Australian School of Business Research Paper No. 2014 ECON 24

Transport Infrastructure Investment and Interindustry Spillovers: The Effects on the Cost Structure of Australian Industries

Amani Elnasri

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Amani Elnasri
School of Economics, Australian School of Business Building - Level 4
University of New South Wales, NSW 2052, Australia

May 1, 2014

Abstract

This paper examines the impact of the provision of public transport infrastructure on the cost structure of the Australian economy within a context that recognises industry agglomeration externalities. The paper extends the symmetric generalised quadratic cost function by incorporating public transportation capital as an external input and adapting the spatial econometric techniques to an industrial context to allow for industry spillovers in the cost analysis. Using industry level data over the period 1990-2010, the paper finds that while public transport has a productive effect in reducing the cost of production, neglecting interindustry spillovers has noticeably overestimates this effect.

Keywords: Transport infrastructure, Interindustry spillovers, Flexible functional forms.
JEL Classification Numbers: D24, H23, H41, H54.

1 Introduction

The majority of Australian research addressing the impact of public infrastructure investment in the economy that evolved during the last two decades has generally adopted a similar approach. Typically, this has been to estimate output/productivity elasticity from an aggregate production function (for example, see Otto and Voss 1994, 1996; Kam 2001; Connolly and Fox 2006; Shanks and Barnes 2008 and Elnasri 2013).[1] Unfortunately, the theoretical framework underlying the production function approach is too limiting to consider the analysis of firm behaviour and the role of input prices. Further, it suffers from the endogeneity problem as a result of treating the quantities of capital and labour as exogenous variables in the model while their supply is expected to vary with the output changes (Morrison and Schwartz 1996).

*I would like to express my deep appreciation to Glenn Otto and Kevin Fox for their advice and encouragement on my Ph.D. thesis, on which this paper is based. The paper has benefited from valuable comments of audience from the Australian Bureau of Statistics, 2012, Canberra and participates at the 12th Economic Measurement Group Workshop, 2012, Sydney. Generous financial support from Australian Research Council Linkage Grants Scheme (project number LP0884095) is gratefully acknowledged. Remaining errors are my own.

[1] Song (2002), Paul (2003) and Wills-Johnson (2011) are three exceptions where the authors have applied the cost function approach.

Another pivotal issue which has been neglected in the existing literature is to consider the disaggregation of infrastructure investments into components when assessing their effects. This represents an essential practice because looking into an aggregate measure of infrastructure will not permit segregation of the effects into components, for example to isolate the effect of transportation service from that of sewerage and drainage. Whereas an element of the overseas literature was directed along this line where analyses were conducted at the disaggregate level to estimate, for example, the individual effects of telecommunications, airports, highways or roads (e.g. Dodgson 1974; Cronin et al. 1990; and Holtz-Eakin and Schwartz 1995), this tradition has rarely been considered in the Australian literature. Only a few studies using the production function approach have attempted to estimate the impact of roads (Otto and Voss 1993) and transport and telecommunications separately (Shanks and Barnes 2008), while the remaining studies have estimated the effect of a broad measure of public capital. Consequently, an attempt is made in this study to fill this gap in the literature by both examining the effect of a class of infrastructure - that is, transportation - and applying a cost function approach.

The enhancement of transportation infrastructure is generally thought to increase the level of economic output, improve the productivity of labour and private capital and reduce the cost of production. Some examples of the potential contribution of transportation is rendering a large scale of activity more accessible due to reductions in costs of travel or travel time; increased throughput (i.e. traffic volume), network-wise or on specific links; improved safety; reduced emissions and enhanced intermodality (Berechman 2002). Shanks and Barnes (2008), citing other papers, have also highlighted relevant cases showing how transportation benefits are manifested in other ways, for instance, the possibility of creating new innovations, such as new products, as a result of the increased accessibility of larger markets or making new inputs available, such as expanding labour market catchments.[2]

Apart from the above direct benefits, another crucial driver of the transport-productivity relationship is the spillovers effect. The improvement in transport provision is not only expected to influence the scope of economic agents' production decisions, but also to generate a wider economic effect by creating linkages through industries and/or space among productive entities. It is evident in the previous literature that spillovers are associated with interdependencies among industries, and in such a case, the links between industries and their customers or suppliers in the productive behaviour could be considerable (Bartelsman et al. 1994 and Morrison Paul and Siegel 1999). Evidence also suggests the existence of spatial linkages where economic activity in one geographical region affects the economic performance in neighbouring regions (e.g., Cohen and Morrison Paul 2003, 2004). Although it is conceivable that less congested transport systems have positive effects on the productivity of certain economies (whether they are industries or regions), their spillover effects can be positive or negative. On one side, transport infrastructure can reduce transportation costs and combine the economic activities of various entities, so that the growth of one entity will drive the growth of other interrelated entities through economic diffusion effects. In contrast, improvement in the accessibility of different activities within these economies can produce local competitive advantages at the expense of other economies; this

[2] See Shanks and Barnes (2008, p. 19) for ample discussion.

represents negative spillovers. Thus, the measurement and recognition of these two types of spillovers (spatial and industry) in productivity and cost analyses is vital for obtaining precise estimates of the effect of transportation.[3]

Generally speaking, performing analysis that accounts for external effects has extensive data requirements (regional, temporal, and industry disaggregated data). This has perhaps been the limiting factor which explains the dearth of research in this area to date. While there are a few studies which address the spatial spillovers of transport within developed countries (e.g., Boarnet 1998, and Cohen and Morrison Paul 2003, 2004 in the U.S.; Moreno et al. 2004, and Ezcurra et al. 2005 in Spain), the industry spillovers associated with transport were notably ignored. Surveying the literature, the singular exception is found in Moreno, López-Bazo, Vaya and Artis (2004) who examined both spatial and industrial spillovers for manufacturers in the Spanish regions, but focused on aggregate public capital. Morrison Paul (2002), has discussed the spillovers which may stem from industry linkages from a theoretical perspective, and has proposed potential mechanisms to incorporate them into productivity and cost analyses in order to account for the bias they may introduce in the effects of explanatory variables. In regards to Australia, there is a complete lack of research that considers either type of spillovers. Unfortunately, our endeavours to collect spatial data to account for transport spatial spillovers were unsuccessful; nonetheless, the availability of data at industry level stimulates us to conduct an analysis which can allow, at least, for industry spillovers. To accomplish this purpose, the analysis adopts the idea of interindustry spillovers motivated by Bartelsman, Caballero and Lyons (1994) in which they incorporated a measure of industry spillovers in a production model; however, similar in spirit to the approach of Morrison Paul and Siegel (1999), we incorporate spillovers in the cost function.

As noted earlier, another aspect that has been neglected in the Australian literature is to examine the effect of public infrastructure on cost structure. Little effort appears to have been expended to implement a cost function approach. The only three studies we are aware of are those of Song (2002), Paul (2003) and Wills-Johnson (2011). By constructing a new data set for private output and capital stock, Song (2002) estimated two models using translog and CES cost functions which incorporate public capital. His results suggest a productive role for public capital in the private sector but one which is subject to congestion.[4] On the other hand, Paul (2003) consistent with the current analysis, used industry level data but focused only on seven industries which he considered to be dominated by private ownership.[5] He estimated a translog cost function for the aggregate private sector as well as for the seven industry groups. The author's results suggest that public infrastructure has a positive and significant impact on productivity in private sector industries. Both studies, surprisingly, have found very high

[3]There is also a third possible dimension of linkages which may need to be addressed: the temporal linkages which are attributed to overtime dependence, i.e. a stance where current production can be affected by past behaviour (Morrison Paul 2002).

[4]Since private sector production is not immediately identifiable in Australia, Song (2002) used the income-based measure of GDP from the ABS national accounts to represent private output.

[5]Paul (2003) identified the private sector as consisting of those industries in which production is predominantly performed by private enterprises (Agriculture, Mining, Manufacturing, Wholesale and retail trade, Recreation and personal services). This definition was originally put forward by Otto and Voss (1994).

estimates of the cost elasticity with respect to public infrastructure, with magnitudes ranging between -0.41 to -1.09. In contrast to the findings of international studies, in which the cost function approach usually suggests smaller magnitudes, these results are in fact higher than many of those using the production function approach.

The third study is a recent work offered by Wills-Johnson (2011) in which he applies translog and symmetric generalised McFadden (SGM) functional forms to seven Australian states' railway data.[6] Wills-Johnson (2011) asserts that neither functional form behaves well as they both lack global concavity when the models are estimated. The author attributes these results to the quality of the data which is thought to be poor.

Likewise, this study implements a cost function approach; however, it departs from the three analyses cited above (and perhaps from other Australian studies) in several important ways. First, it considers a wider range of industries, covering the entire economy and not just private production. Since transport infrastructure may contribute to both private and public production cost, its effect should be measured relative to the aggregate production of the economy as a whole. Second, instead of simply aggregating the information on industries to construct a market sector or total economy measure, the study proposes working with industry data but controlling for industry-specific effects to account for differences in the cost of production across industries. It is well recognised that individual industries possess specific characteristics (for example, technological conditions such as the capital intensity of production - some industries are high-tech while others are low-tech; depreciation rate of capital; barriers to entry, such as sunk costs; import competition; domestic market concentration among other industry structural variables) which may all correlate with the cost of production. This might also reflect differences in the capacity of industries to take advantage of available public transport. Thus, a second way in which we build on previous research is to exploit the panel nature of the data in order to study the role of unobserved heterogeneity in explaining interindustry cost differences. A third dimension of departure is to focus on transport as a single category of infrastructure in preference to assessing the effect of a whole measure of infrastructure. Finally, and most importantly, there is the recognition of interindustry spillovers. In this context, the study estimates a measure to reflect the extent of interdependency among industries by using information available in the input-output tables, and then uses this measure to take account of possible spillovers that may occur. Having recognised the existence of industrial spillovers, it is essential to appropriately identify them in the cost model. For this purpose, the study adapts the techniques of spatial econometrics to fit into industrial context.[7]

In addition to the above issues, the study pays attention to the functional form applied to represent the relationship between cost and transport infrastructure. Flexible functional forms are widely recommended to address the complex relationship between infrastructure capital, output and inputs. To date, the majority of research in this line has focused on the translog and generalised Leontief cost functions. However, as shown by Diewert and Wales (1987), both

[6] Wills-Johnson (2011) is perhaps the first Australian study that applies SGM in the context of infrastructure, while the current study is the second.

[7] Spatial econometrics is basically used to deal with spatial interaction in regression models (Anselin 1988).

functions frequently fail to satisfy the appropriate theoretical curvature conditions. We therefore chose to use the symmetric normalised quadratic, SNQ, cost function (known previously as the symmetric generalised McFadden functional form) introduced by Diewert and Wales (1987), augmented to incorporate transport services and interindustry spillovers. This is because, in contrast to other flexible functional forms, concavity conditions can be imposed in input prices globally without destroying the flexibility property of the cost function.

The empirical evidence of the study suggests a productive role of public transport infrastructure investment. However, neglecting the role of interindustry spillovers has noticeably biased the effectiveness of transport investment in reducing production costs. In addition, allowing for heterogeneity across the individual industries has improved the measurement of the transport effect.

The rest of the paper is organised along the following lines. Section 2 discusses the sources of industry spillovers. Sections 3, 4 and 5 describe respectively the theoretical framework, how spatial econometrics is extended to the case of industry interdependencies, and the functional form applied to represent the cost function. Data construction is included in Section 6. In Sections 7 and 8, the estimation procedure and results are respectively discussed. Section 9 concludes.

2 Sources of interindustry spillovers

The concept of agglomeration economies (diseconomies) or thick (thin) market effects was earlier introduced and examined in the literature to explain the existence of spillovers across industries. Agglomeration economies which imply aggregate increasing returns usually work through knowledge spillovers that may result from the activities of suppliers, customers, and other firms in an industry. These spillovers should be explicitly identified in the economic model to separate their effect from the internal economies arising from internal factors. Hall (1990) has identified scale effects arising from agglomeration spillovers as a potential cause for invariance of the Solow residual. Extending his framework, Caballero and Lyons (1992) and Bartelsman et al. (1994) discussed the issue in more detail. They asserted that in addition to utilisation variations, scale economies, and technical change, there may also be a spillovers effect that needs to be identified and allowed for in the production function. They distinguished between short-run and long-run effects and empirically tested for these externalities. The authors argued that if the linkage between an industry and its suppliers of intermediate goods generates these externalities (supplier-driven externalities), we should aggregate the activity measure based on the share of materials received from other industries. If, however, the linkage operates through the sales to other industries (customer-driven externalities) we should include an output-weighted agglomeration variable in the production function.

Evidence of spillovers across industries are also provided by Terlecky (1974), Venables (1996) and Puga and Venables (1996) among many other studies in which linkages are shown to arise from easier matching between entities during expansions. In all these studies, firms are assumed to link by input-output relationships that create forward and backward linkages. If there are some transport costs, then proximity to industries supplying intermediates reduces costs and gives rise to forward linkages. Similarly, proximity to customers (using intermediate goods) raises sales and profits of intermediate goods suppliers, and creates demand (or backward) linkages.

The thick market economies discussed above, however, can be balanced by counteracting external costs (see Cohen and Morrison Paul 2005). As production expands, industries may experience upward shifts in their cost curves due to agglomeration diseconomies associated with the augmented production in their 'neighbouring' industries. The increase in competition for workers, land, intermediate goods and utility services associated with such production expansion can lead to congestion and higher cost of factor inputs, and negative cost spillovers can therefore reduce other external economies. Ultimately, whether the advantages of agglomeration economies or the disadvantages of agglomeration diseconomies dominate is an empirical issue that requires investigation to quantify and analyse the patterns of both.

In light of the above discussion, it is intuitively reasonable to assume that in addition to the direct effect from transport provision, further effects may arise due to the linkages and interdependencies among industries. It is essential to consider these spillovers when building any transport-cost/productivity model. Thus, one can represent the dependence of the cost of production of industry m on activities (a_n) of all other industries ($n = 1, ..., N$) related to that of industry m, by including the index $\sum_{m \neq n} w_n a_n = WA$ (where W is weighting matrix to reflect the degree of dependence between industries) directly in the cost function of industry m. A fundamental issue that must be addressed here is how one might measure the 'activity' a_n and specify the 'weights' w_n. An elaboration on this point will be offered later in this text.

3 Theoretical framework

Using duality theory, the cost function approach can be seen as an extension to the standard production function framework. Varian (1992) outlined that if firms are assumed to choose input quantities in such a way that they minimise the cost of their production process, then cost minimisation is essentially the same problem as profit maximisation. In measuring infrastructure's impact in the economy, the cost function approach has several practical advantages over the production function approach as a result of incorporating the optimising behaviour of the firms, and avoiding the difficulty of deriving the cost minimising input demand functions.[8]

To describe our cost function model, let us first consider an industry m's aggregate production function for the value-added output y. Assume that there are I types of primary inputs represented by the vector $X \equiv [x_i]$.[9] The external nature of transport infrastructure discussed in the previous section and the possible interindustry spillovers associated with it suggest that primary inputs cannot explain all evidence of scale economies. While changes in the internal inputs represent movement along the isoquant curves, shifts in the curves occur due to external factors. Consequently, we postulate that the production function also depends on another set

[8] As illustrated below, the input demand functions are defined as the partial derivative of the cost function with respect to input prices.

[9] With value-added output, the corresponding primary inputs are capital and labour.

of external factors, denoted by the vector $z \equiv [z_q]$. In this model, z is assumed to include public transport infrastructure investment (g), technical change (reflected by linear time trend t), and spillovers that exist from across industry dependencies (h).[10] Hence, the production function is represented as follows:

$$y = f(X, z). \tag{1}$$

If the firms in industry m face a vector of input prices $P \equiv [p_i]$, the optimisation problem that firms face consists in determining the amount of inputs that minimises the cost for producing a given output y. Thus, the technology depicted in (1) can be represented by the following cost function which will allow for a combination of internal economies in the production process due to primary inputs and external economies that result from external factors:

$$c \equiv PX = c(P, y, z). \tag{2}$$

Assuming that the cost function is a twice continuously differentiable function in all its arguments, then ∇c and $\nabla^2 c$ respectively define a vector of first-order partial derivatives and a matrix of second-order partial derivatives, known as the Hessian matrix. To be regular or well-behaved (i.e. to be consistent with the behavioural postulates of economic theory), $c(P, y, z)$ must satisfy the following conditions:

1. Homogeneity: $c(P, y, z)$ is linearly homogenous in prices; this implies that $c(\lambda P, y, z) = \lambda c(P, y, z)$, $\forall \lambda > 0$.

2. Monotonicity: $c(P, y, z)$ is nondecreasing in inputs prices and output quantities. According to Shephard's lemma (Shephard 1953), since the factor demand for input i is derived as the first derivative of the cost function with respect to p_i ($x_i = \partial c / \partial p_i \equiv \nabla_p c$), then monotonicity in prices requires that demand for all inputs are nonnegative, or equivalently the cost share of input i, given by $s_i \equiv p_i x_i / c = \partial \ln c / \partial \ln p_i$ is nonnegative. On the other hand monotonicity in output requires that total and marginal costs are nonnegative.

3. Curvature: $c(P, y, z)$ is concave in input prices, i.e. the matrix of second order partial derivatives with respect to input prices is negative semidefinite.

The cost function can be used to define the matrix of Allen-Uzawa elasticities of substitution between inputs, $\Sigma \equiv [\sigma_{ij}]$.[11] Uzawa (1962) has shown that Allen partial elasticities of substitution (Allen 1938) can be computed directly from the cost function as follows:

$$\sigma_{ij} = [c(P, y, z) c_{ij}(P, y, z)] / [c_i(P, y, z) c_k(P, y, z)], \tag{3}$$

where $c_i(P, y, z) = \partial c(P, y, z) / \partial p_i$ and $c_{ij}(P, y, z) = \partial^2 c(P, y, z) / \partial p_i \partial p_j$.

[10] The data section discusses in more detail how the industry spillover variable is constructed using information from input-output tables.

[11] Allen-Uzawa elasticities of substitution are derived as a partial estimate of the proportionate change in the ratio of the amounts of the inputs employed divided by the proportionate change in the ratio of their prices.

The partial price elasticity of demand is given as :

$$\xi_{ij} = \partial \ln[x_i(P, y, z)]/\partial \ln p_i = \sigma_{ij} s_j, \tag{4}$$

where s_j is the cost share of input j.

Our primary interest is in understanding the effects of public transport infrastructure on the production costs. Thus, the transport variable is the key element of the analysis that requires careful treatment and representation. Recall that our data consist of several industries, some of which may significantly benefit from an increase in transportation while others may only benefit slightly. In addition, there is a claim that the degree of usage of transport capital across industries can vary. For example, Paul (2003) has highlighted three points showing this variability. First, there are significant swings in the intensity with which public infrastructure is used (for example, variation in rates of road utilisation). Second, public capital is a collective input whose services are shared by all industries and consumers. Third, while a firm may have no influence on the size of the stock of public infrastructure which is freely provided by the government, it can vary its usage (for example, by choice of routes). In addition, Nadiri and Mamuneas (1994) have argued that public capital may be subject to congestion so the amount used by an industry may be less than the total amount supplied.

In light of these arguments, it appears that this heterogeneity in the capital usage and the extent of benefit absorption warrant consideration because these variations can affect the size of the potential spillovers. Consequently, it will be insufficient to simply incorporate a transport variable in the cost equation and measures should be taken to reflect this heterogeneity. Paul (2003) has suggested adjusting the stock of public capital utilised by each industry by using the share on an industry sector in total national output as a proxy for the degree of usage of public capital. This method is based on the assumption that each sector utilises public capital services in the same proportion as its contribution to the total output of the economy. Nevertheless, this assumption may not always hold because practically, the degree of usage of an industry can be more or less than its share in the national output.

In this context, the current study suggests another approach which allows for a divergence in the return to transportation among industries. We develop a relatively complex model which includes terms that are built from the interaction of public transport and dummy variables for each industry. This technique will allow the slopes of the cost-transport relationship to vary by industry group.

4 An extension of spatial econometrics to the case of industry interdependencies

This section illustrates the method employed to incorporate the interindustry spillovers in the model. Since the idea we implement is to adapt the notion of spatial econometrics into an industry context, a brief overview of this technique is warranted.[12]

There are two major aspects of spatial autocorrelation, usually referred to as spatial lag (or spatial dependence) and spatial autocorrelation error. Spatial lag exists when the variables of neighbouring localities enter as explanatory variables in a regression of a particular locality. These spatially lagged variables can be the dependant variable or independent variables. On the other hand, spatial autocorrelation error exists when the error term of the regression of one locality depends on the error terms of neighbouring localities. Following Anselin (1988), the most general structure of the spatial model that includes both a spatial lag term and a spatially correlated error structure is given as:

$$\begin{aligned} \tilde{y} &= \rho W_1 \tilde{y} + X\beta + \mu \\ \mu &= \lambda W_2 \mu + \epsilon \\ \epsilon &\sim N(0, \sigma_\epsilon^2), \end{aligned} \tag{5}$$

where $\tilde{y}$ contains a $d \times 1$ vector of cross-sectional dependent variables and X represents a $d \times f$ matrix of explanatory variables. W_1 and W_2 are known $d \times d$ spatial weight matrices, usually containing contiguity relations or functions of distance. ρ and λ are coefficients on the spatially lagged dependent variable, $W\tilde{y}$, and spatially correlated errors, μ, respectively. From this general model, different special models can be derived by imposing restrictions. For example, setting $W_2 = 0$ produces a spatial lag model shown as:

$$\begin{aligned} \tilde{y} \quad &= \rho W_1 \tilde{y} + X\beta + \mu, \\ &\epsilon \sim N(0, \sigma_\epsilon^2). \end{aligned} \tag{6}$$

Alternatively, setting $W_1 = 0$ produces a spatial autocorrelation error model shown as:

$$\begin{aligned} \tilde{y} &= X\beta + \mu, \\ \mu &= \lambda W_2 \mu + \epsilon, \\ \epsilon &\sim N(0, \sigma_\epsilon^2). \end{aligned} \tag{7}$$

It is now widely agreed in the empirical literature of spatial econometrics that ignoring spatial effects when they are actually present leads at best to inefficient OLS estimators and biased statistical inference, and at worst to biased and inconsistent OLS estimators (LeSage and Pace 2009). Consequently, some models are specified to only include spatial lag, some only include spatial autocorrelation, and some include both types of effects. Typically, researchers start the empirical method by testing for the presence of either or both types of spatial autocorrelation, then depending on the results of these tests, they proceed to choose an appropriate model.[13]

[12] It was outlined earlier that due to the lack of spatial data the study does not, regrettably, conduct a spatial analysis. However, this type of analysis, which transfers the spatial techniques and weight matrix into an industrial context, seems interesting and can add enriched understanding to the drivers of the transport-cost relationship. As mentioned before, the only study we are aware of which implements this technique is Moreno et al. (2004).

[13] There is a range of test statistics that are used in the literature to detect the existence of spatial autocorre-

Although the application of spatial econometrics has grown significantly since the early 1980s, it has been applied in the area of infrastructure only in the late 1990s (e.g., Boarnet 1998 and Kelejian and Prucha 1999).[14] The advancements in spatial econometrics have facilitated the analysis of infrastructure spillovers across localities. However, given the extensive data requirements for a spatial model, most of the studies performed were concentrated mainly in the U.S. (at state and county levels) while a few studies were performed in the Spanish regions. Using both production and cost function approaches, these studies have reached different conclusions. While some studies have found that infrastructure has a productive role, others have found the reverse. Regardless of the disagreement on the impact of infrastructure, there is consensus among these studies that allowing for spatial spillovers in regressions has improved the precision of the impact of infrastructure.

In a similar fashion to that depicted by the above spatial model, though in a different dimension, the current study proposes to adapt the idea of spatial autocorrelation to fit the industry context in order to account for interindustry spillovers. Nonetheless, the focus here is restricted to spatial lag dependence (which we refer to in our framework as 'industry lag dependence').[15] Thus, to specify a suitable 'industry lag' measure we looked into several methods suggested by the previous studies in modelling interindustry spillovers. For example, Caballero and Lyons (1992) included aggregate manufacturing output as the externality index by using two-digit SIC level manufacturing industry data, while Caballero and Lyons (1989) used an aggregate input measure. Burnside (1996) argued that using an aggregate measure of output can result in spurious external effects in industries for which industry output is a large share of the total; he therefore recommended the method of using an aggregate input measure. Unfortunately, all the approaches cited above suffer from one or more of the following limitations: they do not consider the strength of the dependence across industries, and/or by including the dependant variable in the right side of the regression the estimation method suffers from endogeneity problems which in turn may bias the estimated parameters.

To overcome these problems, the study suggests exploiting the notion of the weighting matrix described in the spatial econometrics literature to construct a measure of industry-spillovers that reflect the degree of across-industry dependence. This procedure is similar to that of Bartelsman et al. (1994) who suggested embedding measures of the externalities - given as $\sum_{m \neq n} w_n a_n = WA$ in our notation - into a first-differenced log-linear U.S. manufacturing production function relationship, to identify their productive impact. In addition, our use of duality theory to specify a cost function helps to overcome the endogeneity problem present in the studies cited above when they included aggregate activity measure in the model.

lation, some examples are Moran's I, likelihood ratio and Lagrange multiplier tests.

[14] Spatial econometric techniques have been successfully applied in the economics literature to highlight significant spatial effects in many fields such as growth economics, agricultural and environmental economics, international economics and labour economics (see Rey and Gallo 2009 for a comprehensive survey).

[15] Although the ideal approach to follow in this situation is to first test for the presence of spillovers, detect the types of autocorrelations, and subsequently correct for them by specifying either (5), (6), or (7); this study has assumed the existence of 'industry lag' dependence a priori guided by the findings of the earlier literature on the role of interindustry spillovers. Moreover, some difficulties are encountered with the available computer algorithms because these algorithms do not fit into the structure of our complex model.

5 The functional form for the cost function

While the literature has proposed several empirical functional forms that a general cost function can take, the selection of a specific form that fits the data well and satisfies the economic regularity conditions is essential. In the recent literature of cost, production and profit function approaches, attention has moved away from the restrictive traditional functional forms such as the Cobb-Douglas and constant elasticity of substitution towards more flexible functional forms such as the translog, the normalised quadratic, and the generalised Leontief cost functions. Each of these three widely used cost functions is described as being 'flexible' in the sense that each has sufficient parameters that it can at least provide a local second order approximation to an arbitrary twice-differentiable continuous function at a point (Diewert 1974). Thus, one advantage of a flexible functional form is that it allows the estimation of elasticities of substitution to be unrestricted a priori and can also help to reveal complementarity relationships. This has many crucial implications in applied economics in which the estimation of elasticities is of key interest.

In estimating the cost-infrastructure relationship, previous researchers have widely used the translog cost function (for example see Berndt and Hansson 1991; Lynde and Richmond 1992; and Khanam 1996 among others). Although the translog function has the advantage that homogeneity can be directly imposed on the parameters without destroying the flexibility of the function, and additionally, the computation of elasticities is simple, it usually has a problem with the required curvature conditions (outlined in Section 3 above). In many instances, researchers report that these conditions are not met for a large number of their observations. One solution that has been considered is to impose a concavity condition. However, the imposition of the concavity globally (at all points) is found to destroy the flexibility of the translog, therefore other methods have been suggested to impose curvature conditions locally (Wiley et al. 1973; and Ryan and Wales 1998). Ryan and Wales (1998, 2000) noted that imposing curvature locally - at a reference point - does not destroy the flexibility of the translog, and although it guarantees concavity at one point only, it may well be that a careful choice of reference point leads to the satisfaction of concavity at most or all data points in the sample. Thus, this procedure requires the analyst to check for each observation individually, whether or not the curvature conditions are met.

At the empirical level, some studies have treated the curvature property of the translog as a maintained hypothesis (Ryan and Wales 1998 and Moschini 1999), while others have been assessed as having performed adequately by only reporting a small percentage of failure of the property. In a few cases, curvature was imposed locally and a comparison was made between the case with and without imposition (e.g., Feng and Serletis 2007 and Chua et al. 2005).

In an attempt to provide comparable results with other studies, our investigation started by estimating the translog functional form; however, we encountered violations of the curvature regularity at around 50 percent of the sample points. The case did not improve greatly when local curvature was imposed using the method suggested by Ryan and Wales (1998). Clearly, inferences based on such estimation results are not very convincing. We are indeed cautious about depending on this estimated cost function to evaluate the effects of transport on production cost. As Kohli outlined, 'the frequent violation of required curvature conditions is a major source of frustration when estimating flexible functional forms. These curvature conditions are implied by economic theory and they must be satisfied for the estimates to be meaningful' Kohli (1993, p. 244). With these limitations of the translog function, we preferred to use the symmetric normalised quadratic, SNQ, cost function proposed by Diewert and Wales (1987, 1988) which allows the curvature conditions to be imposed globally without destroying flexibility.[16] Thus, in this study a 'modified' SNQ functional form is used to estimate the cost function. The term 'modified' is used here to indicate that the original SNQ function is amended to allow for the inclusion of other shift factors besides technology, t. Accordingly, the proposed cost function is given as:

$$
\begin{aligned}
c(P,y,t,g,h) \quad &= \left(\sum_i \sum_m \delta_{im} DUM_m p_i\right) y + \Big(\sum_i \beta_i p_i\Big) y + \left(\frac{1}{2}\frac{\sum_i \sum_j \beta_{ij} p_i p_j}{\sum_i \alpha_i p_i}\right) y \\
&+ \Big(\sum_i \beta_{it} p_i\Big) ty + \sum_i \Big(\beta_{ig} + \sum_m \omega_{im} DUM_m\Big) p_i g y + \Big(\sum_i \beta_{ih} p_i\Big) hy \\
&+ \beta_{yy}\Big(\sum_i \phi_i p_i\Big) y^2 + \beta_t \Big(\sum_i \pi_i p_i\Big) t^2 y + \sum_i \gamma_i p_i + \gamma_t \Big(\sum_i \varphi_i p_i\Big) t \\
&+ \gamma_g \left(\sum_i \psi_i p_i\right) g + \gamma_h \left(\sum_i \tau_i p_i\right) h, \\
&\qquad\qquad\qquad\qquad i,j = 1,...I; \qquad (8)
\end{aligned}
$$

where DUM_m is a dummy variable for industry m ($m = 1, ..., 19$) - taking on the value 1 in industry m and 0 otherwise - to control for the industry-fixed effects. Notation on the variables is as indicated earlier. The parameters ϕ_i, π_i, φ_i, ψ_i, and τ_i can be selected arbitrarily; for example if they are selected to equal the sample mean of the observed input vectors, then the elasticities generated by estimating cost function will be invariant to scale changes. Alternatively, if there are ample degrees of freedom, one can set $\beta_{yy} = \beta_t = \gamma_t = \gamma_g = \gamma_h = 1$ and estimate ϕ_i, π_i, φ_i, ψ_i, and τ_i (Diewert and Wales 1987). In this case, the cost function becomes third-order flexible in y and t and therefore the factor-demand equations are second-order flexible in y, t. In regards to the other parameters, the following restrictions are imposed on $B \equiv [\beta_{ij}]$ matrix at some 'reference' price vector P^*: $\beta_{ij} = \beta_{ji}$ for all i, j, $BP^* = 0$ for some $P^* > 0$, $\sum_i \beta_{ij} = 0$. The α_i parameters are nonnegative and predetermined subject to the condition $\sum_i \alpha_i = 1$.[17] The term $\sum_i \alpha_i p_i$ can thus be viewed as a fixed-weighted input price index. The SNQ treats all inputs in the same way: it is necessarily homogeneous of degree one in prices, and it is globally concave if and only if $B \equiv [\beta_{ij}]$ is negative semi-definite. Note that, given $\sum_i \beta_{ij} = 0$, B is at

[16] The number of overseas infrastructure studies that have applied the SNQ is very small. Examples are Nadiri and Mamuneas (1996) and Sturm (2001).

[17] For estimation purposes we set the 'reference' price vector P^* to be a vector of ones and the α_i parameters are set equal to $1/I$.

most of rank $I-1$, it is convenient in the following demonstration to define $\widetilde{B}$ as a matrix that is obtained by deleting the last row and the last column of B (Fox, Kohli and Shiu 2010).

It is outlined above that the SNQ is globally concave if and only if $B \equiv [\beta_{ij}]$ is negative semi-definite. In practice, this requirement may not be satisfied. In such a case, to ensure concavity at all possible prices of the SNQ cost function, we follow Diewert and Wales (1987) and impose the following:

$$B = -ZZ', \tag{9}$$

where $Z \equiv [z_{ij}]$ is an $i \times i$ lower triangular matrix and Z' its transpose (upper triangular matrix) which satisfies $Z'P^* = 0$. Note that, (9) and the lower triangular structure of Z imply:

$$\sum_i z_{ij} = 0, \qquad\qquad i, j = 1, \ldots .I. \tag{10}$$

Using the Cholesky decomposition, we can then reparameterise the model and estimate the parameters in Z instead of the parameters in B (see the Appendix for details); this ensures that the Hessian matrix, $B = -ZZ'$, is negative semi-definite. Applying (9) to $\widetilde{B}$ guarantees that the SNQ cost function is concave in prices. Fox et al. (2010) have used the SNQ to estimate import and export price elasticities for Australia and its major trading partners in Europe and Asia. They asserted that to ensure the SNQ cost function is concave in prices 'the curvature conditions are imposed a priori, as the resulting functional form is a valid flexible functional form in its own right, and correct curvature is required for the model to make economic sense' Fox et al. (2010, p. 517). Following their suggestion, we have imposed the curvature conditions in our model a priori.[18]

Further, it is possible to impose several restrictions on the modified SNQ. For example, if the underlying production function exhibits constant returns to scale on the primary inputs, we can impose the following restrictions: $\beta_{yy} = \gamma_i = \gamma_t = \gamma_g = \gamma_h = 0$ to make its dual cost function linearly homogenous in output (Diewert and Wales 1987, p. 49).

As indicated by Shephard (1953), input demand functions can be derived using Shephard's Lemma. Hence:

$$\begin{aligned} x_i \quad &= \left(\sum_m \delta_{im} DUM_m\right) y + \beta_i y + \left(\frac{\sum_i \beta_{ij} p_i}{\sum_i \alpha_i p_i} - \frac{1}{2}\alpha_i \frac{\sum_i \sum_j \beta_{ij} p_i p_j}{(\sum_i \alpha_i p_i)^2} \right) y + \beta_{it} t y \\ &+ \Big(\beta_{ig} + \sum_m \omega_{im} DUM_m\Big) g y + \beta_{ih} h y + \beta_{yy} \phi_i y^2 + \beta_t \pi_i t^2 y + \gamma_i + \gamma_t \varphi_i t \\ &+ \gamma_g \psi_i g + \gamma_h \tau_i h, \\ & \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad i, j = 1, \ldots .I. \end{aligned} \tag{11}$$

[18]Because we have earlier encountered a dramatic violation in the curvature requirement with our data set when we estimated the translog function, we preferred to impose the curvature a priori provided that the resulting function is valid.

Next, given that total cost and input demand equations are specified we turn to deriving a measure for the effect of public transport provision. In particular, we are concerned with the effect of the transport infrastructure variable g and its interactions with other variables that are of interest in the cost function $c(.)$. This total effect can be measured as an elasticity of $c(.)$ with respect to g:

$$\xi_{cg} = \partial \ln c(.)/\partial \ln g = \left[\sum_i \Big(\beta_{ig} + \sum_m \omega_{im} DUM_m\Big) p_i y\right] \frac{g}{c}. \tag{12}$$

If the transport infrastructure is cost saving, ξ_{cg} will be negative.

A dual measure of the cost saving effect is the output effect $\eta_{yg} = \partial \ln y/\partial \ln g$ where the relationship between the two effects is given by $\eta_{yg} = -\xi_{cg}/\theta_{cy}$, where $\theta_{cy} = \partial \ln c(.)/\partial \ln y$. If the cost function is linear homogenous in output, this relationship can be rewritten as $\eta_{yg} = -\xi_{cg}$. Additionally, the effects of interindustry spillovers on total cost can be computed as:

$$\xi_{ch} = \partial \ln c(.)/\partial \ln h = \left(\sum_i \beta_{ih} p_i y\right) \frac{h}{c}. \tag{13}$$

The first derivatives of the cost function capture demands for primary inputs, $\partial c/\partial p_i$. In elasticity terms these derivatives, ξ_{cp_k} and ξ_{cp_l} , reflect capital and labour cost shares respectively. Our flexible cost-function framework allows us to evaluate not only these first-order (overall) cost effects, but also second-order effects reflecting input substitution and output valuation. Thus, we can compute the elasticity of conditional demand for primary inputs with respect to g (ξ_{ig}) and h (ξ_{ih}) respectively as follows :

$$\xi_{ig} = \partial \ln x_i/\partial \ln g = \left[\Big(\beta_{ig} + \sum_m \omega_{im} DUM_m\Big) y\right] \frac{g}{x_i}, \tag{14}$$

$$\xi_{ih} = \partial \ln x_i/\partial \ln h = (\beta_{ih} y) \frac{h}{x_i}. \tag{15}$$

6 Data

The data used in the analysis correspond to 19 national industrial classifications which are identified under ANZSIC 2006 (the Australian and New Zealand Standard Industrial Classification). These industries, together with their subdivisions, codes, and titles are reported in appendix table A1.[19] For each division, we collect data on output, y, measured as the value-added chain volume measure; net capital stock, k, calculated as the sum of machinery and equipment and non-dwelling construction both evaluated as chain volumes; and labour input, l, measured as

[19] ANZSIC 2006 is a hierarchical classification with four levels, namely Divisions (the broadest level), Subdivisions, Groups and Classes (the finest level). Each of the 19 divisions is identified by an alphabetical letter, that is, ‘A’ for Agriculture, forestry and fishing, ‘B’ for Mining, ‘C’ for Manufacturing, etc.

the total number of employees (full-time and part-time).[20] The price of capital, p_k, is measured in terms of user cost which is defined by $p_k = (r_t + \delta_t)q_k$, where r_t is the real 10-year government bond rate, δ_t is the deprecation rate calculated as the ratio of the consumption of fixed assets to net capital stock, q_k is the investment deflator computed as the ratio of nominal to chain volume gross fixed capital formation. The price of labour is measured as the total compensation per employee (includes the employer contribution). All the above data are published at the ABS website cat. nos. 5204.0 and 6291.0.55.003. The spillovers variable is defined as a weighted average of other industries' output where the input-weighted matrix is constructed following Bartelsman et al. (1994) using input-output (I-O) tables. Figure A1 of the appendix provides details on the Australian National Accounts' I-O tables and how the weighting matrix is constructed.

To estimate public transport capital stock, the perpetual inventory method (PIM) is applied on the engineering construction value of work done (ABS cat. no. 8762.0.) on roads, highways and subdivisions; bridges, railways and harbours by public sector.[21] We estimated a measure to represent the total transportation system by aggregating these four types. Figure 1 displays longer term investment in transport as a percentage of GDP. From this figure, it appears that total investment in transportation remained largely between 0.9 percent and 1.3 percent for the period between 1987 and 2002. From 2002, there was an increase in private sector investment which peaked in 2005 and then gradually declined for the rest of the period. Public investment has continued with a stable increase since 2004, in which year it recorded the lowest level since 1987.

Figure 2 focuses on public sector investment and depicts a comparison between the trends of the four classes of transport. Roads, highways, and subdivisions constitute the largest share of the public transport system, which is around 70 percent on average. From 1987 to 2000, investment in this category was relatively steady at around 6 percent of GDP with a downward trend for the rest of the period, but with an exception over 2008-2009. Investment as a percentage

[20] Due to the nature of the ABS data (which does not distinguish between public and private ownership), the measures used for the factor inputs correspond to the total over all sectors. This issue may raise something of a measurement concern because the data on public transport investment employed in the regression analysis is treated in the Australian National Account Systems as a part of total capital. This situation could be a source of anxiety if the aim is to estimate a production function as described by (1), because in that case both public transport capital and total capital will appear in the right hand side of the regression. Nevertheless, the use of the dual cost function approach, in which only the price of the total capital appears, may minimise this problem. In any case, this situation represents one of the instances in which some measurement errors are unavoidable as empirical researchers are strongly influenced by the quality and availability of data.

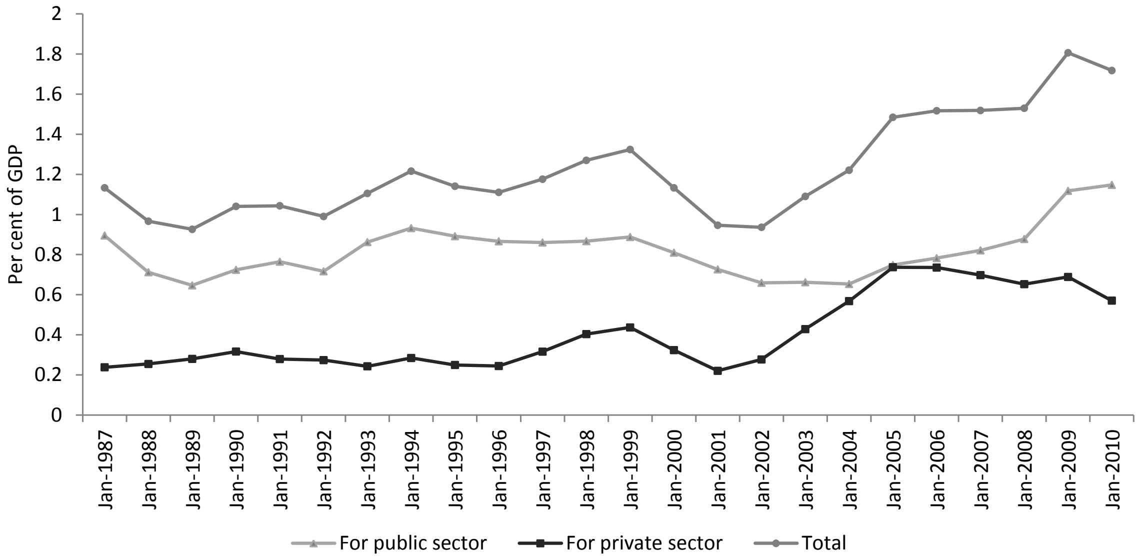
[21] The estimates of value of work done on transport is available only in terms of current prices. Thus, to transfer them into real values we applied a price deflator computed as a ratio between nominal to chain volume measure of all types of engineering construction activities. The PIM is represented by the following formula:

$$K_t = K_{t-1}(1 - \delta_t) + I_t, \tag{16}$$

where K_t is the value of capital stock in the current period; K_{t-1} is the value of capital stock in the previous period; I_t is the value of investment in the current period; and δ_t is a constant rate of depreciation with annual value of 5%. The benchmark, or starting period, capital stock, K_{t^*}, is computed based on the depreciation rate, δ; the value of investment in the initial period, I_t^*; and on the assumption that the average growth rate of the observed total investment, κ, adequately describes the annual growth rate for the indefinitely long preceding unobserved series. Accordingly, $K_{t^*} = \frac{I_t^*}{(\kappa+\delta)}$.

of GDP for harbours remained relatively stable at a low level between 1988 and 2006, but there has been a noticeable investment increase since 2007. Railways as a percentage of GDP is characterised by long swings of positive trends (1989-1997, 2001-2004, and 2008-2010) and downward trends (1997-2201 and 2004-2008). The last class, bridges, also fluctuated around a low share of GDP at the beginning of the period while showing an increase since 2004.

Figure 1 Investment in transport infrastructure, (1987-2010)



Source: Author's calculations using data from the ABS engineering construction activity cat. no. 8762.0).

Table 1 provides descriptive statistics of the averages over the sample for the 19 industries that constitute the total Australian economy. There is a noticeable difference in these measures across the industries. For example, other than Agriculture, forestry and fishing; Mining; Electricity, gas, water and waste services; and Rental, hiring and real estate services, the share of labour in cost is higher than that of capital. It is also evident that industries vary in terms of the growth rates of output and inputs. Information media and telecommunications recorded the higher rate of growth, which reached 5.6 percent per annum, while Manufacturing recorded the lowest rate, around 1.06 percent. Moreover, capital stock has grown very fast in some industries, reaching 9 percent per annum in the Other services industry, while labour has slowly grown and has even shown a negative rate of growth in industries such as Agriculture, Manufacturing, and Wholesale trade. This observation indicates that over time, industries become capital intensive.

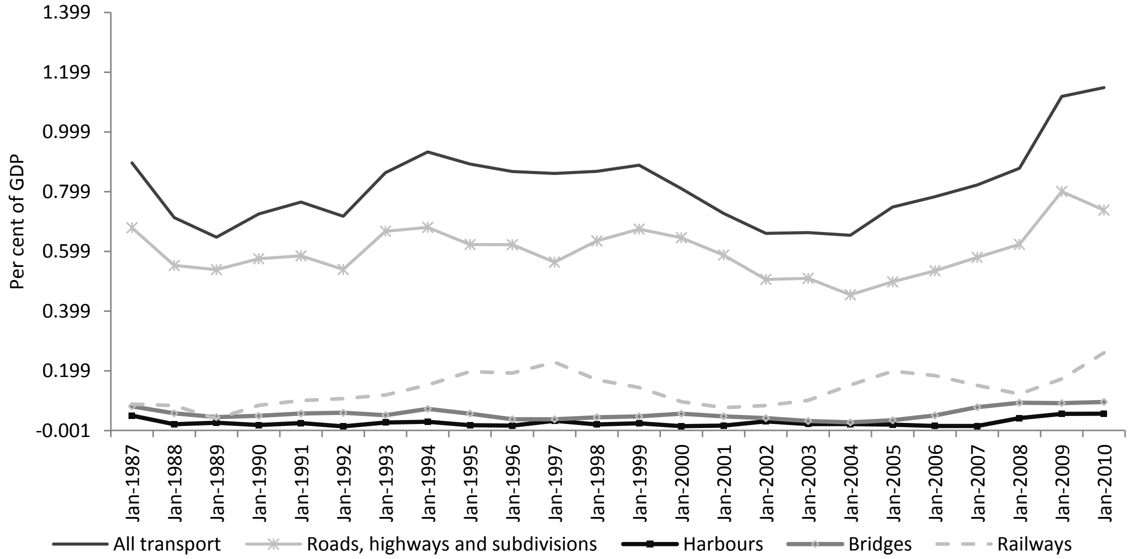
Figure 3 provides a comparison of the industries' cost shares which can also be interpreted as the income shares based on factor cost. The figure shows large differences across the industries. Some industries participate with relatively larger shares (e.g., Manufacturing with a share of 12% and each of Financial and insurance services; Transport, postal and warehousing; and Public administration and safety with 7%) while some other industries participate with smaller

Table 1 Descriptive statistics of the averages over the sample

Industry[a]	y	c	s_k	s_l	$\dot{y}$	$\dot{k}$	$\dot{l}$
Agriculture, forestry and fishing	22320	12723	0.561	0.439	2.64	1.50	-0.80
Mining	70277	20167	0.568	0.432	3.43	5.54	3.03
Manufacturing	98340	59069	0.252	0.748	1.06	2.76	-0.73
Electricity, gas, water and waste services	24475	17201	0.573	0.427	1.63	2.32	0.97
Construction	61846	27650	0.133	0.867	3.79	2.50	2.88
Wholesale trade	40374	25690	0.181	0.819	3.12	2.46	-0.25
Retail trade	41469	27363	0.162	0.838	3.66	2.91	1.51
Accommodation and food services	24733	15469	0.222	0.778	2.45	2.23	2.65
Transport, postal and warehousing	46897	36226	0.456	0.544	3.58	2.69	1.79
Information media and telecommunications	28149	16075	0.414	0.586	5.55	4.74	1.16
Financial and insurance services	76114	36731	0.179	0.821	5.43	1.15	0.16
Rental, hiring and real estate services	22710	14707	0.563	0.437	5.43	4.91	2.15
Professional, scientific and technical services	52693	30797	0.076	0.924	4.76	6.22	4.25
Administrative and support services	24100	14477	0.056	0.944	3.57	6.11	3.92
Public administration and safety	50936	36147	0.205	0.795	2.52	1.42	2.16
Education and training	46787	33153	0.148	0.852	2.18	2.11	2.05
Health care and social assistance	48137	35740	0.110	0.890	4.12	3.44	3.17
Arts and recreation services	7718	5776	0.334	0.666	3.37	4.36	3.72
Other services	19803	9988	0.054	0.946	2.10	9.00	1.28

a 19 industries under Australian and New Zealand Standard Industrial Classification.
y is value-added output (chain volume, constant 2010 \$ in millions), c is total cost (\$ in millions) calculated as the sum of the number of each type of input consumed multiplied by its unit price, s_k is cost share of capital, s_l is cost share of labour, $\dot{y}$ is growth rate of output, $\dot{k}$ is growth rate of capital, and $\dot{l}$ is growth rate of capital.

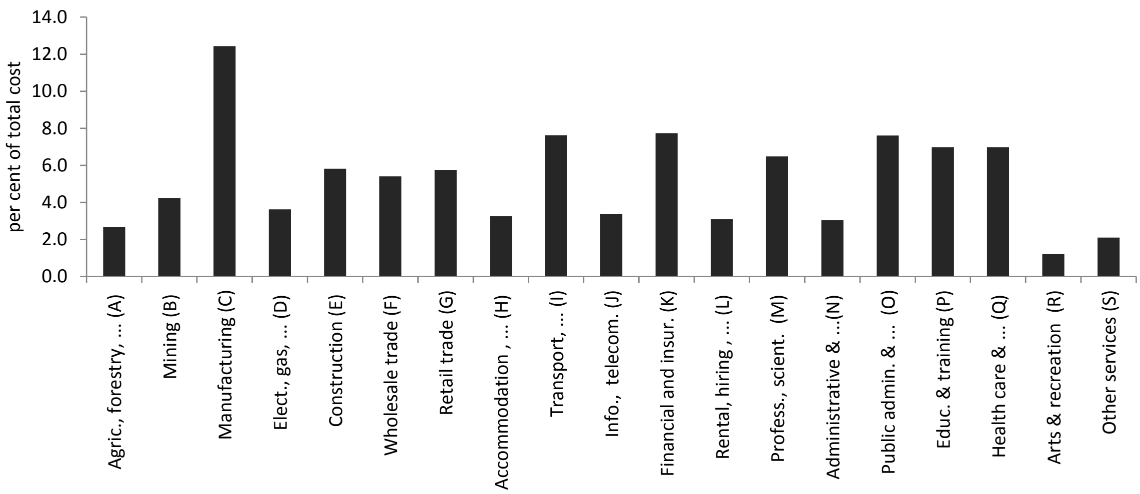
Figure 2 Public sector investment in transport: Roads, Highways, and Subdivisions; Harbours; Bridges; and Railways (1987-2010)



Source: Author's calculations using data from the ABS engineering construction activity cat. no. 8762.0.).

shares (e.g., Agriculture, forestry and fishing (2%), Other services (2%) and Arts and recreation services (1%)).

Figure 3 Industries' cost shares (average over 1990-2010)



Source: Author's calculations using data from the ABS. Each industry cost share is computed as the cost of that industry relative to the total cost over all industries (refer to Table 1 for the full title of each industry).

7 Estimation procedure

Following the literature on the empirical implementation of cost functions, we append to the cost equation given by (8) and the two input demand equations (for labour and capital) given by (11) with error terms. Since the input demand equations are derived by differentiation, they do not contain the disturbance term from the cost function. Further, we assume that the disturbances have a joint normal distribution. Hence, we allow nonzero correlations for a particular industry but impose zero correlations across industries, which permits the estimation of the equations as a system of seemingly unrelated regressions (SUR). To mitigate potential heteroskedasticity problems, the three equations have been divided by output, y.[22]

To better assess the importance of interindustry spillovers in the cost model and to evaluate the significance of the bias they may introduce in the estimated effect of public transport, it will be useful to first provide results from a benchmark model which excludes these spillovers. Thus, models identical to (8) and (11), but excluding the spillovers variable (h) are investigated first. To test the existence of heterogeneity across industries, it will be beneficial to write two versions of each model (with and without allowing for industry specific-effects). By maintaining and relaxing these two hypotheses, four specifications, denoted by A1, A2, B1, and B2, are estimated using an iterative version of Zellner's (1962) method for SUR equations as implemented in SHAZAM - version 9 (White 1978); this method is numerically equivalent to maximum likelihood. There are 21 years of data for each industry, and with 19 industries there are thus $19 \times 21 = 399$ observations for estimating the models. The number of parameters estimated varies in each model depending on the hypotheses tested, and will be indicated in the tables of results.

Adhering to the method of Seitz (1994), Cohen and Morrison Paul (2004), and Monaco and Cohen (2006), among others, the study starts off by jointly estimating the three equations (i.e. the unit cost and input-output demand equations) for each of the four models. Initially, a difficulty arose, because we were not able to obtain indicative estimates and the four models seemed not to be operational. Looking at their structures, we suspected a problem with the disturbance covariance matrix. A crucial issue that needs attention when estimating a system of equations is the singularity of the covariance matrix which arises when the equations included in the model are linearly dependant. Since the demand equations are expressed as quantity shares, as opposed to value shares, linear dependency is not a concern. However, there is still some non-linear dependency between the demand equations and the cost equation since $\sum_i (x_i/y)p_i = c/y$. Kohli (1994) noted this problem earlier when he estimated a model for the Canadian foreign trade using the SNQ and argued that it would be inappropriate to jointly estimate the cost and all input demand equations. Accordingly, he suggested that one equation should be omitted. Following his suggestion, we have chosen to estimate the system of the input demand equations while omitting the cost equation because it does not contain any additional information. With this method we were still able to compute all the first- and second-order elasticities highlighted earlier in Section 5.

[22]This means that the endogenous variables are c/y, k/y, and l/y. This transformation, which is widely applied in literature, does not affect the subsequent interpretation of the estimation results. See the Appendix for a full description of the estimated system.

The method suggested above resolved the problem and we were able to obtain the estimated parameters, but another issue confronted us. The monotonicity property was not met as required by the theory. There were a large number of the points at which the predicted total cost and factor inputs were detected as exhibiting negative values. We sought a solution by attempting to modify the specification of the models and gradually relaxing some of the assumptions until meaningful results were finally obtained. Nonetheless, this entailed the imposition of homogeneity in output; an assumption which implied that the underlying production function was exhibiting constant returns to scale (CRS) over the primary inputs.[23] Sturm (2001) noted that while assuming CRS over all inputs is thought to be a strong assumption in dealing with infrastructure, imposing it only over the private inputs while allowing for increasing returns over all inputs may mitigate this problem. This justification is not straightforward to apply in the present context, because in this study the CRS is instead imposed over the total-sectors' primary inputs.[24]

The results of the four models are presented as elasticity estimates, and all are evaluated at the mean values of the variables entering the elasticity formula.[25] Because there is no direct estimate of the elasticities' standard errors, the following formula is used to compute these measures:

$$se(\sum_i \beta_i x_i) = \Big[\sum_i x_i^2 Var(\beta_i) + 2\sum_{i\neq j} x_i x_j Cov(\beta_i, \beta_j)\Big]^{1/2}, \tag{17}$$

where all variables entering into the formulas, except the parameter estimates, ($\beta' s$), are treated as constants equal to their mean values.[26]

8 Results

The results of elasticities from the benchmark models, along with their estimated standard errors, are presented in Table 2. Since with elasticities we are often interested in the null hypothesis of the estimates being 1 or -1, the significance level associated with each estimate reflects the rejection of this hypothesis. Column A1 corresponds to a model in which neither industry-specific effects nor interindustry spillovers are accounted for (i.e. in addition to the assumption of CRS which entails the restriction $\beta_{yy} = \gamma_i = \gamma_t = \gamma_g = \gamma_h = 0$ in equation (8), the parameters δ_{im}, ω_{im}, and β_{ih} are set to zero). As is shown, while the overall fit looks fairly good with the R^2 being equal to 0.82, the cost elasticity of public transport infrastructure

[23] As noted before, the assumption of CRS entails imposing the following restrictions: $\beta_{yy} = \gamma_i = \gamma_t = \gamma_g = \gamma_h = 0$ on (8).

[24] Recall the discussion put forward earlier about the nature of the ABS data with which the private sector is not identifiable: our 'primary' capital stock measure includes, besides the private capital and other components of public capital, all other types of infrastructure which may exhibit increasing returns to scale.

[25] Because of the generality of the SNQ functional form which includes a large number of interaction terms, reporting the estimated parameters of the model will not provide a complete interpretation to help in answering questions of interest. Therefore, we prefer to present the estimated elasticities which summarise all economically relevant information.

[26] The application of this formula turned out to be rather awkward with many covariance terms, mainly in models which include dummy variables.

(ξ_{cg}) has an unexpected positive sign, and is strongly significant.[27] This finding is not credible on a priori economic grounds because it suggests that transport enhancement increases the cost of production, specifically, a 1 percent rise in public transport infrastructure available to a particular industry will increase production costs of that industry by almost 0.3 percent. Column A1 also includes other interesting results. The capital elasticity of transport infrastructure (ξ_{kg}) is negative and significant, which suggests a strong substitution relationship between transport and capital stock. On the other hand, the labour elasticity of transport infrastructure (ξ_{lg}) suggests a complementary relationship, shown by the positive and strongly significant elasticity.

The first-order input cost elasticities capture primary input cost shares ($\xi_{cp_i},\ i = l, k$) with capital share around 26 percent and labour share around 74 percent. These results are fairly consistent with the Australian factor cost share structure. The standard price elasticities of both primary inputs are all highly significant and have the theoretically correct signs. By contrast, no strong evidence was observed on the effect of technological progress in either cost or input demand, and this is indicated by the small and insignificant elasticities of cost and inputs-usage with respect to the time trend, ξ_{ct}, ξ_{kt}, and ξ_{lt}.

Column A2 presents the results of the second version of the benchmark model, in which industry-specific effects are controlled for (i.e. in addition to the CRS assumption the parameters β_{ih} in equation (8) are set to zero). The performance of the fit has improved, as indicated by the noticeable increase in the value of R^2 (0.91).[28] In terms of the cost elasticity of transport, there is a dramatic change in the result since the estimate has altered sign and become negative and meaningful. Therefore, public transport infrastructure plays an effective role in the production process. More precisely, a 1 percent rise in public transport infrastructure will decrease the production costs of a particular industry by 0.03 percent. Given, the assumption of linear homogeneity in output (which as noted in Section 5 implies $\eta_{yg} = -\xi_{cg}$), the positive productivity impact from a 1 percent increase in public transport is 0.03 percent. The results of other elasticities, in terms of the sign, remain similar to that obtained from model A1 in which the data were simply pooled. However, a slight change in the sizes of the elasticities is observed. In addition, coefficients of industry dummy variables, not presented in the table, were statistically significant, suggesting differences in the cost structure among industries.

Turning to examine the hypothesis of interindustry spillovers, we estimate the system while incorporating the spillover terms and report the results in Table 3. Following an approach similar to that adopted in the benchmark case, we discuss the results from two specifications. In addition, the significance level indicated on the elasticities' estimates reflects the rejection to the

[27] R^2 is defined as the McFadden pseudo R-squared which is computed using the formula $1 - \ell_{ur}/\ell_o$, where ℓ_{ur} is the log-likelihood function for the estimated system, and ℓ_o is the log-likelihood function in the system with only intercepts. Unfortunately, unlike some other computer packages (such as STATA, RATS, and SAS) Shazam within its nonlinear regression does not provide the standard diagnostic statistics which are helpful to assess the fit of the models. However, although we attempted all these packages, our data was only able to converge with Shazam. This may point to differences among computer packages' algorithms.

[28] R^2 is generally used to describe the goodness of the fit. While introducing more parameters in the model is usually found to improve the value of R^2, in models with a large number of parameters it would be insufficient to rely only on the value of R^2 because adding more parameters may result in overfitting. The literature proposes several model selection criteria which are helpful for selecting a preferred model out of a set of candidate models. A brief discussion on the outcome of applying a widely used selection criterion is provided in the text below.

Table 2 Symmetric Normalized Quadratic function, elasticity estimates (1990-2010): specification without industry spillovers

	Column A1		Column A2	
Elasticity	Estimate	Std. Error	Estimate	Std. Error
ξ_{cg}	0.262***	(0.070)	-0.026***	(0.011)
ξ_{kg}	-0.881***	(0.016)	-0.223***	(0.012)
ξ_{lg}	0.640***	(0.053)	0.620***	(0.085)
ξ_{cp_k}	0.255***	(0.113)	0.229***	(0.108)
ξ_{kp_k}	-0.139***	(0.020)	-0.127***	(0.050)
ξ_{lp_k}	0.035***	(0.006)	0.042***	(0.007)
ξ_{cp_l}	0.745	(0.235)	0.771**	(0.121)
ξ_{kp_l}	0.139***	(0.020)	0.127***	(0.050)
ξ_{lp_l}	-0.035***	(0.006)	-0.042***	(0.007)
ξ_{ct}	-0.049	(0.989)	-0.050	(0.997)
ξ_{kt}	0.023	(1.618)	0.031	(1.667)
ξ_{lt}	-0.062	(0.870)	-0.075	(0.978)
Fixed-effects	No		Yes	
No. of observations	399		399	
No. of parameters	9		81	
McFadden pseudo R^2	0.82		0.91	

We test the following two null hypotheses: $H_o : \xi = 1$ against the two-sided alternative $H_1 : \xi \neq 1$, and $H_o : \xi = -1$ against the two-sided alternative $H_1 : \xi \neq -1$.
Terms *,**,*** denote significance at the 10%, 5% and 1% levels respectively at which both null hypotheses are rejected.
Column A1 presents the estimation results of equation (8) with the CRS assumption and the parameters δ_{im}, ω_{im}, and β_{ih} set to zero.
Column A2 presents the estimation results of equation (8) with the CRS assumption and the parameters β_{ih} set to zero.

null hypothesis of the estimates being 1 or -1. First, Column B1 displays the estimated elasticities for a model that includes industry spillovers but does not allow for industries' heterogeneity (i.e. while maintaining the CRS assumption, the parameters δ_{im} and ω_{im} are set zero). In this specification; R^2 is equal to 0.89, which is significantly higher than that of model A1. This observation indicates the role of the spillovers effects in improving the model fit. However, compared to model A2, R^2 remains smaller, which may point to the need to allow for the industry specific-effects. Transport infrastructure appears to have a productive role, as indicated by a significantly negative cost elasticity. In particular, a 1 percent increase in transport results in a 0.12 percent reduction in cost (or 0.12 percent increase in productivity). Results on input cost shares and the technological effect remain the same as in the benchmark model; however, a noticeable difference is observed in the results of the input elasticities of transport as those relationships derived from the benchmark models are now reversed. Specifically, transport and labour become substitutes while transport and capital appear to be, though insignificantly, complements.

Additional estimated effects, not included in the discussion of the benchmark estimations, show the influence of interindustry spillovers. The elasticities of the production cost and inputs-usage with respect to these spillovers (ξ_{ch}, ξ_{kh}, and ξ_{lh}) are strongly positive values. For example, it is suggested that an expansion in other industries (measured by their output) by 1 percent results in the production cost of an individual industry to rising by 0.07 percent. Recalling the arguments reviewed before about the economies of scale associated with thick market effects, this result appears odd and contradicts the findings of authors like Bartelsman et al. (1994) and Morrison Paul and Siegel (1999) who asserted that agglomeration economies can generate positive and significant effects in increasing firms' productivity and can reduce cost. A possible explanation and more discussion of this point will be given later in this section.

In specification B2 we allow for industry-specific effects. This version, as argued below, represents our preferred model because it accounts for two essential mechanisms. The overall fit has considerably improved, as indicated by the increase in the value of R^2 (0.95).[29] The cost elasticity with respect to public transport reveals a significantly negative effect, where a 1 percent increase in transport results in 0.06 percent reduction in cost (or 0.06 percent increase in productivity). As for the relationship between public transport and each factor input, once again and in contrast to the benchmark models, we have reached the conclusion that transport is labour using and capital saving. Results on factor cost shares and technological progress are consistent with those discussed above. The interindustry spillovers have for the second time created an increase in the production cost of individual industries, but with almost double the size of the effect because ξ_{ch} turned out to be 0.12. This is an interesting finding, which has remained robust - as indicated by the sign of the estimate - across the two specifications and is worthy of further attention. The effects of the spillovers on inputs-use remain robust as well as the results on industry dummies, which validates the heterogeneity across industries. From the above overview of the regression results, which model - out of those four versions - has produced the best result on the cost elasticity of transport in terms of theoretical coherence and statistical significance? In the benchmark versions, the results from model A2, which has controlled for the industry specific-effects, are clearly superior - as indicated by the sign of the elasticity estimate and the value of R^2 - to the results from model A1 which ignores industries' heterogeneity. This is because enhancement of public infrastructure (including transport) is often seen to have beneficial effects on economic growth by increasing the productivity of labour and capital, raising production and profitability, and thereby reducing the costs of production. Thus, allowing for the unobserved heterogeneity to explain interindustry cost differences in the analysis has proved informative. Similarly, when the interindustry spillovers are recognised, the result on transport elasticity from a model that controlled for fixed-effects, B2, seems more reasonable, in terms of the size of R^2 and the estimated elasticity.

Comparing the results from models A2 and B2, it may initially appear that model A2 provides a preferable outcome because it suggests a smaller magnitude of the estimated elasticity ξ_{cg}. However, the presence of the spillovers in model B2 with a strongly significant effect on one hand, and the strong correlation found between this externality measure and the transport infrastructure on the other, cast doubt on the appropriateness of the specification of A2. That

[29]This value of R^2 implies that some portion of the variation in the dependant variables remained unexplained. Thus, to improve the fit further, other explanatory variables can be incorporated as a proxy to account for the business cycle effects.

Table 3 Symmetric Normalized Quadratic function, elasticity estimates (1990-2010): specification with industry spillovers

	Column B1		Column B2	
Elasticity	Estimate	Std. Error	Estimate	Std. Error
ξ_{cg}	-0.120**	(0.073)	-0.063**	(0.030)
ξ_{kg}	0.417	(0.886)	0.586	(0.559)
ξ_{lg}	-0.709*	(0.159)	-0.699*	(0.157)
ξ_{ch}	0.067***	(0.027)	0.122***	(0.022)
ξ_{kh}	0.045***	(0.015)	0.039***	(0.115)
ξ_{lh}	0.067*	(0.513)	0.071***	(0.013)
ξ_{cp_k}	0.268**	(0.125)	0.238***	(0.102)
ξ_{kp_k}	-0.124***	(0.018)	-0.165***	(0.023)
ξ_{lp_k}	0.046***	(0.010)	0.056***	(0.008)
ξ_{cp_l}	0.732**	(0.105)	0.762**	(0.146)
ξ_{kp_l}	0.124***	(0.018)	0.165***	(0.023)
ξ_{lp_l}	-0.046***	(0.010)	-0.056***	(0.008)
ξ_{ct}	-0.048	(1.080)	-0.063	(0.878)
ξ_{kt}	0.039	(0.891)	0.040	(0.897)
ξ_{lt}	-0.068	(1.101)	-0.070	(1.015)
Fixed-effects	No		Yes	
No. of observations	399		399	
No. of parameters	11		83	
McFadden pseudo R^2	0.89		0.95	

We test the following two null hypotheses: $H_o : \xi = 1$ against the two-sided alternative $H_1 : \xi \neq 1$, and $H_o : \xi = -1$ against the two-sided alternative $H_1 : \xi \neq -1$.
Terms *,**,*** denote significance at the 10%, 5% and 1% levels respectively at which both null hypotheses are rejected.
Column B1 presents the estimation results of equation (8) with the CRS assumption and the parameters δ_{im} and ω_{im} set to zero.
Column B2 presents the estimation results of equation (8) with the CRS assumption.

is, model A2 may suffer from a serious omitted variable bias, hence it would be inappropriate to prefer it over model B2 on the ground that it offers a smaller estimate for an elasticity of interest. Generally speaking, with such complicated models as B2, which include multiple regressors, it will be difficult, practically, to obtain the direction of the bias due to the existence of partial correlations among all regressors; nonetheless, this bias in the transport estimate has to be recognised. Wooldridge (2009) suggests that in such complicated specifications, an approximation is often practically useful to derive a conclusion on the direction of the bias. To elaborate, recall that our cost function has four arguments besides the spillovers, $c = c(P, y, t, g, h)$. We want to determine the direction of the bias in g (transport infrastructure) when h (the industry spillovers variable) is omitted from the model. Our evidence suggests that while h does not strongly correlate with the other regressors, g demonstrates strong correlations with these variables, thus, one should expect biases in the coefficients of all regressors when h is omitted. Wooldridge (2009) argues that while we cannot strictly determine the direction of the bias in g when h is omitted, we can approximate this by ignoring the other regressors, a reasoning which 'is often followed as a rough guide for obtaining the likely bias estimators in more complicated models' Wooldridge (2009, p. 94). Thus, since the estimate on h is positive, and h and g are positively correlated, the effect of transport obtained in model A2 may possibly have an upward bias.[30]

It is mentioned above that models with a large number of parameters may suffer from overfitting - i.e. a lot of noise could be introduced into the model. A number of selection criteria are suggested in the literature to describe the tradeoff between the accuracy and complexity that results from adding more explanatory variables to the model. These criteria take the form of a penalised likelihood function plus a penalty term, which increases with the number of parameters. To check the robustness of our preferred model, the Akaike Information Criterion (AIC) (Akaike 1973) is employed and the values for each model are reported in appendix table A2. The objective is to find the model which minimises the criterion. As it can be seen from the table, the AIC favours model B2 over all other models, demonstrating that our preferred model is robust to the model selection criterion used.

The reasoning offered above in favour of model B2 stems primarily from econometric perspectives, but it is more interesting to provide an economic rationalisation of the model. An increase in a particular industry's costs in response to an expansion in other industries' activities can be attributed to the presence of external diseconomies which can more than offset any economies of scale arising from thick market effects (i.e. for ξ_{ch} to be positive rather than negative, the thick market effects must have been outweighed by the congestion effect). To illustrate: if transport infrastructure is productive, it can enhance the productivity of most, if not all, industries by enabling activities, extending markets, creating new opportunities, and so forth. With these possible expansions, the growing industries will compete to draw productive resources away from each other (given the assumption of resources mobility across industries) which will lead to higher production costs for those industries with comparatively fewer advantages. There are some similarities in a regional context, though, between this interpretation and those of Boarnet (1998) and Monaco and Cohen (2006), who estimated a production function and a cost function respectively by using regional data for the U.S. and incorporating transport infrastructure in their models.[31] Both studies found negative spillovers to a particular region from transport infrastructure investment in neighbouring regions. Namely, they found that if neighbouring regions improve their transport, this may draw resources away, since the neighbouring regions become more attractive locations. As a result of the less attractive environment for workers, the higher quality workers have an incentive to migrate to the neighbouring region with better transport, and costs rise in that particular region. Consequently, transferring the rationale of Boarnet, and Monaco and Cohen into an industry context, it seems plausible to explain the existence of agglomeration diseconomies across industries.

In sum, enhancement in transport infrastructure can result in two different types of effect

[30] Caution should be taken with this approximation because Wooldridge's suggestion of ignoring other regressors seems acceptable if one deals with a model in which the number of regressors is relatively small. With our flexible function which is augmented with a large number of regressors, however, the direction of the bias can be ambiguous. In all cases, what is very certain and interesting for us is the influence on transport elasticity derived from incorporating the spillovers in the model.

[31] Boarnet (1998) has examined highway capital stocks in Californian counties while Monaco and Cohen (2006) have used state level data to examine port and highway infrastructure.

which may influence the economic performance of each individual industry. First, those effects which are embodied within the boundaries of the industry have created cost savings gains. On the other hand, across the boundaries of the industry, transport has simultaneously generated agglomeration economies and diseconomies. The increase in the output of the supplier industries may give rise to greater technological diffusion (embodied in goods) and higher supplier-driven externalities, which consequently can lower production costs for a particular industry. The expansion in other industries' production, which is derived from transport enhancements, may produce disadvantageous environments such as congestion, higher costs factor inputs, and intense competition in output markets. Our evidence suggests that while across industries positive spillovers associated with transport improvement may have been counteracted by negative spillovers, the scale economies from transport within the boundary of the industry are prevalent.

Having reached this conclusion, it is of interest to compare our results with other studies that examined the impact of public infrastructure on output/productivity. Although the results from the cost function approach are not directly comparable with those from the production function approach, the conclusion most often drawn in the literature is that cost function studies tend to find a smaller contribution from public infrastructure to output growth. However, this is not the case for Australia; for example, if we compare the results of Otto and Voss (1996) with those of Paul (2003).

There is no Australian study - within or without the cost function framework - that is directly comparable to this analysis. This is because of differences in the methodology used, the infrastructure capital coverage, the time periods, the functional forms, and the economic sectors covered. The few studies completed using the cost function approach, cited earlier in this paper, have found much larger estimates of the public infrastructure effect, but considering the difference in the scope of public capital examined, this difference in the estimates should be smaller than it appears to be. In terms of the overseas studies, the most relevant study we found for comparison with this analysis was put forward by Moreno, López-Bazo, Vaya and Artis (2004). Similar to our analysis, those authors recognised the industry spillovers in a cost function framework and employed information from the input-output tables to adapt the spatial econometric techniques to an industry context. However, there are many other areas of discrepancy between the two studies, such as the scope of public capital; the regional dimension of the study (where Moreno et al. (2004) employed data on 15 Spanish regions for 12 manufacturing industries); the functional form adopted to represent the cost function; and the estimation method, which may all prevent comparison of the results between the two analyses from being straightforward.

In line with our argument, Moreno et al. (2004) found evidence on industry spillovers that biased their estimate for public capital: initially, in estimating the model without incorporating industry spillovers, they found the elasticity of variable cost to be 0.305, but after including these mechanisms in the model, the estimate changed to -0.341. The authors interpreted this as evidence of agglomerating economies which have correspondingly lower manufacturing costs. It is worth mentioning that Moreno et al. (2004) did not discuss issues or report evidence about the existence of counteracting agglomeration diseconomies as was done in this study.

Table 4: Hypothesis tests

Hypothesis	Parameters restrictions	q	χ^2/q	$\chi^2_{c,0.01}$/q	Test results
No infrastructure	$\beta_{kg} = \beta_{lg} = \omega_{k1} = \omega_{k2} = ... = \omega_{km} = \omega_{l1} = \omega_{l2} = ... = \omega_{lm} = 0$	38	3.105	1.609	reject
No industry spillovers	$\beta_{kh} = \beta_{lh} = 0$	2	6.120	4.605	reject
(i) No specific-effects	$\delta_{k1} = \delta_{k2} = ... = \delta_{km} = \delta_{l1} = \delta_{l2} = ... = \delta_{lm} = 0$	36	1.890	1.628	reject
(ii) No specific-effects	$\delta_{k1} = \delta_{k2} = ... = \delta_{km} = \delta_{l1} = \delta_{l2} = ... = \delta_{lm} =$	72	2.557	1.428	reject
	$\omega_{k1} = \omega_{k2} = ... = \omega_{km} = \omega_{l1} = \omega_{l2} = ... = \omega_{lm} = 0$				

The likelihood ratio statistic (LR) is calculated using the standard formula $LR = 2(\ell_{ur} - \ell_r)$, where ℓ_{ur} is the log-likelihood value for the unrestricted model and ℓ_r is the log-likelihood value for the restricted model. $LR \overset{a}{\sim} \chi^2_q$, where q is the number of exclusion restrictions. $\chi^2_{c,0.01}$ represents the critical value at 1% significance level.
The test for industry specific-effects is carried out by: (i) setting the coefficients of industry dummies(interacted with input prices) to zero, and (ii) adding to the set of coefficients in (i) the estimates on the interaction between dummies and transport then, set all coefficients equal to zero.

To conclude this section, we use the estimation results of Model B2 to test a number of hypotheses concerning the structure of the cost function. Log-likelihood ratios are used for the tests and the results are presented in Table 4. The likelihood ratio tests suggest strong rejection of the joint hypothesis that coefficients of public transport are zero, and this points to the critically positive role played by transport infrastructure in the economy. We next evaluated the validity of interindustry spillovers; a hypothesis of no spillovers was examined and the test strongly rejected the hypothesis. These tests also suggest a decisive rejection of the joint hypothesis that the coefficients of the industry dummies equal zero, indicating a strong interindustry difference in the cost structure of Australian industries.

9 Conclusion

The flexible Symmetric Normalized Quadratic functional form was used to evaluate the impact of public transportation for the Australian economy over the period 1990-2010. Employing data on 19 industries in a cost-based framework, the study has examined the effect of transport within a framework that explicitly recognises interindustry spillovers. The spatial econometric techniques are adapted into an industry context to incorporate industry spillovers in the model. For the purpose of estimation, the analysis has employed information from the input-output tables to construct a weighting matrix that reflects the interdependence across industries. Moreover, given the heterogenous nature of the industries in our sample, the study has applied measures to allow for possible differences in their cost structure.

The study finds that increasing public transport infrastructure will decrease production costs at industry level, but due to significant negative industry spillovers, these beneficial cost-saving effects are reduced. Public transport infrastructure raises the value of 'neighbouring' industries, which as a result of their expansion, draw resources away from industries with comparatively fewer advantages. To the extent that congestion and adverse competition effects arising from other industries' expansion is high, these diseconomies may dominate the scale economies associated with supplier-driven externalities. Consequently, although transport infrastructure might be productive at industry level, it might yield a smaller gain in terms of reduction in cost over the whole country.

An interesting implication of the finding of the external diseconomies from 'neighbouring' industries is that from society's viewpoint, the overall stock of transport infrastructure may be too large. When choosing the optimal size of transport infrastructure, governments may not account for these diseconomies, and thus may choose too much transport infrastructure. Therefore, the recognition of these spillovers will be helpful for the decision making process in choosing a 'socially' desirable level of transport infrastructure.

Finally, the analysis also finds that controlling industry specific-effects has substantially contributed to improving the measurement of transport effects.

Appendix

Imposing curvature: Cholesky decomposition

A system of three equations, the unit cost (c/y) and two input to output demand equations (k/y and l/y), is described as follows:

$$\begin{aligned}
c/y \quad &= \sum_m \delta_{km} DUM_m p_k + \sum_m \delta_{lm} DUM_m p_l + \beta_k p_k + \beta_l p_l + \frac{1}{2}\frac{\beta_{kk}p_k^2 + \beta_{ll}p_l^2 + 2\beta_{kl}p_k p_l}{(\alpha_k p_k + \alpha_l p_l)} \\
&+\beta_{kt}p_k t + \beta_{lt}p_l t + \left(\beta_{kg} + \sum_m \omega_{km} DUM_m\right) p_k g + \left(\beta_{lg} + \sum_m \omega_{lm} DUM_m\right) p_l g \\
&+\beta_{kh}p_k h + \beta_{lh}p_l h + \beta_{yy}\Big(\phi_k p_k + \phi_l p_l\Big) y + \beta_t\Big(\pi_k p_k + \pi_l p_l\Big) t^2 + \frac{\gamma_k}{y}p_k + \frac{\gamma_l}{y}p_l \\
&+\gamma_t\Big(\frac{\varphi_k}{y}p_k + \frac{\varphi_l}{y}p_l\Big)t + \gamma_g\left(\frac{\psi_k}{y}p_k + \frac{\psi_l}{y}p_l\right)g + \gamma_h\left(\frac{\tau_k}{y}p_k + \frac{\tau_l}{y}p_l\right)h + \mu,
\end{aligned} \tag{A1}$$

$$\begin{aligned}
k/y \quad &= \sum_m \delta_{km} DUM_m + \beta_k + \frac{\beta_{kk}p_k + \beta_{lk}p_l}{(\alpha_k p_k + \alpha_l p_l)} - \frac{1}{2}\alpha_k \frac{\beta_{kk}p_k^2 + \beta_{ll}p_l^2 + 2\beta_{kl}p_k p_l}{(\alpha_k p_k + \alpha_l p_l)^2} + \beta_{kt}t \\
&+\Big(\beta_{kg} + \sum_m \omega_{km} DUM_m\Big) g + \beta_{kh}h + \beta_{yy}\phi_k y + \beta_t \pi_k t^2 + \frac{\gamma_k}{y} + \gamma_t \frac{\varphi_k}{y} t \\
&+\gamma_g \frac{\psi_k}{y} g + \gamma_h \frac{\tau_k}{y} h + \mu_k,
\end{aligned} \tag{A2}$$

$$\begin{aligned}
l/y \quad &= \sum_m \delta_{lm} DUM_m + \beta_l + \frac{\beta_{ll}p_l + \beta_{kl}p_k}{(\alpha_k p_k + \alpha_l p_l)} - \frac{1}{2}\alpha_l \frac{\beta_{kk}p_k^2 + \beta_{ll}p_l^2 + 2\beta_{kl}p_k p_l}{(\alpha_k p_k + \alpha_l p_l)^2} + \beta_{lt}t \\
&+\Big(\beta_{lg} + \sum_m \omega_{lm} DUM_m\Big) g + \beta_{lh}h + \beta_{yy}\phi_l y + \beta_t \pi_l t^2 + \frac{\gamma_l}{y} + \gamma_t \frac{\varphi_l}{y} t \\
&+\gamma_g \frac{\psi_l}{y} g + \gamma_h \frac{\tau_l}{y} h + \mu_l,
\end{aligned} \tag{A3}$$

where k and l denote capital and labour and all other notations remain the same.

$$B = \begin{bmatrix} \beta_{kk} & \beta_{kl} \\ \beta_{kl} & \beta_{ll} \end{bmatrix} \tag{A4}$$

Using Cholesky decomposition we decompose B as:

$$B = -ZZ' = \begin{bmatrix} z_{11} & 0 \\ z_{12} & z_{22} \end{bmatrix} = \begin{bmatrix} z_{11} & z_{12} \\ 0 & z_{22} \end{bmatrix} \tag{A5}$$

Thus, we have the following restrictions:

$$
\begin{aligned}
\beta_{kk} &= -z_{11}^2 \\
\beta_{kl} &= -z_{11}z_{21} \\
\beta_{ll} &= -(z_{12}^2 z_{22}^2)
\end{aligned}
\tag{A6}
$$

Recall that $\sum_i \beta_{ij} = 0$, then the reparametrisation of (A5) is applied to $\widetilde{B}$ of (A1).[32]

[32] Notice that, with the restriction $\sum_i \beta_{ij} = 0$, $\widetilde{B}$ is a one element matrix.

Table A1 ANZSIC division and subdivision codes and titles

A		**Agriculture, Forestry and Fishing**
	01	Agriculture
	02	Aquaculture
	03	Forestry and Logging
	04	Fishing, Hunting and Trapping
	05	Agriculture, Forestry and Fishing Support Services
B		**Mining**
	06	Coal Mining
	07	Oil and Gas Extraction
	08	Metal Ore Mining
	09	Non-Metallic Mineral Mining and Quarrying
	10	Exploration and Other Mining Support Services
C		**Manufacturing**
	11	Food Product Manufacturing
	12	Beverage and Tobacco Product Manufacturing
	13	Textile, Leather, Clothing and Footwear Manufacturing
	14	Wood Product Manufacturing
	15	Pulp, Paper and Converted Paper Product Manufacturing
	16	Printing (including the Reproduction of Recorded Media)
	17	Petroleum and Coal Product Manufacturing
	18	Basic Chemical and Chemical Product Manufacturing
	19	Polymer Product and Rubber Product Manufacturing
	20	Non-Metallic Mineral Product Manufacturing
	21	Primary Metal and Metal Product Manufacturing
	22	Fabricated Metal Product Manufacturing
	23	Transport Equipment Manufacturing
	24	Machinery and Equipment Manufacturing
	25	Furniture and Other Manufacturing
D		**Electricity, Gas, Water and Waste Services**
	26	Electricity Supply
	27	Gas Supply
	28	Water Supply, Sewerage and Drainage Services
	29	Waste Collection, Treatment and Disposal Services
E		**Construction**
	30	Building Construction
	31	Heavy and Civil Engineering Construction
	32	Construction Services
F		**Wholesale Trade**
	33	Basic Material Wholesaling
	34	Machinery and Equipment Wholesaling
	35	Motor Vehicle and Motor Vehicle Parts
	36	Grocery, Liquor and Tobacco Product Wholesaling
	37	Other Goods Wholesaling
	38	Commission-Based Wholesaling
G		**Retail Trade**
	39	Motor Vehicle and Motor
	40	Fuel Retailing
	41	Food Retailing
	42	Other Store-Based Retailing
	43	Non-Store Retailing and Retail Commission-Based Buying and/or Selling
H		**Accommodation and Food Services**
	44	Accommodation
	45	Food and Beverage Services
I		**Transport, Postal and Warehousing**
	46	Road Transport
	47	Rail Transport
	48	Water Transport
	49	Air and Space Transport
	50	Other Transport
	51	Postal and Courier Pick-up and Delivery Services
	52	Transport Support Services
	53	Warehousing and Storage Services
J		**Information Media and Telecommunications**
	54	Publishing (except Internet and Music Publishing)
	55	Motion Picture and Sound
	56	Broadcasting (except Internet)
	57	Internet Publishing and Broadcasting
	58	Telecommunications Services
	59	Internet Service Providers, Web Search Portals and Data Processing Services
	60	Library and Other Information Services
K		**Financial and Insurance Services**
	62	Finance
	63	Insurance and Superannuation Funds
	64	Auxiliary Finance and Insurance Services

Table A1 continued

L	**Rental, Hiring and Real Estate Services Services**		**P**	**Education and Training**	
	66	Rental and Hiring Services (except Real Estate)		80	Preschool and School Education
	67	Property Operators and Real Estate Services		81	Tertiary Education
				82	Adult, Community and Other Education
M	**Professional, Scientific and Technical**		**Q**	**Health Care and Social Assistance**	
	69	Professional, Scientific and Technical Services (Except Computer System Services (Design and Related Services)		84	Hospitals
	70	Computer System Design and Related Services		85	Medical and Other Health Care Services
				86	Residential Care Services
				87	Social Assistance Services
			R	**Arts and Recreation Services**	
				89	Heritage Activities
				90	Creative and Performing Arts Activities
N	**Administrative and Support Services**			91	Sports and Recreation Activities
	72	Administrative Services		92	Gambling Activities
	73	Building Cleaning, Pest Control and Other Support Services	**S**	**Other Services**	
				94	Repair and Maintenance
				95	Personal and Other Services
O	**Public Administration and Safety**			96	Private Households Employing Staff and Undifferentiated Goods- and Service-Producing Activities of Households for Own Use
	75	Public Administration			
	76	Defence			
	77	Public Order, Safety and Regulatory Services			

Input-Output (I-O) tables

Figure A1 I-O table: industry-by-industry matrix

From \ To		Row Prefix	Intermediate Demand					Intermediate usage (sub-total)	Final Demand							Final Demand (sub-total)	**Total supply (grand total)**
			Agriculture, etc.	Mining	Manufacturing, etc.	Construction	Services		Final consumption exp. – household	Final consumption exp. – government	Gross fixed capital form. – private	Gross fixed capital form. – public enterprises	Gross fixed capital form. – general government	Changes in inventories	Exports of goods and services		
	Column Prefix		0101–0400	1101–1500	2101–3701	4101–4102	4501–9601		Q1	Q2	Q3	Q4	Q5	Q6	Q7		
Intermediate inputs	Agriculture	0101–0400	QUADRANT 1 INTERMEDIATE USAGE						QUADRANT 2 FINAL DEMAND								
	Mining	1101–1500															
	Manufacturing, etc.	2101–3701															
	Construction	4101–4102															
	Services	4501–9601															
	Intermediate Inputs (sub-total)																
Primary inputs	Compensation of employees	P1	QUADRANT 3 PRIMARY INPUTS TO PRODUCTION						QUADRANT 4 PRIMARY INPUTS TO FINAL DEMAND								
	Gross operating surplus and gross mixed income	P2															
	Taxes on products (net)	P3															
	Other taxes on production (net)	P4															
	Imports	P5															
	Australian production																

corresponds to aggregates shown as components of gross domestic product, income approach

corresponds to aggregates shown as components of gross domestic product, expenditure approach

Source: ABS (2000), cat. no. 5216.0.

The Input-Output tables are a part of the Australian national accounts (ANA). They contain complete information about the supply and use of products in the Australian economy and about the structure of and inter-relationships between Australian industries. Each table can be described as an array of rows and columns that contain information on the industrial composition of final demand and also the purchases and sales of intermediate goods and services between industries. All of the goods and services produced in a period are identified as being used as inputs by industries in their production process, being sold to final users of the goods and services (either in Australia, or overseas as exports), or contributing to the change in stocks (an increase in stocks if more goods are produced than purchased or a rundown in stocks if demand exceeds supply). For the production system as a whole, the sum of all outputs must equal the sum of all inputs or, in other words, total supply must equal total demand. Figure A1 shows the structure of a typical input-output 'matrix'. The tables may be regarded as consisting of four quadrants. Quadrant 1 (intermediate usage) is usually referred to as the inter-industry quadrant. Each column in this quadrant shows the intermediate inputs into an industry in the form of goods and services produced by other industries, and each row shows those parts of an industry's output which have been absorbed by other industries. Quadrant 2 (final demand) provides details of the sales of goods and services by each industry to final users. Quadrant 3 (primary inputs to production) indicates the use in production of primary inputs such as wages, salaries and supplements, secondhand goods (sales by final buyers) and taxes paid by producers. Quadrant 4 (primary inputs to final demand) presents information on taxes paid by final users, flows of secondhand goods to (positive sign) and from (negative sign) final buyers and imports which are subsequently exported.

The last 6 sets of ANA's I-O tables, available electronically at the ABS web site, are for the years 2007-08, 2006-07 , 2005-06, 2004-05, 2001-02, and 1998-99 and each covers all enterprises, grouped into 111 industries. Earlier tables are not available electronically.[33]

To construct the industry weight matrix, we use the information found in Quadrant 1. For each of the six tables, we aggregated the data into a smaller table to reflect only 19 sectors identified under the ANZSIC 2006 using a concordance file. Thus, the expression for the direct-requirements matrix looks as follows:

$$N = \begin{bmatrix} a_{11} & a_{12} & \cdots & \cdots & a_{1N} \\ a_{21} & a_{22} & \cdots & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & & \vdots \\ \vdots & \vdots & & \ddots & \vdots \\ a_{N1} & a_{n2} & \cdots & \cdots & a_{NN} \end{bmatrix}, \tag{A7}$$

where the element a_{nm} reflects the value of products from industry n used as an intermediate in industry m.

According to Bartelsman et al. (1994), there are two ways to think about the linkages among industries: supplier-driven externalities and customer-driven externalities. To create the input weighted (IW), or supplier, aggregate activity index for industry m, one computes a weighted average of the change in activity of the industries that deliver products to industry m. The weight applied to the activity of industry n when creating the aggregate index for industry m

[33] The ANA I-O tables are not available in a time series format because not all the tables are not created on a consistent basis. Each table is prepared as per statistical standards at the time and any changes to methods, standards or data sources are not applied to the previous sets of tables, therefore the basis underlying each set of tables can differ.

is the nm^{th} element divided by the sum of the m^{th} column of the direct-requirements matrix:

$$\omega_m^{IW} = \frac{a_{nm}}{\sum\limits_{n \neq m} a_{nm}}. \tag{A8}$$

By contrast, to create an output-weighted (OW), or customer, aggregate activity index for industry m, one computes an output-weighted average of percentage changes in activity of all other industries that purchase product from industry m. The weight applied to industry n when creating the aggregate index for industry m is the mn^{th} element of the matrix, divided by the sum of the m^{th} row:

$$\omega_m^{OW} = \frac{a_{mn}}{\sum\limits_{n \neq m} a_{mn}}. \tag{A9}$$

Since our interest is to evaluate the significance of industrial linkages that affect the cost level in each industry, we focus on the supplier-driven externalities as they seem to exert more influence on a priori grounds. Further, assuming contemporaneous industry dependence (that is, the effect of the spillovers is exhausted within the period in which it is generated), then with M industries and T period of time we can define a weight matrix W as a $(M * T) \times (M * T)$ block diagonal matrix: $W = I_T \otimes X$, where I_T is the $T \times T$ identity matrix and X is a $M \times M$ row-standardized weight matrix.

To avoid any possible endogeneity of the weights, we followed an approach similar to Cohen and Morrison Paul (2004) and Case et al. (1993) by using an average of the shares of the six years as the weights. These authors argue that when using averages over several years for the weights, the weights and the explanatory variables are independent of one another. Accordingly, for our weights, which do not vary over time, the residuals and the independent variables are orthogonal.

Model selection criterion

The multi-equation context formulation for the Akaike Information Criterion (AIC) is computed as follows:

$$AIC = -logL(\hat{\beta}) + n, \tag{A10}$$

where $-logL(\hat{\beta})$ is the maximized log likelihood and $n = G \times H$ (G is the number of equations in the system and H is the number of variables in each equation).[34]

Table A2 AIC selection criterion

Model A1	Model A2	Model B1	Model B2
-113.65	-116.22	-114.59	-116.29

Model A1= equation (8) with the CRS assumption and the parameters δ_{im}, ω_{im}, and β_{ih} set to zero.
Model A2= equation (8) with the CRS assumption and the parameters β_{ih} set to zero.
Model B1= equation (8) with the CRS assumption and the parameters δ_{im} and ω_{im} set to zero.
Model B2= equation (8) with the CRS assumption.

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[34] See Fox (1998) for some other forms of selection criteria in a multi-equation context.

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