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Evaluating the benefits from transport infrastructure in agriculture: a hedonic analysis of farmland prices

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Access to transport infrastructure generates a range of benefits to the agriculture sector; many of which are difficult to measure directly. In this study, we use hedonic regression analysis of farm-level data to examine the contribution of transport infrastructure to the value of farmland traded between 2009 and 2011 through its impact on farm productivity. We show that a one per cent reduction in the cost of transportation between farms and ports leads to a 0.33 per cent increase in land prices, and there is no significant difference between rail and road transportation at the aggregate level. Moreover, the benefits generated by particular types of infrastructure services vary between industries and with farm size, suggesting there are multiple channels through which public infrastructure influences agricultural production. Our findings help to inform future investment decisions in Australia and in other countries by providing new evidence regarding the benefits of existing transport infrastructure.

Key words: farmland price, public and private infrastructure, the hedonic function.

1. Introduction

Access to reliable and low-cost infrastructure services makes a significant contribution to the efficiency and profitability of firms in many sectors. Reflecting this, demand for good infrastructure services is often high, creating difficulties for governments and the private sector to choose between alternative investment projects. Making good infrastructure investment decisions requires data on the costs and benefits likely to be generated. While data on costs are readily available, high-quality estimates of the total benefits generated by infrastructure are difficult to obtain, mainly because many benefits are indirect and hard to measure, and some are impractical to capture in project-specific evaluations. The methods presented in this study illustrate one way of obtaining more complete estimates of the benefits generated by access to infrastructure.

The empirical analysis in this study centres on a farming region in the wheat–sheep zone of New South Wales (NSW), Australia. Making smart

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infrastructure investment decisions in the agricultural industry has long been of interest to Australian governments and the private sector, in particular, in the transportation and telecommunication areas. Many farms have specialised in nonirrigated cropping and grazing activities where the returns are influenced by transport and telecommunications costs (Sheng *et al.* 2015; Ball *et al.* 2016). A substantial amount of investment has been made in developing rural infrastructure in the past, with public investment dominating the provision of road, rail, telecommunications and port facilities. The choice of a particular region in this analysis reflects the highly location-specific nature of investments in infrastructure such as rail and roads facilities, so that estimating the benefits of public infrastructure at the local scale is more straightforward and meaningful than estimating at a national or international scale.

While public infrastructure has played an important role in Australian agriculture for many years, estimates of the total benefits and costs associated with investment in infrastructure in rural areas are rare. This is mainly because the benefits generated by investments in infrastructure (both economic and social) are generally spread across long and unpredictable periods of time. Furthermore, the benefits generated by infrastructure are typically spread across the whole community, both publicly and privately, which makes them inherently more difficult to observe and measure than benefits that accrue only to private investors. As a consequence, studies that have relied only on data from infrastructure services providers have tended to neglect the indirect benefits and thus underestimate total economic benefits generated by infrastructure investments (Yoshino and Nakahigashi 2000; Clement *et al.* 2014).

In this study, we address the aforementioned issues by investigating the benefits of infrastructure from a farmer's perspective. Specifically, we endeavour to measure the benefits that accrue to farmers from public infrastructure using farm-level data for NSW, Australia, between 2009 and 2011. Theoretically, the value of farmland traded in a competitive market will include the value of access to infrastructure that facilitates farm production. For example, buyers are likely to pay more for parcels of farmland that are relatively close to markets because it reduces transport costs. However, benefits of this kind are not usually captured in conventional cost-benefit analysis, which leads to underinvestment in infrastructure. To measure these effects empirically, we use hedonic regression analysis to link farmland prices to infrastructure services, while controlling for other variables that also influence farmland prices such as land quality and local population density and dealing with potential endogeneity problems using instrumental variable regression.

To the best of our knowledge, this is the first study that uses farm-level data to estimate the benefits to farmers of access to transport and telecommunications infrastructure in Australia. When combined with data on costs and scaled to the population level, our estimated marginal effects could be used in the calculation of internal rates of return for infrastructure investments related to agricultural production, which may assist governments

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and private entities when making investment decisions. The estimated benefits complement those obtained from the cost–benefit analysis typically used by the providers of infrastructure services in rural Australia. In addition, the estimated coefficients for the control variables used in this analysis provide broader insights into the determinants of farmland prices in Australia. The method could also be readily applied to other farm-level data sets to investigate similar issues in other countries.

Our study complements existing research into the role of infrastructure in affecting economic development in rural communities. For example, Ratner (1983), Aschauer (1989), Mitsui and Inoue (1995) and Yoshino and Nakahigashi (2000) argue that, in theory, infrastructure is an effective factor of agricultural production. Other empirical studies have also examined this subject in developing countries. Banerjee *et al*. (2004) followed by Banerjee *et al*. (2012) estimated the effect of access to transportation networks on regional economic outcomes in China and found that proximity to transportation networks tends to improve per capita GDP levels through increasing labour and capital mobility. Gibson and Rozelle (2003) examined how effective access to infrastructure may help to reduce poverty in PNG, and the results showed that poverty in PNG is associated with poor access to services, markets and transportation. Ghani *et al*. (2012) found that access to education and infrastructure services affected the spatial location of plants and resource allocation in the Indian manufacturing industry. In Australia, Bandias and Vemuri (2005) investigated the relationship between telecommunications infrastructure and sustainable economic and social development. However, most of these studies rely on economic growth theory to examine the effect of infrastructure on macroeconomic productivity while neglecting the spillover effects on farms of access to infrastructure.

The rest of the paper is organised as follows. Section 2 describes the level of infrastructure investment in rural Australia and summarises the literature relating to the methodology and data used to evaluate infrastructure investments. Section 3 develops a theoretical model providing the mechanism through which infrastructure services may affect the value of land through affecting farmers' production costs and productivity. A hedonic regression is derived from the model and used in the empirical analysis. Section 4 contains a summary of the data. Empirical results and a series of robustness checks are presented in section 5. Section 6 finishes with some concluding comments.

2. Infrastructure investment in rural Australia and its evaluation

Strong infrastructure facilitates economic growth and employment and improves the quality of life in rural and urban communities. In Australia, the real value of total investment in public and private infrastructure has been increasing over the past two and a half decades, driven by rapid population and economic growth. In particular, the real value of infrastructure construction work increased from A$ 16.2 billion in 1987 to A$ 58.5 billion

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in 2012 (Figure 1). Rail and road transportations are the two most important infrastructure types, accounting for more than 60 per cent of total annual investment (BITRE 2013). The total stock of 'infrastructure and other (nonbuilding) construction' assets in Australia is valued at A$ 614 billion. This includes road, rail, energy and water assets, which together represent nearly one-fifth of the national capital stock (Productivity Commission 2015).

Historically, governments have been the main source of funding for infrastructure investment in Australia (BITRE 2013). In 1987, the real value (at 2012 prices) of infrastructure engineering construction work undertaken directly by the public sector was A$ 9.4 billion, and construction undertaken by the private sector on behalf of the public sector was A$ 4.7 billion. Together, this represented 87 per cent of the total national investment in infrastructure (Figure 2). However, since the 1980s, regulatory reforms intended to reduce the fiscal burden on governments and improve the productivity of the infrastructure sector, gradually shifted the funding of infrastructure investment towards the private sector. By 2012, the real value of major infrastructure construction work done by the private sector accounted for around 48 per cent of the total.

The increase in private funding has helped to maintain the overall level of infrastructure investment, but has also increased costs to the general public, as private investors usually charge higher rates of return than public investors. In addition, it also shifted the focus of infrastructure investment towards urban regions with relatively rapid population growth, as investing in these regions will most likely generate the highest returns (Productivity Commission 2015). For example, almost 90 per cent of NSW population growth over the last decade has been in the Sydney Greater metropolitan

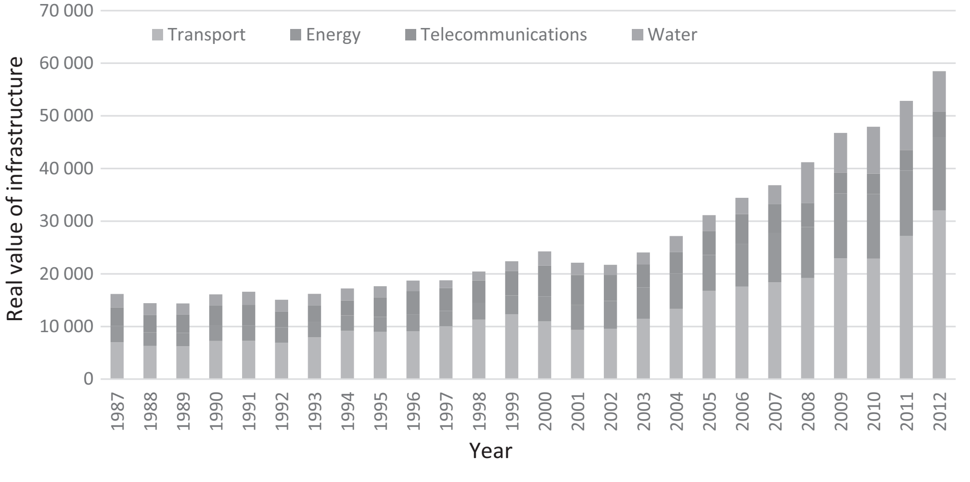

Figure 1 Real value of infrastructure and its composition by industry: 1987 to 2012 (unit: million A$ in 2012 prices). Source: Authors' estimation from BITRE (2013).

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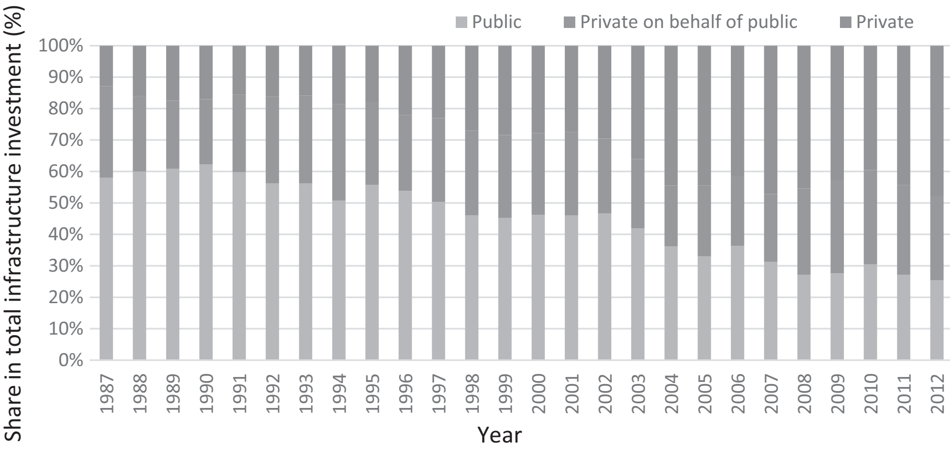

Figure 2 share of infrastructure investment funded by the public sector (unit: %). Source: Authors' estimation from BITRE (2013).

area, and this growth has attracted substantial infrastructure investment from the private sector. In contrast, limited or negative population growth in regional areas may mean that infrastructure investment in these areas is less than ideal. As a consequence, the indirect social and economic benefits to agricultural production that are associated with the spillover effects from infrastructure investment in the rural sector may have been foregone.

For example, one pressing infrastructure issue in regional Australia is access to rail freight. This form of transport infrastructure has gradually become less accessible to farmers in recent years as the cost of maintaining tracks has exceeded the benefits received by the owners of these rail lines from keeping them open. Given the relatively high cost of improving tracks (up to $1 million per kilometre per year) and limited potential users in the region, generating additional investment in these lines and hence maintaining access to rail freight for farmers will either require a substantial increase in the unit cost of using these (and other) transport services to attract private investors, or a large amount of additional public expenditure.

Theoretically, infrastructure investment (such as in road, rail, energy and water assets) provides services that support economic activities (both production and consumption) domestically and facilitate international trade. These services can also generate indirect or flow on benefits, for example: telecommunications infrastructure can increase the opportunity and capacity for businesses to collaborate and innovate, leading to technological and organisational change, and ultimately improved productivity (Productivity Commission 2015). Therefore, it is necessary to look beyond the benefits directly obtained by investors alone to understand the appropriate level of infrastructure investment.

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In this study, we propose to measure the impact of public infrastructure on agricultural production through exploring the relationship between farmland values and the services provided by road and rail infrastructure. A key assumption underlying this exercise is that the infrastructure services present in the neighbourhood of a particular parcel of farmland alter farm productivity and profit and these differences are capitalised into the value of the land in the long-run. This approach has the important advantage that it allows us to capture the indirect benefits to farmers associated with the spillover effects of rural infrastructure investment.

3. The hedonic regression approach and related empirical issues

In the context of agriculture, hedonic regression analysis has generally been used to examine the relationship between the price of farmland and unpriced characteristics such as soil quality and climate conditions (Palmquist and Danielson 1989; Mendelsohn *et al.* 1994; and Grimes and Aitken 2008). Using market prices of land as the dependent variable, this method captures the value of unpriced characteristics as reflected in people's preferences and accounts for the constraints and trade-offs they face when making land purchase decisions.

For the purposes of this analysis, we derive the hedonic regression function by starting with a profit maximisation function for a representative parcel of farmland (Eqn 1):

$$\max_{L,X}\int_t^{t'}[P_s(Y_s)*Y_s-P_{st}(X)]e^{-\rho s}\,ds-[P_t(Z:R,T)-P_{t'}(Z:R,T)]*L_t-\mathrm{FCT}_t$$

$$s.t.\,Y_t=f(A_t,L_t,X_t,\mathrm{INF}_t,E_t), \tag{1}$$

where $P_s(Y_s)$, $P_t(X)$ and $P_t(Z{:}R, T)$ are prices of output, other market inputs and land, respectively, and Y_s, X_t and L_t are quantities of output, other market inputs and land, and Z is land price domain, R is resource-based valuation, and T is the transaction activity. FCT_t represents the fixed costs related to production or the transaction. In Equation (1), the land owner seeks to maximise profit from owning land by using it for production and as a capital asset that can change in value over the period of ownership (t to t'). The profit maximisation process is subject to the constraint that output from the land (Y_t) is a function of the total factor productivity of the farm (A_t), the land area (L_t), the variable inputs used in production (X_t), the infrastructure available to the farm (INF_t) and other exogenous factors (E_t) such as climate conditions.

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Taking the first order condition of Equation (1) with respect to land use yields the land price function (Henneberry and Barrow 1990; Xu *et al*. 1993, and Ma and Swinton 2012):[1]

$$P_t(Z:R,T) = \frac{1}{1-\rho}\frac{\overline{P(Y)}}{\overline{L}} f_{\overline{L}}(\overline{A}, \overline{L}, \overline{X}, \overline{\mathrm{INF}}, \overline{E}) \tag{2}$$

Equation (2) shows that the price of land is a function of the discount rate, the area of the parcel and the long-run average of the factors that influence the profit that can be earned from farm production, namely output prices $P(Y)$ and the other factors defined above, namely A, L, X, INF and E. E also includes non-production-related factors such as local population density (or proximity to towns or cities) and land quality. Reflecting this theoretical derivation, an empirical specification used to define the relationship between the price of land and its characteristics can be written as:

$$P = g(A, L, X, E, \mathrm{INF}), \tag{3}$$

where $g(.)$is a general functional form.

Equation (3) shows that the price of land is a function of farmers' access to local infrastructure, provided that other factors are well controlled for, as infrastructure services affect farms' production function, their capital–labour ratio and their productivity. Compared with Equation (2), Equation (3) excludes the price of outputs and the discount rate. This is because we use a cross-sectional data set in the analysis and thus can assume that the same discount rate and output prices apply to all farms in the same state. In the estimation, we also exclude the variable inputs used in production (X) because of a lack of data.

The benefits of rural infrastructure to farmers can be estimated using Equation (3) provided that two econometric issues are well accounted for. The first issue is potential endogeneity caused by omitted variables or the reverse causality between farmland price and local infrastructure investment. For example, variation in macroeconomic factors such as average income may affect land values and may also affect government decisions about infrastructure investment. Without accounting for such factors, the OLS regression will tend to overestimate or underestimate the effects of infrastructure services on land prices. To solve this problem, we use the instrumental variable (IV) regression approach.[2]

[1] Please refer to Appendix S1 for a more detailed derivation.

[2] The instrumental variables have been included in the analysis of transport and telecommunication infrastructure using a two-stage least squares regression. The efficiency of all IVs has been tested, and the first-stage F-tests are reported in the results.

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The IV method involves using different ‘instruments’ to identify the contribution of transport and telecommunications infrastructure to farmland prices. In particular, the IV used to identify rail transport infrastructure is the average time (i.e. the year) when the railway arrived at the nearest point to each farm parcel, following Gibson and Rozelle (2003). The variable is estimated by first calculating the maximum opening year of the rail line nearest to each farm parcel and then taking the weighted average of these maximum opening years using the direct distance of the farm parcel to the rail line as weights. Opening times for each segment of rail line in the study region was obtained from http://nswrail.net/lines/nsw-map.php (Bozier 2011) and presented in Figure 3.

The rationale for this choice of instrument is that the rail network in NSW was initially built to connect the capital city to the river transport network and mining towns, rather than to service agriculture. When rail lines happened to go through nonfarming land locally, this gave farmers the opportunity to use this infrastructure and thus reduce their transportation costs. However, the average time that the railway lines penetrated the areas near each parcel is unlikely to be directly related to land prices.

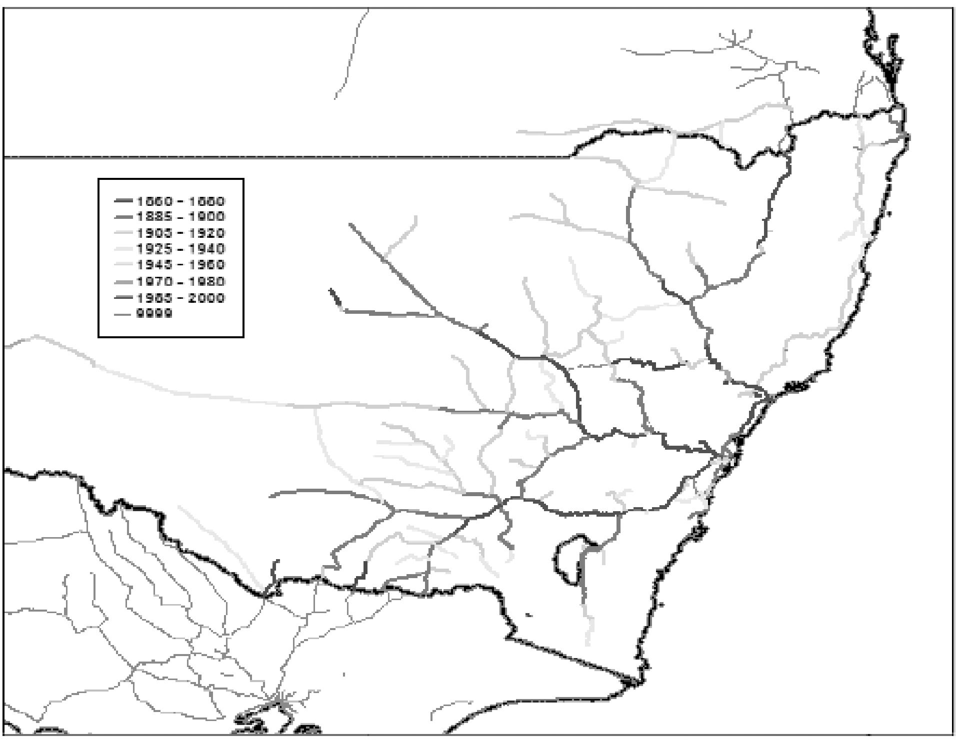

Figure 3 Map 1 Railway network with different opening time in NSW. Source: obtained from http://nswrail.net/lines/nsw-map.php

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The second issue is the multicollinearity problem between variables representing rail and road infrastructure. Because the rail infrastructure variable is strongly positively correlated with the road infrastructure variable,[3] we have to reorganise the two variables using the orthogonal approach (Woodridge 2002). Specifically, the rail infrastructure variable was included in level terms, and road infrastructure was represented as the ratio of road-to-rail travel costs. The null hypothesis under this model specification is that: access to road infrastructure has no effect on land values in addition to the value generated by access to rail infrastructure, and a significant coefficient will measure the extent to which access to road transport infrastructure is worth more or less than access to rail infrastructure.[4]

In addition to endogeneity and multicollinearity, we also adopted the procedure from Ma and Swinton (2012) to adjust standard errors for estimated coefficients caused by potential heteroscedasticity and spatial correlation.

4. Data source and variable definition

Data used in this study were drawn from three main sources: farmland prices were obtained from NSW Land and Property Information (NSW LPI); spatial data sets were used to construct transport cost variables and instruments; and the Australian Population Census was used to construct a control variable. The key features of the data are discussed in this section, and descriptive statistics are presented in Table 1.

4.1 The price of farmland

Market prices of farmland were obtained for all rural property transactions that occurred in the wheat–sheep zone[5] of NSW in 2010 – a total of 2,705 transactions. For each transaction, we obtained the contract and settlement dates, the total land area traded, the address of the property, the identifiers of the lots being traded, the sale price of the parcel and the names of the buyer and seller. Figure 4 shows the location of each parcel of land in the sample:

The wheat–sheep zone of NSW is an inland area mainly used for agricultural purposes. This region was chosen for our analysis for two

[3] Correlation between these variables reflects the fact that the main determinant of both is the distance from the farm to the nearest port or capital city, which is similar when travelling by road or rail. In OLS regressions, the existence of multicollinearity means that the coefficients estimated for the correlated explanatory variables are unlikely to be statistically significant.

[4] Nonetheless, as a sensitivity test, we have also estimated the regression equation with the two transport cost variables represented separately and combined together. Results are presented in Appendix S2.

[5] The wheat–sheep zone is an area of Australia in which agronomic conditions are such that agricultural land use is dominated by mixed farms that produce grains and livestock. A map of this zone is available in ABARES (2011)

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Table 1 Descriptive statistics on farmland price and other related variables

Variable	Mean	Std. Dev.	Min	Max
Land sale price (A$/hectare)	5,828.4	2,033.6	42.5	37,099.0
Land areas (hectare)	308.5	1,520.7	0.01	4,2470.0
Population density for 2 km radius (persons)	16.1	49.4	0.04	533.4
PPI 100 index (0–10)	1.9	0.2	1.3	2.7
Port–rail total transport costs (A$)	266.1	59.3	134.5	489.4
Road–rail total transport costs (A$)	358.2	82.1	204.6	690.8
Port–rail distance (km)	406.0	99.5	201.9	739.2
Road–rail distance (km)	357.2	80.8	205.9	669.9
Proportion of land irrigated (%)	10.0	29.6	0.0	100

Note: The total number of observations is 2,327.
Source: Authors' own estimates.

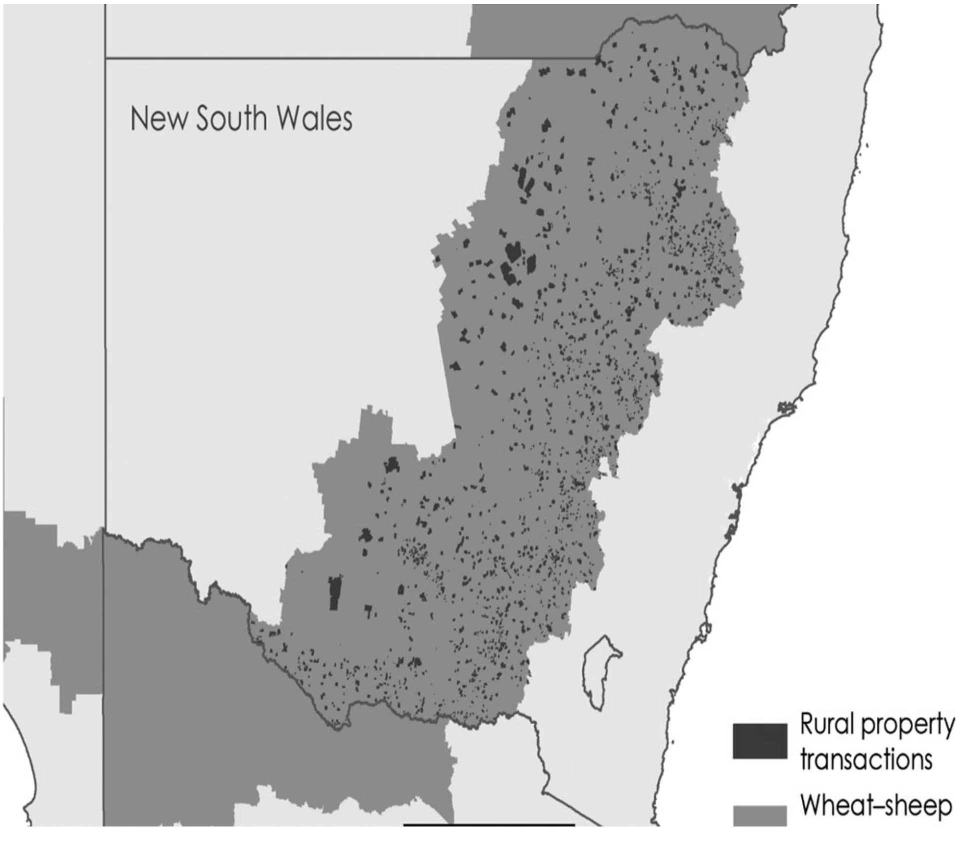

Figure 4 The distribution of farmland sales in NSW: 2009–2010.

reasons. First, our intention is to better understand the value of infrastructure to the agriculture sector, so prices of land used primarily for agriculture are most suitable. In contrast, rural property prices in the coastal areas of Australia are often strongly influenced by nonagricultural factors such as

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urban expansion, commercial development and recreation. Second, relatively similar agricultural activities tend to be undertaken throughout in the wheat–sheep zone. This reduces the impact on the regression of not having data on the specific agricultural activities (including horticulture and on-farm tourism) that are undertaken on each parcel of land in the sample.

The prices obtained from NSW LPI required cleaning prior to estimating the regression because inspection of spatial and other data for properties in the sample revealed that some of the transactions related to land used for residential or other nonagricultural purposes. The market price of land in these transactions is unlikely to adequately reflect the value of land used for agricultural production. For example, some properties in the sample were used for purposes such as water storage, nature conservation, plant nurseries, abattoirs and coal mines. The price of land traded in these transactions is likely to be biased by the value of the capital assets that are present.

To deal with this problem, we removed the following transactions from the sample: land used for coal mining (42 transactions); parcels with very low prices where the transaction was between family members (137 transactions); properties mainly comprised of nonagricultural land (171 transactions); and those with missing information (six transactions). Removing these transactions plus those with incomplete information leaves us with a sample of 2,327 observations.

4.2 Rail and road transport infrastructure

Transport infrastructure variables were defined as the total transportation costs of a metric tonne of agricultural cargo (i.e. grains or livestock) from a particular farm to the final domestic point of sale for commodities, namely the nearest major population centre or commodity port defined as towns/cities with population of more than 500,000 and seaports for agricultural commodity exports. Specifically, the transport cost calculations utilise Dijkstra's algorithm that finds the least cost path for freight (Dijkstra 1959). The rail and road networks are based on Geoscience Australia's GEODATA TOPO 250K Series 3 product (ga.gov.au/metadata-gateway/metadata/record/gcat_63999). The transport costs for each link on the transport network are relative cost rates per kilometre that discriminate between rail lines and roads of different classes and surface types as identified in the Geoscience Australia data. A loading/unloading cost is also included for when wheat is loaded from road to rail or vice versa. These cost parameters were chosen to reflect broad patterns of wheat freight movements.

4.3 Control variables

The control variables included in this analysis were identified from a review of previous studies, including those by Mendelsohn *et al.* (1994), Schlenker *et al.* (2006) and Massetti and Mendelsohn (2011). Four variables were selected from this review, namely the land area of the parcels that were sold,

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the population density of the area around the farm, the Forest Productivity Index used to reflect the agronomic quality of farm parcel and the share of a farm that is irrigated. In addition, dummy variables that represent the contract date for each transaction were included to control for time-specific effects.

Data on the land area of the parcels that were sold was obtained from NSW Land and Property Information.

We control for this variable because larger parcels of land are typically sold at lower prices per-hectare than smaller parcels. The population density of the area around the farm is a proxy for the potential to develop the land for a residential or commercial purpose, which is likely to significantly increase the market price of farmland. To estimate this variable, we used a spatial representation of 2011 Australian population census data (ABS 2011) to calculate the population density of the area surrounding the property within a radius of 2 km.

Agronomic quality is one of the most important determinants of farmland prices. To measure agronomic quality of each parcel in our sample we use the Plant Productivity Index (PPI). This index is estimated by National Carbon Accounting System (and mapped for the whole Australia) using a 'productivity index' model that is based on the relationship between the amount of photosynthetically active radiation absorbed by plant canopies (APAR) and the various productivity modifiers that affect plant growth (i.e. soil quality, temperature, precipitation and extreme weather condition) (Kesteven and Landsberg 2004). The PPI takes the value between 0 and 10, with larger values representing better agronomic quality of land. Factors converting APAR to productivity indices were reduced from presumed optimum values by modifiers dependent on soil fertility, atmospheric vapour pressure deficits, soil water content and temperature.[6] The model used a monthly time step to derive a long-term average productivity index for the period of 1970–2002 (with 1 km resolution). This spatial data was matched with each parcel of farmland in our sample, and the corresponding PPI was retrieved to reflect the agronomic quality of each parcel of farmland.

The proportion of each farm that is irrigated was also included as a control variable. Irrigation is a substitute for rainfall, and therefore has a substantial effect on the amount of profit that can be earned from a particular parcel of land. Data that define this variable for each farm were obtained from a

[6] Both the ANUCLIM and ANUSPLIN programs were used to generate climate surfaces for the continent. Soil fertility and water-holding capacity values were obtained from the CSIRO using the digital Soil Atlas of Australia. Leaf Area Index, essential for the calculation of APAR, was estimated from 10-year mean values of Normalised Difference Vegetation Indices (NDVI), for 1 km pixels, for the entire country. Incoming short-wave radiation – and hence APAR – was corrected for slope and aspect using a Digital Elevation Map (DEM) for the long-term average, but with 1 km pixels being used in the monthly productivity maps derived as this made no significant difference to the results.

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spatial layer constructed by the Australian Collaborative Land Use and Management Program.

Finally, a dummy variable for the date of the transaction was included to capture time-specific (or cohort) effects on land sales.

5. Empirical results

Our results show that transport infrastructure has a significant effect on farmland prices and that these effects vary with farm size and type. We also find that controlling for the potential endogeneity problem changes the magnitude and significance of the estimates obtained for particular kinds of infrastructure.

5.1 Aggregate results

We first estimate the contribution of transport infrastructure to farmland prices, and results are presented in Table 2. The estimates in each column illustrate the effects of controlling for the econometric problems of heteroscedasticity (HE) and endogeneity (through IV regression). In most cases, the effects on estimated coefficients are small; however, these adjustments are necessary to ensure the estimates are accurate and robust to different assumptions.

Our regression explains a substantial proportion (71 per cent) of the variation in land prices in our sample, and most of the variables expected to influence land prices have a significant effect. In particular, parcel size, development potential (i.e. population density), agronomic quality of land (i.e. PPI 100 index) and share of parcel irrigated all have significant effects on land prices with the expected sign. While of little direct interest in this work, the estimated coefficients for control variables provide additional insight into the determinants of farmland values and could be useful in other work, for example into the potential effects of climate change and urbanisation on the farm sector.

In this analysis, the transport infrastructure variables are of most interest. The estimated coefficient for the rail transport variable obtained from the IV regression that controls for heteroscedasticity is significant at the one per cent level and indicates that a one per cent decrease in the transport cost variable is associated with a 0.33 per cent increase in land prices, all else being equal. In contrast, the coefficient for the variable used to represent the relative transport cost when rail is excluded (the ratio of road-to-rail transport costs) is not significant, which indicates there is no additional land price effect associated with access to road infrastructure beyond that generated by access to rail infrastructure. This most likely reflects the fact that road and rail infrastructure are close substitutes in providing transportation services to farms and, therefore, have similar effects on land values.

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Table 2 Impact of transport infrastructure on farmland prices

	OLS Regression		IV Regression	
	No HE	With HE	No HE	With HE
Dependent variable: ln_land_price				
Land size in the transaction (log)	−0.470*** (0.011)	−0.487*** (0.018)	−0.489*** (0.012)	−0.485*** (0.019)
Population density for 2 km radius (log)	0.241*** (0.014)	0.246*** (0.020)	0.241*** (0.016)	0.251*** (0.022)
PPI 100 index (log)	0.514*** (0.116)	0.533*** (0.125)	0.558*** (0.152)	0.472*** (0.166)
Proportion of land irrigated (%)	0.210** (0.089)	0.225*** (0.083)	0.237** (0.099)	0.250** (0.098)
Port-rail transport costs (log)	−0.276*** (0.090)	−0.289*** (0.094)	−0.337** (0.149)	−0.332*** (0.106)
Road-to-rail transport costs ratio	−0.016 (0.232)	0.269 (0.253)	0.326 (0.893)	0.701 (0.899)
Constant	10.822*** (0.669)	11.180*** (0.691)	11.454*** (1.250)	11.670*** (1.290)
Number of observations	2,289	2,289	2,289	2,289
Adjusted R-squared	0.710	0.711	0.710	0.711
IV Regression First-stage F-statistics	–	–	44.55	43.03

Note: Dummy variables have been used to control for contract year, ***represents $P < 0.01$, **represents $P < 0.05$ and *represents $P < 0.1$. The first-stage-IV regression results are available upon request from the authors.

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5.2 Differences between farm types

Analysis of the overall sample shows that greater access to transport infrastructure is associated with higher farmland prices. However, the benefits of improved access to these types of infrastructure are not necessarily evenly distributed between different types of farm. Differences in benefits between farms can provide some insight into the mechanism through which access to infrastructure contributes to agricultural production and therefore land prices. Accordingly, we split the sample into various subgroups and re-examined the contribution of transport and telecommunications infrastructure to the price of land in each subgroup.

Two criteria were used to define farm types – size and industry. In particular, we have distinguished the sale of large properties from small properties using the total area of the parcels sold. ‘Small’ farms are those sales with an area of less than 100 hectares. We have distinguished cropping and grazing farms depending on the dominant land type (e.g. cropping or grazing) on each property, according to the Australian Collaborative Land Use and Management Program (ABARES 2016). The results obtained from these regressions are summarised in Table 3. All results are from the IV regression with adjustments for heteroscedasticity and spatial autocorrelation.

Greater access to rail infrastructure has a positive effect on land prices in almost all subgroups. However the magnitude and significance of the effects differ significantly between farm types. In particular, the rail infrastructure variable is highly significant for large farms (at the 1 per cent level). It is significant at the 10 per cent level for cropping farms and not at all significant for grazing farms. Similarly, the road transport variable (the ratio of road-to-rail transport costs) is positive and significant at the 1 per cent level for large farms and at the 10 per cent level for cropping farms, but not for grazing farms. This indicates that access to improved road infrastructure is worth substantially more than access to rail infrastructure for large and cropping farms, but not for grazing farms. For grazing farms, transport costs to saleyards, feedlots and abattoirs are likely to be more relevant than transport costs to major ports. This effect could be investigated in future work.

5.3 Sensitivity analysis

Three robustness checks have been used to establish the sensitivity of our results to the regression method and sample of farms used in the analysis.

First, the sample of transactions used in this analysis comprises most of the rural land transactions that occurred in the wheat–sheep zone of NSW in 2009–2010. While we removed a number of abnormal transactions when constructing the sample (for example, those not related to agricultural production), substantial variation in land prices remains. To reduce effects

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Table 3 Impact of rail and road infrastructure on land prices by property type

	Large Properties	Grazing Properties	Cropping Properties
Dependent variable: ln_land_price			
Port–rail transport costs (log)	−1.083*** (0.192)	−0.291 (0.246)	−0.845* (0.485)
Road-to-rail transport costs ratio	0.3131*** (0.156)	−0.065 (0.127)	0.833** (0.309)
Land size in the transaction (log)	0.076*** (0.026)	−0.498*** (0.024)	−0.241*** (0.078)
Population density for 2 km radius (log)	0.223*** (0.026)	0.235***	0.173*** (0.059)
PPI 100 Index (log)	0.371** (0.168)	0.695*** (0.223)	1.353*** (0.353)
Proportion of Land Irrigated	0.709*** (0.129)	0.237 (0.204)	0.636** (0.280)
Constant	13.643*** (1.460)	10.432*** (1.889)	15.274*** (3.211)
Number of observations	1,058	1,640	485
Adjusted R-squared	0.339	0.618	0.159
IV Regression First-state F-statistics	14.93	31.47	13.51

Note: ***represents $P < 0.01$, **represents $P < 0.05$ and *represents $P < 0.1$. The first-stage-IV regression results are available upon request from the authors.

that may be caused by the presence of outliers, we remove the highest and lowest 5 per cent of observations in the sample and re-estimated the regression equations. Results obtained from the restricted sample were generally consistent with those obtained from the unrestricted sample.

Second, although an IV regression strategy was used to identify the contribution of the infrastructure variables to land prices, our estimates may nonetheless be influenced by the choice of control variables. To examine the sensitivity of our results to these choices, we re-estimated the regression equations with different control variables. For example, we included the value of funds available to local councils in the transport regression, as councils are responsible for maintenance of much of the rural road network. Performing this exercise did not result in any significant changes to the regression results.

Third, in the analysis presented above, we represented rail and road transport infrastructure in separate regressions to simplify the inclusion of IVs. This approach implies that these two forms of infrastructure do not interact. However, different transport infrastructure could work together to affect farmland prices. To determine whether this is the case, we performed the exercises again using a single regression that includes both transport infrastructure. There were no significant differences in the coefficients obtained when using this approach.

Finally, we also estimated the impact of transport infrastructure on farmland price using subsamples that represent small, noncropping and nongrazing farms respectively and using different function forms (i.e. quadratic). The results are generally consistent with our expectations.

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6. Conclusions

In this study, we derive the relationship between farmland prices and access to transport infrastructure and test this relationship using farm-level data for the wheat–sheep zone of NSW, Australia in 2009–2010. This analysis generates estimates of the spillover effects generated by rural public infrastructure to the farm sector, in particular, the value of access to public infrastructure services that are capitalised into land values through the private buying and selling decisions of farmers. These estimates are potentially quite different to estimates that would be generated by examining the direct costs and benefits alone.

Our results show that better access to rail and road transport infrastructure has a positive effect on farmland prices reflecting the contribution to agricultural production that is provided by these forms of infrastructure. Our results also show that the effects of different types of infrastructure on land prices vary with farm type. In particular, the price of land used by large and cropping farms appears to be affected by access to transport infrastructure. This suggests that infrastructure affects agricultural production through a number of different channels.

There are a number of ways in which this analysis could be extended in future research. Most significantly, the coefficients obtained here could be used to estimate the marginal value of additional infrastructure to the farms in the study region, and extending the analysis to other regions (or subregions) and other countries would reveal the areas in which additional infrastructure investment is likely to create the greatest benefits. When combined with estimates of the cost of improving infrastructure in particular regions, such an analysis could provide powerful insights for the allocation of infrastructure investment funds. Finally, we note that while interesting, our estimates should be viewed with some caution, since we encountered a number of data constraints (for example in relation to industry coverage and control variables) that could bias the estimates.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. The Theoretical Relationship between Land Price and Transportation and Telecommunication Infrastructure

Appendix S2. Additional robustness checks

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