The fundamental assumption of regression applies that the dependent variable (price, or value in this case) is known precisely.

[7]Using a log transformation of land prices as the dependent variable accounts for the value of unpriced characteristics, which reflects the people's preferences and the trade-offs and constraints involved in land purchase decisions.

[8]See Diewert (2003) and Malpezzi (2003) for a discussion of some of the advantages of the semi-logarithm model in this context.

$$y = \alpha + X\beta + D\gamma + \epsilon \tag{3.2}$$

where y is a F x 1 vector of ln prices, p_f (that is, $y_f = ln(p_f)$); X is an F x B matrix of characteristics; D is an F x (C - 1) matrix of time (period) dummy variable; and ϵ is an F x 1 vector of random errors. F denotes the number of farms. The parameters to be estimated are B x 1 vector of the characteristics shadow prices β and (C - 1) x 1 vector of time period prices γ.[9]

In the time-dummy method, data on the prices and quality characteristics of a product are pooled over time. In the model, the logarithm of price is represented by an intercept, the quality characteristics and time-dummy variables. The time-dummy parameter directly accounts for the effect of 'time' on the logarithm of price. Thus, the quality-adjusted price index, P_t^* for period t, can be calculated by taking the exponential of the estimated time-dummy coefficient, γ_t^*, obtained from the hedonic model (Eq. 3.3).

$$P_t^* = \exp(\gamma_t^*) \tag{3.3}$$

When the relative price of land is compared between two periods, for any quality configuration, the ratio is equivalent to the corresponding exponential of the time-dummy variables. Hence, the advantage of the time-dummy model includes its simplicity. Its functional form is neither continuous nor smooth with respect to time.

The time-dummy method to construct hedonic price indexes is applied frequently in academic research; however, this is not the case by statistical agencies. Some theoreticians object to the time-dummy technique, favouring alternative hedonic approaches - of which the imputation method is the most popular (Silver & Heravi 2001). Diewert et al. (2007) and Hill (2013) discussed other approaches of constructing hedonic price indexes (for example, the average characteristics method), which are not explored in this chapter.[10]

[9] The base period price index is normalised to 1.

[10] Average-characteristic methods typically construct an average farm for each period. A price is imputed for this hypothetical farm as a function of its characteristics based on the shadow prices derived from the hedonic model. As farms are unique with many characteristics, this method will yield results that are arguably difficult to interpret.

3.4.3 Hedonic imputation method

In this approach, instead of compiling one hedonic regression (like in the time-dummy method), two entirely separate hedonic regressions are derived. These are β_t in period t and β_{t+1} in period $t + 1$. Thus, the hedonic imputation method estimates a different hedonic model for each period. The time horizon for each model is partly dependent on the size of the dataset. Fortunately, there are enough observations in our Australian dataset to derive a separate model for each year.

Let $p^*_{t+1,f}(x_{t,f})$ signify the imputed price in period $t + 1$ of a farm sold in period t. The prices for individual farms are imputed as shown in Eq. 3.4 whereby characteristic X, of farm f, sold in period t is substituted into the hedonic model estimated for the period $t + 1$. These imputed price indexes can be inserted into standard price index formulas.

$$p^*_{t+1,f}(x_{t,f}) = \exp(\sum_{b=1}^{B} \beta^*_{b,t+1} x_{b,t,f}) \tag{3.4}$$

The Laspeyres-type index considers the farms sold in an earlier period of t. In contrast, the Paasche-type index considers the farms sold in period $t + 1$. A single-imputation price index (Paasche or Laspeyres) imputes prices in only one period. In comparison, a double-imputation index imputes prices in both periods (see de Haan 2004; Hill & Melser 2008; Hill & Scholz 2017). Equal weight is given to each farm under these price indexes.

In the context of farms, an unweighted structure (that is, each sale of a farm comes with its own quantity, which is equal to one) is in our opinion more appropriate than using expenditure share to weight each farm.[11] The advantage of the Fisher index is that it treats both periods symmetrically. The single-imputation price index between periods t and $t + 1$ is calculated in Eq. 3.5 to Eq. 3.7, while the double imputation price indexes is shown in Eq. 3.8 to Eq. 3.10.

$$\text{Laspeyres single imputation: } P^{LS}_{t,t+1} = \prod_{f=1}^{F_t} \left[\left(\frac{p^*_{t+1,f}(x_{t,f})}{p_{t,f}} \right)^{1/F_t} \right] \tag{3.5}$$

[11] Hill and Scholz (2018) advocated for the use of democratic weighting structure in the housing context.

$$\text{Paasche single imputation: } P_{t,t+1}^{PS} = \prod_{f=1}^{F_{t+1}} \left[\left(\frac{p_{t+1,f}}{p^*_{t,f}(x_{t+1,f})} \right)^{1/F_{t+1}} \right] \tag{3.6}$$

$$\text{Fisher single imputation: } P_{t,t+1}^{FS} = \left[P_{t,t+1}^{PS} \times P_{t,t+1}^{LS} \right]^{1/2} \tag{3.7}$$

$$\text{Laspeyres double imputation: } P_{t,t+1}^{LD} = \prod_{f=1}^{F_t} \left[\left(\frac{p^*_{t+1,f}(x_{t,f})}{p^*_{t,f}(x_{t,f})} \right)^{1/F_t} \right] \tag{3.8}$$

$$\text{Paasche double imputation: } P_{t,t+1}^{PD} = \prod_{f=1}^{F_{t+1}} \left[\left(\frac{p^*_{t+1,f}(x_{t+1,f})}{p^*_{t,f}(x_{t+1,f})} \right)^{1/F_{t+1}} \right] \tag{3.9}$$

$$\text{Fisher double imputation: } P_{t,t+1}^{FD} = \left[P_{t,t+1}^{PD} \times P_{t,t+1}^{LD} \right]^{1/2} \tag{3.10}$$

3.4.4 Comparison of hedonic methods

The essence of the hedonic time-dummy method is that it comprises only one regression. In this case, the data in each period appears as dependent variables. The hedonic dummy method constrains the value of the parameters of characteristic variables to be constant over time (that is, characteristics are valued at typical 'prices'). Due to these restrictions, the hedonic time-dummy method lacks flexibility in that shadow prices cannot evolve. For each new period added to the dataset, all the results need to be recompiled. However, the constant-quality price index requires something to be held constant over time to differentiate the price change from the quantity mix. Generally, the hedonic imputation method involves deriving a hedonic price function for each period. This function is then used to impute estimated prices for non-matched models. The hedonic imputation method utilises two regression equations based on holding coefficient estimates constant over two consecutive periods. These prices are then conventionally used in an index formula.

Inherently, the hedonic imputation method is more flexible, as it allows for shadow prices of characteristics to evolve, and this is a significant advantage. Nevertheless, the coefficients estimated in the hedonic imputation method are also held constant at average prices for characteristics of the two separate hedonic regressions. To date, there has been research comparing the two approaches conducted by Berndt et al. (1995), Berndt and Rappaport (2001), Diewert (2003), Silver and Heravi (2003), de Haan (2004), Triplett (2004), Silver and Heravi (2007) and Melser (2006).

Diewert et al. (2007) advocated for hedonic imputation methods, but recognised that this method uses more degrees of freedom and could potentially lead to a less reproducible estimate of price change between the two periods. They suggested that in the case that the time-dummy and hedonic imputation approaches make symmetric use of data in two periods and have the same functional form, a plausible approach when different results arise between the two methods is to take a (geometric) mean of the two.

Berndt and Rappaport (2001) favoured the use of hedonic imputation indexes when parameters are unstable, and Triplett (2004) noted that product differentiation with significant turnover in models is a feature of today's product markets. The inability of the matched models method to sufficiently deal with high product turnover is sufficient motivation to use hedonic regression techniques. Compared to the time-dummy, hedonic imputation methods are not as widely used because they are conceptually more complicated and also require large datasets. To the best of our knowledge, the only use of an imputation method is for for the FNC Residential Price Index in the US and RP Data-Rismark in Australia. The FNC index (see Dorsey et al. 2010) uses the double-imputation Laspeyres formula, whereas RPData-Rismark uses a non-parametric method (see Hardman 2011). Regardless of which index-construction method is used, they both allow for inclusion of environmental attributes, categorical variables, interaction terms between characteristics, and functions of characteristics. Common concerns with these hedonic models are multicollinearity and heteroskedasticity.

3.4.5 Methods for incorporating location in hedonic regression models

Regional dummy variables

Location is an important price-determining factor. There are various ways to account for locational effects in hedonic models. A common ambition is to eliminate locational variation by assigning shadow prices to locations. The easiest way to do this is to include an identifier of the region in which a farm is located.

Distances to amenities

The distance of each farm to amenities impact on the cost of running a farm. With the availability of spatial points, we can measure the distance from a farm to a city centre, nearest train station or port, or closest water source. We can then include the data on these distances as additional characteristics in the hedonic models. Nevertheless, using kilometres to amenities as characteristics to account for location is problematic for several reasons. First, it makes limited use of the geospatial information, discarding potentially useful information. Second, the location of the farm and aspects like rainfall and climate of a region are relevant. Third, the effect of distance from amenities on the price of a farm may be difficult to determine and is not necessarily monotonic. For example, some crops may grow in specific locations that are not too close to the city centre or transport.

Nonparametric approaches

An alternative to parametric modelling is the use of non-parametric methods. These methods avoid the problems highlighted by Pinkse and Slade (2010)[12], as they can be used to create flexible, topographical surfaces showing how price varies by location, holding the other characteristics constant. Geospatial data presents opportunities to improve the quality of a hedonic pricing model. The exact longitude and latitude for each parcel of agricultural land can be used to control for locational effects. As hedonic methods can be applied to any functional form (parametric or non-parametric), they are very flexible to estimate.

Non-parametric methods provide a natural way of including geospatial data such as a spline into the index calculation. To the best of our knowledge, only the studies by Bao and Wan (2004), Brunauer et al. (2010) and Hill and Scholz (2017) have used splines to

[12] The paper by Pinkse and Slade (2010) raises that typically spatial econometrics is applied in a mechanical fashion, with variables introduced in spatial econometric models due to being significant, but without theoretical justification (or priori rationale).

estimate hedonic models of the real estate market.[13]

3.5 Model estimation

This section presents four empirical models. The literature does not clearly preference any functional form for the hedonic model. Models 1 and 2 are semi-parametric, while Models 3 and 4 are non-parametric.[14] Model 1 provides a base model that excludes a locational variable of the property. Model 2 is an ordinary least squares model that contains the locational dummy variable defined by SA4. Model 3 is a generalised additive model (GAM) and includes a geospatial spline to estimate variation in prices across location smoothly. Model 4 is also a GAM and accounts for the nonlinear nature of not only location but also other dependant variables.

3.5.1 Semiparametric models

Model 1 and Model 2 can be expressed as in Eq. 3.11 and Eq. 3.12, respectively,

$$y = \alpha + X\beta + \epsilon \tag{3.11}$$

$$y = \alpha + X\beta + D\gamma + \epsilon \tag{3.12}$$

where y is a F x 1 vector of log-price, X is an F x B matrix of land characteristics, D is an F x $C-1$ matrix of time (period) dummy variables, and all the observable is reflected in the error term ϵ. F denotes the number of farms.

[13]Hill and Scholz (2017) applied a semi-logarithm hedonic model with locational results captured using a geospatial spline to estimate house price indexes for Sydney over the period 2001 to 2011. The characteristics in their model are merely the number of bedrooms, number of bathrooms and land area.

[14]See Hardle et al. (2004) for an overview of semiparametric models, their properties and estimation.

3.5.2 Nonparametric models

We allow for a more flexible functional form by introducing splines to the dependent variables to account for nonlinearity in these variables in Models 3 and 4. In Model 3, the geospatial data was modelled non-parametrically using a spline function to account for any topographical (locational) effects in farm values. Model 4 applies splines to both geospatial data and the selected land characteristics. A GAM, as used in Models 3 and 4, has the advantage of being relatively straightforward to include a smooth function of the longitude and latitude in the regression process (Hill & Scholz 2017). Further, GAM is more flexible than a semi-logarithm model, as it avoids the common issue of dimensionality in fully non-parametric models (for example, see Stone 1986). Model 3 takes the form in Eq. 3.13 and Model 4 is expressed in Eq. 3.14,

$$y = \alpha + X\beta + s(c_{lat}, c_{long}) + \epsilon \tag{3.13}$$

$$y = \alpha + X\beta + s(c_{lat}, c_{long}) + \sum_{g=1}^{G} f_g(Z_g) + \epsilon \tag{3.14}$$

where $s(c_{lat}, c_{long})$ denotes a non-parametric function $s(.)$ defined on the latitude and longitude of the property, c_{lat}, c_{long}. $f(Z_g)$ is the function defined on land characteristics Z_g. The functional form for $s(c_{lat}, c_{long})$ and Z_g is not determined beforehand but driven by the data.

Model 3 utilises a geospatial spline using spatial coordinates (latitude and longitude) of the land's location. In this model, the locational effect is estimated smoothly over the observation area. Precise modelling of locational effects is needed if there is much variation within regions. Model 4 includes the smoothing of land characteristics to account for their non-linear relationship with land values.

GAMs are often described as 'wiggly models'. These models are generally estimated with an optimal low-rank approximation of a thin plate spline[15] (which has n unknown parameters). Smoothing parameters are selected to minimise prediction error where n is not known. The generalised cross-validation (GCV) score is generally preferred, as the

[15]Thin plate splines are a technique used to estimate smooth functions of continuous variables.

model does not need to be refitted to subsets of the data, which saves computational time and effort, noting that the selection of GCV smoothness can result in under-smoothing when the GCV profile is relatively flat. Here, the random variation can result in 'too wiggly' a fit. Another smoothing parameter option is a restricted maximum likelihood (REML). The REML method penalises over-fitting, however a disadvantage is that the result could change in a different run. Thus, the models are fitted using REML, which Wood (2011) has shown to be more robust to under-smoothing. It is also the smoothing method used by Hill and Scholz (2017). Practically, the functional form of the splines is estimated using the GAM function from the R package 'mgcv'. For further description of the GAM function and its smoothness selection criteria, see appendix B4 and appendix B5.

3.5.3 Independent variables

As is common with large datasets, we found a key challenge to be the selection of a set of sensible, independent variables for the models. Table 3.2 presents the list of variables selected, and Table 3.3 displays the summary of independent variables used in each hedonic model. Multicollinearity between variables was a significant issue, as it is difficult to separate the individual effects of collinear variables. This can cause variables to appear statistically insignificant when they are significant (for example, between average temperature and rainfall). Thus, the land characteristics were selected after a review of factors significant in previous studies, fine-tuning (based on hedonic regression results) and to control for multicollinearity.

The first independent variable, log-HEC, is the natural log of agricultural land area in hectares. Typically, larger parcels of land are sold at higher overall prices but at lower prices per hectare than smaller land parcels. The second group of independent variables is locational type. As Model 1 provides a base model, we did not include a locational variable. For Model 2, the location of the farm was included as a dummy variable using the SA3 regions. The SA3 region dummy variable helped to determine if there are any differences in the base prices for different regions. If they are significantly different from 0, this supports the assumption that Australia is not a single market for agricultural land.

We also included variables indicating the road distances from each property to the nearest

Table 3.2 – **List of independent variables**

Data type	Variable	Type	Description
Farm size	log-HEC	Numeric	Land size for transacted property in hectares
Location	LAT and LONG	Numeric	Geospatial location coordinates (latitude, longitude)
	SA3 and SA4	Categorical	ABS SA3 and SA4
	TKM10	Numeric	Distance from property to the nearest town with population of 10,000
	DIST	Numeric	Distance from property to the closest road network
Structure	BED	Numeric	Number of bedrooms if house is present
	BATH	Numeric	Number of bathrooms if house is present
	HOUSE	Numeric	Number of residential buildings points
	SHED	Numeric	Number of agricultural buildings points
Environmental attributes	LANDUSE	Alphanumeric	Dummy variable to identify land use for purposes such as: grain, crops, livestock, mixed farming, dairy, vineyards, vacancy and horticulture
	SLOPE	Numeric	percentage of land parcel that is flat based on the SR digital-elevation model
	AvgRAIN	Numeric	Annual rainfall assigned to farm by year of sale (BoM AWAP)
	MaxTEMP	Numeric	Average annual maximum temperature by statistical area assigned to farm by year of sale
	MinTEMP	Numeric	Average annual minimum temperature by statistical area assigned to farm by year of sale
	ErACID	Numeric	percentage of land at risk of acidification
	ErWATER	Numeric	percentage of land at risk of water erosion
	ErWIND	Numeric	percentage of land at risk of wind erosion
	GRAZ	Numeric	percentage of land used for grazing
	CROP	Numeric	percentage of land used for cropping
	WATs2	Numeric	Water cover based on Geoscience Australia Water Observations from Space data in square meters
	IR	Categorical	1 indicating irrigation and 0 indicating no irrigation

AWAP: Australian Water Availability Project; BoM: Bureau of Meteorology;
SA3/SA4: Statistical Area Level 3/4
Source: Chancellor et al. 2019

Table 3.3 – **List of independent variables**

Data type	Variable	Model 1	Model 2	Model 3	Model 4
Farm size	log-HEC	✓	✓	✓	✓
Location	LAT, LONG	x	x	✓(spline)	✓(spline)
	SA3	x	✓	x	x
	TKM10	✓	✓	✓	✓(spline)
	DIST	✓	✓	✓	✓(spline)
Structure	BED	✓	✓	✓	✓
	BATH	✓	✓	✓	✓
	SHED	✓	✓	✓	✓
Environmental Attributes	LANDUSE	✓	✓	✓	✓
	SLOPE	✓	✓	✓	✓(spline)
	AvgRAIN	✓	✓	✓	✓(spline)
	MaxTEMP	✓	✓	✓	✓(spline)
	MinTEMP	✓	✓	✓	✓
	ErACID	✓	✓	✓	✓
	ErWATER	✓	✓	✓	✓
	ErWIND	✓	✓	✓	✓
	GRAZ	✓	✓	✓	✓(spline)
	CROP	✓	✓	✓	✓(spline)
	WATs2	✓	✓	✓	✓(spline)
	IR	✓	✓	✓	✓

unsealed road and the town centre with a population of 10,000 people. The road network distances (named DIST in our models) in kilometres were calculated between nodes (intersections) on the road network based on Geoscience Australia TOPO 250k Series 3 data. Town centre location information is from the ABS Urban Centres and Localities, derived from the 2016 Australian population census.[16]

The third group of independent variables considers the structures located on the property. The value of agricultural land generally increases with the number of structures, with higher values associated if the structure is a residence (or homestead) that contains a large number of bedrooms and bathrooms. The number of structures (residence or sheds) is determined using geographic information systems mapping of land cover. The data is only available for New South Wales (NSW), Victoria, Queensland, South Australia (SA), Western Australia (WA) and Tasmania.

One of the most important determinants of agricultural land prices is land use and soil

[16]Where multiple nodes overlap the property polygon(s), the selection of which one to use is arbitrary. For vast properties, this adds a potential error. Another source of error is where a property contains non-adjacent polygons and the part closest to a road network node is not representative of the bulk of the property. These issues are similar when assigning a node to town centres.

quality. The fourth group of independent variables contains environmental attributes of the soil on the property. To measure the quality of each land parcel, we used the exposure of soil to wind, water and acid as an indicator for erosion. We hypothesised that the coefficients of these indicators have a negative sign, implying that a buyer pays less for agricultural land that is potentially more susceptible to erosion.

We also included average rainfall, average minimum and maximum temperature, and water area, as these various productivity modifiers affect plant growth (Kesteven et al. 2004). Rainfall can often be a substitute for irrigation and therefore, can substantially affect the productivity of the parcel of land. These variables were constructed using spatial layer data from the Australian Collaborative Land Use and Management Program. Further, we constructed a land-use variable using keywords in the CoreLogic primary land-use variable. These variables are useful, as they provide an indication of production type at the time of sale and, according to CoreLogic, are maintained continuously and generally considered to be high quality.

The slope of the land is classified based on the SR digital-elevation model. The four classes range from '1' for flat to '4' for steep. We included a variable indicating the percentage of land classified as Class 1 (no slope) under this model. Water is an essential resource for agricultural production. However, as excessive water coverage might present flood risk, it is difficult to predict the effect of water on agricultural land values. We expect the sign of the estimated coefficient will be positive. A positive relationship would support the hypothesis that land with higher-quality soil has a higher value, holding all other variables constant.

3.6 Results

This section examines the qualities that are awarded a premium in the Australian agricultural land market from 1974-1975 to 2017-2018, and compares the results obtained from the four hedonic models. Regression results at the Australian level for all estimated agricultural land hedonic models are presented in Table 3.4.

Overall, the fit of all models is reasonable. Model 2 (regional dummy model) explains about 67 per cent of average price change variation. In contrast, Model 1 (no locational

Table 3.4 – **Regression results, selected agricultural land characteristics (Australia)**

	Model 1	**Model 2**	**Model 3**	**Model 4**
log(H)	0.46*** (0.02)	0.47*** (0.02)	0.47*** (0.02)	0.47*** (0.02)
Beef	0.11** (0.04)	0.14*** (0.04)	0.14*** (0.04)	0.16*** (0.04)
Dairy	0.35*** (0.04)	0.29*** (0.04)	0.28*** (0.04)	0.31*** (0.04)
Forestry	−0.51*** (0.05)	−0.23*** (0.05)	−0.220*** (0.04)	−0.187*** (0.05)
General	0.347*** (0.04)	0.115*** (0.04)	0.178*** (0.04)	0.181*** (0.04)
Grain and oth crops	0.151*** (0.04)	0.18*** (0.04)	0.135*** (0.04)	0.158*** (0.05)
Horticulture	0.406*** (0.04)	0.408*** (0.04)	0.366*** (0.04)	0.394*** (0.04)
Livestock-Crops	0.122*** (0.04)	0.108*** (0.04)	0.114*** (0.04)	0.131*** (0.04)
Mixed farming	0.477*** (0.04)	0.133*** (0.04)	0.148*** (0.04)	0.128*** (0.04)
Other livestock	0.12*** (0.04)	0.09** (0.04)	0.10** (0.04)	0.11*** (0.04)
Sheep	0.075* (0.05)	0.05 (0.04)	0.04 (0.04)	0.04 (0.04)
BED	0.014*** (0.02)	0.015*** (0.02)	0.013*** (0.02)	0.01*** (0.02)
BATH	0.111*** (0.03)	0.085*** (0.03)	0.09*** (0.03)	0.09*** (0.03)
HOUSE	0.017*** (0.01)	0.038*** (0.01)	0.03*** (0.01)	0.03*** (0.01)
SHED	0.083*** (0.04)	0.084*** (0.04)	0.09*** (0.04)	0.08*** (0.04)
ErACID	0.003*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.003*** (0.00)
ErWATER	−0.003*** (0.00)	−0.003*** (0.00)	−0.00*** (0.00)	−0.00** (0.00)
ErWIND	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.005*** (0.00)
minTEMP	0.043*** (0.02)	0.050*** (0.02)	0.056*** (0.03)	
maxTEMP	−0.044*** (0.01)	−0.020*** (0.02)	−0.016*** (0.03)	
avgRAIN	0.01*** (0.00)	0.00*** (0.00)	0.01*** (0.00)	
DIST	−0.00*** (0.00)	−0.00*** (0.00)	−0.00*** (0.00)	−0.00*** (0.00)
TKM10	−0.02*** (0.00)	−0.02*** (0.00)	−0.02*** (0.00)	
GRAZ	−0.019*** (0.06)	0.011* (0.06)	−0.02 (0.06)	
CROP	−0.014** (0.07)	0.063*** (0.07)	0.10*** (0.07)	
SLOPE	0.397*** (0.07)	0.046*** (0.06)	0.06*** (0.06)	
WATm2	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
IR	0.179*** (0.01)	0.18*** (0.01)	0.19*** (0.09)	0.19*** (0.09)
Constant	7.62*** (0.09)	7.748*** (0.07)	7.161*** (0.07)	7.40*** (0.05)
Approximate significance of smooth terms:			edf (F-stat)	edf (F-stat)
s(LAT,LONG)			28.9***(359.4)	28.9***(293.5)
s(minTEMP)				7.50*** (70.6)
s(maxTEMP)				7.79*** (48.2)
s(avgRAIN)				8.91***(416.9)
s(TKM10)				7.79*** (412.8)
s(GRAZ)				7.88*** (19.9)
s(CROP)				5.50*** (53.8)
s(SLOPE)				8.56*** (64.9)
Observations	147,638	147,638	147,638	147,638
Adjusted R^2	0.64	0.67	0.67	0.68
UBRE			140,768	137,983

*p<0.1; **p<0.05; ***p<0.01

Note: Coefficients generated from semi-log hedonic regression model. Model 2 coefficients for regional dummy are shown in Figure 3.4. Model 3 coefficients for the geospatial splice are shown in Figure 3.5. Missing coefficient indicates the variable was not included in the model.

variable) only had an explanatory factor of 64 per cent. These results confirm that location is an important price-determining factors. Model 3 (GAM with a geospatial spline) generated almost identical explanatory power of 67 per cent. This result suggests that there is little to be gained from using a geospatial spline over a model that uses a regional dummy variable. One interpretation of this outcome is that the precise modelling of locational effects has already been explained by the land characteristics included in the model. Thus, the locational quality shift within regions are not observed. Consequently, Model 4 is the best performing model (R-squared of 68 per cent). This suggests that higher explanatory power could be achieved by introducing nonlinear functions for the independent variables.

Land size (log(H)) is significant and positive, suggesting that the price tends to be higher for larger farms. Also, farm characteristics such as average rainfall (avgRAIN), minimum temperature (minTEMP), land gradient (SLOPE), water availability (WATm2), irrigation (IR) and having structures on the farm (BED, BATH, HOUSE and SHED) all appear to affect agricultural land values positively. The following discussion refers to the regression results of Model 2.

The presence of a house or buildings affects land prices. Specifically, the number of buildings has a significant and positive relation to price. Having a residence on a farm (based on Model 2) is associated with 3.8 per cent higher price (all other factors held constant), while having sheds adds 8.4 per cent to the land value. A bathroom adds 8.5 per cent to land value; however, the total number of bathrooms may be a proxy of the size (and quality) of the residence on a farm.

Flat terrain has a significant effect on agricultural land prices, suggesting that hilly land may result in a slight reduction in price. Features such as water cover (WATm2) have more nuanced relationships with agricultural land value. The negative drivers include average maximum temperatures, water erosion risk (ErWATER) and use of land for grazing (GRAZ) and cropping (CROP) purposes. A 1 per cent increase in average maximum temperature results in a 2.0 per cent decrease in price.

Both distance to the nearest road (DIST) and distance to the nearest town (TKM10) are statistically significant and negative, suggesting that land value falls with increases in remoteness and reduced access to infrastructure. The comparison of the type of land use is in contrast to vacant land. Forestry contributes negatively to land price compared to vacant land. The most significant adjustment to price based on land use is horticulture (40.8 per cent). One reason for this is that horticulture farms are more likely to be located closer to urban areas or that they are more profitable per hectare. Dairy farming adds 29.2 per cent value compared to vacant land.

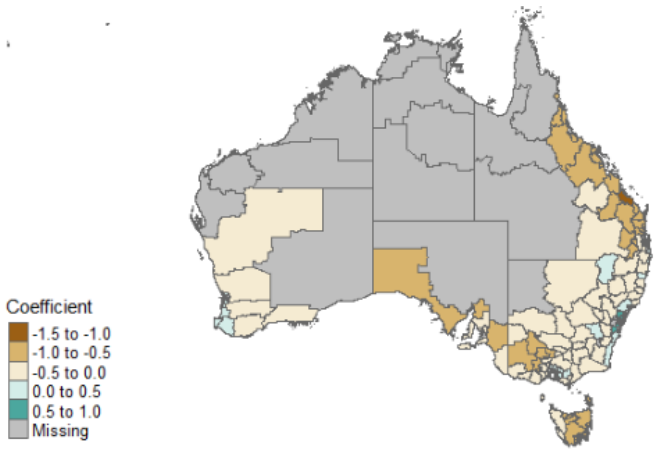
While the coefficients align with expectations for most of the variables, results from the soil variables, ErAcid and ErWind, was unexpected. A high risk of acidification and wind erosion both appear to have a (slight) positive relationship to land values. Although this seems counterintuitive, it could potentially be endogenous due to omitted variables on soil quality such as the fraction of organic carbon mass, clay, silt, sand, and soil nutrients that a presence in the soil.[17] Another reason could be due to the intensity of land use versus farmers' investment in land management.

Figure 3.4 presents the coefficients by SA3. As shown, the SA3 towards the south and those SA3s closer to urban regions and the east coast generally have higher coefficients. These results align with our expectations. Farms along the Australian coastline are typically smaller and tend to benefit from higher rainfall. In contrast, farms in the western region of Australia are generally larger than in the south and experience moderate climate conditions suitable for large-scale cropping. Farms in the centre or Australia are generally large-scale grazing properties, which seemed to attract lower prices on a per-hectare basis.

Figure 3.5 shows the coefficient for the smooth latitude and longitude under Model 3.

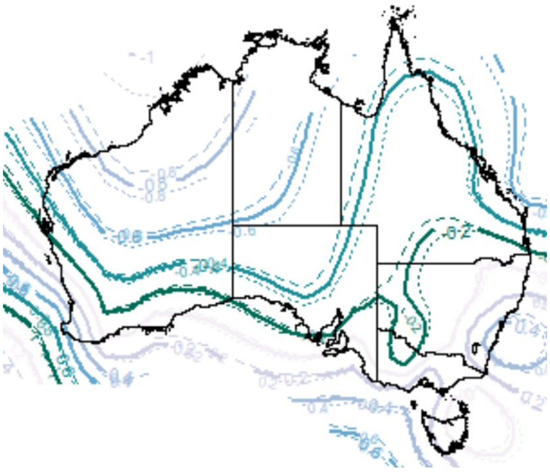
[17]See CSIRO Soil and Landscape Grid of Australia for a description of soil quality indicators at https://www.csiro.au/en/research/natural-environment/land/soil-grid.

Figure 3.4 – **Model 2, SA3 region coefficients**



The solid line indicates changes in the coefficient, while the dotted lines are the standard errors of the coefficient. Similar to Model 2, the estimated coefficients are larger towards the southern areas of Australia closer to the coast. These regions generally experience higher levels of average rainfall and are located closer to highly populated regions.

Figure 3.5 – **Model 3, Smooth location coefficient of longitude and latitude**



3.6.1 Model fit

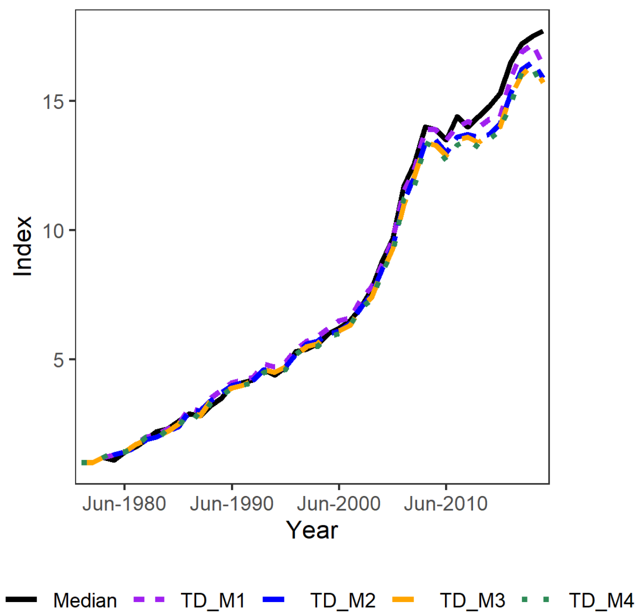
There are several ways to explore the model fit. The most common is to look at the akaike information criterion (AIC) and bayesian information criterion (BIC), with the smaller values indicating a 'better' fit. Table 3.5 compares the model fit using two different criteria. The geospatial spline model underperforms its regional dummies counterpart (Model 2) based on the BIC and AIC. However, the use of additional smoothing on farm characteristics (Model 4) outperforms the other models based on the BIC. Thus, we conclude that including a location-type variable in the model (whether using a regional dummy code or using a latitude and longitude spline) is essential.

Table 3.5 – **Comparing the performance of the semi-log models**

	Akaike info. criterion	**Bayesian info. criterion**
Model 1 (M1)	269493.0	270247.8
Model 2 (M2)	251854.6	261344.3
Model 3 (M3)	262222.2	263260.2
Model 4 (M4)	257431.2	258989.2

Figure 3.6 shows how the predicted mean indexes of the time dummy hedonic models track the mean sales price index. In all cases, the price index is normalised to one at period 1. For all other years, the index value denotes the cumulative price change. The result indicates that the time dumhedonic models perform reasonably well in estimating agricultural land prices. Generally, all the models track relatively well between predicted models and the actual sales price mean measures, with small divergences observed from 2009 onwards.

Figure 3.6 – **Australian median land price indexes (1975-76 to 2017-2018) (predicted v. actual)**



Notes: 'TD' refers to the time dummy method;'M1' refers to model 1; 'M2' refers to model 2; 'M3' refers to model 3; 'M4' refers to model 4.

The agricultural land market experienced an extended boom beginning around 1995. Although there was a slight correction around the global financial crisis in 2008 and 2009, the boom resumed from 2011 onwards, albeit at a slower growth rate. The Australian

Bureau of Agriculture and Resource Economics and Science (ABARES) Australian Farm Survey Results (2013) found significant jumps in land values between 2009 and 2013 and a growing disconnect with farm incomes. The agricultural land market experienced an extended boom beginning around 1995. Although there was a slight correction around the global financial crisis in 2008 and 2009, the boom resumed from 2011 onwards, albeit at a slower growth rate. Most notably in 2013, prices jumped from AU$220–$240 to over AU$1,200 a hectare on average across Australia. Those outcomes vary enormously, depending on how the land is used and on local conditions.

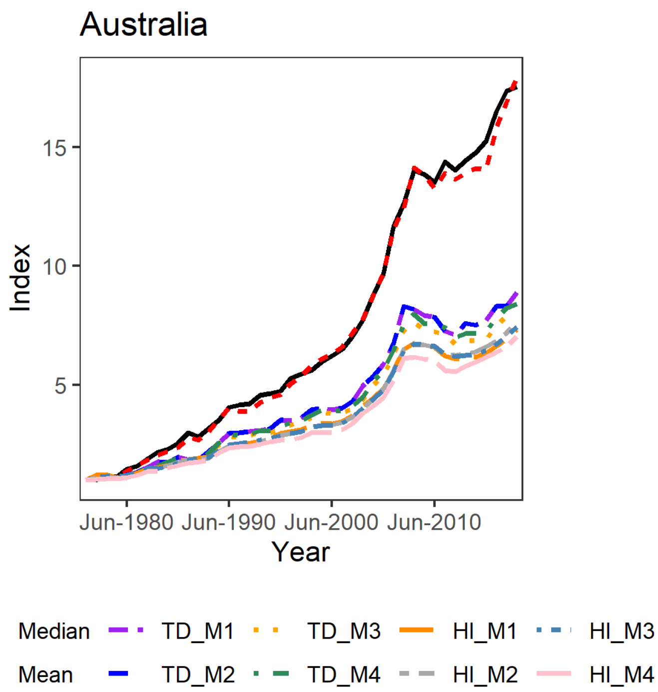
3.6.2 Constant-quality price indexes

Hedonic methods compare 'like with like' to construct a pure price comparison of the same product offered over time. These models are generally used to construct quality-adjusted price indexes to price products (such as residential property), which can differ from one period to the next. The agricultural land market is an extreme example in that every farm is different. The mean and median indexes may not eliminate heterogeneity in agricultural land to a sufficient degree. Therefore, they might suffer from structural shifts and substitution effects leading to, in the case of agricultural land, an upward bias over time.

Figure 3.7 shows the price indexes obtained from all the models as well as the simple median and mean indexes using the sales data. The results of the four hedonic models obtained using the time-dummy method and the hedonic imputation method are almost indistinguishable. This suggests that there is minimal gain from including a geospatial spline in preference to a regional dummy. Nevertheless, more significant variations at the state level are observed, which is discussed in Section 3.6.3.

The constant-quality agricultural land price indexes revised the cumulative price change downwards from 1975 to 2018 by around 140 per cent. This result suggests that the average quality of the agricultural land being sold over time has been increasing. One explanation of why the quality of land has increased over time could be due to more sophisticated land management practices, such as reductions in the intensity of agricultural chemical; more careful use of fertilisers; and more flexible approaches to grazing management to reduce soil erosion. Another reason is the increased investment

Figure 3.7 – **Comparison of Australian land price indexes (1975-76 to 2017-2018)**



Notes: 'TD' refers to the time dummy method; 'HI' refers to the hedonic imputation method; 'M1' refers to model 1; 'M2' refers to model 2; 'M3' refers to model 3; 'M4' refers to model 4.

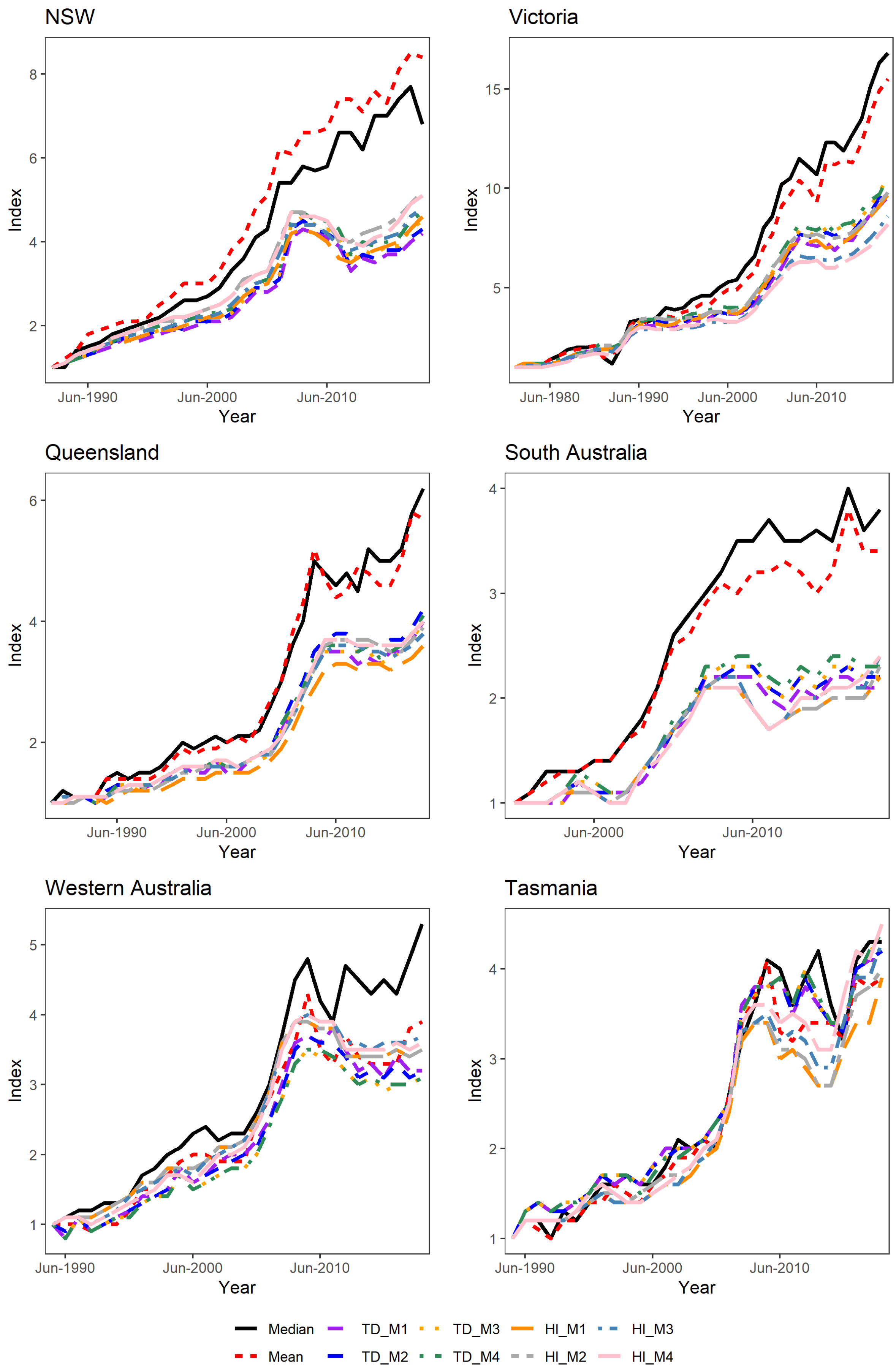
in capital (for example machinery and equipment and agricultural buildings), which over the past 20 years has more than doubled (ABS, 2017a).

3.6.3 State level results

This section presents a summary of results for six states (New South Wales, Victoria, Queensland, South Australia, Western Australia and Tasmania). The growth rates in agricultural land price vary significantly across states. Some of the critical factors include weather patterns and land use, which can also vary over time. Additional results for different states are in Appendices B.3.1 and B.3.2.

Figure 3.8 depicts the cumulative price indexes based on two price-construction methods (time-dummy model and double imputation), four spatial hedonic pricing models for six states, and the mean and median indexes based on sales data. We evaluated the constant-quality price indexes for their overall robustness for different models. Ideally, all price indexes under the four hedonic models should follow a similar pattern so that the selection of the method does not influence the results. Overall, the resulting price indexes for agricultural land are typically increasing, with the price indexes accounting for quality

Figure 3.8 – **Comparison of different methods of price measurement**



being below the mean and median indexes, except for Western Australia.

There are some significant differences across price index construction methods at the state level. For example, the price trends for SA under double imputation differs from the price trends under the time-dummy method. In contrast, both methods of hedonic regression produce similar results for Queensland and Victoria. In the case of Western Australia, the time-dummy model exhibits higher volatility compared with the imputation method. The NSW time-dummy indexes for Model 2 recorded much lower growth patterns compared to other models.

Land price indexes are volatile due to outliers and nonlinear relationships between agricultural land prices and land characteristics. Divergence between the mean and median price indexes for Victoria and the constant-quality price indexes started to increase around 2006, coinciding with the managed investment scheme tree-plantation policy in south-west Victoria's dairy region. The dip in 2012 in Queensland may be due to the suspension of live exports introduced that year.

Table 3.6 displays the percentage difference between the cumulative price indexes of the four models using the time-dummy and imputation method, compared to the sales price mean and median. The results are striking in two respects. First, the constant price indexes derived using the imputation method (on average) discount the price of agricultural land more than under the time-dummy method for the more populous states (New South Wales and Victoria) - the opposite of which occurs for Queensland, South Australia, Western Australia and Tasmania. The gap varies quite substantially by state and by model. One explanation for this finding is that the average locational quality of the agricultural land sold in more populous states such as New South Wales and Victoria is declining over time. Our hedonic models under the imputation-method correct for this quality shift. In contrast, the time-dummy-based indexes do not. Many of the land price drivers identified at the national level are the same at state level. See Appendix B.3 for a more detailed analysis of state level coefficients.

State level model fit

Figure 3.9 shows how the predicted model tracks with the sales data. Each predicted model tracks relatively well when compared to the actual sales price mean and median

Table 3.6 – **Descriptive measures of different index methods by state (% change)**

		Time-dummy method				Double-imputation method			
		M1	M2	M3	M4	M1	M2	M3	M4
NSW	Average	2.6	2.7	2.8	3.1	2.3	2.4	2.4	2.3
	Standard deviation	(1.1)	(1.1)	(1.2)	(1.4)	(1.0)	(1.1)	(1.1)	(1.1)
	Diff. from mean	-44.8	-41.8	-40.4	-30.2	-46.8	-42.1	-43.8	-46.4
	Diff. from median	-49.9	-47.1	-45.9	-36.5	-51.7	-47.4	-49.0	-51.3
Vic	Average	4.0	4.3	4.4	4.6	3.8	4.2	3.8	4.1
	Standard deviation	(2.5)	(2.7)	(2.8)	(2.9)	(2.4)	(2.6)	(2.3)	(2.6)
	Diff. from mean	-44.1	-39.2	-38.0	-34.3	-46.4	-41.8	-47.3	-42.9
	Diff. from median	-39.8	-34.6	-33.4	-29.3	-42.3	-37.4	-43.3	-38.5
Qld	Average	2.0	2.1	2.1	2.1	2.1	2.4	2.2	2.3
	Standard deviation	(1.0)	(1.0)	(1.0)	(1.0)	(1.0)	(1.2)	(1.1)	(1.1)
	Diff. from mean	-50.0	-47.8	-48.9	-49.6	-48.1	-39.2	-45.5	-44.1
	Diff. from median	-53.9	-51.9	-52.8	-53.5	-52.1	-43.9	-49.7	-48.4
SA	Average	1.5	1.5	1.8	1.9	1.5	1.5	1.8	1.5
	Standard deviation	(0.5)	(0.5)	(0.6)	(0.6)	(0.5)	(0.5)	(0.7)	(0.5)
	Diff. from mean	-49.1	-47.6	-34.6	-32.5	-40.5	-47.9	-21.0	-34.9
	Diff. from median	-43.8	-42.2	-27.8	-25.5	-34.4	-42.5	-12.9	-28.3
WA	Average	2.7	2.7	2.7	2.8	2.9	2.9	2.6	2.6
	Standard deviation	(1.1)	(1.2)	(1.2)	(1.3)	(1.5)	(1.5)	(1.1)	(1.1)
	Diff. from mean	-28.9	-27.8	-28.1	-26.0	-16.0	-16.0	-33.0	-33.0
	Diff. from median	-11.5	-10.1	-10.5	-7.9	4.6	4.6	-16.7	-16.7
Tas	Average	2.4	2.3	2.3	2.3	2.4	2.4	2.4	2.3
	Standard deviation	(1.0)	(1.0)	(1.0)	(1.0)	(1.1)	(1.1)	(1.1)	(1.1)
	Diff. from mean	-22.3	-26.9	-28.9	-27.8	-26.3	-26.3	-25.0	-34.8
	Diff. from median	-14.8	-41.2	-52.4	-45.9	-37.5	-37.5	-30.2	-85.8

measures, except for NSW. The indexes compiled using geospatial splines (Models 3 and 4) increase quicker than the indexes calculated without a location indicator in Model 1 and using regional dummies in Model 2. One explanation for this is that a part of the quality shift must be locational.

Table 3.7 shows the R-squared for Model 2. The hedonic time-dummy generally achieved higher R-squared results compared to the average R-squared from the double-imputation method. The differences between methods fall within a relatively small range for most states. The exception is Victoria, where the time-dummy method performs significantly better, with Model 2 recording 72 compared to an average of 0.58 under the double-imputation method. The performance of each method appears to depend on the state. Whereas for Victoria and New South Wales double imputation performs best, in Queensland, Western Australia and Tasmania, the time-dummy appears to perform well.

Figure 3.9 – **Median land price indexes, predicted v. actual (state level)**

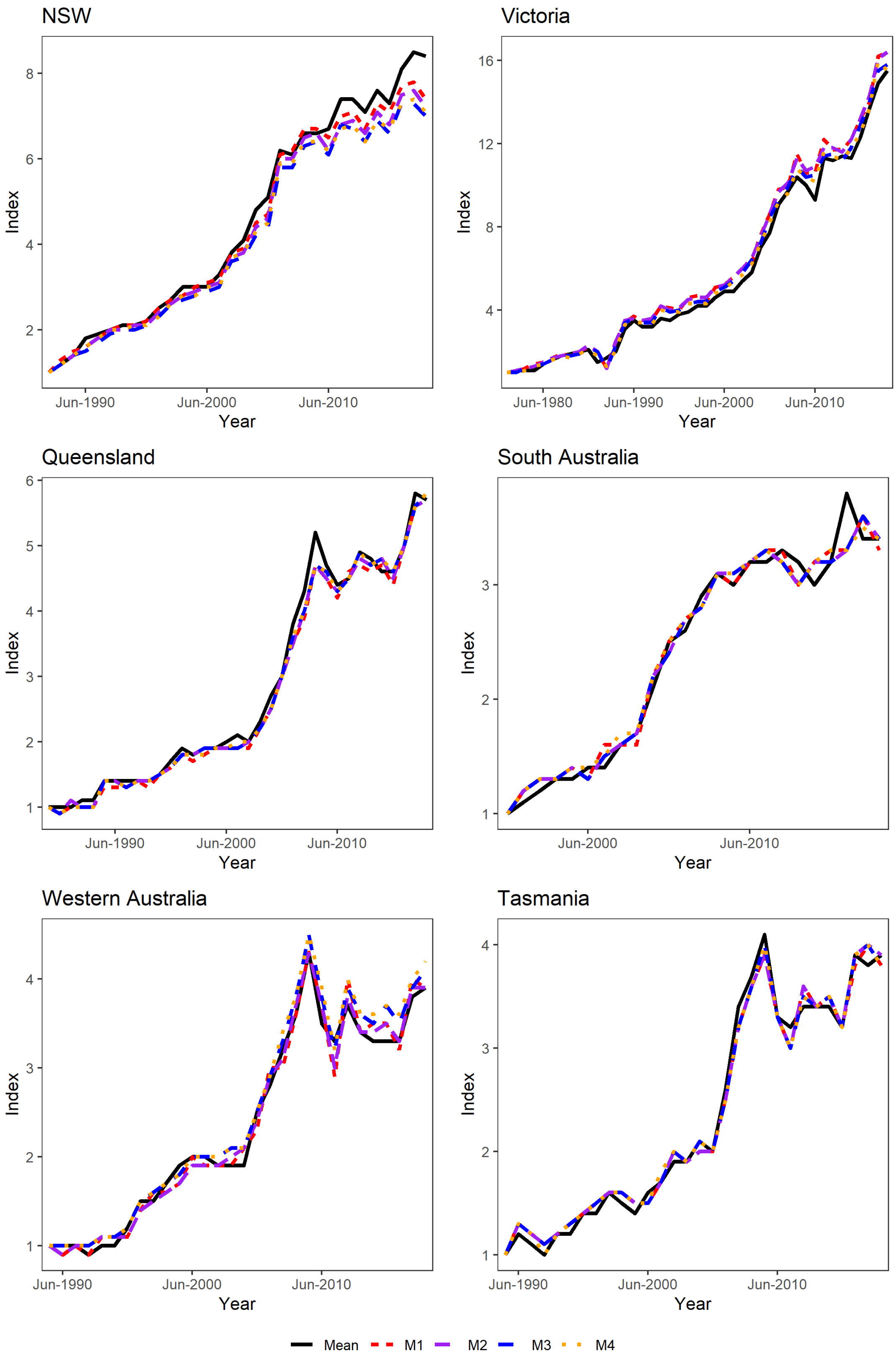


Table 3.7 – ***R*-squared comparison for Model 2 (state level)**

	NSW	Vic	Qld	SA	WA	Tas
Hedonic-imputation	0.59	0.58	0.51	0.69	0.65	0.58
Time-dummy	0.62	0.72	0.64	0.72	0.71	0.69

3.7 Conclusion

This chapter identifies and quantifies the drivers of Australian agricultural land prices. Recent availability of more administrative and spatial datasets on Australian agricultural land offer opportunities and benefits to produce new indicators of agricultural value and the provision of an alternative source of data to produce constant-quality price indexes. For example, geospatial data allows for the use of spatial linkages to integrate sales data with characteristics of a farm. Thus far, there does not seem to be a consensus in the literature outlining how best to apply geospatial data in the farm context.

This chapter presented a selection of spatial hedonic models to measure the variation in agricultural land prices, allowing for great insight into the diverse characteristics that influence land prices. In the models that include a geospatial spline, the locational effect is smoothly estimated over the entire area. Precise modelling of locational effects is needed when there is much variation within regions. We find that location is an important driver of agricultural land prices, and further showed that splines (or some other non-parametric methods) provide a flexible way of incorporating geospatial data into a hedonic model.

This chapter makes two contributions to the area of agricultural land valuations. First, the research advanced our understanding of the fundamental drivers and determinants of agricultural land values by considering new hedonic pricing methods. In general, the results show that the environmental attributes of farm property significantly affect price. More precisely, rainfall, temperature, farm size, land use, land gradient and structures on a farm positively affect agricultural land values. Features, such as distance to the nearest road or town, rainfall and water cover have more nuanced relationships with agricultural land values. As the relationship between land and its determinants are better understood, it may be possible to estimate its values more precisely.

Two methods for constructing constant-quality price indexes are applied to investigate if different methods reveal significantly different growth rates in agricultural land. The results show that the imputation indexes achieve lower standard errors, while the time-dummy indexes achieve higher explanatory power. The imputation approach is more flexible, as coefficients are allow to varying over time. The time-dummy approach becomes impracticable for long periods because of the need to revise the whole time series for every new period added.

The chapter shows the importance of accounting for quality in agricultural land. The constant-quality price index at the Australian level revises downwards the cumulative price change, compared to the median sales price index from 1975 to 2018, by around 140 per cent. Similarly, the constant-quality price index for NSW, Victoria, Queensland and SA revises downwards the cumulative price change between the ranges of 60 per cent to 140 per cent. Interestingly, WA's constant-quality price index has a relatively similar profile to the mean price index. Standard errors across all the models are generally very low, indicating stable results.

The empirical findings of this chapter suggest that when both locational and environmental land attributes are used to explain land prices, one sees a significantly lower growth rate in prices. One interpretation of this result is that the average quality of the agricultural land being sold over time has been increasing. By drawing on data from transaction sales, we have shown that it is possible to compile quality-adjusted price indexes for agricultural land at state levels.

Chapter 4

MFP Growth and the Australian Agriculture Sector

4.1 Introduction

Policymakers have long recognised increasing productivity as an important source of growth in Australia's agriculture sector. Over the past two decades, Australian governments have employed several reforms to encourage market competition, increase farming-related research and development and reduce regulatory burden (Commonwealth of Australia 2015; Gray et al. 2014). While these reforms facilitated structural change, it is not easy to link reforms to productivity growth. Lack of sufficient data is an essential factor. The assessment of land quality is vital for improving and maintaining productivity and economic growth in the agricultural industry. In many countries, including Australia, agricultural land (or 'land') is a significant environmental asset[1] in the national balance sheet. In 2020, land (commercial and rural) represents 91 per cent of the value of Australian environmental assets (or 46 per cent of non-financial assets).

Australian farms may have depleted natural resources; however, environmental costs of loss of land and water quality — and thus, biodiversity — have never been adequately measured (Aplin 2002). Over the long term, agricultural output has risen steadily, while

[1]Environmental assets in the national balance sheet include land, subsoil assets and timber.

short-term changes remain very volatile. The causes of these fluctuations can be linked to demand shocks in international markets and weather conditions. The pattern of output, land prices and productivity is highly correlate to these weather occurrences. Australia experienced prolonged drought in the 1980s and again from 1994–1995, 2002–2003 and 2006–2007. Bushfires in 1983, 2003, 2006 and 2009 affected large areas of agricultural land and caused loss of livestock and infrastructure. In the last decade, two major cyclones have devastated banana and sugarcane crops in Northern Australia. The ensuing 2010 and 2011 floods damaged crops and livestock across Eastern Australia (ABS 2010).

Scientists forecast climate change will affect weather patterns in Australia, with predictions of a wetter and warmer climate in Northern Australia. At the same time, the southern regions will experience drier and warmer temperatures (International Panel on Climate Change 2007). Scientists have also predicted an increase in the frequency and severity of droughts and natural disasters such as cyclones, fires and floods.

Given the importance of farm output for food security, understanding the contribution of land quality in agricultural productivity is an essential public policy issue. The most common measure of productivity is multifactor productivity (MFP), which measures how efficiently farmers produce output based on all their inputs. MFP is derived by an index of output compared with an index of inputs (for example, labour, capital and intermediate use), and land is a factor of production, as it is a crucial asset required to produce farm outputs.

Over the past 20 years, agricultural MFP growth has slowed, declining to 0.9 per cent a year from the late 1990s onwards (ABS 2015; Sheng et al. 2010). The unique characteristics of the agriculture sector warrant careful interpretation of official measures of productivity produced. This is because agricultural activity relies heavily on land size and quality; however, land quality is not accounted for in official productivity measures produced by the Australian Bureau of Statistics (ABS). The ABS MFP measure of the agriculture productivity assumes that the volume of land does not change over time. In other words, land has zero volume growth. This assumption implies that in volume terms, the effects of land degradation, deforestation, reforestation or land improvements and rural–urban rezoning net to zero.

This chapter aims to enhance estimates of productivity in Australia's agriculture sector by accounting for changes in the quality of agricultural land . We apply constant-quality land price indexes which reflect the evolution of the prices of agricultural land with the level of quality being fixed to show the relationship between productivity and land quality. Data from the national accounts and administrative data sources were combined to develop adjusted measures of productivity accounting for land quality. Two adjustments were applied to the agriculture sector MFP and are described in Section **??**. First, the productive capital stock (PKS) of agricultural land is adjusted for changes in quality. Second, the user cost of capital is adjusted by applying constant-quality price indexes for land. These modifications materially affect the rate of growth of land volume and thus, productivity estimates.

Section 4.2 provides previous analyses of Australian agriculture productivity, and Section 4.3 describes the productivity framework. The adjustments used to account for changes in quality to agricultural land are provided in Section 4.4. Section 4.5 evaluates the adjusted productivity performance for Australia and the states, and Section 4.6 concludes the chapter.

4.2 Related Literature

MFP studies can be broadly divided into two categories — those that use firm-level data and those that use national accounts (macro-level) data. The earliest firm-level data study, to the author's knowledge, was conducted by Lawrence and McKay's (1980). They developed an MFP estimate of the Australian sheep industry using data from the Australian Sheep Industry Survey covering the period between 1952–1953 and 1976–1977. MFP growth over this period recorded an average of 2.9 per cent per year, mainly driven by reallocation between labour and capital. Similarly, Knopke (1988) produced MFP estimates of the Australian dairy industry, which showed that average dairy farms' MFP growth between 1967–1968 and 1982–1983 was 1.5 per cent annually, noting that this growth rate varied across regions.

Knopke et al. (1995) and Mullen and Cox (1996) estimated MFP growth for the broadacre agriculture industry using the Australian Agricultural and Grazing Industry Survey data. They showed that average MFP growth was around 2.5 per cent per year between 1952–1953 and 1993–1994. They also noted that agricultural MFP was sensitive to different index-construction methods. Later, Zhao et al. (2012) developed MFP estimates using farm-level data for the Australian broadacre and dairy sectors. Between 1977–1978 and 2010–2011, they showed that the growth rate of broadacre MFP was an average of 1.4 per cent annually.

While firm-level data studies provide deeper insight into the productivity of agriculture subsectors, they are typically limited in scope and coverage. For example, the Australian Bureau of Agricultural and Resources Economics and Science (ABARES) farm survey data has limited industry coverage. It does not include information on the quality of inputs (such as land, capital and labour).

Powell (1974) published the first study that utilised national accounts data to measure Australian agricultural MFP growth. The author constructed output by deflating value added by a producer price index. In contrast, total input was constructed by deflating current price series for capital and labour by appropriate price indexes. Powell (1974) found that Australian agricultural productivity rose by 2.0 per cent a year between 1920–1921 and 1969–1970, predominately due to technological progress.

The Australian Bureau of Statistics (ABS) first attempted to measure agricultural MFP growth using aggregate national accounts data in 2000 and later in 2007. The ABS produced both value-added and gross output MFP measures for the Australian agriculture industries. These series are available for value-added estimates from 1989–1990 and only from 1994–1995 for gross output estimates. The Productivity Commission (2005) subsequently extended ABS estimates to cover the period from 1970–1971 to 2002–2003.

Importantly, agricultural production produces some outputs (such as greenhouse gases and environmental amenities) that are not traded in markets. Such environmental impacts, which are a potential concern for measures of production and productivity more broadly (Feldstein 2017), are not explicitly addressed in either the ABS or ABARES measures of agriculture sector productivity.

4.3 Methodology

4.3.1 MFP framework

Productivity growth is commonly measured as growth in outputs relative to the growth of factor inputs. Typically, growth in outputs can be achieved through supplying more inputs or through increases in the efficiency by which inputs are used to produce outputs. Statistical agencies (including the ABS) generally use the growth-accounting method to measure MFP (Ball, Bureau, Nehring et al. 1997; Economic Research Service 2009; Fuglie & Wang 2012; OECD 2010). The first use of a growth-accounting-based index to compile MFP estimates was by Jorgenson and Griliches (1967).

In the Solow (1957) growth accounting framework, A_t is period t MFP and the growth rate of A_t represents MFP growth. The measure of MFP growth in period t within the above framework is given by Eq. 4.1,

$$MFP_{t,t-1} = \frac{Y_{t,t-1}}{I_{t,t-1}} \tag{4.1}$$

where $Y_{t,t-1}$ is (1 plus) the growth rate of outputs and $I_{t,t-1}$ denotes the growth rate of aggregate inputs, consisting of produced capital and labour. That is, $I_{t,t-1}$ is a weighted combination of the growth rate of aggregate productive capital services ($K_{t,t-1}$) and the growth rate of aggregate labour ($L_{t,t-1}$).

To construct the aggregate inputs growth measure ($I_{t,t-1}$), the growth rate of different inputs must be weighted. According to production theory (under some simplifying assumptions), the weights are factor income (or cost) shares, which are derived using the total input costs. Eq. 4.2 shows the total input costs at time t (X_t),

$$X_t = u_t^K \cdot K_t + w_t \cdot L_t \tag{4.2}$$

where $u_t^K = (u_{1,t}^K, .., u_{j,t}^K, .., u_{J,t}^K)$ denotes the user costs of produced capital, and $w_t = (w_{1,t}, .., w_{h,t}, .., w_{H,t})$ denotes the wage rates of different types of workers. The prices of capital inputs (produced) are represented by user costs,[2] and the cost of inputs is obtained by multiplying the price vectors (u_t^K, w_t) with the corresponding quantity vectors (K_t, L_t). Thus, the factor income (or cost) shares are defined as follows: $S_t^K \equiv u_t^K \cdot K_t/X_t$ for produced capital inputs and $S_t^L \equiv w_t \cdot L_t/X_t$ for labour inputs.

For every period, income (or cost) shares are derived and combined with growth rates of factor inputs to produce the growth rate of aggregate inputs. Specifically, $I_{t,t-1}$ is computed as in Eq. 4.3,

$$I_{t,t-1} = (K_{t,t-1})^{\bar{S}_t^K}(L_{t,t-1})^{\bar{S}_t^L} \tag{4.3}$$

where $\bar{S}_t^K$, and $\bar{S}_t^L$ are the corresponding average of the factor income (or cost) shares in period t and t - 1 of produced capital and labour, respectively. The terms $K_{t,t-1}$ and $L_{t,t-1}$ are the growth rates of aggregate productive capital services and aggregate labour, respectively.

By taking the natural log of Eq. 4.1 and with rearrangement, the contribution of MFP to output growth components that are additive can be measured by Eq. 4.4.

$$\begin{aligned} ln(Y_{t,t-1}) &= ln(MFP_{t,t-1}) + ln(I_{t,t-1}) \\ &= ln(MFP_{t,t-1}) + \bar{S}_t^K ln(K_{t,t-1}) + \bar{S}_t^L ln(L_{t,t-1}) \end{aligned} \tag{4.4}$$

The growth accounting framework, as shown in Eq. 4.4, is used to measure the contribution of input factors to output growth and to estimate the rate of MFP growth indirectly. The rate of output growth is the same as the growth rate of MFP, plus a weighted average of capital and labour growth. The additive nature of this framework enables the role of all inputs and MFP to output growth to be quantified. It supports analysis of the compositional change of the inputs over time due to variations between produced capital and labour inputs.

[2]User costs capture the marginal productivity of each kind of capital service. Since under cost minimisation the marginal productivity of each input factor equals its real input price, user costs can be used as prices of capital inputs.

4.4 Data Construction

4.4.1 Output

The output measure applied was a volume measure of value-added, which is the same as that provided by the ABS (2017a). Volume measures are not sensitive to price and exchange rate changes. A common tool for assessing productivity trends is the value-added MFP measure.[3]

4.4.2 Labour input

The labour input is calculated by using H_t, the indexes of hours worked at time t in the agriculture sector. This index is derived using total hours worked based on the ABS (2017b) Labour Force Survey, as given by $L_{t,t-1} = \frac{H_t}{H_{t-1}}$. The survey derives hours worked by averaging employment and average hours worked. Hours worked is the preferred concept, as it provides a more accurate measure of labour input compared to employment (or wages).

4.4.3 Capital input

Following the ABS (2016b), the produced capital inputs were compiled at the asset-type level. The number of asset types of produced capital used in the production model is denoted by J (indexed $j = 1...J$). The assumption is that the service flow of each type of produced asset ($K_{j,t}$) is proportional to the produced capital stock ($PKS_{j,t}$) is applied. That is, $K_{j,t} = \gamma_t PKS_{j,t}$, where γ_t is the capacity utilisation rate and $PKS_{j,t}$ is the productive capital stock. The capacity utilisation rate is assumed to be constant over time. Thus, for each type of asset, the growth rate of produced capital services equals the growth rate of produced capital stock. The growth rate of PKS for all assets ($K_{t,t-1}$) is calculated as the growth rate of the stock of each produced asset types weighted by their

[3]The ABS value-added MFP measure recognised capital (including land) and labour as inputs into the production process. The MFP measure is derived as a Tornqvist index.

user cost shares. Specifically, $K_{t,t-1}$ is computed using a Törnqvist index (Eq. 4.5),

$$K_{t,t-1} = \prod_{j=1}^{16} \left(\frac{K_{j,t}}{K_{j,t-1}} \right)^{\bar{s}^K_{j,t}} = \prod_{j=1}^{16} \left(\frac{PKS_{j,t}}{PKS_{j,t-1}} \right)^{\bar{s}^K_{j,t}} \tag{4.5}$$

where $\bar{s}^K_{j,t} = \frac{1}{2}\left(\frac{u^K_{j,t}K_{j,t}}{\sum_{j=1}^{16} u^K_{j,t}K_{j,t}} + \frac{u^K_{j,t-1}K_{j,t-1}}{\sum_{j=1}^{16} u^K_{j,t-1}K_{j,t-1}} \right)$ are weights calculated as the two-period average value share of each type of capital services.

Productive capital stock (PKS), $PKS_{j,t}$, is estimated using a perpetual inventory method (PIM)[4] to gross-fixed capital-formation (investment) volumes at the asset-type level, combined with age-efficiency profiles.

The user cost of produced capital, $u^K_{j,t}$, is derived using the end of period traditional user cost approach. We further let $V_{j,t-1}$ and $V_{j,t}$ denote the market value of asset type j at the beginning and end of period t. Also, let $P^K_{j,t}$ denote the ex-ante expected price of one unit of asset type j at the beginning of period t and $S_{j,t}$ the corresponding stock of asset type j so that $V_{j,t} = P^K_{j,t}S_{j,t}$. Thus, it is assumed that in every period, the market values can be disaggregated into their price and quantity components. Now, let the period t expected inflation rate for the price of a unit of asset type j (denoted as $i^K_{j,t}$) be defined as $1 + i^K_{j,t} \equiv \frac{P^K_{j,t}}{P^K_{j,t-1}}$ and the period t depletion rate of asset type j. Applying these to the definition of the end of period t user cost value of asset type j, yields Eq. 4.6.

$$u^K_{j,t} \equiv P^K_{j,t-1}[r - i^K_{j,t} + (1 + i^K_{j,t})\delta^K_{j,t}]S_{j,t-1} \tag{4.6}$$

The user cost method faces several challenges, most notably to form the expected values for $\delta^K_{j,t}$ and $i^K_{j,t}$ in an unambiguous manner, and also the sensitivity of the user cost estimates to the choices of these parameters.[5]

[4]The PIM is used to transform all capital assets of different vintages into equivalent efficiency units, and then add them into an estimate of the productive capital stock. A more detailed description of the capital stock method is provided by the ABS (2016b, Chapter 14).

[5]This is especially important when user cost estimates become negative.

4.4.4 Land input

In the traditional productivity model, land is generally recorded as a non-depreciable asset. Therefore, land capital services is simply a volume measure that is constructed by dividing the nominal value of land by an appropriate price deflator.

Value of land

We used estimates of nominal value of land from the ABS release of the Australian System of National Accounts (ASNA)(ABS 2017a). The definition of land in the ASNA concerns the ground itself, including the soil covering and any associated surface water (UN et al. 2009, para. 10.121). One challenge with this approach is that it is often hard to disentangle the land beneath structures.[6]

The estimates of land in the ASNA is based on data from the Commonwealth Grants Commission, which consists of agreed valuations presented for each state and territory by the respective government's Valuer-General. The estimates represent the approximated site value of land and are separated according to land purpose. The value of land is categorise by use: rural, residential and commercial.[7] It does not include any environmental properties or the monetary value has been assigned to the environmental value over and above the economic value of land.

Constant-quality land price indexes

To account for changes in land quality for effects such as land degradation, deforestation, land improvement and exogenous factors (such as climate and rainfall), a set of constant-quality land price indexes were constructed. Hedonic pricing models enable the price of land to be revalued based on a set of characteristics related to its use for agricultural production and factors such as location (Ball et al. 1997).

[6] For example, see work by Diewert & Shimizu (2013)

[7] The ABS publish annual data on quantities and values of the stocks of key natural resources. For further information, see the National Balance Sheets for Australia: Issues and Experimental Estimates, 1989 to 1992 (Cat. No. 5241.0).

The literature does not state a set functional form for the hedonic equation, which is generally determined empirically. The semi-logarithmic functional form seems to be adequate.[8]. Here, the model is an ordinary least squares model that contains the locational variable defined by the ABS statistical area code. The spatial hedonic model[9] can be expressed as Eq. 4.7,

$$y = \alpha + X\beta + D\gamma + \epsilon \tag{4.7}$$

where y is a F x 1 vector of log-price, X is a F x B matrix of land characteristics, D is a F x $(C-1)$ matrix of time (period) dummy variables and ϵ is a random error term. The parameters to be derived are B x 1 vector of characteristic shadow prices, β, and $(C-1)$ x 1 vector of time (period) dummy shadow prices, γ.

Common concerns with these hedonic models are multicollinearity, heteroskedasticity and omitted variables bias. De Haan (2016) has shown that multicollinearity is not a big issue when estimating time-dummy indexes, as the interest is in the predicted prices rather than the estimated characteristics parameters. The omitted variables in hedonic regressions can lead to bias in the resulting price indexes.

The dependent variables included in the model are the same as those shown in Table 3.2 for Model 2. Some aspects of land degradation[10] are captured through sufficient differentiation of the land characteristics.

This study used a unique dataset containing a census of farm-level sales records for Australian constant-quality spatial hedonic pricing indexes. Land price data was sourced from sales data compiled by CoreLogic. Geospatial mapping undertaken by ABARES, was based on location coordinates and used to overlay environmental attributes of the land.

[8]See Hardle et al. (2004) for an overview of semi-parametric models, their properties and estimation.

[9]The model using a simple regional indicator was selected, as the results in Chapter 3 show that while location is an essential driver of agricultural land values, a suitable regional indicator over geospatial splines is just as valid.

[10]Degradation 'considers changes in the capacity of environmental assets to deliver a broad range of ecosystem services ... and the extent to which this capacity may be reduced through the action of economic units' (UN et al. 2014, para. 5.90). Thus, degradation is a broader concept than depletion, and is more complicated to measure. See Appendix C.1.

Land Volume

The volume measure of land applied by in ABS MFP estimates is constant over time, that is, land has zero volume growth. This assumption implies that in volume terms, the effects of land degradation, deforestation, reforestation or land improvements and rural–urban rezoning net to zero. A question that arises is the sensibility of maintaining no volume change. While the land area in hectares of a country changes minimally over time, land volume can vary due to quality changes from natural processes or economic activity. A volume measure reveals 'changes in the quantities of a specified set of goods or services between two periods of time'. Volume measures differ from a strictly physical quantity in that they are 'adjusted to reflect changes in quality' (UN et al. 2009, para. 15.13).

In economic analysis, physically identical products are considered to be of differing quality if they are present in different locations or time periods. Thus, an asset, such as land, could experience quality changes without undergoing physical improvements (such as roads and utilities). According to the 2008 SNA:

> It is generally assumed in economic analysis that whenever a difference in price is found between two goods and services that appear to be physically identical there must be some other factor, such as location, timing or conditions of sale, that is introducing a difference in quality (UN et al. 2009, para. 15.67).

A good example is the event of agricultural land being rezoned to urban land could be considered a change in the quality and, consequently, a change in the volume of agricultural land. This quality change is likely embodied in the value of the land.

In this study, the volume measure of land is constructed by dividing the nominal value of land by the constant-quality price index.

Land capital services

Land capital services is derived as the productive land stock multiplied by a rental price (or user cost of natural capital). The land stock is defined as the volume of agricultural land operated by a farmer.

Let j represent land, the nominal rate of return $r_{j,t}$ equals the ABS endogenous rate of return for the agriculture sector. The nominal rate of return embodies the expected rate of return within an industry. The ABS calculates an 'endogenous' rate of return, which assumes that the return of capital services exhausted gross operating surplus (GOS). Also similar to the ABS model, the rate of economic depreciation $\delta^K_{j,t}$ is 0. One differentiation is that a constant-quality price index replaces price change P^K_t. Importantly, these price changes are used to represent the capital gains $\tau^K_{j,t}$ where $\tau^K_{j,t} \equiv P^K_{j,t} - P^K_{j,t-1} = i^K_{j,t} P^K_{j,t-1}$. Without depreciation (that is $\delta = 0$) this user cost equation implies that the owner of the capital has paid a 'rental price' that comprises an expected rate of return and any capital gains attributable to capital.

4.4.5 Agricultural MFP by State

The method used to produce state agricultural MFP aligns with the ABS methodology. State GVA and capital stock are sourced from ABS State Accounts (ABS 2019), and labour inputs were sourced from the ABS (2017b) quarterly Labour Force Survey. One key challenge of producing state dimension MFP is the availability of appropriate data at this level. To overcome this challenge the following assumptions were adopted:[11]

- Stock of inventories is allocated to states using state current price GVA proportions.
- State gross-mixed income is estimated using this income proportion in GOS and mixed income at the national level.
- State capital stock utilises the same price deflators, mean asset lives, retirement distributions, age-efficiency functions and age-price functions as those used for national-level capital stock. The exception is land, where constant-quality price indexes by state were applied.
- Rental prices by state and by sector adopt the national industry asset rental prices, with the exception of land. This method assumes there is no variation in rental price between states for all assets excluding land. For example, the rental price of machinery and equipment is assumed to be the same across all states and territories.

[11] While these assumptions are not ideal, in practice, the difficulty around data availability made them necessary. The ABS (2018) have tested the robustness of state MFP estimates to these assumptions. They found that, in general, state MFP was relatively robust to the various choices.

While this assumption does not account for variations in rental prices between states, variations in rental prices between industries are captured.

4.5 Results

This section presents the estimates of agricultural sector productivity adjusted for land quality. In producing the productivity estimates, we followed the same methodology as the ABS - but this was modified when estimating productive capital stock and the rental price for agricultural land. The modification, which utilised constant-quality price indexes, allows for consideration of land quality.

4.5.1 Land capital services

The proportions in which businesses combine the various forms of capital (both natural and produced) imply some capital structure, resulting from the specific investment mix. While the investment mix and capital structure are likely to vary between individual farms, it is useful to compare the overall levels of productive capital stock. Of particular interest is the contribution of land capital services, which remained constant over the period according to the ABS.

Table 4.1 shows the contribution of PKS assets to the agriculture sector. The flat trend in the volume index of land is immediately visible. Despite the ongoing and intensive use of agricultural land, the overall volume has not changed. The ABS measure does not convey a plausible picture of land volume and does not account for any changes in quality. When the quality of land is considered, the average annual growth of land PKS is 4.5 per cent compared to the no-growth assumption. Linked to an earlier discussion on the choice of prices, it is highly likely that there is a difference in price for different production purposes. Therefore, different types of land use should be treated as separate assets with varying prices of land. Further, if price divergence reflects land-use potential, it may also be relevant to capture zoning developments.

Two elements influence the contribution of an asset to the overall index: First is the asset share, and second is the rate by which the assets grow or deplete. Figure 4.1

Table 4.1 – **Productive capital stock (asset level)**

	Share of PKS		Average growth per
	1995-1996	**2017-2018**	**year, (%)**
Computer software	0.0	0.0	2.0
Inventories (farm)	0.9	1.6	2.7
Land	**77.0**	**73.0**	**0.0**
Livestock	5.9	2.4	-3.5
Orchards, plantations and vineyards	0.9	1.8	3.3
Computers	0.0	0.0	16.9
Electrical and electronic equipment	0.1	0.3	6.4
Industrial machinery and equipment	3.4	4.9	1.8
Research and development	0.0	0.2	8.1
Road vehicles	1.8	2.9	2.3
Other transport equipment	0.1	0.2	3.0
Other plant and equipment	0.5	0.8	2.6
Non-dwelling construction	8.5	11.3	1.4
Ownership transfer costs	0.9	0.6	-1.7
Land - adjusted for quality$^{(1)}$	**54.6**	**73.0**	**4.5**

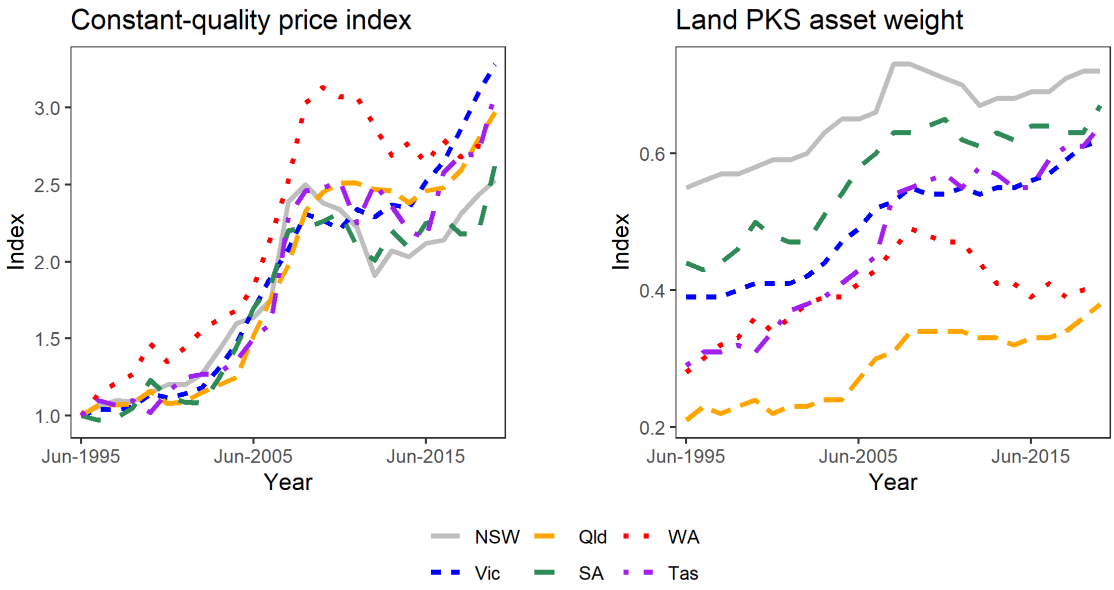
Source: ABS Estimates of Industry Multifactor Productivity (2020) and author's estimate
Note: (1) This is the land productive capital stock measure which has been adjusted using constant-quality land indexes.

shows constant-quality price indexes and the high-level asset weights for land within the agriculture sector by state. The effect of the constant-quality land price indexes is reflected in the weight assigned to land. The asset weights highlight the implausibility that the largest asset of a farm provides zero capital services to the production process over time. Some factors that have driven the increase in land values over the last decade include a rise in operating profits from farmers and a continuing demand for agricultural land expansion. Macro-economic factors like a falling Australian dollar and RBA cash rates at low levels have encouraged agricultural land purchases and improved export competitiveness (Lefroy 2019). Commodities such as wool, beef and sheep have been trading at highly profitable prices, which directly link into operating profits (Cunningham & Smith 2019).

4.5.2 Agricultural MFP

Productivity is an important measure of Australian agricultural performance. Growth in the ratio of outputs produced to inputs used translates to improved profitability and competitiveness for farmers. Previous Australian studies have concluded that productivity growth contributed to over two-thirds of the growth in farm output with most of the growth in farm profits being recorded over the postwar period (Mullen 2010; Productivity

Figure 4.1 – **State level constant-quality price indexes and land PKS asset weight**



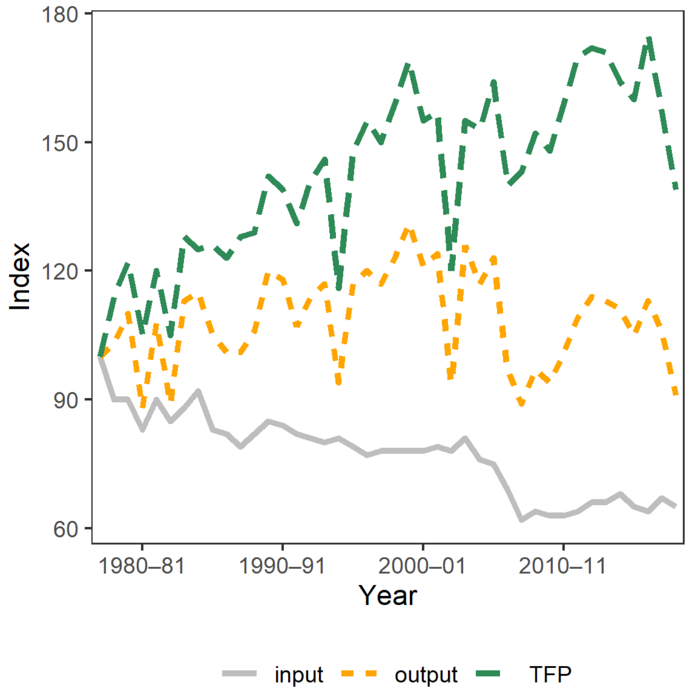
Commission 2011). Since the late 1970s, there has been a noticeable reduction in public investment in agricultural R&D (Sheng et al. 2010). Another contributing factor could be that technology advances and market reforms in the 1980s and 1990s have produced productivity gains that are not currently being replicated.

Figure 4.2 shows the annual growth in MFP and input and output growth over the period 1977–1978 to 2017–2018. The average annual MFP growth over this period was 1.0 per cent. Throughout the 1990s, strong growth in outputs led to higher demand for inputs. As a consequence, in that decade, gross input grew at 1.5 per cent annually. From the early 2000s onwards, growth in input prices led to declining input use (at –0.8 per cent a year) resulting in a compositional shift in the inputs over time.

Using the national accounts data and other data sources, we analysed agriculture productivity from 1994–1995 to 2017–2018 and adjusted MFP by using a measure of land quality, as described in Section 4.3.

Figure 4.3 compares the official ABS agricultural MFP to two measure of adjusted MFP. The first measure is adjusted MFP using simple median price indexes (not adjusted for quality). The second measure is adjusted MFP using constant-quality price indexes. In addition, the second measure of adjusted MFP is calculated using a 'top-down' method as well as a 'bottom-up' method. In the top-down method, the constant-quality land index was derived at the national level. Notably, a characteristic

Figure 4.2 – **MFP for broadacre industries**



Source: ABARES Australian Agricultural Productivity (ABARES 2021)

of the national level constant-quality land index is that it exhibits less volatility than state level constant-quality land indexes. One reason for this is that the output of the agricultural industry is highly affected by the weather, in the same period one state's agricultural industry could be affected by drought, while other state could be experiencing bumper crops. At the national level, the growth in the constant-quality price index is more stable from year to year.

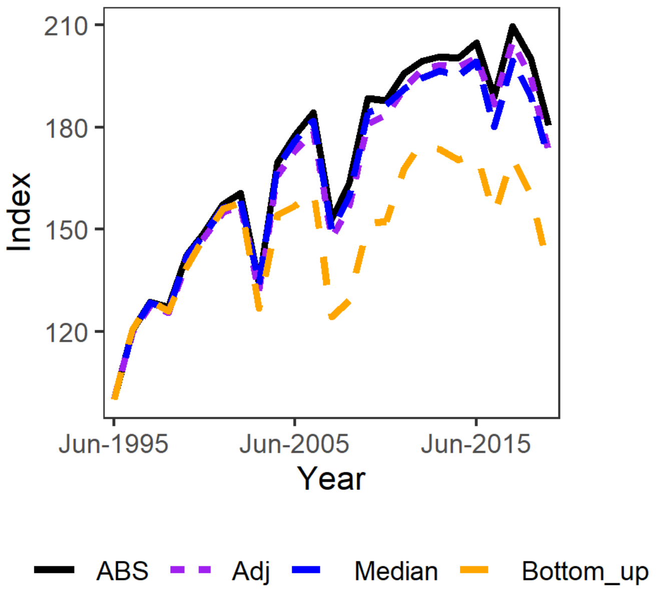
The bottom-up series is constructed, using the domar aggregation approach. This approach constructs the growth rate of an aggregated Australian MFP, as a weighted average of the growth rates of the state level MFP.[12] The weights for each state when adding their MFPs together is the ratio of the real value of each state's output (gross value added) to the total Australian output. The reason why the bottom-up series differ significantly from the Adjusted and Median MFP series is due to the extreme volatility of the state constant-quality land price indexes compared the national aggregate constant quality land price index.

Figure 4.3 shows that agricultural MFP in Australia grew on average by 2.0 per cent a

[12] To aggregate to national level unadjusted agricultural MFP for Australian Capital Territory and the Northern Territory were included

year between 1998–1999 and 2017–2018. Productivity growth in this sector has mainly been due to technological progress and changes in the mix of outputs and inputs of farms and resource reallocation. Agricultural productivity is sensitive to the effects of climate, with productivity falling in both 2016–2017 and 2017–2018 primarily due to widespread drought across much of eastern Australia. The fall in unadjusted MFP from 2000–2001 to 2010–2011 was 0.3 per cent. MFP growth fell further between 1999–2000 and 2009–2010 with a rebound between 2010–2011 and 2013–2014. The slowdown in productivity during these periods and in recent years is mainly attributed to severe drought.

Figure 4.3 – **Australian agricultural MFP comparison**



Source: ABS Estimates of Multifactor Productivity (ABS 2020) and author's estimates

The unadjusted MFP for Australia grew at a rate of 0.2 per cent a year over the same period. While the effect at the national level based on the top-down approach is small, as shown in Figure 4.3, the result using the bottom-up approach is more dramatic. Adjusted agricultural MFP under the bottom-up approach is 1.3 percentage points lower on average over the period.

Table 4.2 displays the contribution of agricultural GVA to the total state GVA. Strikingly, the agriculture sector, while only contributing 1.8 per cent to total GVA in New South Wales, contributed around 11.3 per cent in Tasmania and 5.8 per cent in South Australia.

Figures 4.4 and 4.5 compare the MFP for the agriculture sector at the state level. There were some significant differences between states for the adjusted agricultural MFP at state level when land price is measured using the median price indexes. Interestingly,

Table 4.2 – **Percentage contribution of sector GVA (chain volume measure) by state, 2018-2019**

	NSW	**Vic**	**Qld**	**SA**	WA	Tas
Agriculture, forestry and fishing	1.79	2.14	2.76	5.78	2.55	11.25
Mining	3.62	1.38	14.09	3.55	35.92	4.07
Manufacturing	6.11	8.07	6.81	7.18	5.49	6.99
Electricity, gas, water and waste services	2.43	3.26	3.60	4.34	1.94	3.62
Construction	8.82	9.18	8.64	8.48	7.04	7.79
Wholesale trade	4.79	5.05	4.12	5.19	3.66	3.49
Retail trade	4.99	5.60	4.88	5.74	3.44	5.32
Accommodation and food services	3.05	2.38	3.01	2.94	1.86	2.95
Transport, postal and warehousing	5.79	5.39	5.91	4.72	4.46	4.63
Information media and telecommunications	3.80	3.58	1.63	2.46	1.20	4.07
Financial and insurance services	14.13	12.61	6.92	8.98	4.92	6.56
Rental, hiring and real estate services	4.58	3.35	3.29	2.82	2.19	2.06
Professional, scientific and technical services	9.97	9.19	6.65	5.85	5.90	3.47
Administrative and support services	4.80	4.50	3.94	3.29	2.48	2.09
Public administration and safety	5.34	5.30	6.05	6.55	4.41	6.68
Education and training	5.43	6.16	5.62	6.92	3.97	7.23
Health care and social assistance	7.50	9.44	8.83	11.86	6.18	14.53
Arts and recreation services	0.99	1.34	0.91	0.76	0.56	1.28
Other services	2.09	2.09	2.34	2.57	1.84	1.92

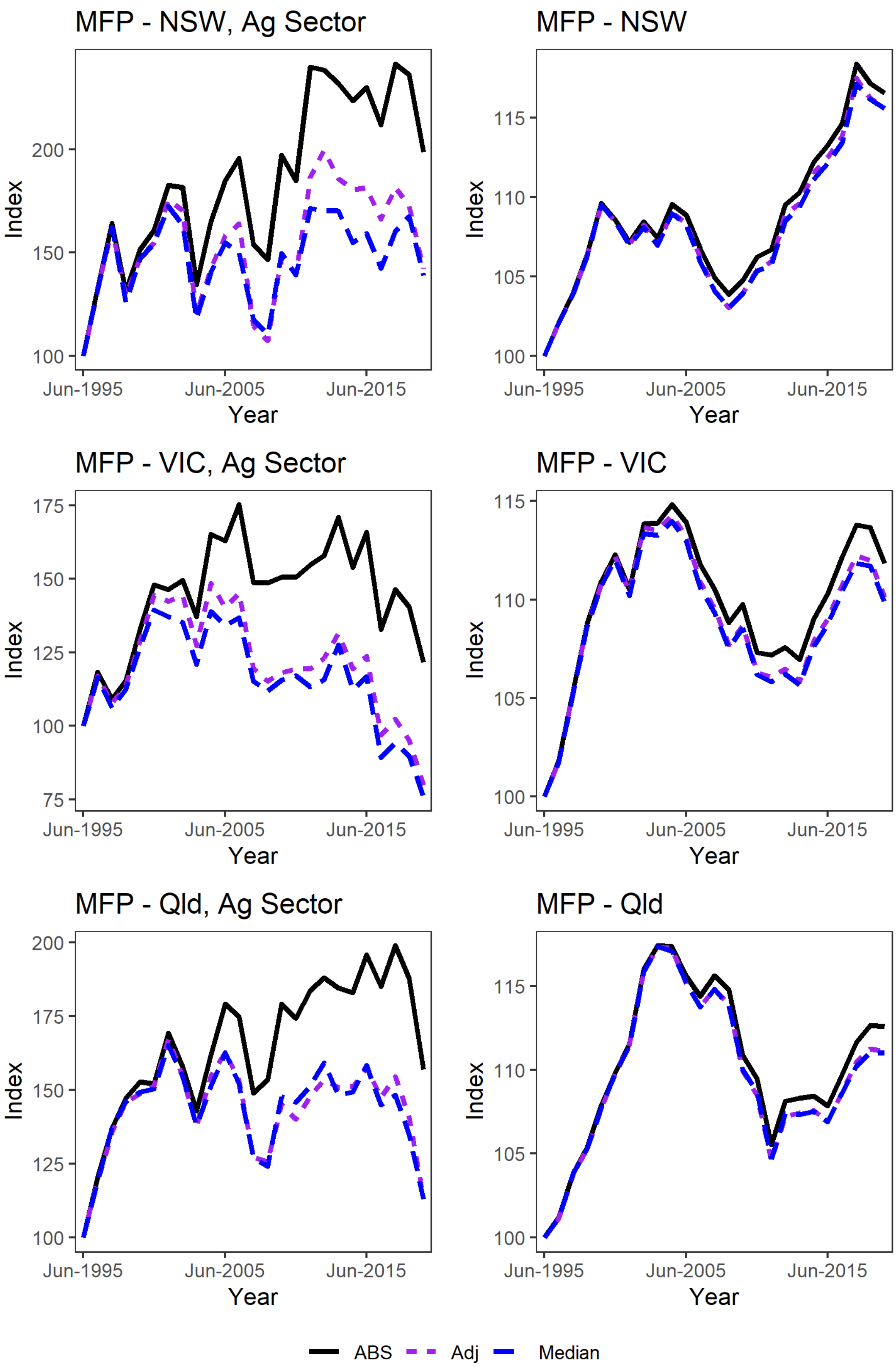
Source: ABS, Australian National Accounts: State Accounts, 2018-2019 (ABS 2018)

the adjusted productivity profile that included the constant-quality price indexes is not significantly different for most states, except for South Australia and New South Wales. This highlights that the assumption of zero volume growth in the ABS method is flawed and can present a misleading view of agricultural productivity. This is particularly pronounced for Tasmania and South Australia, where the value-added contribution of agriculture in those states is much higher.

Tasmania recorded the highest annual growth rate in MFP of 4.9 per cent and Victoria recorded the second highest of 4.1 per cent annually. Victoria's record growth rates were driven by family farm consolidation and corporate entry, particularly in the western region. In northern Victoria, numerous family operations continue to seek land for expansion, while in north central Victoria lifestyle influence is adding to demand (Rural Bank 2016). In contrast, the annual growth rate over the last decade in Western Australia was only 0.7 per cent and Queensland even lower at 0.3 per cent. Part of this difference was due to the 'intensity of production', being in drier regions. There seems to be a premium on agricultural land that experiences steady rainfall.

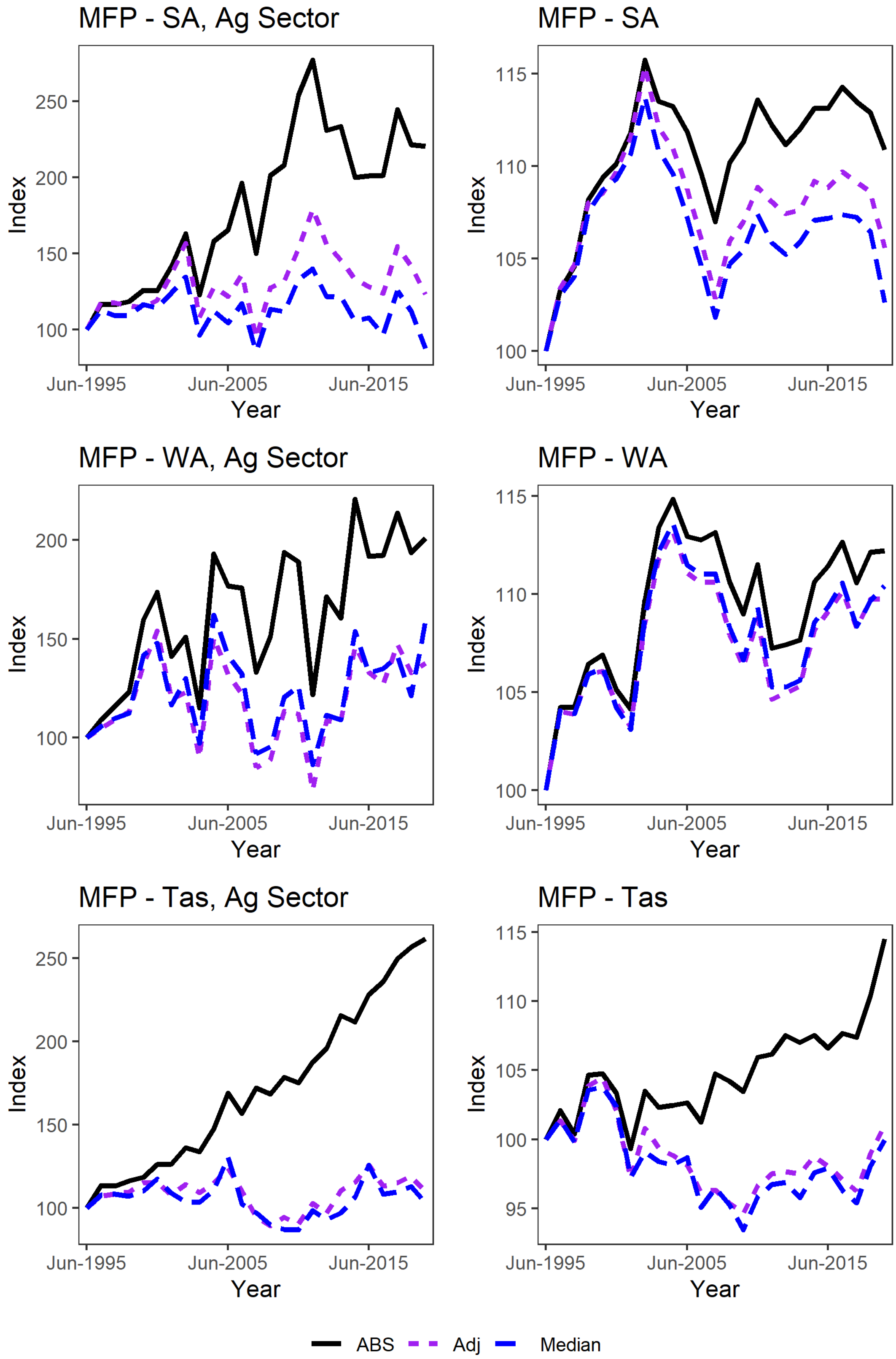
When a constant-quality price index measure was applied, the effect on the state

Figure 4.4 – **State level MFP comparison (NSW, Victoria and Queensland)**



Note: The 'ABS' agricultural state level MFP estimates are based on ABS estimates of Industry MFP (ABS 2018) and author's calculations.

Figure 4.5 – **State level MFP comparison (SA, WA and Tasmania)**



Note: The 'ABS' agricultural state level MFP estimates are based on ABS estimates of Industry MFP (ABS 2018) and author's calculations.

agricultural sector can be observed with a downward adjustment to MFP, particularly from around 2006 onwards. The smaller weight on land at the start of the series is distributed across other asset types, as the weights sum to unity. Assets with higher rental prices have a more substantial influence on the estimates. At the state level, the impact is substantial, lowering agricultural MFP growth by between 1.2 to 3.6 percentage points per year.

4.6 Conclusion

This chapter used the value-added model to estimate aggregate output, input and MFP for Australia's agriculture sector. Several key messages emerged from this chapter. First, the measurement of land values can be improved at the national level by accounting for changes in land quality. Second, it is feasible to construct standard volume and price indexes using spatial hedonic pricing models. These price indexes can be used to extend official estimates of MFP to factor in the contribution of agricultural land. In volume terms for land, this will equal the current price of land divided by an appropriate constant-quality deflator. Third, the chapter showed that it is straightforward to include constant-quality price indexes in measures of the capital services of agricultural land.

The choice of price deflator used to derive a volume measure, and the user cost of land can have a marked effect on the resulting productivity picture of the agriculture sector. An analysis of the various land price deflator options indicates that applying constant-quality price indexes provides more plausible estimates in the Australian context. The adjusted agricultural sector productivity estimates give a better representation of the underlying sustainability of current productivity growth, as factors such as land degradation are included. The price of land should reflect all the attributes unique to the property. Thus, they provide a more realistic representation of changes in the agriculture sector's production functions.

The literature shows that agricultural MFP growth has slowed over the past decade (Sheng et al. 2010). When land quality is accounted for, this slowdown is more pronounced. The adjustment to aggregate productivity growth for Australia's agriculture sector between 1995–96 and 2017–18 is relatively large, potentially detracting from growth by 1.3 percentage points per year. The impact is more significant at the state level, lowering growth by between 1.2 and 3.6 percentage points per year.

Although the estimates presented in this chapter have been derived using the best available methods, some limitations should be noted. In particular, the absence of some necessary data prevents significant adjustments for differences in the quality of some intermediate inputs such as crop chemicals, medicines and seed. In general, this limitation will tend to bias estimates of productivity upwards.

Chapter 5

Conclusions

5.1 Research Questions

This thesis responds to the following research questions: *How to account for natural capital depletion? Will a failure to account for this depletion be a risk to the future wellbeing (increase in material standards of living) of Australians?* To answer these questions, this thesis explicitly values natural capital, and its service flows in the context of productivity analysis. The secondary research questions are: *What are the economic consequences of the extraction and depletion of subsoil assets on potential productivity growth for the Australian mining sector? What are the effects on productivity of the Australian agricultural sector over time from accounting for the land quality?* The common thread running through these research questions is how to include natural capital in economic measures of productivity.

5.2 Contributions

This thesis responds to several fundamental measurement issues which arise when valuing natural capital services for the explicit inclusion of natural resources in productivity measures. In doing so, this thesis reduces the indivisibility between the economy and natural capital, by better accounting for the connection between them. These enhanced productivity measures are of particular interest to economists and policymakers because of their implications for improved living standards and long-term economic growth. For example, productivity growth plays a crucial role in maintaining both international competitiveness in an environment of climate variability and constraints on the use of natural capital. The key contributions of this thesis are summarised as follows:

Chapter 2 advances measurement frameworks for natural capital to support economic-environment accounting and productivity. It is the first study to compare the application of three different methods for estimating natural capital user cost values in the context of productivity analysis, hence providing insight into each method's plausibility and the issues involved in their implementation. The first is the unit resource rent method suggested by Brandt et al. (2017). The second is the residual value method recommended by SEEA 2012 (UN et al. 2014a). Diewert and Fox (2016a) proposed the third method.

Comparison of the methods reveals that user cost values derived from the unit resource rent method are rarely negative, are less volatile and provide a more realistic representation of production functions over time. The residual value method produced implausible estimates for natural capital with often repeated 0 values, and the estimates of the traditional user costs method were sensitive to the choice of parameters. Overall, the unit resource rent method seemed to outperform the other two techniques. The results also showed that while the different approaches yielded different MFP estimates, the most influential adjustment to traditional productivity measures was the inclusion of natural capital. This generated substantial productivity gains for the Australian mining sector, where natural capital added at least 1.0 per cent growth to annual productivity between 1995–1996 and 2015–2016.

Chapter 3 calculates the contributions of spatial and environmental attributes to rural land values using a real estate sales record. The chapter, inspired by Hill and Scholz (2017), directly applies spatial coordinate information to allow more flexible modelling of location parameters using spline functions. These spatial hedonic models were estimated over time and at both national and regional levels. The main contribution is to provide, for the first time, a dynamic portrait of the past 40 years of Australian agricultural land values accounting for land quality. In addition, it explores the appropriateness of using a time-dummy method or a hedonic imputation method as the index-construction method for agricultural land. Both methods correct price changes for differing land quality and allow the indexes to account for unmatched farms between consecutive periods. While results were generally insensitive across hedonic models and index-construction methods, a few clear findings emerged following analysis. Accounting for land quality revises the cumulative price change of agricultural land in Australia, downwards by around 140 per cent over the selected study period. These results highlight the importance of using semi-parametric regression models, as many covariates interact with land prices in a non-linear way. By explicitly modelling and presenting the spatial results visually, the chapter also provides insight into the spatial structure of Australian agricultural land values.

Chapter 4 highlights the importance of accounting for land quality in order to improve and maintain the productivity of Australia's agriculture industries. Official ABS state level MFP estimates for the agricultural sector were adjusted to account for changes in land stock due to shifts in quality. The significance of this study lies in the novelty of explicitly including quality-adjusted land price indexes in Australian productivity estimates, not only at the national level but also at the state level. The results show that the adjustment to aggregate productivity growth for Australia's agriculture sector between 1995–1996 and 2017–2018 is relatively large, reducing growth by 1.3 percentage points per year. The impact is more significant at the state level, lowering growth by between 1.2 to 3.6 percentage points per year. Overall, the results support policy interventions to raise productivity growth in the agricultural sector, focusing on the appropriate incentives for land management practices, given that lower-quality land reduces productivity growth.

In summary, the thesis highlights that it is undoubtedly possible for productivity growth to improve the efficiency of natural capital. However, increases in economic growth would likely lead to overall increases in the use of natural capital. In turn, this affects the natural environment and the long-term capacity of the economy, which relies in many ways on the use of natural capital.

The research presented in this chapter provides an original analysis of how adjusted productivity measures can be of use to policymakers - distinct from information already provided from economic estimates such as GDP and environmental accounts. These additional measures provide information on the unmeasured effects of changing quantities and qualities of natural capital. Thus, the outcomes may be used to improve decision-making in several ways, including a broader public policy agenda item used by the government to target more efficient uses of natural capital in Australia.

The thesis also informs policymakers on fundamental issues such as changes in intergenerational equity and income distributions resulting from potentially irreversible environmental change. Unsustainable developments have the potential to affect long-term economic outcomes and can lead to inaccurate national budget forecasts, as well as inappropriate industry support and taxation policies.

5.3 Recommendations for Future Research

Chapter 2 developed valuation techniques for non-renewable resources required for national accounting and compared different user cost approaches for considering subsoil assets in productivity statistics of the mining sector. An extension of this work is to apply the techniques to other sectors and a broader class of environmental assets, such as renewable resources and ecosystem services. This would allow for estimates of depletion for a range of renewable resources that conform for inclusion in a traditional user cost framework. While estimates for a range of these resources exist, there remain numerous issues of practical concerns. For example, measuring the depletion of renewable resources (such as fish stocks) relies on bio-economic modelling, but accounting for intertemporal stock changes would require further research.

Another area for future research is to develop analytical frameworks that extend the System of Economic and Environmental Accounts Central Framework for valuing renewable resources and their depletion. Given the importance of renewable resources such as forests for biodiversity, climate stability and soil integrity, the social value of living trees should be much higher than the market price of the produced wood. Hence, accounting for the contribution of renewable resources to economic growth is associated with significant uncertainties, such as lack of appropriate data and difficulties in setting the price of wood. The prices in the user cost model from logging, for example, do not reflect the total social cost of using renewable resources or its depletion profile.

A potential extension of Chapter 3 would be to include the exploration of other non-parametric hedonic models. Obtaining sufficiently detailed data to explain individual property values is very challenging, and there could be omitted variable bias. Thus, additional farm characteristics from other survey data or taxation data could make the analysis more robust. Further linking of spatial administration datasets, for example, linking land sales' data with the Australian Bureau of Agricultural and Resources Economics and Science (ABARES) farm survey and CSIRO Soil and Landscape Grid of Australia, may yield different interpretations of the constituent components. It would also be helpful to extend research on the relationship between land values and alternative uses of land. This is because the Australian agricultural land market is not transparent, and information about the market is often difficult to obtain. Another extension would be to incorporate essential ecosystem services relevant to agriculture such as soil nutrients, water and grass for livestock, and pollination to develop a complete productivity model to understand agricultural production sources better. To conclude, the exclusion of natural capital in productivity measures is an enduring measurement gap that needs to be addressed. Research to date, including the results from this thesis, strongly suggests that failure to account for the depletion of natural capital distorts productivity estimates as measured under the traditional growth accounting framework. The increasing availability of administrative spatial data on natural capital will provide an essential tool for researchers and statisticians to resolve (or come to a consensus) how best to measure and account for the price and quantity of natural capital in productivity analysis.

Appendix A

Appendix for Chapter 2

A.1 Endogenous Rates of Return

The user cost of capital could be considered as a market rental price for the asset. As the capital rental markets are almost non-existent, the user cost is most commonly approximated as an implicit rent that owners of capital are considered to be charging themselves. For a given industry, the ABS (2016b) use the following unit user cost (Eq. A.1) for the produced capital of asset j in period t:

$$u_{j,t}^{K} = \eta_{j,t}(r_t P_{j,t-1}^{K} + \delta_{j,t}^{K} P_{j,t}^{K} - \tau_{j,t}^{K}) + \mu_t P_{j,t-1}^{K} \tag{A.1}$$

where $\eta_{j,t}$ is the income tax parameter of asset j, r_t is the nominal rate of return, $P_{j,t-1}^{K}$ is the price of capital asset j at the beginning of period t, $\delta_{j,t}^{K}$ is the economic depreciation rate of asset j, $P_{j,t}^{K}$ is the price of capital asset j at the end of period t, $\tau_{j,t}^{K}$ is the capital gain effect due to the revaluation of asset j and μ_t is the average non-income tax rate on production. The nominal rate of return, in Eq. A.1, r_t represents the rate of return that is expected within a given industry. An endogenous rate of return is derived for all assets in a given industry by equating the entire gross operating surplus (GOS) of the given industry, GOS_t, to the rental price (unit user cost), multiplied by the quantity of produced capital services used in production, $K_{j,t}$. This is expressed in Eq. A.2,

$$GOS_t = \sum_j u^K_{j,t} K_{j,t} \tag{A.2}$$

Substituting Eq. A.1 in Eq. A.2 and rearranging to solve for the rate of return gives Eq. A.3.

$$r_t = \frac{GOS_t - \sum_j K_{j,t}(\eta_{j,t}(\delta^K_{j,t} P^K_{j,t} - \tau^K_{j,t}) + \mu_t P^K_{j,t-1})}{\sum_j K_{j,t} \eta_{j,t} P^K_{j,t-1}} \tag{A.3}$$

When natural capital is included, it is assumed that Eq. A.4 holds.

$$GOS_t = \sum_j u^K_{j,t} K_{j,t} + \sum_m UCV^N_{m,t} \tag{A.4}$$

where $UCV^N_{m,t}$ is the end of period t user cost value of asset type m of natural capital. To solve for the rate of return, the user cost value derived by the traditional user cost method (Diewert and Fox 2016a) is used. This is expressed as Eq. A.5.

$$\begin{aligned} UCV^N_{m,t} &= P^N_{m,t-1}[r - i^N_{m,t} + (1 + i^N_{m,t})\delta^N_{m,t}] NCS_{m,t-1} \\ &= (r P^N_{m,t-1} + \delta^N_{m,t} P^N_{m,t} - i^N_{m,t} P^N_{m,t-1}) NCS_{m,t-1} \\ &= (r P^N_{m,t-1} + \delta^N_{m,t} P^N_{m,t} - \tau^N_{m,t}) NCS_{m,t-1} \end{aligned} \tag{A.5}$$

Note that $UCV^N_{m,t}$ has the form of traditional user cost value of capital, but it is not the same. In particular, while for produced capital the user cost value equals the unit user cost multiplied by $K_{j,t}$ (the 'quantity' of produced capital services used in production), for natural capital we do not have a 'unit user cost' per se; rather, the user cost value equals $(r P^N_{m,t-1} + \delta^N_{m,t} P^N_{m,t} - \tau^N_{m,t})$ multiplied by $NCS_{m,t-1}$, where the latter is the **stock** level of natural capital services at the beginning of the period. To derive a unit user cost for natural capital, we need to divide the expression for the user cost value by depletion $(D_{m,t})$.

Substituting Diewert and Fox's (2016a) user cost value for natural capital in the GOS equation and solving for the rate of return yields Eq. A.6.

$$r_t = \frac{GOS_t - \sum_j K_{j,t}(\eta_{j,t}(\delta^K_{j,t} P^K_{j,t} - \tau^K_{j,t}) + \mu_t P^K_{j,t-1}) - \sum_m (\delta^N_{m,t} P^N_{m,t} - \tau^N_{m,t}) NCS_{m,t-1}}{\sum_j K_{j,t}\eta_{j,t} P^K_{j,t-1} + \sum_m P^N_{m,t-1} NCS_{m,t-1}} \tag{A.6}$$

This method has a degree of intuitive appeal, as all the observed capital assets are utilised to generate capital income, hence, treating the user cost of capital as marginal revenue.

A.2 Sensitivity Analysis of the Traditional User Cost Method

Given that the user cost is so dependent on the assumptions in the model, a sensitivity analysis was conducted. Table A.1 presents 16 models that were used to assess the sensitivity of the traditional user cost method, based on different combinations of assumptions for the choice of parameters. The table examines the effects of using an exogenous versus an endogenous rate of return, as well as the effect of smoothing the inflation rate or dropping the capital gains term altogether. The results of the sensitivity analysis are shown in Table A.2.

The sensitivity analysis shows that the choice of parameters within the traditional user cost method matters. Interestingly, whether the capital gains term is included or excluded yields the most significant difference. When capital gains are excluded, there is a considerable reduction in the number of negative user cost values for individual subsoil assets compared with the other models. The results support the observation made in MacGibbon (2010) that the exclusion of capital gains from the user cost of capital could provide more plausible asset weights that display markedly less volatility. Another tentative conclusion is that the use of an endogenous rate of return in the computation of user costs produces a more substantial number of negative values compared with the other models. According to the OECD (2009), the difference between GOS for market producers, as defined in the national accounts, and GOS, as derived by the ex-ante method, yields an expected result. The differences can change sign as they oscillate around a long-run value near zero, suggesting that any divergence between the ex-post and ex-ante value is a 'surprise' term.

The differences between the 16 traditional user cost models are relatively large for the mining sector, recording on average, one percentage point in annual growth over the period. These results indicate how the selection of rates of return and a price deflator can offer more reasonable user costs for natural capital. Interestingly, the major influencing factor on the estimated cost shares of the unit resource rent and residual value methods is the choice of the rate of return used in calculating the user cost of produced capital. The exogenous rate of return greatly affects the magnitude of the cost shares allocated to produced capital and natural capital. The choice of a traditional user cost model could also imply materially different views on the pattern of productivity growth at the individual subsoil asset level.

Table A.1 – **Traditional user cost models**

	Natural capital			**Produced capital**
Model	r^N	$i^N_{m,t}$	$\tau^N_{m,t}$	r^K
1	RBA business loan rate	Price deflater	Yes	RBA cash rate
2	RBA business loan rate	Exponential *smoothing*[c]	Yes	RBA cash rate
3	RBA business loan rate	Geometric *smoothing*[d]	Yes	RBA cash rate
4	RBA business loan rate	Price deflater	No	RBA cash rate
5	RBA cash rate	Price deflater	Yes	RBA cash rate
6	RBA cash rate	Exponential smoothing	Yes	RBA cash rate
7	RBA cash rate	Geometric smoothing	Yes	RBA cash rate
8	RBA cash rate	Price deflater	No	RBA cash rate
9	ABS endogenous *rate*[a]	Price deflater	Yes	RBA cash rate
10	ABS endogenous rate	Exponential smoothing	Yes	RBA cash rate
11	ABS endogenous rate	Geometric smoothing	Yes	RBA cash rate
12	ABS endogenous rate	Price deflater	No	RBA cash rate
13	K and N endo. *rate*[b]	Price deflater	Yes	K and N endo. rate
14	K and N endo. rate	Exponential smoothing	Yes	K and N endo. rate
15	K and N endo. rate	Geometric smoothing	Yes	K and N endo. rate
16	K and N endo. rate	Price deflater	No	K and N endo. rate

Notes: [a] This rate refers to the ABS endogenously derived rates of return for produced capital.
[b] Refers to the endogenous rates of return including both produced and natural capital.
[c] Exponential smoothing over five periods, using dampening factor of 0.9.
[d] Based on Diewert and Fox's (2016a, p. 20) method.
Source: Estimates of industry MFP (ABS 2018); Australian System of National Accounts (ABS 2017a); RBA (2020a, Table F5) indicator lending rates.

Table A.2 – **Comparison of traditional user cost models MFP growth rates**

Average MFP growth rates (%)					
Period	ABS	Model 1	Model 2	Model 3	Model 4
1995/96 - 2000/01	1.4	1.8	1.9	1.8	1.8
2001/02 - 2005-06	-4.4	-3.7	-3.3	-3.3	-2.4
2006/07 - 2010/11	-4.1	-2.3	-1.9	-1.9	-0.7
2011/12 - 2015/16	2.4	1.8	1.1	1.5	1.9
1995/96 - 2015/16	-1.6	-0.5	-0.4	-0.2	0.2
Period		Model 5	Model 6	Model 7	Model 8
1995/96 - 2000/01	n/a	1.8	1.9	1.9	1.8
2001/02 - 2005-06	n/a	-3.9	-3.4	-3.3	-2.6
2006/07 - 2010/11	n/a	-2.5	-2.1	-1.2	-0.9
2011/12 - 2015/16	n/a	1.7	1.0	1.3	1.7
1995/96 - 2015/16	n/a	-0.6	-0.5	-0.2	0.1
Period		Model 9	Model 10	Model 11	Model 12
1995/96 - 2000/01	n/a	1.8	1.9	1.8	1.9
2001/02 - 2005-06	n/a	-3.6	-3.2	-3.1	-2.4
2006/07 - 2010/11	n/a	-1.8	-1.3	-0.5	-0.2
2011/12 - 2015/16	n/a	1.9	1.0	1.4	2.1
1995/96 - 2015/16	n/a	-0.3	-0.3	0.0	0.4
Period		Model 13	Model 14	Model 15	Model 16
1995/96 - 2000/01	n/a	2.1	2.3	2.1	2.3
2001/02 - 2005-06	n/a	-3.8	-3.3	-3.6	-2.5
2006/07 - 2010/11	n/a	-2.3	-1.7	-1.5	-0.1
2011/12 - 2015/16	n/a	1.2	0.5	0.3	2.6
1995/96 - 2015/16	n/a	-0.6	-0.4	-0.6	0.7

Appendix B

Appendix for Chapter 3

B.1 The Data

Table B.1 – **Constructed variables**

Constructed identifier	**Cl_primary land use equals:**
Cropping	“Crop”, “Cropping”, "Crops", "Grain", "Grains", "Cereals"
Livestock	"Cattle", "Pastoral", "Sheep", "Beef", "Livestock", "Grazing", "Wool", "Pigs", "Poultry", "CAMEL", "Mutton", "Goats"
Mix	"Mix", "Mixed", "Cereals and Sheep", "Cereals and Cattle"
Dairy	"Dairy", "Milk", "Cream"
Vineyard	"Vines", "Vineyard", "Vineyards", "Vinyard", "Vinyards"
Sugar	"Sugar"
Lifestyle	"Lifestyle", "House", "Housesite", "Dwelling", "Residential"
Horticulture	"Orchards", "Vegetables", "Citrus", "Pineapples", "Fruits”, "Groves", "Cotton", "Peanuts", "Pineapples", "Pome", "Almonds" "Berry"
Irrigated	"Small Crops and Fodder - Irrigated", "Vines - Irrigated", "Citrus - Irrigated", "Vines and Others - Irrigated", "Farming-Dairy-Part Irrigated", "Cattle-Dairy - Irrigated Pasture", "Farming-Dairy-Part Irrigated", "Citrus and Others - Irrigated", "Vegetables - Irrigated", "Stone Fruits - Irrigated", "Stone and Pome Fruits - Irrigated", "Cotton", "Peanuts", "Pineapples", "Vegetables - Irrigated", "Almonds - Irrigated", "Grazing/Pastoral-Part Irrigate", "Farming-Mixed-Part Irrigated"

Table B.2 – **CoreLogic data variables**

Data field	**Definition**
Property ID	Unique record key for the property.
Real Property Description	The legal parcel(s) description of the property, depending on the scheme adopted for each state.
Lot Number	Lot Number component of the parcel's description. NSW, Vic, QLd, WA, SA, Tas, NT only
Full Property Address	Property Address
Property Type	CoreLogic identified category for the property such as House, Unit, Flats, Land, Business (that is, House, Unit, Flats, Business, Commercial, Community, Farm, Land, Storage Unit)
Property Type Minor	Corelogic minor category for properties such as Cattle Dairy, General, Grain and Other Crops, Hobby, Horticulture/Fruit Growing, Other Livestock,Poultry, Sheep Studio, Townhouse/Villa, Triplex
Primary Land Use	The Primary Land Use of the property such as single Unit Dwelling, House etc.
Latitude	The geographical latitude of the property.
Longitude	The geographical longitude of the property.
Bedrooms	The most recently recorded bedrooms count.
Bathrooms	The most recently recorded count of bathrooms for the property.
Land Area	Total size of the parcel/s in square metres.
Transfer ID	Unique record key within the core database for the transfer
Contract Date	Contract date of transfer which indicates the date on which the sale price was contractually committed between a vendor and a purchaser.
Transaction Date	Contract date for states were VG contract date is provided; this include NSW, Vic, Qld, WA, Tas and ACT only
Contract Price	A proxy Contract Date with Settlement Date substituted for states where no VG Contract Date is provided. Allows for ordering transfers by the time that the transfer occurred.
Multi Sale	Sale price of transfer indicating the consideration for the property changing ownership (if available)

Source: CoreLogic and Chancellor et al. (2019)

VG: Valuer-General

B.2 Constant-quality indexes (State Level)

This Appendix documents the different constant quality price indexes for each of the six states.

Table B.3 – **NSW price indexes, 1986–1987 to 2017–2018**

Financial	Time Dummy Method				Hedonic Imputation Method				Sample	
year ending	model 1	model 2	model 3	model 4	model 1	model 2	model 3	model 4	mean	median
Jun-1987	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Jun-1988	1.07	1.07	1.09	1.09	1.12	1.07	1.09	1.09	0.99	1.20
Jun-1989	1.17	1.16	1.19	1.20	1.32	1.30	1.27	1.27	1.35	1.38
Jun-1990	1.27	1.26	1.29	1.29	1.41	1.42	1.38	1.39	1.51	1.78
Jun-1991	1.42	1.44	1.47	1.49	1.49	1.54	1.48	1.52	1.62	1.90
Jun-1992	1.53	1.56	1.60	1.63	1.60	1.74	1.64	1.74	1.80	1.96
Jun-1993	1.66	1.69	1.74	1.81	1.63	1.79	1.68	1.80	1.93	2.11
Jun-1994	1.63	1.67	1.71	1.78	1.69	1.88	1.76	1.89	1.96	2.06
Jun-1995	1.75	1.78	1.83	1.90	1.78	1.99	1.86	2.00	2.09	2.25
Jun-1996	1.83	1.88	1.93	2.00	1.89	2.05	1.94	2.07	2.23	2.47
Jun-1997	1.93	1.96	2.02	2.10	1.95	2.13	2.01	2.16	2.43	2.72
Jun-1998	1.91	1.95	2.01	2.10	1.99	2.21	2.07	2.22	2.64	2.98
Jun-1999	2.01	2.05	2.12	2.20	2.10	2.33	2.16	2.31	2.58	3.04
Jun-2000	2.11	2.14	2.21	2.31	2.17	2.40	2.20	2.37	2.69	3.02
Jun-2001	2.12	2.15	2.21	2.29	2.23	2.48	2.30	2.47	2.87	3.33
Jun-2002	2.21	2.26	2.32	2.41	2.39	2.70	2.50	2.65	3.28	3.78
Jun-2003	2.48	2.55	2.60	2.68	2.68	3.06	2.82	3.02	3.65	4.13
Jun-2004	2.77	2.85	2.90	3.01	2.85	3.22	2.99	3.21	4.05	4.82
Jun-2005	2.84	2.92	3.02	3.14	2.98	3.33	3.11	3.33	4.26	5.07
Jun-2006	3.01	3.12	3.18	3.34	3.55	3.96	3.69	3.95	5.41	6.16
Jun-2007	4.14	4.26	4.38	4.51	4.22	4.73	4.44	4.72	5.41	6.09
Jun-2008	4.35	4.46	4.57	4.73	4.25	4.70	4.43	4.64	5.81	6.62
Jun-2009	4.17	4.25	4.36	4.52	4.16	4.63	4.35	4.59	5.74	6.58
Jun-2010	4.08	4.17	4.30	4.45	4.02	4.47	4.24	4.47	5.81	6.74
Jun-2011	3.91	3.97	4.10	4.28	3.60	4.01	3.87	4.08	6.55	7.41
Jun-2012	3.34	3.40	3.55	3.72	3.53	3.96	3.82	4.02	6.58	7.40
Jun-2013	3.61	3.70	3.82	3.99	3.71	4.20	3.94	3.87	6.22	7.09
Jun-2014	3.53	3.63	3.74	3.89	3.80	4.29	3.97	4.09	7.03	7.64
Jun-2015	3.66	3.78	3.89	4.04	3.86	4.39	4.05	4.21	7.03	7.26
Jun-2016	3.72	3.83	3.94	4.12	4.02	4.58	4.24	4.50	7.43	8.10
Jun-2017	4.01	4.13	4.28	4.46	4.29	4.87	4.56	4.87	7.70	8.47
Jun-2018	4.22	4.34	4.49	4.68	4.56	5.20	4.84	5.12	6.76	8.38

Table B.4 – **Victoria price indexes, 1975–1976 to 2017–2018**

Financial	Time Dummy Method				Hedonic Imputation Method				Sample	
year ending	model 1	model 2	model 3	model 4	model 1	model 2	model 3	model 4	mean	median
Jun-1976	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Jun-1977	1.08	1.07	1.07	1.11	1.20	1.08	1.09	0.99	0.98	1.05
Jun-1978	1.22	1.15	1.16	1.24	1.21	1.12	1.13	1.03	1.18	1.06
Jun-1979	1.08	1.08	1.10	1.18	1.10	1.06	1.11	1.03	1.12	1.09
Jun-1980	1.12	1.14	1.17	1.24	1.18	1.15	1.18	1.07	1.43	1.38
Jun-1981	1.27	1.26	1.27	1.35	1.30	1.26	1.30	1.18	1.58	1.60
Jun-1982	1.42	1.45	1.47	1.52	1.47	1.41	1.46	1.33	1.86	1.82
Jun-1983	1.64	1.62	1.64	1.68	1.65	1.59	1.62	1.47	1.96	1.93
Jun-1984	1.75	1.71	1.74	1.80	1.73	1.71	1.75	1.61	2.04	1.99
Jun-1985	1.78	1.83	1.87	1.96	1.86	1.87	1.90	1.73	2.11	2.10
Jun-1986	2.02	2.04	2.09	2.25	1.90	2.05	1.91	1.68	1.53	1.48
Jun-1987	1.85	1.88	1.90	1.96	1.86	2.05	1.84	1.62	1.16	1.68
Jun-1988	2.01	1.99	2.03	2.18	2.16	2.31	2.21	1.96	1.97	1.99
Jun-1989	2.57	2.66	2.74	2.76	2.84	3.02	2.56	2.69	3.30	3.05
Jun-1990	3.04	3.19	3.32	3.32	3.12	3.40	2.88	2.99	3.39	3.46
Jun-1991	3.09	3.28	3.38	3.41	3.19	3.45	2.91	2.95	3.33	3.20
Jun-1992	3.11	3.27	3.36	3.42	3.21	3.46	2.89	2.90	3.51	3.16
Jun-1993	3.05	3.26	3.35	3.48	3.11	3.43	2.89	2.92	4.04	3.57
Jun-1994	3.02	3.29	3.38	3.51	3.20	3.45	2.90	2.92	3.86	3.52
Jun-1995	3.23	3.33	3.40	3.51	3.49	3.54	3.03	3.07	4.00	3.85
Jun-1996	3.39	3.47	3.56	3.73	3.43	3.52	3.04	3.11	4.39	3.91
Jun-1997	3.32	3.47	3.58	3.83	3.47	3.55	3.10	3.16	4.56	4.15
Jun-1998	3.46	3.54	3.64	3.89	3.81	3.82	3.33	3.39	4.56	4.18
Jun-1999	3.79	3.79	3.87	4.09	3.83	3.84	3.34	3.38	4.98	4.57
Jun-2000	3.70	3.73	3.83	4.02	3.78	3.84	3.33	3.33	5.26	4.93
Jun-2001	3.69	3.80	3.92	3.99	3.74	3.88	3.31	3.30	5.40	4.91
Jun-2002	3.76	3.91	4.01	4.07	3.99	4.14	3.55	3.52	6.14	5.41
Jun-2003	4.29	4.37	4.48	4.63	4.52	4.70	4.01	3.93	6.63	5.83
Jun-2004	4.78	4.90	5.02	5.25	5.10	5.32	4.56	4.46	7.97	6.98
Jun-2005	5.38	5.61	5.76	6.00	5.71	5.97	5.11	4.98	8.60	7.75
Jun-2006	6.02	6.31	6.50	6.80	6.33	6.62	5.68	5.52	10.18	9.06
Jun-2007	6.75	6.92	7.15	7.45	7.11	7.34	6.27	6.11	10.54	9.74
Jun-2008	7.54	7.70	7.92	8.24	7.34	7.66	6.57	6.31	11.53	10.39
Jun-2009	7.22	7.55	7.79	8.04	7.28	7.62	6.52	6.27	11.05	10.01
Jun-2010	7.11	7.37	7.57	7.95	7.38	7.67	6.54	6.37	10.74	9.33
Jun-2011	7.34	7.79	8.04	8.22	6.96	7.49	6.39	6.01	12.32	11.28
Jun-2012	6.86	7.62	7.89	7.83	7.12	7.54	6.43	6.01	12.28	11.15
Jun-2013	7.39	7.87	8.12	8.17	7.34	7.60	6.58	6.27	11.87	11.36
Jun-2014	7.45	7.83	8.12	8.31	7.63	7.81	6.75	6.48	12.66	11.26
Jun-2015	8.06	8.39	8.60	8.92	8.10	8.21	7.08	6.76	13.51	12.32
Jun-2016	8.67	8.83	9.11	9.39	8.65	8.67	7.48	7.15	15.09	13.73
Jun-2017	9.13	9.53	9.78	9.70	9.07	9.28	8.00	7.71	16.32	14.89
Jun-2018	9.56	10.29	10.60	10.53	9.72	9.83	8.56	8.24	16.84	15.49

Table B.5 – **Queensland price indexes, 1983–1984 to 2017–2018**

Financial	Time Dummy Method				Hedonic Imputation Method				Sample	
year ending	model 1	model 2	model 3	model 4	model 1	model 2	model 3	model 4	mean	median
Jun-1984	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Jun-1985	1.03	1.04	1.05	1.05	1.02	1.03	1.05	1.05	1.15	0.96
Jun-1986	1.03	1.05	1.06	1.06	1.03	1.04	1.07	1.06	1.10	1.03
Jun-1987	1.10	1.13	1.12	1.12	1.06	1.10	1.13	1.14	1.10	1.06
Jun-1988	1.01	1.03	1.02	1.04	1.06	1.10	1.15	1.14	1.10	1.07
Jun-1989	1.10	1.15	1.14	1.15	1.03	1.07	1.12	1.12	1.40	1.38
Jun-1990	1.22	1.28	1.26	1.26	1.11	1.16	1.21	1.24	1.50	1.38
Jun-1991	1.23	1.32	1.29	1.31	1.17	1.25	1.28	1.32	1.44	1.36
Jun-1992	1.20	1.29	1.24	1.26	1.16	1.25	1.28	1.32	1.50	1.37
Jun-1993	1.28	1.34	1.30	1.32	1.18	1.25	1.29	1.34	1.50	1.39
Jun-1994	1.35	1.40	1.36	1.38	1.24	1.32	1.35	1.41	1.55	1.50
Jun-1995	1.46	1.50	1.46	1.49	1.33	1.40	1.43	1.50	1.75	1.66
Jun-1996	1.57	1.61	1.56	1.59	1.43	1.52	1.54	1.62	2.00	1.86
Jun-1997	1.54	1.61	1.55	1.59	1.45	1.54	1.56	1.62	1.85	1.81
Jun-1998	1.54	1.62	1.56	1.58	1.44	1.56	1.55	1.60	1.95	1.94
Jun-1999	1.66	1.74	1.67	1.70	1.51	1.65	1.64	1.68	2.10	1.95
Jun-2000	1.52	1.62	1.57	1.60	1.50	1.62	1.64	1.66	2.00	2.01
Jun-2001	1.55	1.64	1.59	1.61	1.46	1.63	1.62	1.64	2.10	2.11
Jun-2002	1.67	1.72	1.67	1.70	1.54	1.69	1.68	1.73	2.10	1.97
Jun-2003	1.76	1.80	1.73	1.77	1.65	1.77	1.76	1.83	2.20	2.28
Jun-2004	1.82	1.87	1.79	1.84	1.72	1.85	1.83	1.91	2.63	2.72
Jun-2005	2.19	2.29	2.20	2.25	1.92	2.06	2.06	2.14	3.00	3.03
Jun-2006	2.53	2.65	2.53	2.61	2.24	2.45	2.42	2.52	3.60	3.80
Jun-2007	2.86	2.98	2.83	2.90	2.57	2.81	2.78	2.90	4.00	4.25
Jun-2008	3.33	3.50	3.30	3.39	2.95	3.21	3.19	3.30	4.95	5.19
Jun-2009	3.48	3.69	3.54	3.64	3.24	3.56	3.51	3.68	4.75	4.70
Jun-2010	3.53	3.78	3.54	3.61	3.33	3.70	3.62	3.69	4.60	4.40
Jun-2011	3.46	3.77	3.55	3.66	3.34	3.73	3.61	3.71	4.80	4.46
Jun-2012	3.32	3.71	3.48	3.54	3.23	3.73	3.57	3.63	4.54	4.87
Jun-2013	3.45	3.69	3.46	3.56	3.27	3.67	3.52	3.65	5.20	4.80
Jun-2014	3.32	3.57	3.34	3.43	3.26	3.60	3.47	3.61	4.95	4.59
Jun-2015	3.52	3.69	3.44	3.53	3.23	3.52	3.41	3.55	4.95	4.63
Jun-2016	3.51	3.73	3.49	3.60	3.27	3.54	3.48	3.65	5.22	5.03
Jun-2017	3.71	3.90	3.68	3.80	3.37	3.68	3.64	3.80	5.76	5.75
Jun-2018	4.01	4.19	3.97	4.05	3.58	3.91	3.83	3.96	6.22	5.73

Table B.6 – **SA price indexes, 1995–1996 to 2017–2018**

Financial	Time Dummy Method				Hedonic Imputation Method				Sample	
year ending	model 1	model 2	model 3	model 4	model 1	model 2	model 3	model 4	mean	median
Jun-1995	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Jun-1996	0.97	0.97	0.97	0.97	0.96	0.96	0.96	0.95	1.12	1.10
Jun-1997	0.97	0.98	0.97	0.99	1.00	1.00	0.99	0.99	1.25	1.20
Jun-1998	1.04	1.05	1.05	1.08	1.11	1.11	1.11	1.11	1.30	1.26
Jun-1999	1.22	1.23	1.24	1.26	1.15	1.14	1.16	1.16	1.30	1.34
Jun-2000	1.14	1.13	1.16	1.18	1.08	1.08	1.09	1.08	1.35	1.36
Jun-2001	1.07	1.09	1.11	1.14	1.01	1.02	1.00	0.97	1.45	1.43
Jun-2002	1.06	1.08	1.08	1.11	1.06	1.07	1.05	1.01	1.60	1.57
Jun-2003	1.23	1.25	1.26	1.30	1.27	1.30	1.31	1.26	1.75	1.68
Jun-2004	1.43	1.45	1.47	1.50	1.48	1.50	1.51	1.45	2.10	2.09
Jun-2005	1.67	1.70	1.73	1.79	1.66	1.70	1.70	1.63	2.60	2.45
Jun-2006	1.80	1.85	1.87	1.93	1.86	1.91	1.89	1.82	2.82	2.62
Jun-2007	2.15	2.20	2.23	2.29	2.06	2.12	2.12	2.05	3.04	2.94
Jun-2008	2.16	2.22	2.29	2.34	2.11	2.18	2.20	2.14	3.20	3.07
Jun-2009	2.20	2.26	2.30	2.39	2.11	2.16	2.17	2.10	3.50	3.01
Jun-2010	2.22	2.32	2.32	2.38	1.86	1.93	1.93	1.88	3.50	3.25
Jun-2011	2.03	2.10	2.14	2.22	1.71	1.71	1.72	1.70	3.66	3.23
Jun-2012	1.94	2.01	2.05	2.14	1.77	1.78	1.80	1.77	3.50	3.25
Jun-2013	2.13	2.20	2.21	2.27	1.91	1.92	2.00	1.98	3.50	3.25
Jun-2014	2.01	2.09	2.12	2.20	1.94	1.94	2.02	2.04	3.55	3.03
Jun-2015	2.17	2.25	2.26	2.36	1.99	1.98	2.06	2.08	3.50	3.24
Jun-2016	2.23	2.28	2.28	2.35	2.01	2.00	2.11	2.12	4.00	3.76
Jun-2017	2.08	2.18	2.20	2.29	2.00	2.01	2.14	2.16	3.60	3.39
Jun-2018	2.07	2.18	2.17	2.27	2.24	2.30	2.41	2.40	3.75	3.43

Table B.7 – **WA price indexes, 1988–1989 to 2017–2018**

Financial	Time Dummy Method				Hedonic Imputation Method				Sample	
year ending	model 1	model 2	model 3	model 4	model 1	model 2	model 3	model 4	mean	median
Jun-1989	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Jun-1990	0.85	0.85	0.83	0.83	1.12	1.12	1.07	1.07	1.10	1.05
Jun-1991	1.09	1.07	1.05	1.06	1.13	1.13	1.07	1.05	1.21	0.99
Jun-1992	0.89	0.89	0.88	0.88	1.11	1.11	1.04	1.03	1.15	0.90
Jun-1993	0.98	0.99	0.99	0.99	1.20	1.20	1.15	1.13	1.30	1.02
Jun-1994	1.10	1.09	1.06	1.05	1.29	1.29	1.22	1.19	1.28	1.04
Jun-1995	1.23	1.17	1.11	1.10	1.43	1.43	1.36	1.32	1.43	1.20
Jun-1996	1.38	1.33	1.28	1.27	1.55	1.55	1.48	1.43	1.65	1.47
Jun-1997	1.38	1.41	1.40	1.40	1.61	1.61	1.57	1.51	1.80	1.51
Jun-1998	1.50	1.49	1.45	1.44	1.81	1.81	1.75	1.65	2.00	1.70
Jun-1999	1.76	1.71	1.67	1.66	1.82	1.82	1.77	1.67	2.12	1.87
Jun-2000	1.55	1.57	1.54	1.54	1.75	1.75	1.71	1.64	2.30	2.00
Jun-2001	1.68	1.68	1.64	1.63	1.90	1.90	1.88	1.81	2.40	2.01
Jun-2002	1.88	1.80	1.72	1.72	2.06	2.06	2.04	1.96	2.20	1.88
Jun-2003	2.03	1.90	1.80	1.79	2.11	2.11	2.09	2.01	2.25	1.91
Jun-2004	2.01	1.96	1.84	1.83	2.19	2.19	2.17	2.11	2.32	1.94
Jun-2005	2.20	2.15	2.03	2.02	2.48	2.48	2.45	2.39	2.60	2.45
Jun-2006	2.53	2.51	2.38	2.39	2.91	2.91	2.89	2.82	3.03	2.85
Jun-2007	2.99	2.95	2.81	2.80	3.59	3.59	3.55	3.47	3.65	3.21
Jun-2008	3.65	3.53	3.31	3.33	3.92	3.92	3.91	3.86	4.50	3.64
Jun-2009	3.69	3.65	3.54	3.54	3.93	3.93	3.99	3.97	4.75	4.33
Jun-2010	3.56	3.58	3.45	3.45	3.84	3.84	3.87	3.87	4.20	3.48
Jun-2011	3.75	3.58	3.40	3.43	3.78	3.78	3.94	3.89	3.88	3.28
Jun-2012	3.48	3.35	3.17	3.18	3.43	3.43	3.59	3.52	4.70	3.68
Jun-2013	3.17	3.13	3.01	3.04	3.42	3.42	3.59	3.53	4.45	3.41
Jun-2014	3.31	3.23	3.07	3.10	3.38	3.38	3.53	3.49	4.30	3.30
Jun-2015	3.13	3.08	2.94	2.96	3.44	3.44	3.56	3.51	4.45	3.32
Jun-2016	3.40	3.26	3.03	3.05	3.52	3.52	3.63	3.59	4.30	3.29
Jun-2017	3.18	3.12	2.97	2.97	3.39	3.39	3.55	3.47	4.80	3.82
Jun-2018	3.16	3.20	3.12	3.11	3.54	3.54	3.69	3.62	5.30	3.89

Table B.8 – **Tasmania price indexes, 1988–1989 to 2017–2018**

Financial	Time Dummy Method				Hedonic Imputation Method				Sample	
year ending	model 1	model 2	model 3	model 4	model 1	model 2	model 3	model 4	mean	median
Jun-1989	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Jun-1990	1.26	1.27	1.29	1.29	1.19	1.18	1.19	1.19	1.18	1.21
Jun-1991	1.44	1.44	1.45	1.43	1.23	1.22	1.23	1.22	1.19	1.08
Jun-1992	1.34	1.35	1.34	1.32	1.18	1.18	1.19	1.18	1.01	1.01
Jun-1993	1.33	1.34	1.37	1.37	1.21	1.20	1.22	1.25	1.29	1.20
Jun-1994	1.37	1.37	1.40	1.41	1.32	1.31	1.33	1.33	1.23	1.24
Jun-1995	1.55	1.54	1.53	1.53	1.42	1.41	1.43	1.46	1.43	1.37
Jun-1996	1.70	1.69	1.66	1.66	1.49	1.48	1.50	1.55	1.57	1.39
Jun-1997	1.64	1.64	1.67	1.66	1.42	1.46	1.44	1.48	1.55	1.56
Jun-1998	1.69	1.70	1.70	1.69	1.38	1.42	1.39	1.41	1.66	1.52
Jun-1999	1.58	1.57	1.56	1.54	1.40	1.45	1.44	1.44	1.61	1.41
Jun-2000	1.79	1.78	1.75	1.72	1.51	1.56	1.54	1.55	1.61	1.55
Jun-2001	1.95	1.93	1.91	1.87	1.58	1.65	1.61	1.64	1.79	1.69
Jun-2002	1.97	1.96	1.96	1.94	1.62	1.69	1.65	1.71	2.15	1.93
Jun-2003	1.97	1.98	1.97	1.96	1.72	1.79	1.76	1.80	2.03	1.88
Jun-2004	2.09	2.10	2.09	2.09	1.87	1.96	1.93	1.97	2.09	2.07
Jun-2005	2.32	2.32	2.34	2.33	2.00	2.10	2.06	2.11	2.00	2.04
Jun-2006	2.47	2.47	2.49	2.47	2.42	2.52	2.48	2.55	2.63	2.60
Jun-2007	3.57	3.54	3.46	3.48	3.23	3.28	3.29	3.44	3.24	3.44
Jun-2008	3.84	3.80	3.74	3.77	3.38	3.41	3.44	3.63	3.58	3.68
Jun-2009	3.84	3.81	3.77	3.78	3.40	3.44	3.46	3.64	4.14	4.07
Jun-2010	3.88	3.89	3.87	3.88	3.03	3.07	3.17	3.40	3.97	3.29
Jun-2011	3.45	3.47	3.57	3.57	3.07	3.14	3.26	3.45	3.55	3.15
Jun-2012	3.84	3.86	3.97	3.98	2.95	3.01	3.20	3.39	3.94	3.44
Jun-2013	3.63	3.64	3.64	3.69	2.66	2.73	2.93	3.08	4.18	3.43
Jun-2014	3.37	3.39	3.45	3.45	2.66	2.73	2.91	3.14	3.64	3.41
Jun-2015	3.32	3.31	3.42	3.42	3.11	3.23	3.44	3.74	3.20	3.23
Jun-2016	4.03	3.97	3.87	3.91	3.44	3.73	3.87	4.16	4.08	3.86
Jun-2017	4.14	4.15	4.17	4.24	3.44	3.76	3.88	4.12	4.30	3.83
Jun-2018	4.12	4.16	4.29	4.36	3.90	4.02	4.31	4.50	4.33	3.89

B.3 Hedonic Regression Models: State-level Coefficients

This appendix provides a more detailed discussion of the regression coefficients at the state level. It also offers a closer look at the differences in dynamics between methods by analysing the volatility of the regression coefficients. The time-dummy model assumes that regression coefficients of characteristics remain stable over time, while the imputation method allows the coefficient to evolve over time.

B.3.1 State-level regression results

Table B.9 presents a sample set of results by state for Model 2. Across all states, all characteristic variables in the model are statistically significant. In particular, the presence of a house or shed on the land appears to be significant and positive. A large house or residence (in terms of the number of bedrooms and bathrooms) appears to be more critical in NSW, and a high number of buildings (that is, sheds and houses) appear equally relevant to value in Victoria. Agricultural land in all states is price sensitive to size, such that increasingly large farms may attract lower values on a price-per-hectare basis.

Increased distance from the nearest road and the nearest town with a population of over 10,000 negatively affects land value, suggesting that increased remoteness is an adverse land-value driver. Land values in all states also appear to be somewhat driven by favourable climatic conditions, with increased average rainfall being both positive and significant. Conversely, high average maximum temperatures appear to drive value downwards considerably across all states, along with high risk of wind, water and acid erosion in terms of agricultural land.

Production type also appears to be essential to value, with cropping farms positively affecting value compared to grazing land in some states (NSW, Queensland and SA). It seems that desirable cropping areas in some states attract higher values, particularly when compared to less desirable grazing areas where climate conditions are hotter and dryer. The relatively different explanatory power, as indicated by the adjusted R-squared values, may imply a relatively heterogeneous market for agricultural land.

Table B.10 compares the R-squared for Models 1 and 2 by period and by state. The explanatory power by period under the hedonic imputation method is extremely volatile from year to year. As such, the Breusch–Pagan test was utilised to test for heteroscedasticity. The results indicate these models suffer from heteroscedasticity.

Table B.9 – **Selected Model 2 regression results (state level)**

	NSW	VIC	QLD	SA	WA	Tas
Log(H)	0.44*** (0.0)	0.41*** (0.0)	0.49*** (0.01)	0.59*** (0.0)	0.48*** (0.0)	0.60*** (0.01)
Beef		0.15*** (0.04)				
Dairy		0.28*** (0.04)	0.13*** (0.02)	0.15*** (0.03)		
Forestry						−0.58*** (0.04)
General		0.11*** (0.04)				−0.23*** (0.05)
Crops	0.03 (0.04)	0.07* (0.04)	0.10*** (0.01)	0.21*** (0.03)	−0.03 (0.06)	
Horticulture	0.21*** (0.06)	0.44*** (0.04)	0.19*** (0.02)	0.53*** (0.02)		0.05 (0.05)
Livestock-crops		0.13*** (0.04)		−0.10*** (0.02)		−0.26*** (0.03)
Mixed farming				−0.08*** (0.03)	−0.01 (0.01)	−0.06* (0.03)
Other livestock	0.01 (0.03)	0.12*** (0.04)	0.07*** (0.02)	−0.10*** (0.02)	−0.06 (0.06)	−0.34*** (0.03)
Sheep		0.09** (0.04)	−0.11*** (0.03)	−0.19*** (0.02)		
BED	0.01*** (0.0)	0.01*** (0.0)	0.02*** (0.0)	0.02*** (0.01)	0.01 (0.01)	0.03*** (0.01)
BATH	0.11*** (0.01)	0.07*** (0.01)	0.06*** (0.01)	0.08*** (0.01)	0.07*** (0.01)	0.10*** (0.02)
ErACID	−0.0** (0.0)	0.0* (0.0)	0.0*** (0.0)	0.0 (0.0)	−0.0 (0.0)	0.0*** (0.0)
ErWATER	−0.0** (0.0)	0.0*** (0.0)	−0.0*** (0.0)	−0.0 (0.0)	−0.0*** (0.0)	0.0 (0.0)
ErWIND	0.0*** (0.0)	0.0*** (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	−0.0*** (0.0)
minTEMP	0.07*** (0.01)	0.12*** (0.01)	0.04*** (0.01)	−0.03*** (0.01)	0.11*** (0.01)	0.02* (0.01)
maxTEMP	−0.04*** (0.0)	−0.06*** (0.01)	−0.02** (0.01)	0.05*** (0.01)	−0.03*** (0.0)	0.04*** (0.01)
avgRAIN	0.0*** (0.0)	0.0*** (0.0)	0.0** (0.0)	0.0*** (0.0)	0.0*** (0.0)	0.0 (0.0)
SHED	0.08*** (0.01)	0.05*** (0.0)	0.03*** (0.0)			
HOUSE	0.21*** (0.01)	0.01 (0.01)	0.02*** (0.01)			
DIST	−0.0*** (0.0)	−0.0*** (0.0)	−0.0*** (0.0)	−0.0*** (0.0)	−0.0*** (0.0)	−0.0*** (0.0)
TKM10	−0.0*** (0.0)	−0.0*** (0.0)	−0.0*** (0.0)	−0.0*** (0.0)	−0.0*** (0.0)	−0.0*** (0.0)
CROP	0.08*** (0.01)	0.03** (0.01)	0.13*** (0.02)	0.05*** (0.02)	0.07*** (0.02)	0.43*** (0.04)
GRAZ	−0.08*** (0.01)	0.12*** (0.01)	−0.08*** (0.02)	−0.13*** (0.02)	0.21*** (0.02)	0.29*** (0.02)
SLOPE	0.10*** (0.01)	0.12*** (0.01)	0.11*** (0.02)	−0.10*** (0.01)	−0.21*** (0.01)	0.16*** (0.03)
WATm2	0.0*** (0.0)	0.0*** (0.0)	0.0*** (0.0)	−0.0** (0.0)	0.0*** (0.0)	−0.0** (0.0)
Constant	8.87*** (0.12)	7.68*** (0.12)	8.39*** (0.14)	7.20*** (0.18)	7.82*** (0.10)	7.13*** (0.24)
Observations	45,711	39,216	20,814	16,088	19,567	6,242
Adjusted R^2	0.61	0.72	0.66	0.71	0.70	0.63

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.10 – ***R*-squared comparison for Models 1 and 2 (state level)**

Financial	**NSW**		**Vic**		**Qld**		**SA**		**WA**		**Tas**	
year ending	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2
Hedonic-imputation												
Jun-1975			0.64	0.76								
Jun-1976			0.59	0.71								
Jun-1977			0.60	0.69								
Jun-1978			0.64	0.75								
Jun-1979			0.64	0.72								
Jun-1980			0.66	0.72								
Jun-1981			0.60	0.68								
Jun-1982			0.65	0.70	0.50	0.55						
Jun-1983			0.63	0.70	0.50	0.56						
Jun-1984			0.60	0.67	0.53	0.57						
Jun-1985			0.55	0.76	0.46	0.51						
Jun-1986			0.70	0.87	0.48	0.57						
Jun-1987			0.59	0.80	0.54	0.58						
Jun-1988	0.51	0.72	0.45	0.62	0.60	0.63			0.78	0.79	0.67	0.68
Jun-1989	0.68	0.81	0.48	0.62	0.49	0.54			0.67	0.68	0.75	0.75
Jun-1990	0.47	0.61	0.42	0.59	0.49	0.52			0.65	0.67	0.62	0.63
Jun-1991	0.57	0.66	0.33	0.55	0.50	0.53			0.59	0.62	0.61	0.61
Jun-1992	0.56	0.62	0.38	0.51	0.44	0.47			0.62	0.65	0.72	0.72
Jun-1993	0.54	0.63	0.44	0.53	0.49	0.52			0.68	0.70	0.57	0.57
Jun-1994	0.53	0.56	0.37	0.50	0.44	0.46	0.70	0.73	0.65	0.66	0.63	0.64
Jun-1995	0.44	0.48	0.43	0.51	0.45	0.47	0.70	0.72	0.69	0.70	0.58	0.58
Jun-1996	0.52	0.55	0.41	0.51	0.45	0.48	0.72	0.73	0.65	0.67	0.71	0.71
Jun-1997	0.53	0.55	0.36	0.50	0.46	0.51	0.66	0.69	0.66	0.68	0.57	0.57
Jun-1998	0.49	0.52	0.44	0.55	0.48	0.53	0.63	0.64	0.61	0.61	0.52	0.52
Jun-1999	0.48	0.51	0.45	0.52	0.51	0.56	0.68	0.70	0.71	0.72	0.56	0.56
Jun-2000	0.52	0.55	0.38	0.52	0.53	0.55	0.73	0.75	0.63	0.63	0.61	0.61
Jun-2001	0.53	0.55	0.33	0.48	0.48	0.51	0.63	0.67	0.70	0.71	0.57	0.59
Jun-2002	0.49	0.51	0.37	0.49	0.53	0.55	0.63	0.66	0.69	0.69	0.57	0.58
Jun-2003	0.47	0.50	0.33	0.43	0.51	0.53	0.64	0.66	0.65	0.66	0.62	0.62
Jun-2004	0.52	0.55	0.30	0.41	0.49	0.53	0.59	0.62	0.68	0.69	0.52	0.52
Jun-2005	0.52	0.55	0.37	0.48	0.49	0.52	0.59	0.63	0.67	0.68	0.65	0.65
Jun-2006	0.51	0.55	0.33	0.45	0.43	0.45	0.62	0.65	0.58	0.58	0.56	0.56
Jun-2007	0.55	0.58	0.32	0.44	0.38	0.45	0.64	0.67	0.62	0.63	0.43	0.43
Jun-2008	0.53	0.55	0.40	0.51	0.42	0.43	0.58	0.61	0.61	0.61	0.45	0.45
Jun-2009	0.47	0.50	0.36	0.47	0.31	0.34	0.60	0.64	0.68	0.68	0.46	0.46
Jun-2010	0.47	0.50	0.37	0.48	0.34	0.37	0.64	0.69	0.56	0.56	0.56	0.56
Jun-2011	0.52	0.55	0.37	0.50	0.49	0.55	0.60	0.65	0.64	0.64	0.34	0.32
Jun-2012	0.52	0.54	0.41	0.53	0.38	0.43	0.72	0.76	0.61	0.61	0.54	0.53
Jun-2013	0.56	0.59	0.38	0.51	0.50	0.53	0.67	0.70	0.57	0.58	0.62	0.62
Jun-2014	0.58	0.60	0.39	0.51	0.45	0.50	0.64	0.67	0.62	0.63	0.57	0.58
Jun-2015	0.59	0.61	0.44	0.55	0.44	0.51	0.65	0.72	0.62	0.62	0.58	0.59
Jun-2016	0.60	0.62	0.44	0.54	0.47	0.51	0.68	0.71	0.69	0.69	0.63	0.63
Jun-2017	0.59	0.61	0.39	0.53	0.46	0.49	0.74	0.76	0.58	0.57	0.56	0.60
Jun-2018	0.60	0.62	0.41	0.54	0.42	0.45	0.74	0.76	0.64	0.64	0.59	0.60
Average	**0.54**	**0.59**	**0.46**	**0.58**	**0.47**	**0.51**	**0.66**	**0.69**	**0.65**	**0.65**	**0.58**	**0.58**
Time-dummy	**0.61**	**0.62**	**0.67**	**0.72**	**0.60**	**0.64**	**0.70**	**0.72**	**0.70**	**0.71**	**0.64**	**0.69**

B.3.2 State-level coefficients: time-dummy v. imputation method

The time-dummy method essentially is a pooled regression model with no time-varying (fixed effects) variables, other than dummies for time. This section examines the stability of estimated coefficients of variables in the models over time. We observe whether holding the coefficient stationary over time is a valid assumption. Figures B.1 to B.7 show selected double-imputation coefficients of Model 2 for each state.

Interestingly, the coefficients across all six states for the soil quality variables, ErACID, ErWATER, ErWIND, minTEMP, maxTEMP and avgRAIN are very close to 1 over time. However, the coefficients for maxTEMP and avgRAIN are more volatile. This suggests that weather patterns have a significant effect on land values and this pattern is not constant over time.

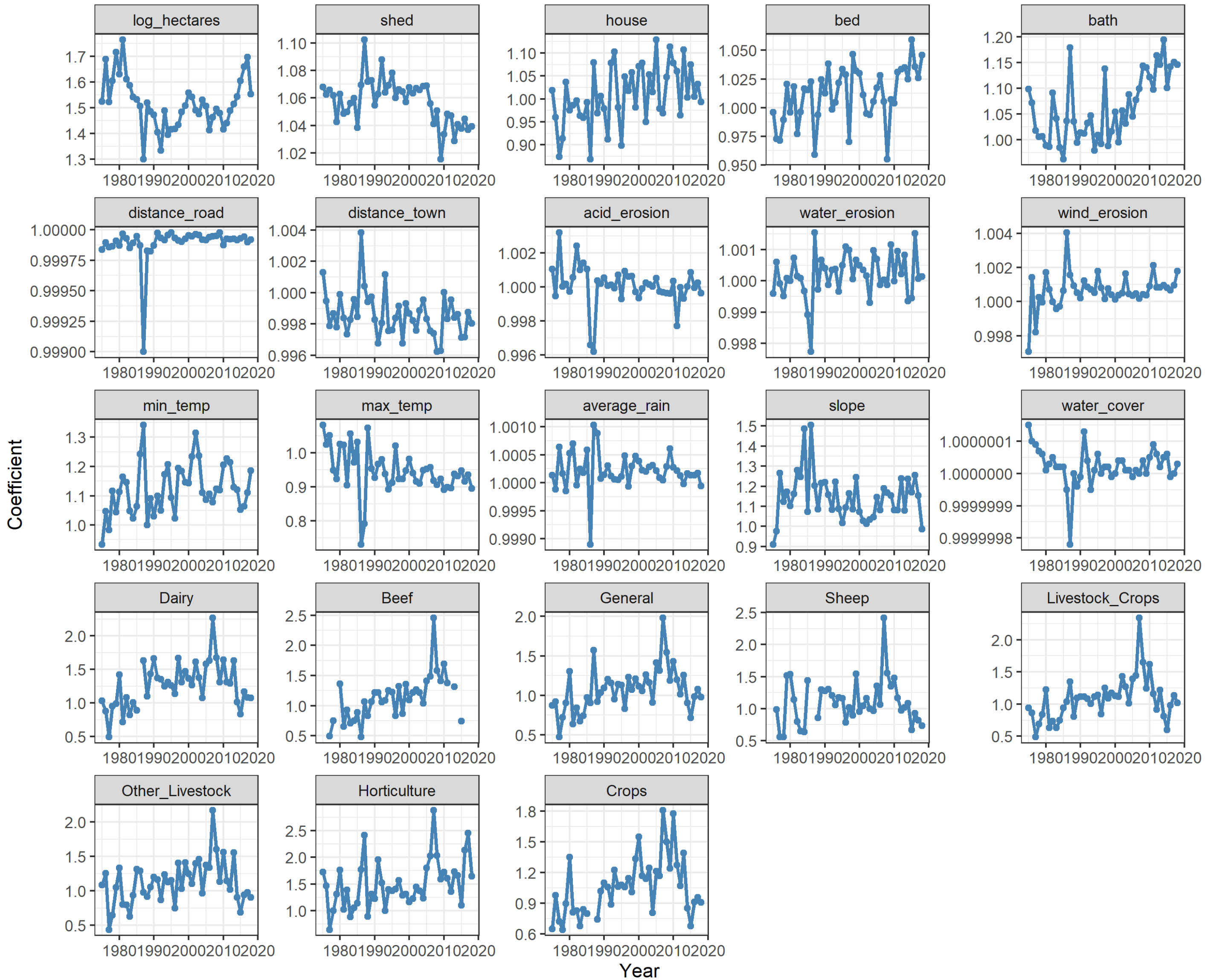
We observe relatively stable coefficients for DIST and TKM10 over time. The access to water (WATm2) over time is volatile which may reflect the greater importance of water access in times of drought.

The estimated coefficient for the dummy variable LandUse are compared to Vacant Land. The LandUse variable can be somewhat tricky to interpret because it was constructed using CoreLogic sales data. This information is collected from each state's Valuer-General (land registry office) where each state has different levels of details and labels for land use. For example, Western Australia only has a handful of records that label land use for beef grazing, with the majority of records labelled as 'farming'. Given that different land uses have a different effect on land values, we avoid comparison across states. In New South Wales, horticulture is the most volatile over time and contributes significantly to land value. For Victoria, Tasmania and Queensland, the pattern is volatile but more uniform across land-use categories, perhaps signalling substitutability of land use implying less of a premium in land prices in these states for land-use type.

Figure B.1 – **Coefficients of Model 2 over time, New South Wales**

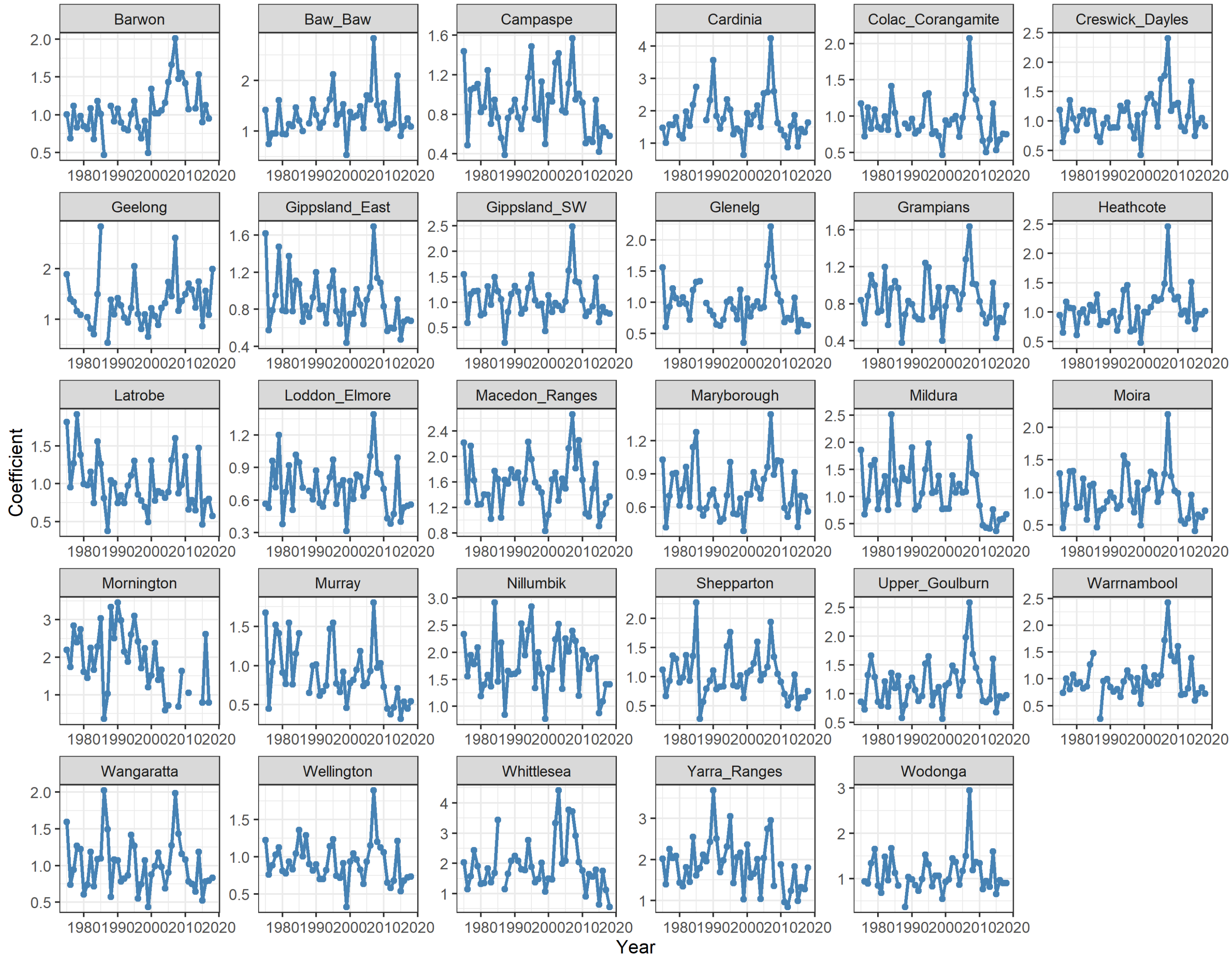
Notes: OLS regression model. Missing coefficient indicate no transaction in that category. The base case for land use is vacant land; for region is SA4 Capital Region.

Figure B.2 – **Coefficients of Model 2 over time, Victoria**



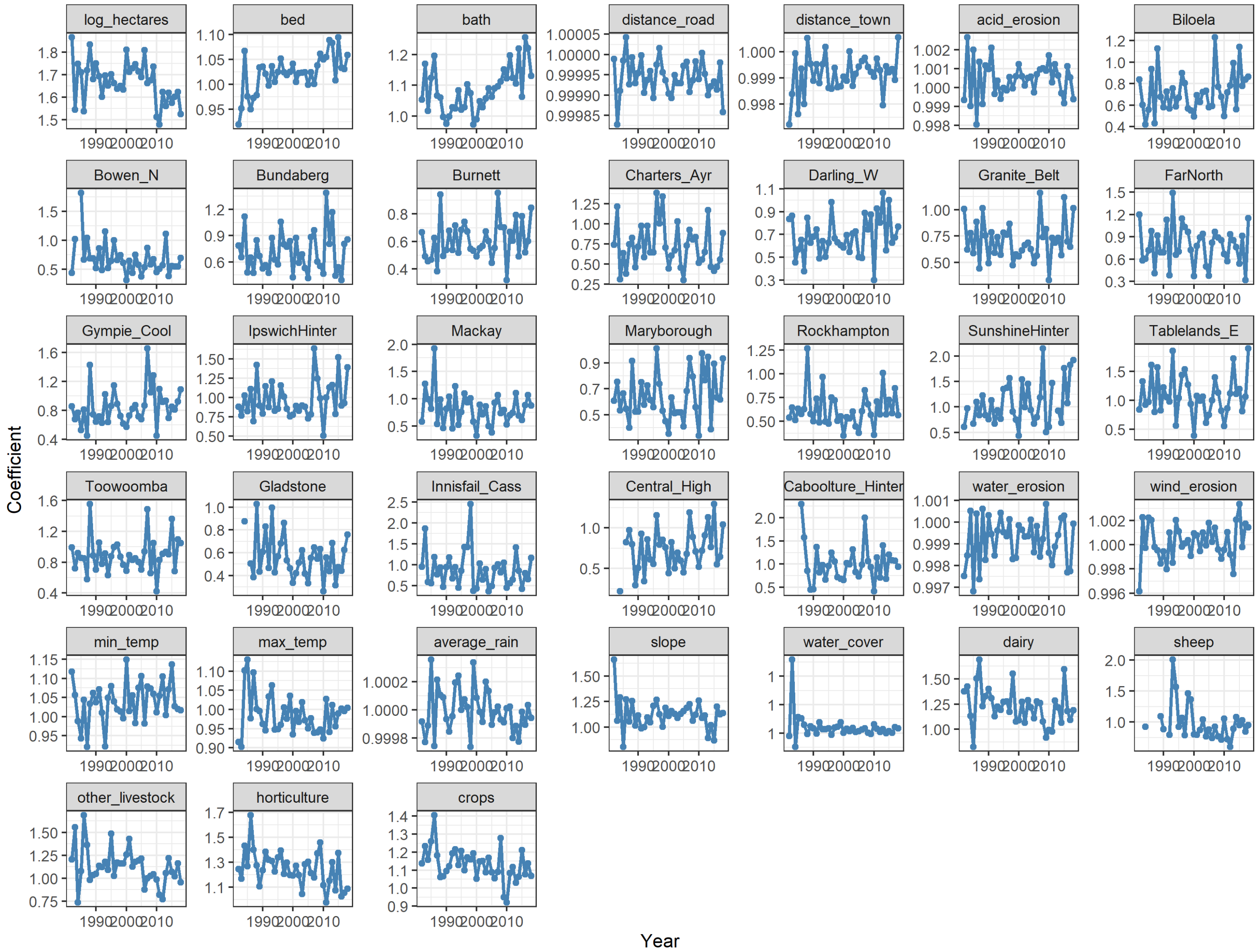
Notes: OLS regression model. Missing coefficient indicate no transaction in that category. The base case for land use is vacant land; for region is SA3 Ballarat.

Figure B.3 – **Coefficients of Model 2 over time, Victoria - continue**



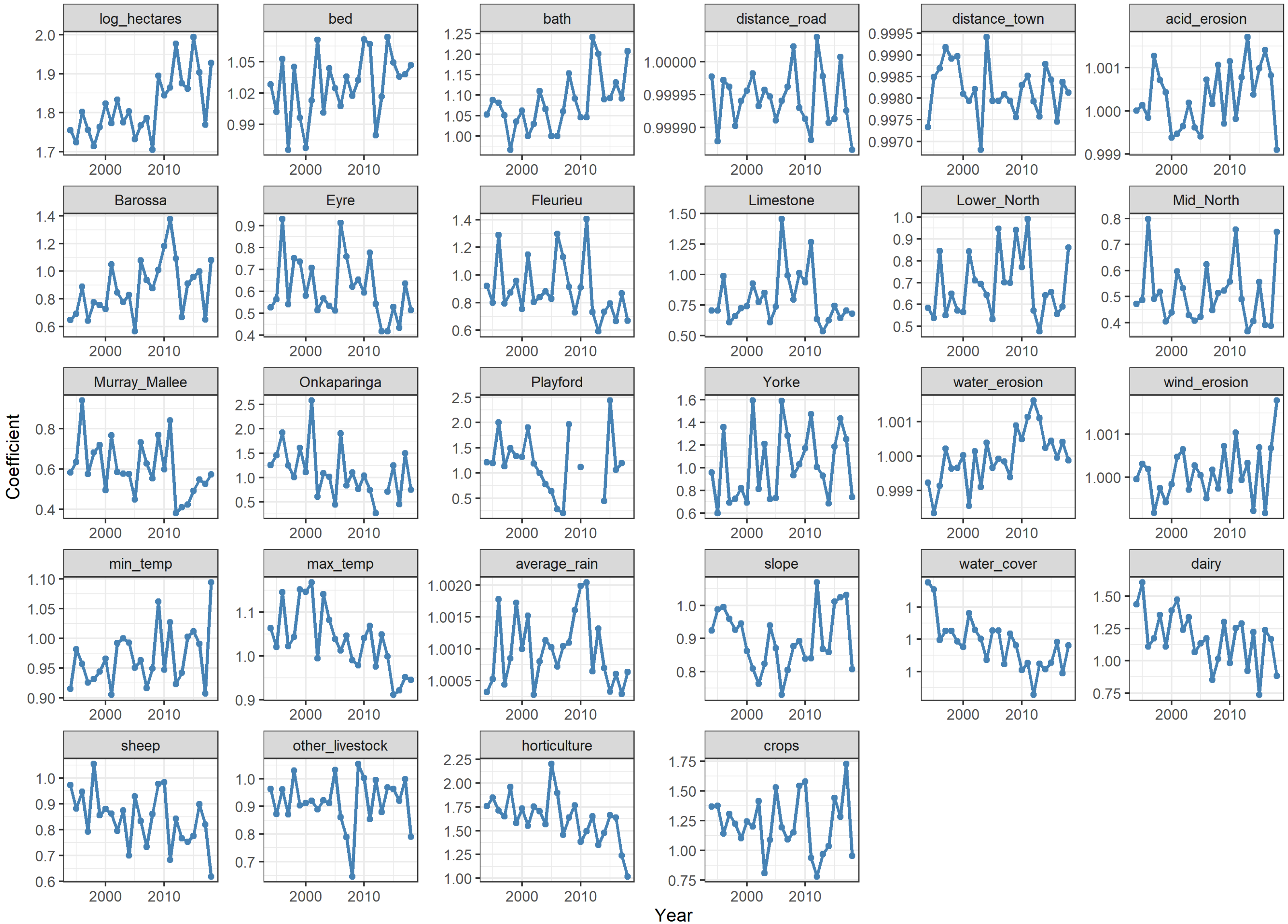
Notes: OLS regression model. Missing coefficient indicate no transaction in that category. The base case for land use is vacant land; for region is SA3 Ballarat.

Figure B.4 – **Coefficients of Model 2 over time, Queensland**



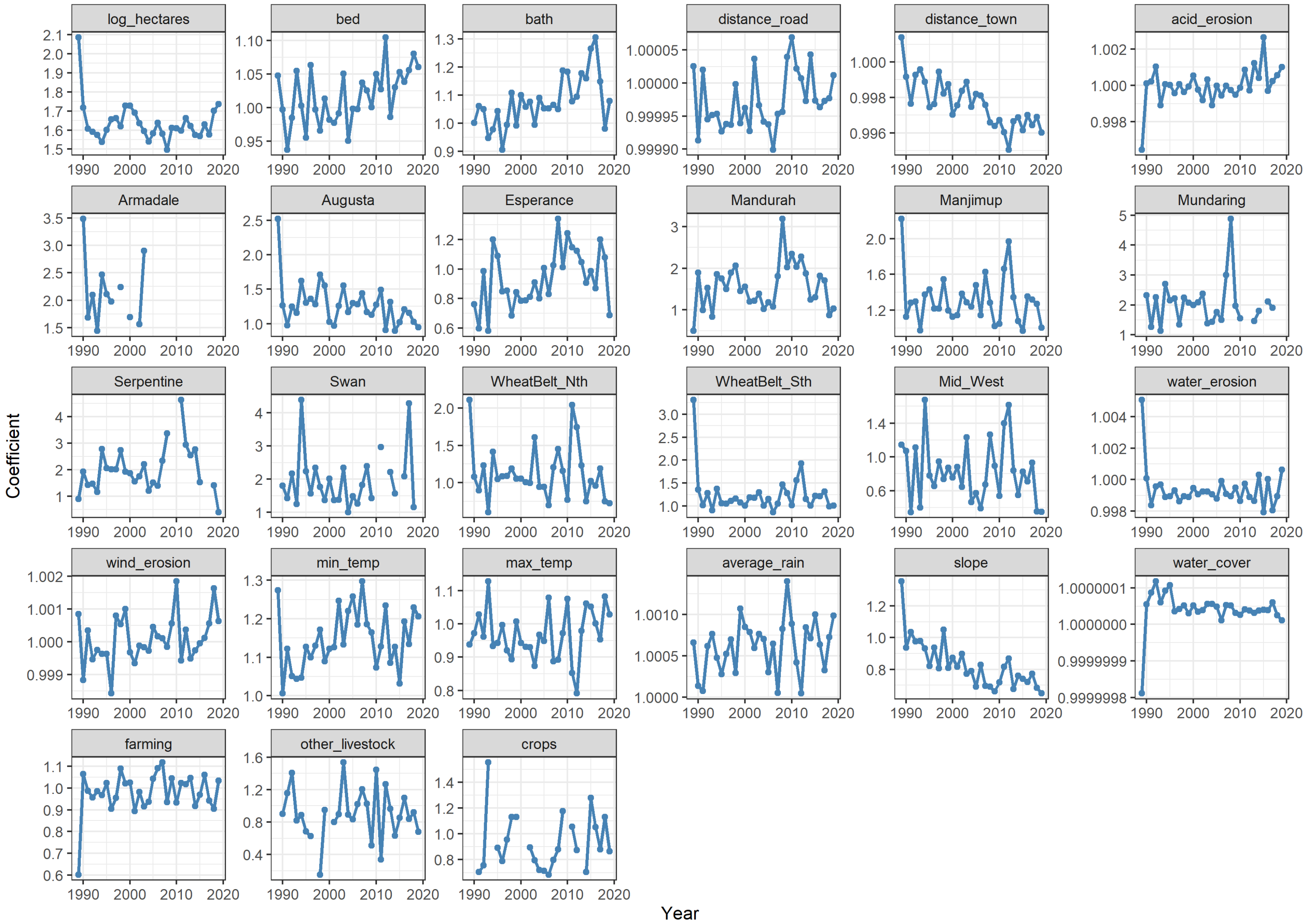
Notes: OLS regression model. Missing coefficient indicate no transaction in that category. The base case for land use is vacant land; for region is SA3 Beaudesert.

Figure B.5 – **Coefficients of Model 2 over time, South Australia**



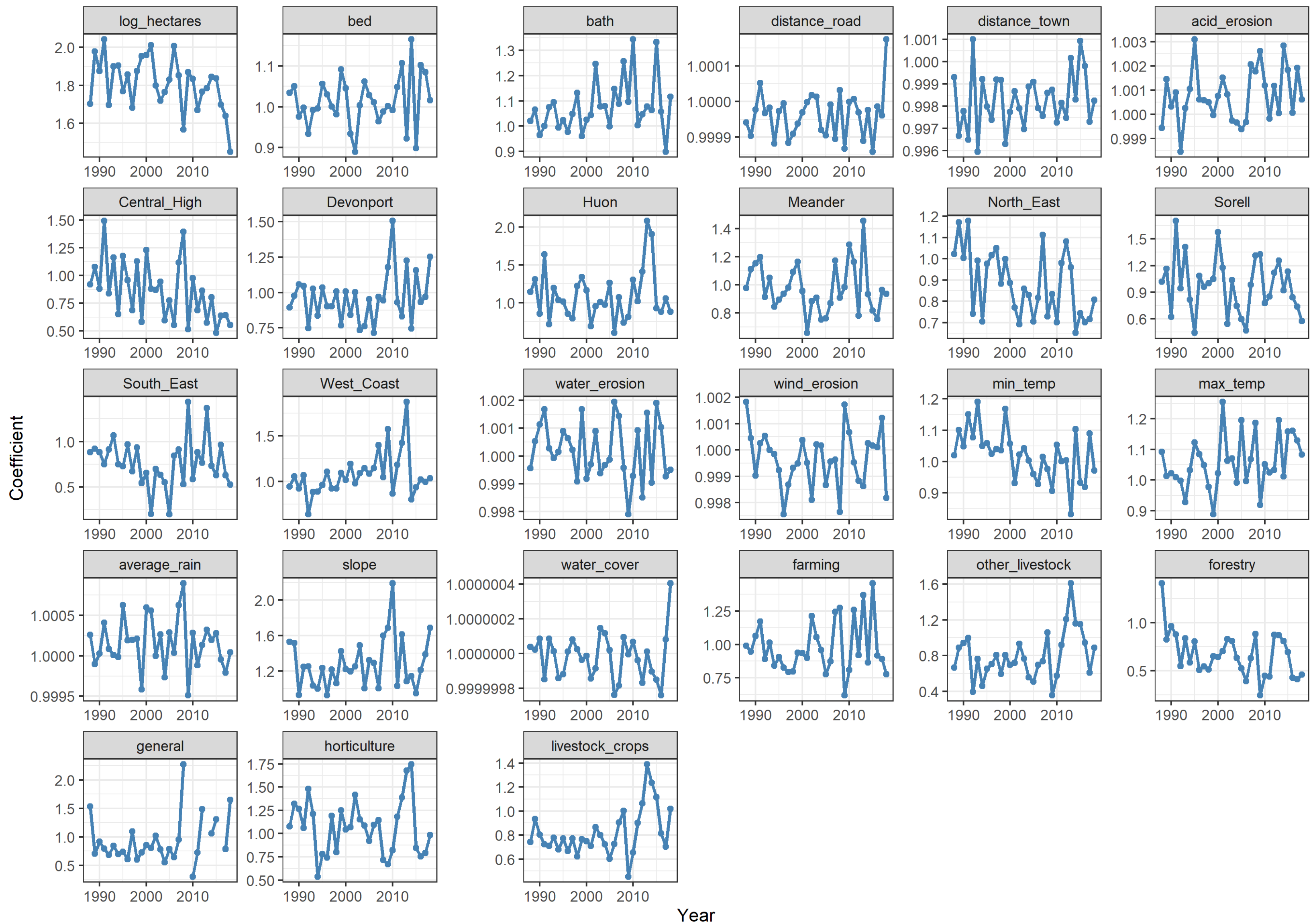
Notes: OLS regression model. Missing coefficient indicate no transaction in that category. The base case for land use is vacant land; for region is SA3 Adelaide Hills.

Figure B.6 – **Coefficients of Model 2 over time, Western Australia**



Notes: OLS regression model. Missing coefficient indicate no transaction in that category. The base case for land use is vacant land; for region is SA3 Albany.

Figure B.7 – **Coefficients of Model 2 over time, Tasmania**



Notes: OLS regression model. Missing coefficient indicate no transaction in that category. The base case for land use is vacant land; for region is SA3 Burnie - Ulverstone.

B.4 GAMs: Smoothing Function

This section provides details on how the GAMs were selected, as well as an overview of smoothness selection. It also discusses the selection process of the independent terms in the models.

GAM is a generalised linear model, whereby the linear predictor is explained using a combination of the linear predictor and a specified sum of smooth functions of the covariates. GAMs provide an effective way of fitting more flexible, nonlinear models using smooth techniques, as a mixture of linear and nonlinear terms can be specified. The nonlinear terms can be in the form of smoothing splines, natural cubic splines, polynomial functions and step functions.

The idea of splines is to fit smooth, nonlinear functions on several predictors X_i. Where a smooth function is applied in the model fitting, the maximum likelihood estimation of this model would produce over-fitting estimates. Thus, GAMs are usually fitted using a penalised likelihood maximisation, where likelihood in the model is altered by a penalty for each smooth function to penalise its 'wiggliness'. The trade-off between penalising wiggliness and penalising model fit is controlled by a penalty, multiplied by an associated smoothing parameter.

B.5 Smoothness Selection Criteria

GAM endeavours to determine the appropriate smoothing parameter for each nonlinear predictor by applying a likelihood-based method or prediction error criteria. The prediction error criteria applied are the GCV criterion when k, the scale parameter, is unknown (as shown in Eq. B.1) or an unbiased risk estimator (UBRE) criterion when k is known (as in Eq. B.2).[1]

$$n\frac{Z}{(n-d)^2} \tag{B.1}$$

[1]Craven and Wahba (1979) and Wahba (1990) provide a detailed discussion of generalised cross-validation and unbiased risk estimators.

$$\frac{Z}{n} + 2k\frac{d}{n-k} \tag{B.2}$$

where n is the number of data, k the scale parameter, Z is the deviance, and d the effective degrees of freedom of the model. It is worth noting that UBRE is essentially AIC rescaled, but only when k is known.

Likelihood-based methods used are the restricted maximum likelihood (REML) for the selection of smoothness. REML treats the smooth components in the model as random effects. Thus, the variance for the smooth random effect is derived by a scale parameter, divided by the parameter for smoothing. When there are smooth components with more than one penalty, there will be multiple variance components.

The choice of k is important, but the critical observation is that k needs to be large enough to capture the dimensionality of the underlying function. The GCV and UBRE scores sometimes display local minima if they become constant with changing smoothing parameters. These 'flat' areas can be separated from lower-score areas by a small 'lip'. While this appears to be the most common local minimum form, it can be avoided by removing extreme smoothing parameters in optimisation, and by avoiding large jumps in smoothing parameters during the optimising process. In the literature, Wood (2011) and others have proven REML to be much more robust under smoothing, as it is less decumbent to local minima than other criteria, but at a computational expense.

B.6 Testing Other Models

We undertook robustness checks to test the sensitivity of our results to the models selected. First, we removed a number of abnormal transactions (for example, transactions of rural properties where mainland use is not generally associated with agricultural production). We noticed that substantial variation in land prices remains. To minimise the effect of outliers, several observations in the sample were removed and the regression equations were re-estimated. The results from the outliered sample were generally consistent with those from the non-outliered sample.

To determine the sensitivity of the model results to the choice of variables, the regression equations were re-estimated with different dependent variables. The effect of different hedonic models on agricultural land price using subsamples and using various functional forms were also estimated. Some variables included were availability of water capacity in the top 5 inches, distance from the farm to the nearest town centre, topsoil depth, and different interactive terms. The distance from the farm to the nearest town centre and the available water capacity were not statistically significant in all the models. The statistical insignificance could relate to their respective interactions with other variables in the model (such as rainfall), and the fact that the exact location coordinate is included. In addition, the irrigation dummy was not statistically significant in the state models. An explanation for this result is that land that requires drainage is already irrigated within that region, thus, it does not contribute to the price of the land.

One of the most common ways for deciding which predictors to select is to compare GCV, UBRE and REML scores for the models, including and excluding the term. For example, we can compare the score for the model containing a smooth term with the score where the smoothing term is replaced by parametric terms. Dependant variables that could be removed can also be identified by observing the confidence band for estimated terms and by reference to the approximate p-values. While it is possible to undertake backward selection[2] using p-values, this method suffers from similar problems as stepwise procedures, with the extra caveat that p-values are only an approximate.

[2]Backward selection involves sequentially removing a variable with the largest non-significant p-value and refitting the model until all variables are significant.

Appendix C

Appendix for Chapter 4

C.1 Measuring land degradation

Land degradation is defined as a decrease in the quality of land and hence, its value. The degradation of farmland is of particular importance as this affects agricultural productivity. It can also lead to clearance of forests and native grasslands, loss of amenity values, offsite pollution, and increased use of other natural resources to repair the land (for example, water for reducing irrigation, salinity or lime for neutralising acidity).

The value of land reflects its productive capacity and the environmental services it provides. Market values are the preferred measure for valuing agricultural land. Nevertheless, market value includes considerations other than the land's productive capacity, such as input and commodity prices, 'lifestyle' and zoning considerations. Thus, it is inappropriate to value land degradation based on changes in the market value.

Two Australian studies have used alternative concepts to measure economic losses due to land degradation. First, Kemp and Connell (2001) estimated change in the capital value of farms adjusted for degradation. They considered that this value represents the total accumulated losses in the value of farmland due to degradation. In another study, the National Land and Water Resources Audit (2002) estimated the value of soil degradation on lost profit at full equity. In their estimates, they included a resource rent and a return to owner for use of produced capital. The resource rent comprised a component for resource depletion and a return to owner for non-produced capital use.

The ABS (2010) released estimates for depletion-adjusted GDP that account for land degradation and depletion of subsoil assets. The method used for estimating annual change in land value due to degradation assumed that degradation occurs at a constant rate. Constant prices of land were derived by applying an appropriate deflator to the current price time series.

The chosen deflator was the chain volume price index for GDP. The reason behind this choice was that it provides a more stable time series than agricultural income-type deflators. It should be noted that these estimates are not included in official national accounts statistics because the national accounts framework does not treat land degradation as a transaction.

Appendix D

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