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Abstract

This paper presents new evidence on the impact of public infrastructure on the Australian economy. The contribution of the paper is three-fold. First, it estimates measures of multifactor productivity for each of the states and territories. Second, it employs a new data set on public infrastructure. Third, the paper applies detailed econometric investigations in an attempt to readdress the crucial econometric shortcomings of earlier studies. The analysis presented here is designed to investigate two widely-debated questions. First, whether aggregate time-series analysis is incapable of capturing infrastructure spillovers to productivity and, consequently, results in incredibly high estimates of infrastructure elasticity. Second, whether state-specific characteristics exhibit a significant role in explaining effects on productivity. To answer the first question, the study applies time-series regressions on both a national and state-by-state basis. Results from this approach confirm the implausibly large effect of infrastructure for the whole economy and four states. To examine the second issue, the paper develops a panel cointegration model which controls for state fixed effects. In sharp contrast with findings from aggregate time-series, results from the fixed effects approach are more plausible and robust to sensitivity tests. In another piece of evidence, estimation of an error-correction model reveals that a long-run identification and modelling of the relationship (i.e. a cointegration) reflects the important positive role of infrastructure on productivity. However, short-run dynamics provide no support for a positive effect which explains why earlier studies which employed differenced data found infrastructure has no discernible effect on productivity. In addition, applying a causality test suggests a long-run unidirectional causality running from public infrastructure to productivity.

Keywords: Productivity, Public Infrastructure, Cointegration, Disaggregated analysis.
JEL Classification Numbers: H54, O47.

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1 Introduction

The question of 'how productive is public infrastructure?' has remained an issue on the research agendas of many decades. Since Aschauer's (1989) work, which suggests a strong influence of public capital on productivity, researchers have continued to investigate this issue by using different methodologies and data sets. Nevertheless, no agreement on the nature and size of the effect has yet been achieved. Authors have followed several approaches to examine the relationship between public infrastructure and productivity. The aims, assumptions, and findings of these approaches have extensively been reviewed and assessed in the theocratical and empirical literature.[1] Most of the first generation studies that followed Aschauer (1989) in applying aggregate level analyses have found incredibly large elasticity estimates of productivity (e.g Munnell 1990*b*; Wylie 1996; and Fernald 1999). This finding has prompted the use of disaggregate data (e.g., state, region, metropolitan areas) as opposed to aggregate data (see Munnell 1990*a*; and Garcia-Mila and T.McGuire 1992 for example). The main argument of regional studies relates to the existence of positive geographic externalities from infrastructure which are not captured by aggregate analysis. By employing regional data (and hence allowing for the externalities), such studies find a considerable reduction in the estimated effect on productivity. However, all of the first generation studies, whether using aggregate or disaggregate data, have been criticised from different perspectives such as obtaining a wide range of estimates, and the lack of robustness to more sophisticated econometric techniques (for example, see Holtz-Eakin 1994; Cashin 1995; Baltagi and Pinnoi 1995).

The subsequent generation of researchers has attempted to respond to the criticism by using more appropriate econometric methods, but the findings are controversial. While one group of studies continues to assert a strong positive effect, the other group has found insignificant or negative impact (see Makin and Paul 2003 for an overview on recent literature). The conflicting outcomes have left researchers and policy makers in a quandary as to what the accurate effect on productivity could be and whether, given the tight federal budgetary policies, resources have to be shifted from or to public infrastructure investments.

Recently, there has been redirection of the research towards spatial/regional panel analyses. There is some consensus that regions have individual characteristics which affect the role of infrastructure. These characteristics have to be accounted for when assessing the benefit on productivity. Although applying disaggregated analyses seems to provide some avenues to overcome the limitations of the aggregate analyses, the unavailability of suitable data has continued to hamper the efforts of this approach. Therefore, panel productivity analyses have been conducted in only a few countries outside the U.S.; some examples are Stephan (2003) for West Germany, Destefanis and Sen (2005) for Italy, and Cadot, Roller and Stephan (2006) for Spain.

In Australia, the limited availability of regional/state data has restricted previous investigations to the national level only. When surveying the empirical literature, only three panel analyses are found, namely, Productivity Commission (2007), Louca (2003) and Burgio-Ficca

[1] See Bom and Ligthart (2008), Romp and de Haan (2007) and Infrastructure Canada (2007) for comprehensive coverage of this literature.

(2004) in which the authors examine the effects of research and development (R&D) investment on productivity. The dearth of evidence using state level data has motivated us to examine the topic using state-by-state and panel data frameworks. Thus, to make this goal possible, data at state level have first to be constructed.

The contribution of this paper is three-fold. First, since the official data available for multifactor productivity (MFP) are estimates for the market sector of the whole economy, the present study provides estimates of MFP for each of the Australian states and territories.[2] Second, we aim to carefully select a relevant measure of public infrastructure capital. In particular, we emphasise the role of economic infrastructure such as transport, telecommunication, water and gas (in contrast to social infrastructure) as a subset of infrastructure that has a more immediate influence on the production process. One of the reasons that earlier studies have achieved divergent results is that various authors have modelled a variety of different indicators of infrastructure. In many cases (often due to the lack of data) the scope of infrastructure is defined to encompass a wide range of public assets such as educational institutions and hospitals, which in turn has resulted in a large estimated effect of infrastructure. To construct an appropriate measure for public economic infrastructure (or, as it is interchangeably called, core infrastructure) we utilise the engineering construction data published by the Australian Bureau of Statistics (ABS). These data, to a great extent, are similar to the spending on core infrastructure. As we are not aware of any other study within our context of investigation that has made use of these data, this adds one more dimension of departure from other Australian studies. Third, the estimated data are employed to develop a comprehensive econometric approach which aims to investigate two questions that have been widely discussed in earlier studies. More precisely, the intention is to inquire what Australian data says with respect to the argument of (i) inability of time series analysis to produce sensible results, and (ii) the impact of state characteristics in explaining productivity.

The econometric analysis attempts to address the crucial econometric shortcomings, such as spurious regression and endogeneity of regressors which have not received adequate treatment in the earlier Australian studies. For this purpose, we estimate long and short-run cointegration approaches to investigate the relationship between public infrastructure and productivity. To examine the first question, nationwide and state-by-state time series regressions are conducted. The estimated elasticity of public infrastructure for the whole economy and four states is found to be incredibly large. Thus, arguments against time-series analysis find some support from Australian data. Next, being able to construct estimates for the key variables at the state level gives us some hope with a set of data that has both cross section and time series dimensions. This, perhaps, has enabled us to overcome some of the limitations associated with aggregate time-series by making use of some recent developments in unit root and cointegration testing procedures and the advancements in panel data estimation techniques.

In contrast to the findings from aggregate analysis, using panel Dynamic Ordinary Least Squares (panel DOLS) and panel Error-Correction Model (ECM), which are widely recommended approaches to estimate panel cointegration coefficients, we find that the control of the

[2]From now on, whenever 'state' is referred to in the text, it also encompasses the two territories.

state individual characteristics produces long-run elasticities that are often reasonably in line with economic theory. Moreover, the panel ECM provides us with evidence on the different quality of productivity responses to changes in public infrastructure provision during the short- and long-run. We find that in the short-run, when infrastructure investments are perhaps not fully operational, no clear benefit appears in the production sector; however, during the longer terms, the positive benefits are well captured by the business sector. An extra piece of evidence relates to the debate on the causal link between infrastructure provision and productivity. Our error-correction model suggests that there is a long-run unidirectional causality running from public infrastructure to MFP.

Finally, the clear inconsistency between the outcomes of the state-by-state results and panel results induces us to question the homogeneity restriction inherent in panel procedures, which assumes that the estimated parameters are equal across the states. Applying formal poolability tests does not reveal statistical support for the homogeneity assumption. We look at the issue of poolability in some detail.

The paper proceeds as follows. The next section briefly discusses the major econometric problems in the earlier literature. The theoretical framework and the setup of econometric models are put forward in Section 3. In Section 4, we describe the sources of data and the construction of the variables used in the estimation procedures. Section 5 presents the results of unit root and cointegration tests on individual and panel series. In Section 6 we present the estimation techniques and the analysis of the results. Section 7 conducts sensitivity testing of the results by relaxing the assumption of constant returns to scale (CRS), which is imposed to derive MFP indexes. In Section 8 we present the rate of return of public infrastructure that is implied from our preferred results. Some discussion on the issue of data poolability is offered in Section 9. Section 10 tests the direction of causality between public infrastructure and productivity and Section 11 concludes.

2 Earlier literature and major criticisms

To highlight the shortcomings that need to be addressed, this section focuses on the main features of the criticism raised against the general approach adopted by earlier studies. Briefly speaking, and following Munnell (1992), one can summarise these criticisms as follows:

Spurious correlation

Some critics argue that the data on output and public infrastructure used in the earliest models are non-stationary, which in turn has a serious implication regarding the long-term relationship, because a strong correlation appearing between non-stationary series variables might not result from a causal effect but reflect a spurious relationship.

Generally speaking, researchers have followed two approaches to deal with the issue of spurious correlation. The first group (e.g., Aschauer 1989 and Munnell 1990*b*) avoids the notion of spurious regression and assumes a causal relationship between infrastructure and productivity.

Although on some occasions the non-stationarity of the data is acknowledged, that group of studies handles the problem of non-stationarity by either including a deterministic time trend or simply assuming cointegration without performing a formal cointegration test. The other group of studies shows concern with the issue of non-stationarity. One possible solution suggested to solve this problem is to estimate the production function using first differences. For example, Tatom (1991) has estimated a production function and tested for unit root in the level of the variables in his estimated equation. According to his evidence, non-stationarity cannot be rejected for most of the employed variables. To overcome the potential spurious correlation, the author suggests to first-difference the data.

Munnell (1992) has responded to authors like Tatom by mentioning that the approach of first-differencing the data has important shortcomings because it is less likely that the growth in the stock of public capital will correlate with the growth of output or productivity in the same year. This is also justifiable for all the other factors of production. Hence, using first differences may result in non-significant estimates, not only for public capital, but also for the other factors. In addition, Munnell argues that 'first-differencing destroys any long-term relationship in the data, which is exactly what one is trying to estimate' Munnell (1992, p. 193).

In this light, Munnell emphasises that a better approach is to use cross-section data. By comparing the results from studies using national data (such as Aschauer 1989 and Munnell 1990*b*) with those using regional or state data (e.g., Munnell 1990*a*; Mera 1973; and Eisner 1991), the author concludes that the estimates of the elasticity of public capital are sensitive to geographical disaggregation: the more disaggregated the data, the smaller the estimated elasticity. Besides Munnell's (1992) argument, Engle and Granger (1987) have earlier shown that a first-differenced model of non-stationary variables is misspecified if the elements of the data vector are cointegrated, in which case an error-correction model is the proper specification. Thus, to preserve the long-run information, some studies have proceeded to formally test and model for cointegration.

Specification problems

Although there is some support for employing disaggregate data, critics argue that the studies of regions, states or metropolitan areas suffer from a specification problem. For instance, Holtz-Eakin (1994) emphasises that an estimation of the production function that neglects the important factors of differentials in regional productivity will result in biased parameters. To avoid this bias, Holtz- Eakin proposes allowing for state-specific characteristics such as location, climate, and endowments of natural resources when estimating production function.

Reverse causality

Is the positive correlation found between output and infrastructure due to the positive return from public infrastructure to output, or due to the effect of output on the demand for the quantity of public capital? Could causality run from the two directions simultaneously? These questions on the risk of reverse causation reflect another challenge facing the earlier aggregate approach, since variables on the regression are likely to be endogenous and this will indicate a problem with the single equation model (see Hurst 1994, p. 62). To account for the risk of reverse causality, some studies construct a simultaneous equations model (e.g., Flores De Frutos and Pereira 1993), while others apply the Granger causality test; for example, Tatom (1993), who has concluded that the Granger test shows strong evidence of reverse causality. Nonetheless, Fernald (1999) does not agree with the direction of causality that results from Tatom's study.

Missing explanatory variables

One more limitation raised against the earlier models is the failure to include other important explanatory variables besides infrastructure. In relation to a finding in the U.S., for example, Tatom (1991, p. 7) observes that: 'The omission of energy price effects on productivity after 1973 could result in attributing energy-related productivity losses to the decline in the growth of public capital'. In addition, Gramlich (1994) claims that the decrease of public infrastructure expenditure was one of many usual explanatory variables of the lower productivity level in the U.S. after the oil shocks in the seventies.

3 Theoretical framework

The theoretical framework adopts a conventional production function approach in which public capital represents a separate input in the production process. A general Cobb-Douglas representation of the production function with Hicks-neutral technical change is assumed and given by:[3]

$$Y = AL^{\beta_1} K_1^{\beta_2} K_2^{\beta_3}, \tag{1}$$

where Y is the total output (for private and public sectors); A is multifactor productivity (MFP) representing technological change; L, K_1, and K_2 are labour, private capital, and public capital (including public economic infrastructure) respectively. The exponential coefficient of each input represents the elasticity of output with respect to that input.
Taking the natural logarithm, the Cobb-Douglas production function is rewritten in the form:

$$\ln Y = \ln A + \beta_1 \ln L + \beta_2 \ln K_1 + \beta_3 \ln K_2. \tag{2}$$

In infrastructure studies, some authors estimate models based on (2) to assess the effect of public infrastructure on output or on labour productivity by dividing all terms in the equation by L. Others follow a two-step method where the index of MFP is derived independently in the first step, and the result is used in an estimation procedure with infrastructure in the second step. The two-step method has the advantage of conserving the degrees of freedom relative to (2) and could help to avoid multicollinearity between inputs. Thus, following Shanks and Barnes (2008), Shanks and Zheng (2006), and others, we first derive the indexes of MFP. The

[3]As Connolly and Fox (2006) mention, evidence from previous studies has shown identical results from both the Cobb-Douglas functional form and from more flexible functional forms, such as the CES or translog functions.

procedure adopted to estimate MFP index conforms to the ABS method, which is based on Solow's (1956) growth accounting approach, to estimate the MFP index. Within the framework of growth accounting, we maintain two assumptions: (i) constant returns to scale (CRS) over labour, private and public capital (i.e. $\beta_1+\beta_2+\beta_3=1$), and (ii) competitive equilibrium in both input and output markets in which factors are rewarded according to their marginal products. Given these two assumptions, (2) can be rewritten as:

$$\ln MFP \equiv \ln Y - s_1 \ln L - s_2 \ln K_1 - s_3 \ln K_2 = \ln A, \tag{3}$$

where s_1, s_2, and s_3 are income shares of labour, private and public capital respectively.[4]

In the second step, one can use (3) to estimate the effects of factors which were not accounted for in the construction of MFP. Although public infrastructure - being a part of K_2 - is included in the calculation of MFP, this does not necessarily mean we have fully accounted for all its effects. To elaborate this point, let us consider how public infrastructure is deemed to affect productivity in the earlier literature. Generally speaking, services provided by public infrastructure are assumed to have two types of effects on the production process. These are direct and indirect effects. Direct services such as water, power, sewerage and transportation facilities can be seen as intermediate inputs necessary for the production process. In addition, infrastructure could have indirect effects on the productivity of other inputs, since it can be a complement or a substitute to these inputs and hence affects their productivity. Furthermore, public infrastructure indirectly enables, facilitates and/or creates opportunities for innovations in other sectors. These latter effects are called production spillovers. Shanks and Barnes (2008) provide a detailed discussion of these effects with examples of spillovers by type of infrastructure capital.

The method applied to construct MFP indexes in this study has captured the direct free input effect of public infrastructure and the direct effect with user charges. However, the spillovers effect has not been accounted for; thus, we re-enter the public infrastructure, G, in Model (3) as an additional explanatory variable.[5] Also, to avoid omitted variable bias other factors affecting productivity are included and represented by a vector $Z(n \times 1)$:

$$\ln MFP = \ln A + \gamma \ln G + \theta Z, \tag{4}$$

where $\ln G$ is the natural logarithm of public infrastructure and θ $(n \times 1)$ is a vector of coefficients.

Finally, we allow for an error in the CRS assumption. As mentioned earlier, CRS over labour,

[4]Notice that the state level multifactor MFP estimates pertain to the whole (public and private) economy. Conventionally, authors are inclined to evaluate the effect of public infrastructure on private sector productivity. However, in our case, the data on hand for labour and output are not separated into private and public sectors. To avoid major measurement errors in the estimation of MFP, we preferred to calculate a measure for the whole economy. Furthermore, in the definition of MFP, we apply a share for the public capital which is commonly treated in other studies as a free input that enters the private sector production function. This mainly due to the nature of the Australian System of National Accounts data mentioned above. Thus, in our calculations we combined public and private capital to construct a joined measure that is consistent with the joined capital income share.

[5]This approach was followed by Shanks and Barnes (2008), who employed the ABS market sector estimates of MFP, which includes public capital as a component of usual capital.

private and public capital is assumed to construct the MFP index. Although it is conventional to assume CRS over private inputs (labour and private capital), there is some argument about the return to scale on public infrastructure. Given that increasing economies to scale are usually associated with the public provision of goods and services, one can argue that public infrastructure has increasing returns to scale in the production process. By contrast, in some cases the additional provision of infrastructure might lead to decreasing returns. One example of this is the problem of congestion in the case of transport infrastructure.

In sum, if the assumption of CRS does not hold, the coefficient on public infrastructure will not only capture the effect of the production spillovers, it will also capture the scale effect and this in turn will bias the estimate of the coefficient. One way to allow for an error in CRS assumption, is to enter a scale control variable in the model. To demonstrate how this works, let us suppose that a scale control variable is denoted by S with a coefficient equal to $(\omega - 1)$, where ω is the true scale technology. Thus, $(\omega - 1) \gtreqless 0$ if, $\omega \equiv \beta_1 + \beta_2 + \beta_3 \gtreqless 1$. In other words, if the true technology is CRS, the coefficient on S will be zero, $(\omega - 1) = 0$; if the true technology is increasing returns to scale, the coefficient will be positive, $(\omega - 1 > 0)$ while if it is decreasing returns to scale the coefficient will be negative, $(\omega - 1 < 0)$. Therefore, by including S as an explanatory variable, the hope is that the coefficient on public infrastructure will entirely reflect the spillover effects.[6]

Economists have used different measures as proxies for the scale variable. Some examples are labour, capital or a combination of the two inputs. The current study follows Otto and Voss (1994) who apply a combination index for labour and capital inputs.[7] Hence, by including the scale variable in the model, the resultant model will be:

$$\ln MFP = \ln A + \gamma \ln G + (\omega - 1)S + \theta Z. \tag{5}$$

The subsequent task is to determine what other factors, apart from capital and labour, influence the level of output. In other words, what variables are included in the vector Z. Previous theoretical and empirical models in Australia and other countries suggest a range of determinant variables in explaining the variation in output and productivity. For example, Aschauer (1989) using U.S. data and Otto and Voss (1994) using Australian data have controlled for the effect of the business cycle by including a capacity utilisation variable when they study the impact of public capital on productivity. On the other hand, Munnell (1990*a*) has used the unemployment rate to control for cyclical fluctuation in productivity in the U.S. Connolly and Fox (2006), who examine the role of high-tech capital use on productivity at the industry level in Australia, have included R&D, openness, and terms of trade in addition to some environment variables as control variables. Among others, Madden and Savage (1998) suggest some determinants for Australian labour productivity such as fixed capital, human capital, and telecommunications, plus trade openness and international competitiveness. In a productivity commission working paper designed to investigate the relationship between R&D and productivity growth in Aus-

[6] This could be true if there are no misspecification problems or other omitted variables bias.

[7] The labour and capital indexes are combined using their respective income shares to form an aggregate input index using a Tornqvist methodology.

tralia, Shanks and Zheng (2006) have used human capital among other explanatory variables to control for the variations in productivity.

In terms of the studies published at the level of the Australian states to examine the return of R&D on MFP and output, Louca (2003) has controlled for the rates of industrial disputation to account for labour market reform, high school retention rates to capture the rise in potential human capital stock, and capacity utilisation to account for the cyclical swings in MFP. In addition, another study by the Productivity Commission (2007) uses, among other variables, the percentage of state residents with a post-schooling qualification as a proxy for human capital, while Burgio-Ficca (2004) has controlled for deregulation through tariff reductions and industry protection.

Guided by the model specifications of earlier work, although being limited by the availability of data at the state level, we were able to construct measures for the following variables: openness, capacity utilisation, human capital, unemployment rate, union density, and finally, industrial disputation.[8] Definitions and the sources of data used to construct these variables are presented in the data section below.

The model presented in (5) can be expressed in the following two linear regression equations

$$\ln MFP_t = \mu + \gamma \ln G_t + \sum_{i=1}^{n} \theta_i Z_{it} + (\omega - 1)S_t + \nu_t, \tag{6}$$

$$\ln MFP_{st} = \mu + \gamma \ln G_{st} + \sum_{i=1}^{n} \theta_i Z_{ist} + (\omega - 1)S_{st} + \nu_{st}, \tag{7}$$

where $t = 1, ..., T$ and $s = 1, ..., M$ index the time-series and state respectively; γ is the MFP elasticity with respect to public infrastructure.
The two equations are identical except for the state subscript in the second equation. (6) represents the basic econometric setting for time-series estimation, while (7) represents the basic econometric setting for pooled-data estimation.

As indicated in the introduction section, the critics of public capital hypothesis stress that the shortcomings of aggregate time-series analysis are the main causes of implausible results in previous studies. Consequently, regional studies assert the role of the state or region as a source of information on the spillovers (externalities) from public capital. For example, Munnell (1990*a*) uses pooled cross-section annual time series for the 48 continental states and obtained elasticity coefficient of 0.15 which was a reduction of around a third compared with the first studies by Aschauer (1989) and Munnell (1990*b*). Hulten and Schwab (1991) and Holtz-Eakin and Schwartz (1995) also find a relatively small elasticity of output with respect to public capital in the range of 0.00-0.15. In addition, an earlier study than Aschauer's was accomplished by Eberts (1986). By using 38 U.S. metropolitan areas, the author finds a very low rate of return to public infrastructure; in particular, the estimated elasticity of output is found to be 0.03.

The issue of observing a sizeable discrepancy between results from regional level and national

[8]Economic theory suggests that capacity utilisation, openness, and human capital will have positive effects on productivity, while the unemployment rate, rate of disputation and trade unionisation are expected a priori to have negative effects on productivity.

level has received attention from some researchers such as Gramlich (1994), Boarnet (1998), and Lall (1999). To explain such disparity in the results, these authors have focused on the positive geographic spillovers in productivity benefits that are not captured by highly disaggregated analyses. To elaborate on this, Munnell, says 'as the geographic focus narrows, the estimated impact of public capital becomes smaller. The most obvious explanation is that, because of leakages, one cannot capture all of the payoff to an infrastructure investment by looking at a small geographic area.' Munnell (1992, p. 193).

That generation of state studies has been criticised for neglecting to consider the impact of regional characteristics (such as the natural resource endowment, size, location, climate, and amenities) in explaining productivity. A strand of literature (e.g., Islam 1995, Temple 1999, and Holtz-Eakin 1994) asserts the role played by the state-specific effects in productivity analysis. The argument of this literature can be summarised as follows. The effects of public infrastructure on productivity may correlate with some omitted variables which have been shown to play an important role in productivity. Thus, to disentangle the effect of public infrastructure on productivity, we need control over these state characteristics; ' because the prosperous states are likely to spend more on public capital, there will be a positive correlation between state specific-effects and public sector capital. This should not be confused, however, with the notion that greater public capital leads a state to be more productive' (Holtz-Eakin 1994, p. 13). From his econometric evidence, Holtz-Eakin suggests that there are no quantitatively important spillover effects across states.

From an Australian perspective, the current study aims to perform two levels of investigation. First, it seeks to inquire whether aggregate time-series analysis has severe limitations that make it unsuitable for the examination of the infrastructure spillovers to productivity, hence, (6) is employed to perform regressions for each individual state and the whole country. Second, it aims to test the hypothesis of regional characteristics of Holtz-Eakin; hence, an alternative assumption to adopt is that each of the Australian states possesses individual characteristics which result in differential productivity across them. To account for these effects, the error term in (7) is rewritten as follows:

$$\nu_{st} = \mu_s + \eta_t + \epsilon_{st}, \tag{8}$$

where μ_s is state-specific effects which captures those characteristics of the production function in each state and does not vary over time; η_t is a time-specific effect that captures the shocks to the production function that are common to all states in each time period; and ϵ_{st} is an idiosyncratic error. Substituting (8) in (7) results in the following equation:

$$\ln MFP_{st} = \mu_s + \eta_t + \gamma \ln G_{st} + \sum_{i=1}^{n} \theta_i Z_{ist} + (\omega - 1) S_{st} + \epsilon_{st}. \tag{9}$$

To establish an intuitive long-run relationship, the estimation of (6) and (9) entails that all the variables included in the equation should have specific statistical properties. A minimum requirement is that all variables should be stationary. If the variables are non-stationary, then estimating these equations in levels will result in spurious regression unless the variables are cointegrated. Most of the disputes associated with the results from other studies centre on the issue of the non-stationarity of the data and the method employed to deal with the problem. Therefore, after describing the construction of the data in the following section, we proceed to investigate the statistical time series properties of the series.

4 Data

All the data are primarily sourced from the ABS for the eight Australian states and territories of New South Wales (NSW), Victoria (VIC), Queensland (QLD), South Australia (SA), Western Australia (WA), Tasmania (TAS), Northern Territory (NT), and Australian Capital Territory (ACT) over the period 1990-2009. Because of the lack of data for some variables, ACT is not included in all regressions. Thus, the analysis is based on the data of seven (or eight) states and a twenty-year span, forming in total 140 observations.[9] The variables employed in the regressions are defined and sourced as follows:

Multifactor productivity (MFP)

Although Australia first published estimates for multifactor productivity for the market sector in 1985, and recently started to construct equivalent measures for individual industries, these indexes are restricted to the national level. This stance is perhaps not surprising since the process of establishing and maintaining productivity statistics requires a sizeable investment of resources; see Fox (2007) and Griliches (1994) for discussions on difficulties and challenges in the measurement of productivity. An initial exercise to perform, then is to construct a productivity measure for each of the states.

In line with the ABS method, we apply the Tornqvist index number approach which establishes a link between the production function, in the context of the growth accounting framework set out by Solow (1956), and index number theory. Briefly, MFP is defined as the ratio between an output measure and an input measure, i.e. $MFP = \frac{Y}{Q_{K,L}}$ where Y is a volume measure of value added output; and $Q_{K,L}$ is a combined index of capital and labour inputs.[10] Using the Tornqvist method to estimate the inputs index requires data on capital, labour, and their income shares. The output is defined as gross value added, while the labour input is measured as number of hours worked. The capital stock is constructed using the perpetual inventory method (PIM). Income shares for labour and capital are calculated as the share of compensation on employees plus the labour component in mixed income, and the gross operating surplus plus the

[9]When ACT is included, the period of the study is reduced to cover only up to 2007; hence, the corresponding number of observations is 144.

[10]If only capital and labour are included as inputs, the appropriate measure for output is value added output and the corresponding MFP index is known as value added output-based MFP . Alternatively, if intermediate inputs are also included, the appropriate measure of output should be the gross output, and the corresponding MFP index is known as gross output-based MFP. See Schreyer (2001) for more description on the difference between the value added and gross output-based MFP indexes.

capital component in mixed income in the total factor income respectively.[11]

Figure 1 below shows a plot of the estimated series of MFP indexes for all the states over the period 1990-2009. It is noticeable from the figure that all states, with the exception of NT, have experienced an upward trend in MFP which indicates a growth during the 1990s. Since 2005, productivity growth has slowed. It is also clear that the productivity level varies across the states. South Australia is an exception, as it exhibits a relatively higher level of productivity in comparison with the rest of the states from the mid-1990s until the end of the period. The higher level of SA productivity is mainly driven by the decrease in total capital stock during the period of the study.[12]

Infrastructure

The choice of an appropriate measure that correctly defines public infrastructure service has always been a challenge facing infrastructure researchers. One example is the complexity of issues relating to ownership, such as how to isolate the public from private ownership given the condition of the privatisation of assets over time. Another example is the scope of measuring infrastructure capital. For instance, one can think about the difference of the effects between economic infrastructure, such as roads and communications, with their relatively immediate effect on the production process, versus social infrastructure such as hospitals and educational institutions with their long-term effects. Because there is no standard definition of infrastructure, using a variety of approaches in measurement by previous studies has resulted in a wide range of outcomes. In the Australian context, often because of data limitations, most of the earlier studies have employed the official data on general government and public corporation net capital stock published by the ABS. The problem of public net capital stock is that it includes a wide range of public assets and does not distinguish between economic infrastructure and other types of public capital.

The present study exploits estimates of engineering construction activity which were compiled from the Engineering Construction Survey (ECS) and published by the ABS. The estimates cover the value of work done in each of the states on: roads, highways and subdivisions; bridges, railways and harbours; electricity generation, transmission etc. and pipelines; water storage and supply, sewerage and drainage; telecommunications; heavy industry; recreation and other. This data source has many advantages. First, the ECS covers all capital types which it is relevant to define as true economic infrastructure. Second, the availability of the data at the level of the state, sector, or industry, and the type of capital, opens some channels for further disaggregate empirical investigations. Also, we are not aware of any other work that exploits this data within the same framework of analysis.

[11] Details of the construction of these variables and a demonstration of the Tornqvist method are provided in the Appendix

[12] Using PIM to estimate public corporation capital stock for SA resulted in a decreasing trend series. This is explained by the fact that public corporation gross fixed capital formation in SA continuously decreased from 1990 until it recorded negative values in 2000 and 2001. Such a negative investment level indicates that the amount of public investment was not enough to offset the depreciation. After 2002, public corporation investment started to increase.

Figure 2 looks at the investment in economic infrastructure as a proportion of GDP by public and private sectors separately. It is quite noticeable that for most of the states since the end of the 1990s and the beginning of the 2000s, the decline in public sector investment in core infrastructure has been more than off-set by private sector investment. Although the composition of the ECS data reflects a variety of advantages and opens interesting investigation avenues for infrastructure researchers, yet there are two issues with these data which are sources of concern. First, the ECS merely reflects the amount of investment in new infrastructure capital; however, it is generally recognised that what actually matters for the production process is the flow of services from the stock, and not just the amount of new investments. Because of the lack of data on the flow of capital services, researchers tend to assume that the flow of capital services is proportional to the capital stock. Thus, using the stock of infrastructure represents a good approximation of infrastructure services. In most of the cases, empirical studies employ the PIM method to construct public infrastructure capital. The approach adopted in the present study applies the PIM to estimate the stock of infrastructure capital from ECS data to handle the problem of data lack on infrastructure services flow.[13]

Another concern with ECS data, is the complexity in dealing with the event of privatisation.[14] Australia was subjected to increased privatisation through the 1980s and 1990s as the ownership of some assets has transferred from public sector to private sector. This notion implies difficulties when construction of public capital stock is considered. To estimate capital stock using PIM, all previous investment expenditures are assumed to be involved in the accumulation process. However, when a public corporation is privatised the allocation of previous investments would need to be changed in statistical collections.

To avoid the problem of recent extent of privatisation and the difficulties in dealing with them, previous empirical studies of Australia have tended to focus on public infrastructure owned by general government. Nevertheless, with the current structure of ECS data, the course of excluding public corporations in order to obtain more accurate measures for public infrastructure capital seems infeasible.[15] Because of the difficulties mentioned above, the analysis undertaken here does not take into account the recent event of privatisation. The econometric analysis only focuses on the estimates of engineering construction by the public sector as a measure for public economic infrastructure investment.

Openness

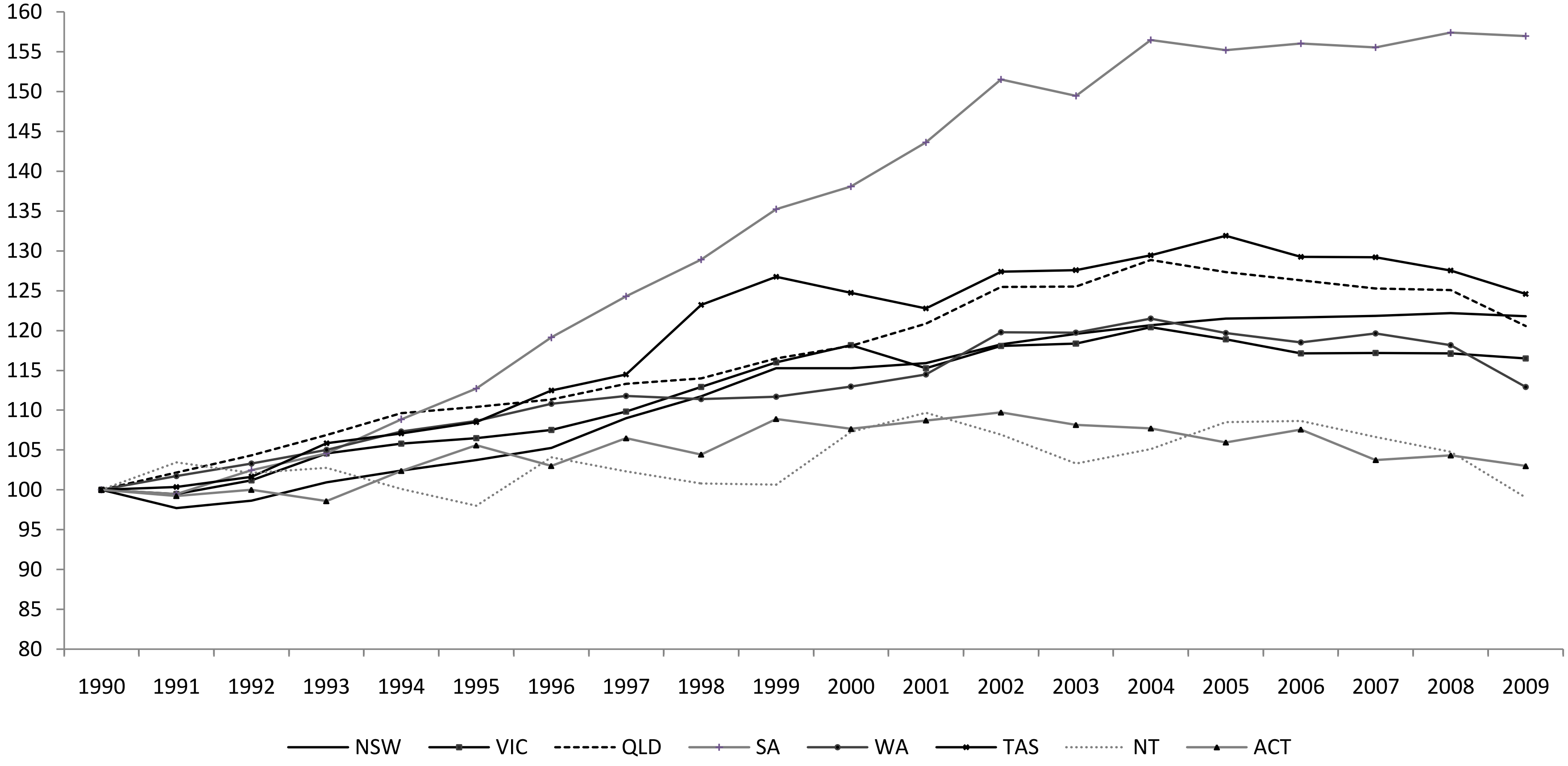
The variable openness represents a proxy for trade openness and is constructed as a sum of export and import of goods and services relative to gross state product. Data sources are ABS cat. no. 5220.0 and 5206.0.

[13]Readers can refer to the Appendix for a full description of PIM.

[14]Privatisation exists if the private sector finances an infrastructure project, or as an asset transfers ownership from the public to private sector

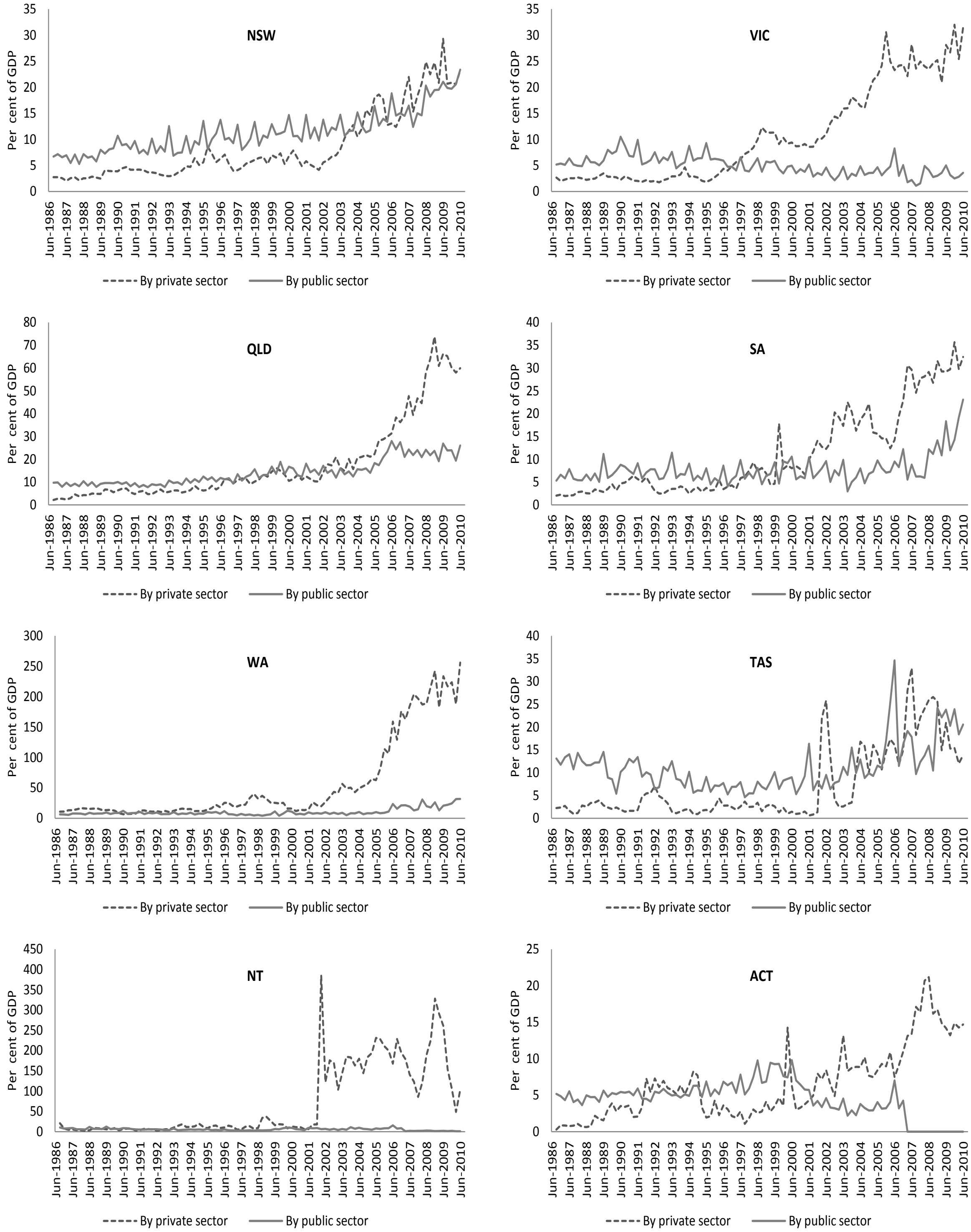
[15]The available composition of ECS data captures the sector that an organisation belongs to, i.e. public or private sector. For the public sector, it further identifies the level of government (Federal, State and local). However, there is no detail as it would be possible to classify expenditure under the general government or public corporations.

Figure 1 State level MFP estimates, 1990-2009



Source: Author's calculations using data from the ABS.

Figure 2 Ratios of public and private infrastructure investment to GSP q_3:1989-q_2:2008



Source: ABS, cat. no. 8762.0.

Capacity utilisation

Capacity utilisation is measured as the difference between the natural logarithm of output and its trend. The trend is calculated using Hodrick-Prescott filter (Hodrick and Prescott 1997) with the smoothing parameter equal to 1,600.[16]

Human capital

Human capital is measured as high school retention rates and is calculated as the proportion of students in their first year of high school that remained in high school until year 12. Data source is the ABS (cat. no. 4221.0).

Unemployment rate

The unemployment rate is the number of unemployed persons expressed as a percentage of the labour force (Labour force cat. no. 6202.0).

Union Density

This variable is constructed to reflect trade union membership (ABS 63100TS0001 Employee earnings, benefits and trade union membership).

Dispute

Dispute reflects the rate of industrial disputation and is calculated as the number of working days lost per 1000 employees due to industrial disputes, (ABS cat. no. 6321.0.55.001).
Summary statistics of all variables are presented in Table 1.

5 Integration and cointegration testing

In this section, we examine the time series properties of the data. Performing formal unit root tests for both the individual time-series and panel data reveals that our measures for productivity indexes and public infrastructure capital stock are integrated of degree one. Given such a non-stationarity feature of the data, it becomes necessary to test for cointegration to ensure that the estimated effect of infrastructure on productivity is not due to spurious relation, but that it stems from a well-established long-term relationship. Thus, formal cointegration tests are applied to state-by-state and panel data. Detailed descriptions of these tests and their results are presented in the following subsections.

5.1 State-by-state unit root and cointegration tests

A widely used test for non-stationarity in the time series literature is the Augmented Dickey-Fuller (ADF) test which entails testing the null of hypothesis $H_o : \theta = 0$ in the following

[16] Since the series of the gross state product are smooth, using different values of the smoothing parameter produces almost exactly the same trend.

Table 1: Summary statistics for state-level data, 1990-2009

	NSW	VIC	QLD	SA	WA	TAS	NT	ACT
$\Delta \ln$ **MFP**								
Mean	0.010	0.008	0.010	0.024	0.006	0.012	-0.001	0.001
Std. Dev	0.013	0.016	0.018	0.023	0.019	0.025	0.032	0.022
$\Delta \ln$ **G**								
Mean	0.032	-0.023	0.037	0.012	0.029	0.003	-0.027	-0.029
Std. Dev	0.007	0.007	0.011	0.012	0.020	0.016	0.011	0.008
Capacity utilisation								
Mean^a	5.0E-11	8.2E-11	9.3E-11	1.4E-10	1.0E-10	1.6E-10	1.4E-10	3.8E-11
Std. Dev	0.023	0.023	0.012	0.025	0.018	0.020	0.048	0.018
Openness								
Mean	0.193	0.232	0.270	0.192	0.561	0.207	0.506	0.506
Std. Dev	0.054	0.036	0.023	0.030	0.059	0.014	0.086	0.086
$\Delta \ln$ **Human capital**								
Mean	0.012	0.011	0.004	0.004	0.008	0.019	0.007	-0.000
Std. Dev	0.032	0.039	0.030	0.061	0.032	0.073	0.090	0.032
Union (000)								
Mean	713.757	530.121	367.179	176.542	169.937	60.200	18.437	40.363
Std. Dev	96.299	92.551	32.549	38.743	29.336	12.574	4.727	8.806
Dispute								
Mean	100.205	99.265	61.780	40.375	73.420	33.600	29.210	26.955
Std. Dev	106.229	93.079	49.332	51.891	65.228	55.239	27.576	33.538
Unemployment rate								
Mean	6.770	7.165	7.390	7.745	6.500	8.600	5.875	5.245
Std. Dev	1.741	2.257	2.069	2.093	2.073	2.148	1.487	1.709

Union and dispute stand for union density and rate of industrial disputation respectively.
a numbers are the absolute values.

regression:

$$\Delta y_t = \alpha + \theta y_{t-1} + \sum_{p=1}^{m} \Delta y_{t-p} + \epsilon_t, \tag{10}$$

where y is the variable tested, and ϵ is a white noise error term. We reject the null hypothesis against the alternative $H_1 : \theta < 0$ if $t_{\hat{\theta}} < c$ where $t_{\hat{\theta}}$ is the t-test statistic and c is the critical value.[17]

Extensions could be made to allow for time trend and/or drift. We first perform an ADF test on the level of all individual data series (key plus control variables) using Schwartz Information criteria to determine the optimal lag length. Three forms of non-stationarity of all variables are examined: (I) random walk with drift, (II) random walk with drift and deterministic trend and (III) pure random walk. Results of the tests are presented in Table 2.[18] Although there is not much evidence on random walk with drift in most of the series, the evidence that each of the series possesses either pure random walk, random walk with drift and deterministic trend or both is strong in all the states. Next, employing test I and III to examine the first difference of the variables concludes that all of those variables are first difference stationary.[19] With such strong evidence on unit root, the subsequent step is to test for cointegration. The well-known Engle and Granger (1987) procedure is employed. This procedure examines the stationarity of the OLS residuals from the estimated cointegrating relationship. Throughout this analysis, we consider four different specifications (labelled Models 1-4) to estimate the relationship between MFP and infrastructure. A general representation of this relationship is described by (6); nevertheless, in each specification we include a different set of control variables.[20] For each of the four specifications, an augmented Dickey-Fuller regression is applied to the corresponding OLS residuals to test for the null hypothesis of no cointegration. Reading Table 3, which presents the results, indicates that the null hypothesis is rejected across the four specifications in each of NSW, SA, NT and ACT. Specification 1 does not reflect a cointegration vector in TAS while specification 2 does not reflect a cointegration vector in VIC, QLD and WA. In addition, in WA only specification 1 represents a cointegration vector. Thus, using state data, there is in general good evidence that productivity and public infrastructure cointegrate. The few cases in which we failed to find evidence on cointegration are attributed mainly to the short span of data employed in the test. A major and widely cited setback with the ADF test is the inherent low power when it is applied to short data sets.[21] Hence, with the short time span in our sample

[17]Note that since under the H_o, y_{t-1} is assumed to have unit root, the standard t statistic is not valid; however, assuming that t has DF distribution, we can conduct the t test using DF tabulated critical values (Dickey and Fuller, 1979).

[18]Unit root and cointegration tests, in addition to the regression analysis presented in the paper are all performed using the computer package STATA.

[19]A random walk with or without a drift can be transformed to a stationary process by differencing. A non-stationary process with drift and deterministic trend becomes stationary by first removing the trend, or detrending and then differencing.

[20]Exact details on the four specifications is presented in the footnote of Table 3.

[21]The power of the test is the ability to reject the null of non-stationarity when it is false; because DF has low power, it may suggest that a series has a unit root while it is stationary. One suggested solution to improve the power of DF is to increase the number of observations by increasing the span of data.

Table 2 State-by-state unit root test(1990-2009)

State	I	II	III	I	III	I	II	III	I	III
	$\ln MFP$			$\Delta \ln MFP$		$\ln G$			$\Delta \ln G$	
NSW	0.035	0.992	0.289	0.023	0.004	0.046	0.988	0.362	0.001	0.008
VIC	0.052	1.000	0.399	0.001	0.009	0.917	0.533	0.997	0.011	0.002
QLD	0.104	0.994	0.614	0.046	0.386	0.778	0.305	0.991	0.041	0.033
SA	0.034	0.927	0.224	0.001	0.004	0.201	0.660	0.798	0.018	0.048
WA	0.070	0.997	0.488	0.049	0.406	0.922	0.955	0.997	0.066	0.552
TAS	0.051	0.995	0.388	0.024	0.038	0.065	0.855	0.449	0.037	0.014
NT	0.143	0.926	0.707	0.042	0.023	0.157	0.706	0.733	0.037	0.059
ACT	0.009	0.995	0.152	0.084	0.000	0.912	0.935	0.997	0.182	0.775
	Openness			Δ Openness		Cap. utilis.			ΔCap. utilis.	
NSW	0.512	0.141	0.961	0.009	0.058	0.026	0.722	0.219	0.000	0.000
VIC	0.002	0.601	0.173	0.002	0.016	0.036	0.907	0.290	0.028	0.006
QLD	0.616	0.157	0.977	0.008	0.051	0.052	0.743	0.397	0.048	0.012
SA	0.121	0.987	0.659	0.046	0.012	0.006	0.801	0.037	0.000	0.000
WA	0.372	0.488	0.920	0.001	0.002	0.012	0.372	0.222	0.001	0.007
TAS	0.132	0.706	0.683	0.001	0.001	0.043	0.413	0.340	0.013	0.090
NT	0.008	0.254	0.053	0.023	0.035	0.027	0.107	0.224	0.006	0.029
ACT	0.007	0.189	0.038	0.018	0.043	0.063	0.784	0.439	0.002	0.005
	ln Hum. cap.			Δ ln Hum. cap.		Unemp.			Δ Unemp.	
NSW	0.283	0.230	0.873	0.012	0.090	0.042	0.979	0.332	0.011	0.077
VIC	0.102	0.695	0.607	0.016	0.012	0.053	0.670	0.401	0.0001	0.000
QLD	0.073	0.587	0.505	0.034	0.013	0.441	0.815	0.944	0.017	0.022
SA	0.016	0.801	0.140	0.041	0.000	0.202	0.829	0.798	0.021	0.013
WA	0.020	0.408	0.162	0.005	0.022	0.271	0.540	0.864	0.013	0.092
TAS	0.110	0.960	0.628	0.038	0.079	0.791	0.312	0.992	0.001	0.001
NT	0.110	0.317	0.630	0.041	0.001	0.065	0.544	0.615	0.065	0.001
ACT	0.142	0.026	0.699	0.002	0.002	0.301	0.494	0.884	0.054	0.001
	Dispute			Δ Dispute		Union			Δ Union	
NSW	0.017	0.053	0.144	0.012	0.088	0.011	0.191	0.079	0.025	0.000
VIC	0.181	0.064	0.064	0.004	0.000	0.002	0.771	0.004	0.014	0.001
QLD	0.208	0.008	0.806	0.005	0.028	0.209	0.002	0.806	0.006	0.025
SA	0.042	0.003	0.338	0.000	0.000	0.053	0.945	0.396	0.063	0.000
WA	0.084	0.013	0.548	0.000	0.000	0.053	0.815	0.035	0.022	0.015
TAS	0.023	0.012	0.187	0.000	0.000	0.022	0.991	0.172	0.019	0.007
NT	0.079	0.462	0.527	0.005	0.026	0.017	0.114	0.133	0.009	0.054
ACT	0.232	0.568	0.829	0.001	0.003	0.299	0.300	0.882	0.052	0.049

The Values in the columns are p-value of the tests.
I, II, and III stand for random walk with drift, random walk with drift around a stochastic trend, and random walk without drift and trend respectively.
'Cap. utilis.' stands for capacity utilisation, 'unemp.' stands for unemployment rate, and 'Hum. cap.' stands for human capital.

(20 years) performing an ADF test for each state individually to test the stationarity of the OLS residuals might, in some cases, not reject the null hypothesis of unit root. A relatively recent, though popular, response to the problem of low power in time-series tests is the use of panel data. There is a great advocacy in the literature that combining cross-sectional and time-series information in the form of a panel can provide significant power improvement over an individual unit root test over each cross section (Baltagi, 2005). This is explored in the following subsection.

Table 3 State-by-state augmented Engle and Granger cointegration test (1990-2009)

State	Model 1	Model 2	Model 3	Model 4
NSW	0.0015(1)	0.0015(1)	0.000(1)	0.022(1)
VIC	0.004(0)	0.147(0)	0.075 (2)	0.009(0)
QLD	0.010(2)	0.621(0)	0.004(1)	0.004(1)
SA	0.008(0)	0.005(0)	0.001(0)	0.005(0)
WA	0.007(0)	0.480(0)	0.238(0)	0.289(0)
TAS	0.390(3)	0.008(0)	0.005(0)	0.008(0)
NT	0.000(1)	0.004(1)	0.013(1)	0.010(1)
ACT	0.006(0)	0.023(0)	0.087(0)	0.091(0)

The table shows the P-values of the ADF test. The numbers in parentheses are the number of lags as determined by Schwartz Information criteria.
Model 1: $\ln MFP_t = \mu + \gamma \ln G_t + \theta_1 Cap.\ Utilis. + \theta_2 Dispute + \theta_3 Union + \nu_t$.
Model 2: $\ln MFP_t = \mu + \gamma \ln G_t + \theta_1 Cap.\ Utilis. + \theta_2 Hum.\ Cap. + \theta_3 Dispute + \nu_t$.
Model 3: $\ln MFP_t = \mu + \gamma \ln G_t + \theta_1 Cap.\ Utilis. + \theta_2 Unemployment + \nu_t$.
Model 4: $\ln MFP_t = \mu + \gamma \ln G_t + \theta_1 Cap.\ Utilis. + \theta_2 Openness + \theta_3 Dispute + \nu_t$.
Cap. Utilis. stands for capacity utilisation, and *hum. cap.* stands for human capital.

5.2 Panel unit root and cointegration tests

Recent years have witnessed the development of a variety of panel data unit root tests. Generally speaking, two groups of these tests are well documented. The first group assumes independence across cross sections; some examples for these tests are Levin, Lin and Chu (2002), Harris and Tzavalis (1999), Breitung (2000), Im, Pesaran and Shin (2003), and Fisher type ADF and PP tests presented by Maddala and Wu (1999). On the other hand, the second group assumes a cross section dependence, e.g., Pesaran (2004), Bai and Ng (2004), Moon and Perron (2004) and Phillips and Sul (2003). Our focus will be on the cross-section independence category since these are well established and widely used in panel empirical literature.[22]

The main idea of these tests is based on the following regression:

$$\Delta y_{st} = \theta_s y_{s,t-1} + z'_{st}\gamma_s + \epsilon_{st}. \tag{11}$$

Depending on the options specified in the test, the term z'_{st} represents either panel fixed-effects, linear time trend or both.

The null hypothesis tested is $H_o : \theta_s = 0\ \forall s$ against the alternative $H_o : \theta_s < 0$. All the tests share the option that allows the inclusion of individual constants and time trends. Nevertheless, they postulate different assumptions about the heterogeneity of the unit root process. For example Levin et al. (2002), Harris and Tzavalis (1999) and Breitung (2000) assume the unit root process is common to all cross sections, while the approach of Im et al. (2003) and Fisher type ADF and PP tests allow for an individual unit root processes. Another difference is embodied in the definition of the alternative hypothesis. As the Im et al. (2003), Fisher type

[22]Readers interested in more details of these two groups of panel unit root tests are directed to Baltagi (2005).

ADF and PP tests allow some of the series to be non-stationary, the remainder of the tests assume that all series are stationary.

Table 4 reports the results on unit root at the level of $\ln MFP$ and $\ln G$ using five different tests. As reflected in the table, there is consistent evidence against the rejection of the unit root hypothesis. In regards to $\ln MFP$, the inclusion of an individual trend crucially affected the result of Levin et al. (2002). If the deterministic trend is removed, the test gives a flawed conclusion. Since the inclusion of the trend removes the trend from the series when it exists and does not affect the test itself, our focus will be on the tests that include both trend and individual constant. Regarding the variable $\ln G$, all the tests have strong evidence for the existence of unit root. Thus, our conclusion from these tests will be that both $\ln MFP$ and $\ln G$ are integrated of order one.

Table 4 Panel unit root test for $\ln MFP$ and $\ln G$ (1990-2009)

variable	LLC	HT	Breitung	IPS	PP
$\ln MFP(c)$	-4.836	0.915	2.595	-1.432	0.528
	(0.000)	(0.867)	(0.995)	(0.076)	(0.299)
$\ln MFP(c\&t)$	5.176	0.939	4.777	-0.6795	-2.614
	(1.000)	(0.999)	(1.000)	(0.996)	(0.995)
$\Delta \ln MFP(c)$	-3.669	0.078	-3.553	-4.269	12.397
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln G(c)$	0.599	2.608	8.12348	4.298	-0.417
	(0.725)	(0.995)	(1.000)	(1.000)	(0.338)
$\ln G(c\&t)$	0.152	2.487	3.959	0.598	0.083
	(0.561)	(0.994)	(1.000)	(0.725)	(0.533)
$\Delta \ln G(c)$	-1.327	0.473	-1.459	-1.877	2.590
	(0.092)	(0.000)	(0.072)	(0.030)	(0.005)

P-values of the test statistic are presented in parentheses. (c) denotes individual constant. (c&t) denote individual constant and trends.

Given this result, and from the discussion offered earlier on spurious regression, one runs a risk by using the levels of $\ln MFP$ and $\ln G$ in a regression analysis. Some authors suggest that a safe course to follow is to difference the variables before employing them in linear regression models (Tatom 1991). Although Tatom's approach was highly criticised on the basis of destroying the long-run information, we find it important to examine the properties of the first-difference series. Applying the same category of tests used with the level variables, we test for unit root in the first time-differences, i.e. the growth rates of MFP and public infrastructure.[23] As shown in Table 4, the results indicate that the two growth rates are difference-stationary.

Besides the two core variables, the statistical properties of the control variables are examined and presented in Table 5. Reading the P-values associated with those five tests suggests that all variables are almost integrated of degree one.

The next part of our analysis continues on the assumption (supported by the tests performed

[23] The only distinction with the case of differenced data is that the alternative hypothesis is stationarity without a trend, since any time trend in levels is removed by differencing.

Table 5 Tests of panel unit roots for explanatory variables

Variable	LLC	HT	Breitung	IPS	PP
Openness	-0.979	0.576	2.328	-0.090	0.903
	(0.164)	(0.000)	(0.990)	(0.464)	(0.183)
ΔOpenness	-6.760	-0.118	-1.557	-3.014	119.703
	(0.000)	(0.000)	(0.059)	(0.001)	(0.000)
Cap. utilis.	1.708	0.559	1.837	-2.121	1.208
	(0.956)	(0.092)	(0.966)	(0.117)	(0.114)
ΔCap. utilis.	-5.880	0.267	-1.559	-7.179	83.005
	(0.000)	(0.000)	(0.059)	(0.000)	(0.000)
Hum. cap.	0.730	0.6294	0.529	0.444	0.323
	(0.767)	(0.345)	(0.702)	(0.672)	(0.373)
ΔHum. cap.	-10.748	0.174	-1.104	-10.552	23.329
	(0.000)	(0.000)	(0.135)	(0.000)	(0.000)
Unemp.	3.738	0.930	-0.755	1.708	4.816
	(0.999)	(0.921)	(0.225)	(0.956)	(0.996)
ΔUnemp.	-7.956	0.396	-1.287	-6.435	5.469
	(0.000)	(0.003)	(0.099)	(0.000)	(0.000)
Dispute	-1.590	-0.007	-1.705	-1.185	-1.149
	(0.056)	(0.000)	(0.144)	(0.118)	(0.128)
ΔDispute	-4.011	-0.431	-4.556	-12.889	57.705
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Union	0.415	0.589	0.876	0.944	19.114
	(0.661)	(0.244)	0.809	(0.827)	(0.263)
ΔUnion	-9.992	-0.322	-7.781	-8.933	44.095
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Probabilities of the test statistic are presented in the parentheses.
(c) denotes individual constant.
and (c&t) denote individual constant and trends.

above) that the log-level of MFP and public infrastructure follow non-stationary processes, while the log-differences of the variables follow stationary processes.

The literature on panel cointegration tests is relatively new, going back only to the end of the 1990s; for example, see Pedroni (1999, 2004) and McCoskey and Kao (1998). Roughly speaking, there are two broad approaches to panel cointegration tests. First are the residual-based tests which take no cointegration as a null hypothesis. Tests within this class are basically extensions of the original panel unit root tests based on the residuals from a first-step cointegration regression, in the essence of the two-step cointegration test approach by Engle and Granger (1987). If the residuals from the panel regression are found to be stationary, the panel regression is said to be cointegrated. An important contribution in this category is Pedroni (1999, 2004). The second approach is the error-correction-based (EC-based) tests put forward by Westerlund (2007) and Persyn and Westerlund (2008). This approach is designed to test the null hypothesis that the error-correction term in a conditional error-correction model is equal to zero. Thus, if the null of no error-correction is rejected, then the null of no cointegration is also rejected.

The power of residual-based tests depends on the assumption of 'common factor restriction' due to Kremers et al. (1992), and it means that the long-run cointegrating vector for the variables in their levels being equal to the short-run adjustment process for the variables in their differences. If the common factor restriction fails, then the residual-based test may have low power and we may fail to reject the null of no cointegration even in cases in which cointegration is strongly suggested by the theory. Westerlund (2007) aims to avoid the limitations of the residual-based tests by allowing for differences between the long-run cointegrating vector and the short-run adjustment process. However, EC-based tests depend crucially on the weak exogeneity assumption; if it fails, the tests may have low power. Hence, the difference between the two competing tests is expressed in terms of the trade-off in their power.

In the context of the current model, the Westerlund (2007) cointegration test can be expressed by the following equation:

$$\begin{aligned}\Delta \ln MFP_{st} &= \delta_s' d_t + \alpha_s(\ln MFP_{s,t-1} - \beta_s' \ln G_{s,t-1}) + \sum_{j=1}^{p_t} \alpha_{sj} \Delta \ln MFP_{s,t-j} \\ &\quad + \sum_{j=-q_t}^{p_t} \gamma_{sj} \Delta \ln G_{s,t-j} + \epsilon_{st}, \qquad (12)\end{aligned}$$

where p_t and q_t are the orders of lags and leads and are permitted to vary across individuals; d_t is a vector of deterministic components of both the level and first differenced relationships, and for which there are three cases: (i) $d_t = 0$, so (12) has no deterministic terms; (ii) $d_t = 1$, so $\Delta \ln MFP_{st}$ is generated with a constant; and (iii) $d_t = (1,t)'$, so $\Delta \ln MFP_{st}$ is generated with both a constant and a trend. The coefficient β_s represents the cointegration coefficient between $\ln MFP_{st}$ and $\ln G_{st}$. The parameters α_{sj} are the corresponding short-run adjustment coefficients of $\Delta \ln MFP_{st}$. The linear combination $(\ln MFP_{s,t-1} - \acute{\beta_s} lnKG_{s,t-1})$ is by assumption stationary. A key parameter in this equation is α_s which determines the speed at which the system corrects back to the equilibrium relationship after a sudden shock. If α_s has a significantly negative value, this indicates that there is error-correction and hence $\ln MFP_{st}$ and $\ln G_{st}$ are cointegrated. Alternatively, if $\alpha_s = 0$ then there is no error-correction which implies no cointegration.

Westerlund (2007) offers four statistics to test for panel cointegration. Two of them are referred to as group-mean statistics:

$$G_\tau = \frac{1}{N}\sum_{i=s}^{N} \frac{\hat{\alpha_s}}{SE(\hat{\alpha_s})} \ ,$$

$$G_\alpha = \frac{1}{N}\sum_{s=1}^{N} \frac{T\hat{\alpha_s}}{\hat{\alpha_s}(1)} \ ,$$

where $SE(\hat{\alpha_s})$ is the conventional standard error of the estimate $\hat{\alpha_s}$ and $\hat{\alpha_s}(1) = 1 - \sum_{j=1}^{p_s} \hat{\alpha_{sj}}$. The null and alternative hypotheses are formulated as, $H_o : \alpha_s = 0$ for all s, while the alterative does not require α_s to be equal, hence, $H_1 : \alpha_s < 0$ for at least one s. This test suggests that a rejection should be taken as evidence of cointegration for at least one of the cross-sectional units.

The second pair of statistics is the panel statistics:

$$P_\tau = \frac{\hat{\alpha_s}}{SE(\hat{\alpha_s})} \ ,$$
$$P_\alpha = T\alpha_s \ ,$$

The null hypothesis remains the same, $H_o : \alpha_s = 0$ for all s, versus $H_1 : \alpha_s < 0$ for all s; α_s is assumed to be equal for all s. This indicates that a rejection should be taken as evidence of cointegration for the panel as a whole. As Westerlund (2007) demonstrates, the four tests could be adjusted to individual-specific short-run dynamics, including serially correlated error terms and non-strictly exogenous regressors, individual specific intercept and trend terms. Full details on the test construction and asymptotic distributions are found in Westerlund (2007). In sum, if weak exogeneity is satisfied, Westerlund's (2007) test has the advantage of greater power over the popular residual-base tests; in addition, the test allows for heterogeneity across the individual units of the panel.[24] The model could also be generalised to account for cross-sectional dependence by simulating the finite sample distribution of each estimator via the bootstrap procedure. We present the Westerlund (2007) EC-based test in Table (6).[25] The table reports both the computed test statistics and the associated p-values.[26] Having established a long-run

Table 6 Westerlund error-correction based cointegration tests for panel data, 1990-2007

Statistic	Value	Z-value	P-value
G_t	-4.520	-7.621	0.000
G_a	-15.338	-1.463	0.072
P_t	-7.161	-1.380	0.084
P_a	-29.775	-9.859	0.000

Westerlund (2007) takes no cointegration as the null hypothesis.
Tests are based onNewey and West (1994) variance estimator.
Test regression is fitted with $4(T/100)^2/9$ lags and leads.

cointegrated relationship between public infrastructure and productivity, it is important now to carefully select an appropriate estimation strategy that can effectively address the serious econometric issues discussed earlier.

[24]The study provides a discussion section and a test for weak exogeneity. The evidence from the test suggests that infrastructure is weakly exogenous; this in turn validates the implementation of the Westerlund (2007) cointegration test.

[25]Results presented in this table reflect a cointegration vector that includes only $\ln MFP$ and $\ln G$. However, as with the case of state-by-state, four different cointegration vectors (corresponding to the four specifications) are formed and tested. Results in all cases support panel cointegration.

[26]Westerlund (2007) provides two sets of p-value. The first set that we report is based on asymptotic normal distribution, and the second set is based on bootstrapped distribution.

6 Estimation and results

This section provides empirical investigations on the effect of public infrastructure on productivity by using cointegration models from both time-series and panel data analyses. Note that throughout this section we maintain the assumption of constant returns to scale (CRS). In other words, our regression models at this stage do not include the scale variable S. Nonetheless, results obtained in this section will be subjected (in a later section) to a sensitivity testing by relaxing the CRS assumption and including S in the models.

The estimation methodology considers a two-step procedure. The first step estimates the coefficients of the long-run equilibrium relationship by employing the dynamic OLS approach which is a widely used method to estimate single equations when there is cointegration. The second step extends the analysis to estimate an error-correction mechanism, which allows modelling the short-run dynamics explicitly. In each step, we present results from state-by-state as well as panel data models and highlight the differences.

Before commencing the proposed two-step strategy, it worth first exploring whether the data on hand confirm the main findings of the earlier work; namely, by replicating some earlier prominent models, we would like to investigate whether the implausibly large effects of public infrastructure obtained from using aggregate time-series by those models are still evident in the recent data.

6.1 Estimation of aggregate production function

The regression exercise performed here replicates the standard approach of earlier researchers, which focuses on estimating a level-equation of the aggregate economy in order to determine the significance of any long-run elasticity of MFP to public infrastructure. This can be described by the following equation:

$$\ln MFP_t = \mu + \gamma \ln G_t + \sum_{i=1}^{n} \theta_i Z_{it} + \epsilon_t. \tag{13}$$

Some of the most influential work in the U.S. which has received great attention from economists and policy makers are Aschauer (1989), which examines the period 1949 to 1985 and finds an elasticity of productivity with respect to total net public capital ranging from 0.34 to 0.39; and Munnell (1990*b*), which uses data over the period 1949 to 1987 and finds estimates ranging from 0.31 to 0.37. Otto and Voss (1994), using Australian data over the period 1966-67 to 1989-90, have obtained results ranging from 0.38 to 0.45, which are obviously similar to Aschauer's and Munnell's estimates. These authors control for capacity utilisation and include time trends in their models, with the exception of Munnell (1990*b*) who excludes the time trend. Therefore, we run analogous regressions, generally described by (13), and we present the results in Table 7.

Model I in the table shows that the elasticity of MFP with respect to public infrastructure after controlling for capacity utilization is 0.94. This level of estimated effect is extremely high (even

Table 7 Australian aggregate production function (1990-2009)

Dependant Variable: $\ln MFP$		
	Model I	Model II
$\ln G$	0.942***	-2.879***
	(0.161)	(0.809)
Capacity utilisation	0.394	0.447
	(0.377)	(0.285)
Time	-	0.046***
		(0.010)
Constant	0.282	17.824
	(0.757)	(1.152)
D-W	0.40	0.63
$\bar{R}^2$	0.86	0.94

Heteroskedasticity and autocorrelation robust Newey-West standard errors in parentheses. Terms*,**,*** denote significance at the 10%, 5% and 1% levels respectively.

greater than the estimated effects of Aschauer and Otto and Voss); however, it is in line with some earlier aggregate studies in Australia and other countries in which the elasticity estimates reached more than one. In sum, this result supports the argument that aggregate time-series generally results in implausibly high estimates.

On the other hand, Model II of Table 7 allows for linear time trends besides capacity utilisation. The inclusion of a time trend was significant, but it has led the coefficient on the public infrastructure to change to an unexpectedly negative and significant magnitude. This counter-intuitive result can be due to inappropriate inclusion of linear time trend with series which are not trend stationary.[27]

Finally, it is noteworthy that results of Aschauer (1989) and Otto and Voss (1994) have not proved robust to more sophisticated analysis of the time-series. Some recent studies by using more advanced econometric techniques, tend to find a smaller effect of public infrastructure than those of studies cited above.[28] The following two sections implement the proposed DOLS and ECM estimation procedures on a state-by-state basis and using panel data.

6.2 Dynamic OLS

In the standard cointegrating regressions, it is well recognised that the ordinary least squares (OLS) estimates of the long-run static model, represented by (6) and (9), are 'superconsistent' and possess, at the limit, a normal distribution. However, in finite samples the OLS estimates have a non-standard distribution and suffer from strong finite sample bias caused by the en-

[27] Some authors, for example Otto and Voss (1994) and Connolly and Fox (2006), prefer not to use the unit root tests due to the small sample time-series data and choose instead to augment their models with linear time trend, although they acknowledge that the inclusion of time trend is potentially irrelevant.

[28] At this stage, to estimate the national aggregate production function we follow the earlier traditional literature where the standard OLS regression is utilised. However, since the resultant estimates can suffer from omitted variable bias, and - as we are going to argue - can also suffer from endogeneity bias, in the subsequent section we apply the DOLS estimator to correct for these deficiencies.

dogeneity of regressors (Phillips and Moon 1999; Kao and Chiang 2000). To correct for the problems of endogeneity, Saikkonen (1991) and Stock and Watson (1993) among others suggested the DOLS estimator which entails including leads and lags of the first difference of the explanatory variables. Another approach to correct for the endogeneity is the Fully Modified OLS (FMOLS) (Phillips and Hansen 1990) where, in contrast to DOLS, the bias is corrected in a non-parametric way.[29] Extensions of the DOLS estimator to panel data are suggested by Kao and Chiang (2000) and Mark and Sul (2003). For the FMOLS, extensions are suggested by Pedroni (2001) and Phillips and Moon (1999). Kao and Chiang (2000) apply Monte Carlo studies to examine the finite sample properties of OLS, FMOLS and DOLS and conclude that DOLS outperforms OLS and FMOLS in estimating cointegrated panel regressions.
The only concern with DOLS, as Wooldridge (2009) mentions, is the potential of serial correlation in the error term. To overcome this problem, Wooldridge (2009) suggests the use of serial correlation-robust standard errors or a correction method such as the Cochrane-Orcutt procedure.

Because of the advantage of DOLS stated above, we adopt the approach of Saikkonen (1991) and Stock and Watson (1993) to estimate state-by-state cointegration coefficients, and Mark and Sul (2003) to estimate the panel cointegration coefficients. Within the context of this study, these two approaches of DOLS (p_1,p_2,q_1,q_2) are expressed respectively as follows:

$$\begin{aligned}\ln MFP_t &= \mu + \gamma_1 \ln G_t + \sum_{i=1}^{n} \theta_{1i} Z_{it} \\ &+ \sum_{j=-q_1}^{q_2} \gamma_{2,j} \Delta \ln G_{t-j} + \sum_{i=1}^{n} \sum_{k=-p_1}^{p_2} \theta_{2ik} \Delta Z_{i,t-k} + \epsilon_t, \end{aligned} \tag{14}$$

$$\begin{aligned}\ln MFP_{st} &= \mu_s + \eta_t + \lambda_s t + \gamma_1 \ln G_{st} + \sum_{i=1}^{n} \theta_{1i} Z_{ist} \\ &+ \sum_{j=-q_1}^{q_2} \gamma_{2,j} \Delta \ln G_{s,t-j} + \sum_{i=1}^{n} \sum_{k=-p_1}^{p_2} \theta_{2ik} \Delta Z_{is,t-k} + \epsilon_{st}, \end{aligned} \tag{15}$$

where all notations remain unchanged.

6.2.1 State-by-state results

From the discussion above one can anticipate that an estimation of model (14) - which hopefully adjusts for some of the crucial econometric problems - yields an infrastructure elasticity with a sensible size. This obviously would be the case if we neglect the claim on infrastructure spillovers to productivity. Put somewhat differently, an estimation of (14) would be useful to judge on the supposition of the innate limitation of time-series analysis to account for infrastructure spillovers. A plausible magnitude of the estimated effect of infrastructure will refute this claim, while an implausible magnitude would, somewhat, verify it. Nevertheless, the complex form of

[29] See Patterson (2000) for an intuitive derivation of FMOLS.

this model with many parameters to estimate requires a large sample size in order to produce a good fit. In the context of the current study, there is a challenge of a limited number of observations at the state level. We wish if it is possible to collect a longer series; in such a case one can regress the model in (14) with more confidence. Given this shortage of the data, it appears that the strategy to perform a state-by-state estimation is subjected to a trade-off between employing parsimonious models to reserve degrees of freedom while potentially suffering from omitted variables bias, and complex models with better explanatory power but which run the risk of losing many degrees of freedom.

Using different sets of control variables, the general estimation approach adopted in this study focuses on four specifications that were indicated earlier by Model 1-Model 4 (see Table 3).[30] However; because of the challenge of a small time span, presenting results from some parsimonious regressions will be useful to assess the validity of the complex models. Table 8 presents results from three parsimonious specifications of (14). The first one estimates $\ln MFP$ as a simple function of an intercept and the level of $\ln G$. In the second and the third specifications we include only one other explanatory variable. A great number of earlier studies included a business cycle variable in the productivity equation. Following this group of researchers we control for the business cycle by including capacity utilisation as a proxy in one regression, and in another by including the unemployment rate. Stock and Watson (1993) recommended the inclusion of two leads and lags of the first difference of all explanatory variables; however to avoid losing many observations, only the contemporaneous changes are included. This still helps to solve the contemporaneous endogeneity between $\ln G$ and the error term, (Wooldridge 2009).[31] To preserve against serial correlation Newey-West standard errors are employed. As shown in the table, the coefficient on (the log of) infrastructure for each of NSW, QLD, SA, and WA has the expected positive sign; however, the coefficients have unacceptably large size, with average values of 0.41, 0.36, 2.60 and 0.33 for these states respectively. By contrast, infrastructure shows significantly negative effects in each of VIC, TAS, NT, and ACT with average estimated coefficients of -0.38, -1.60, -0.14, and -0.18 respectively. This negative effect is certainly not what we expect from investing in infrastructure.

As has been mentioned, results from parsimonious models could suffer from omitted variable bias. To correct for this bias, we next move to estimate four complex forms of (14) by including additional explanatory variables. However; to preserve degrees of freedom, only the contemporaneous changes are included. Results of the regressions are presented in Table 9 which indicate a positive and large coefficient on infrastructure in each of NSW (with average elasticity of 0.47 across the specifications), QLD (0.37), SA (2.3), and WA (0.33); and a negative and significant coefficient in each of VIC (-0.23), TAS (-1.68), NT (-0.11), and ACT (-0.23). The apparent consistency between results presented in Table 8 and 9 suggests that no serious omitted variable bias in the estimates from the parsimonious models.

Recall the claim on the innate limitation of time-series analysis to account for infrastructure

[30] Readers may refer to Section 4 to review the definitions and statistics of the control vector.

[31] Although the inclusion of leads and lags of the changes of explanatory variables is recommended in the DOLS estimator, each time we add an additional lead or lag, we lose one observation and this can be costly unless we have a large sample size.

Table 8: State-by-state parsimonious estimation results (1990 – 2009)

Dependent variable: $\ln MFP$	NSW			VIC			QLD			SA		
$\ln G$	0.428*** (0.029)	0.425*** (0.012)	0.380*** (0.033)	-0.384* (0.088)	-0.385*** (0.085)	-0.386*** (0.133)	0.317*** (0.059)	0.316*** (0.055)	0.454*** (0.049)	2.75*** (0.317)	2.802*** (0.156)	2.195*** (0.109)
Capacity utilisation		0.659*** (0.090)			0.632*** (0.520)			1.056 (0.791)			1.632*** (0.326)	
Unemployment			-0.007 (0.001)			0.000 (0.005)			0.017*** (0.003)			-0.025*** (0.004)
Constant	2.620*** (0.060)	2.729*** (0.032)	2.888*** (0.173)	6.414*** (0.393)	6.421*** (0.377)	6.423*** (0.556)	3.195*** (0.290)	3.195*** (0.268)	2.391*** (0.248)	-8.199*** (1.512)	-8.426*** (0.737)	-5.346*** (0.529)
D-W	0.64	1.70	0.77	0.23	0.24	0.23	0.32	0.30	0.60	0.73	0.70	1.32
$\bar{R}^2$	0.95	0.99	0.95	0.70	0.74	0.68	0.81	0.83	0.85	0.90	0.96	0.96
	WA			**TAS**			**NT**			**ACT**		
$\ln G$	0.326*** (0.107)	0.333** (0.102)	0.253 (0.206)	-1.300 (1.008)	-1.151 (1.129)	-1.577*** (0.359)	-0.095* (0.052)	-0.103 (0.059)	-0.190*** (0.053)	-0.168** (0.062)	-0.166** (0.064)	-0.205** (0.044)
Capacity utilisation		-0.593 (0.497)			0.439 (1.217)			0.280** (0.106)			0.149 (0.348)	
Unemployment			-0.006 (0.009)			-0.030*** (0.004)			0.012** (0.004)			0.004 (0.003)
Constant	3.139*** (0.517)	3.102*** (0.495)	3.532*** (1.054)	10.777** (4.44)	10.088* (5.193)	12.309*** (1.644)	5.052*** (0.232)	5.088** (0.261)	5.380*** (0.228)	5.386*** (0.273)	5.623*** (0.282)	5.523*** (0.202)
D-W	0.34	0.55	0.35	0.09	0.08	0.46	1.13	1.02	1.08	0.87	0.80	0.96
$\bar{R}^2$	0.61	0.62	0.60	0.09	0.04	0.52	0.14	0.27	0.20	0.45	0.42	0.43

Estimations cover the period 1990-2009 except for ACT only up to 2007.
Heteroskedasticity and autocorrelation robust Newey-West standard errors in parentheses. Terms*,**,*** denote significance at the 10%, 5% and 1% levels Respectively. *a* Estimations cover the period 1990-2009 except for ACT only up to 2007.

spillovers. Since a result of a negative effect of infrastructure is unacceptable on economic grounds, the focus will be only on cases with a positive expected effect. Consequently, the incredibly high estimates of infrastructure elasticity - which remains robust across different specifications in four states - point to the effective inability of time-series analysis to model the effects of infrastructure on productivity.

6.2.2 Panel results

Bearing in mind the above implausible findings obtained from individual time-series regressions, we next turn to apply a pooled estimation using a panel regression technique. A fundamental intent of panel techniques is to account for unobserved state-specific effects so that one can take into consideration the state heterogeneity when assessing the impact on productivity. As we argued earlier, states could have specific characteristics which do not vary with time, but systematically could relate to the level of investment in infrastructure. In that case, an estimation using pooling across states or aggregate national data without accounting for these characteristics will produce biased and inconsistent parameters. A standard and widely applied method to estimate panel models is the fixed-effects method which, in principle, allows differences in the intercepts while assuming the same slopes across the states.[32]

To estimate the long-run cointegrated relationship between infrastructure and productivity, we therefore apply the panel DOLS given by (15). Following Mark and Sul (2003), Okubo (2008) and Hämäläinen and Malinen (2009), we use one lead and one lag for all explanatory variables.[33] This approach simultaneously allows for state fixed-effects and corrects for the endogeneity in the regressors.

In the framework of Mark and Sul (2003), the authors assume a homogeneous cointegration vector across individuals; however, they allow for individual heterogeneity to be captured via short-run dynamics, individual-specific fixed-effects and individual-specific time trends. In addition, they assume that the inclusion of a common time-effect is useful in eliminating some degree of cross-sectional dependence. The panel DOLS estimate from (15) is consistent with a normal limiting distribution. Mark and Sul (2003) point out that the sequential limit distribution is the same if we include only state fixed-effects; fixed-effects and common time effects; or fixed-effects, common time effects, and trend.

Table 10 presents the results from the panel DOLS illustrated above. In addition, the table presents results for Australia's aggregate production function using time-series DOLS. As in the case of individual states; due to the short time span and to avoid losing many observations, only the contemporaneous changes of explanatory variables are included. The purpose of presenting results of Australia's aggregate production function here is to use them as a benchmark to compare the outcomes from panel analysis. Note that while the results from the panel DOLS

[32]There is great controversy in the literature regarding poolability of the data. In fact, pooling the data and performing fixed or variable effects is based on the assumption of the stability of long-run parameters across cross sections. If this assumption does not hold, according to one strand of literature, we cannot pool. However, as we are going to discuss later with more detail, even if the hypothesis of poolability is rejected, we might sometimes need to trade some bias for a reduction in variance.

[33]The inclusion of further leads and lags changes our point estimates only marginally.

Table 9: State-by-state DOLS estimation results (1990 – 2009)

Dependent variable: $\ln MFP$

	NSW				VIC				QLD			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
$\ln G$	0.463*** (0.065)	0.389*** (0.017)	0.474*** (0.019)	0.591*** (0.046)	-0.021 (0.076)	-0.186*** (0.021)	-0.416*** (0.120)	-0.101 (0.125)	0.301*** (0.057)	0.276*** (0.041)	0.540*** (0.040)	0.199 (0.150)
Openness	-	-	-	-0.612*** (0.144)	-	-	-	0.747 (0.484)	-	-	-	1.010 (1.126)
CU	0.685*** (0.140)	0.768*** (0.130)	0.882*** (0.147)	0.473*** (0.082)	0.648*** (0.184)	1.729*** (0.142)	1.779*** (0.426)	0.802** (0.528)	0.029 (0.706)	1.201* (0.632)	2.174** (0.454)	1.064* (0.525)
ln HK	-	0.168* (0.087)	-	-	-	0.337** (0.134)	-	-	-	0.439 (0.298)	-	-
U	-	-	0.008** (0.002)	-	-	-	0.015* (0.007)	-	-	-	0.029*** (0.004)	-
Union	0.0002 (0.000)	-	-	-	-0.001*** (0.000)	-	-	-	0.001 (0.002)	-	-	-
Constant	2.375*** (0.411)	2.103*** (0.300)	2.343*** (0.119)	1.940*** (0.209)	5.054*** (0.279)	4.067*** (0.634)	6.412*** (0.499)	4.966*** (0.654)	0.654*** (0.316)	1.450 (1.271)	1.889*** (0.225)	3.504*** (.433)
D-W	1.72	1.83	1.80	2.13	1.24	1.90	1.51	1.09	0.67	0.75	0.78	0.82
$\bar{R}^2$	0.99	0.99	0.99	0.99	0.96	0.97	0.93	0.92	0.90	0.89	0.96	0.87

	SA				WA				TAS			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
$\ln G$	1.033** (0.401)	2.895*** (0.060)	2.614*** (0.162)	2.779*** (0.202)	0.215** (0.079)	0.458*** (0.020)	0.163** (0.069)	0.506*** (0.161)	-0.370 (0.262)	0.474 (1.141)	-1.476*** (0.334)	-1.897* (0.891)
Openness	-	-	-	0.194 (0.466)	-	-	-	-0.249 (0.372)	-	-	-	-2.406 (2.294)
CU	0.665** (0.185)	0.747** (0.251)	0.918*** (0.234)	1.195*** (0.350)	-0.804*** (0.227)	-1.407*** (0.223)	-1.075*** (0.250)	-0.968** (0.326)	0.462*** (0.144)	2.596** (0.983)	0.328 (0.903)	0.483 (1.017)
ln HK	-	0.053 (0.056)	-	-	-	-1.101*** (0.156)	-	-	-	0.711** (0.254)	-	-
U	-	-	-0.012** (0.004)	-	-	-	-0.018*** (0.004)	-	-	-	-0.030*** (0.005)	-
Union	-0.002*** (0.000)	-	-	-	-0.001** (0.000)	-	-	-	-0.010*** (0.000)	-	-	-
Constant	0.435 (1.996)	-9.079*** (0.460)	-7.423*** (0.799)	-8.340 (0.902)	3.866*** (0.436)	7.251*** (0.614)	4.097*** (0.361)	2.445*** (0.590)	6.892*** (1.201)	-0.360 (6.174)	11.863*** (1.563)	-
D-W	2.18	2.26	1.31	1.60	1.26	1.98	2.05	1.24	1.41	1.11	1.14	0.40
$\bar{R}^2$	0.98	0.98	0.99	0.97	0.92	0.94	0.90	0.81	0.96	0.74	0.70	0.10

Table 9: continued

	NT				ACT			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
$\ln G$	-0.006 (0.125)	-0.079 (0.072)	-0.106** (0.046)	-0.050 (0.032)	-0.134 (0.161)	-0.251** (0.109)	-0.209** (0.076)	-0.222*** (0.026)
Openness	-	-	-	0.073 (0.103)	-	-	-	-0.041 (0.054)
CU	0.352*** (0.099)	0.550* (0.257)	0.273* (0.141)	0.238 (0.145)	0.317 (0.301)	0.617** (0.268)	0.778* (0.390)	0.957** (0.418)
ln HK	-	-0.099 (0.108)	-	-	-	0268 (0.378)	-	-
U	-	-	0.007* (0.004)	-	-	-	0.006 (0.005)	-
Union	-0.003 (0.004)	-	-	-	-0.001 (0.002)	-	-	-
Constant	4.752*** (0.460)	5.421*** (0.723)	5.093*** (0.184)	4.858 (0.124)	5.369*** (0.636)	5.014*** (1.272)	5.585*** (0.305)	5.750*** (0.117)
D-W	2.11	2.08	1.95	2.07	1.73	1.37	1.95	2.08
$\bar{R}^2$	0.64	0.65	0.59	0.60	0.60	0.56	0.60	0.76

Estimations cover the period 1990-2009 except for ACT only up to 2007.
CU, U and $\ln HK$ stand for capacity utilisation, unemployment rate and natural logarithms of human capital respectively. Heteroskedasticity and autocorrelation robust Newey-West standard errors in parentheses. Terms*,**,*** denote significance at the 10%, 5% and 1% levels respectively.
The variable 'dispute' is dropped from the regressions since it always appears with a very small and insignificant parameter.

stem from an approach that pools states-level data and then allows for heterogeneity across the states; the results from time-series DOLS are essentially based on data constructed for an aggregate economy.[34] Concisely, Table 10 is composed from two panels. In Panel A, dynamic fixed-effects results are reported in the first columns with the label 'DFE' while the results from the dynamic time-series are reported in the second columns and labelled 'DTS'. Again, the four specifications used prior and denoted by Model 1-Model 4 are implemented here with each of the two approaches.

The results from the DFE on the coefficient of $\ln G$ (which reflects the elasticity of public infrastructure) is consistently positive and significant across the specifications. In particular, the magnitude of the elasticity ranges from 0.10-0.13 with an average of 0.12. This implies that, on average if public infrastructure were increased by 1 percent, ceteris paribus, MFP would increase by 0.12 percent. Our diagnostic test of panel serial correlation using Wooldridge (2002) and Drukker (2003) strongly rejects the null of no serial correlation in all of the specifications. To guard against this problem, therefore, we apply Driscoll and Kraay (1998) heteroskedasticity and autocorrelation robust standard errors. On the other hand, the results from the DTS are also positive and significant across the four specifications with an average of 0.70. This elasticity implies that, ceteris paribus, a 1 percent increase in infrastructure will boost productivity by 0.70 percent. This certainly is a very high level of effect and it is approximately equivalent to six multiples of the estimated effect of fixed-effects regression.

One issue with the panel DOLS estimator worth mentioning is that, unlike time series, its asymptotic properties depend on the assumption of cross-sectional independence in the error terms. Mark and Sul's Monte Carlo studies suggest that the inclusion of the common time-effect is useful in eliminating some degree of cross-sectional dependence. Thus, following Mark and Sul (2003), results from the fixed-effects model are compared to a model with time trends and time-specific effects. Panel B of Table 10 shows the results.[35] As is quite noticeable and in line with the suggestions of Mark and Sul, the results obtained are robust to the inclusion of time trend and time-specific effects.

It is well evident that the findings from panel dynamic specifications reflect plausible and considerably small coefficients on public infrastructure when they are compared with the findings from other studies in Australia.[36] This considerable difference in results is obviously not attributable to factors such as a disparity in the control variables, the econometric estimation method, or a difference in the structure of data employed (e.g., the definition, measurement, scope of variables or time horizon of the sample). The strategy accomplished in the current study demonstrates that with the adoption of identical model specifications, econometric estimator, and data set, the aggregate time-series regressions have led to a significantly higher effect on productivity than panel fixed-effects regressions. Moreover, some other measurements

[34] Methods used to construct the national level MFP index, public infrastructure capital, and the rest of the control variables are identical to the methods used to construct state-level data.

[35] Panel B of the table reports the results on public infrastructure only, however the four specifications applied in this part are similar to those of panel A. The performance of the control variables does not vary much from the one presented in Panel A.

[36] A detailed survey on Australian studies and others is provided in Shanks and Barnes (2008).

Table 10: Dynamic OLS production function estimates (8 states, 1990-2007)

Dependant variable: $\ln MFP$

Panel A	**Model 1**		**Model 2**		**Model 3**		**Model 4**	
	DFE	DTS	DFE	DTS	DFE	DTS	DFE	DTS
$\ln G$	0.104	0.544	0.135	0.566	0.124	1.343	0.127	0.314
	(0.002)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.591)
Openness	-	-	-	-	-	-	0.231	0.873
							(0.440)	(0.359)
CU	1.197	0.597	1.185	2.192	0.952	1.681	1.474	1.089
	(0.458)	(0.001)	(0.077)	(0.001)	(0.639)	(0.304)	(0.440)	(0.001)
ln HK	-	-	0.071	0.445	-	-	-	-
			(0.396)	(0.059)				
U	-	-	-	-	-0.028	0.023	-	-
					(0.000)	(0.015)		
Dispute	-0.001		-0.001		-	-	-0.001	
	(0.014)		(0.000)				(0.000)	
Union	-0.001	-0.001	-	-	-	-	-	-
	(0.041)	(0.004)						
Constant	4.433	2.393	4.055	0.169	4.370	-1.755	4.112	3.051
	(0.000)	(0.002)	(0.000)	(0.728)	(0.000)	(0.034)	(0.000)	(0.238)
R^2(adjusted/within)	0.58	0.99	0.60	0.97	0.72	0.97	0.56	0.95
Durbin-Watson	-	2.67	-	2.06	-	1.74		1.83
Wooldridge's	(0.002)	-	(0.001)	-	(0.001)	-	(0.0004)	-

Panel B	**Model 1**			**Model 2**			**Model 3**			**Model 4**		
	FE	TE	Trend	FE	TE	Trend	FE	TE	Trend	FE	TE	Trend
$\ln G$	0.154	0.154	0.140	0.138	0.138	0.130	0.138	0.138	0.127	0.165	0.165	0.142
	(0.000)	(0.000)	(0.000)	(0.000)	((0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Within R^2	0.82	0.82	0.79	0.82	0.82	0.78	0.81	0.81	0.76	0.82	0.82	0.77
Wooldridge's	(0.01)	(0.01)	(0.005)	(0.004)	(0.004)	(0.002)	(0.017)	(0.017)	(0.006)	(0.008)	(0.008)	(0.001)
State-fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed-effects	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
State time trend	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes

DFE stands for panel dynamic OLS with fixed-effects regression. DTS stands for dynamic OLS with time series regression.
CU, U and $\ln HK$ stand for capacity utilisation, unemployment rate and natural logarithms of human capital.
Numbers in parentheses are p-values.
p-values on the coefficients from DFE correspond to heteroskedasticity and autocorrelation robust Driscoll-Kraay standard errors.
p-values on the coefficients from DTS correspond to heteroskedasticity and autocorrelation robust Newey-West standard errors.
The null hypothesis of Wooldridge's test for autocorrelation is: H_o: no first-order autocorrelation
R^2 corresponding to time series adjusted R^2 and fixed-effects within R^2.
Panel B presents result from DFE only; results on the control variables are not reported.

are made to address a number of factors highlighted by the critics as a potential source of high magnitude estimates. To adjust for spurious correlation, formal unit root and cointegration tests are performed, then applying DOLS which is a well known consistent estimator in cointegrated data. To account for missing explanatory variable bias, a set of control variables suggested by other studies is applied with different specifications. The estimated elasticities from aggregate analysis still remain unacceptably high and far from what the fixed-effects regressions suggest.

Having accounted for all these potential factors, this striking finding motivates us to search for another probable explanation. Bring to mind that the core difference between the panel DOLS and the time-series DOLS presented in Table 10 is the control of the state characteristics; the results obtained suggest that the literature on the impact of regional characteristics in explaining productivity (Islam 1995; Temple 1999; Holtz-Eakin 1994) seems to be firmer ground to rest on.

Results on the control variables are broadly acceptable and consistent with theory and prior empirical findings. The results from both the panel and time-series approaches show that capacity utilisation has a positive effect on productivity although it not significant in all of the specifications. Human capital has the expected positive effect with both regression methods, although it is statistically insignificant only with fixed-effects. In addition, with fixed-effects the coefficient on unemployment rate indicates the a priori expected negative impact on productivity; however, time-series regression implies an unexpected positive effect. Openness has an ordinary positive effect with the two types of regressions, however, it is insignificant in the two cases. Results on the rate of disputation and trade unionisation are statistically negative, as expected, although the small size of the coefficient does not suggest a sizeable effect on productivity.

Finally, to conclude the first step of our estimation strategy, one may legitimately ask whether the large results obtained from national level aggregation are completely driven by the effects on the productivity of one particular state. To answer this question and to provide more evidence in support of the above findings, we perform a series of eight groups of regressions similar to those presented in Table 10. The only alteration is that instead of including the eight states in estimating the indexes of MFP, public infrastructure and the rest of the control variables, each time we exclude one of the states and utilise the data on seven states to construct the aggregate economy indexes. This exercise is repeated eight times to produce eight tables of results alike in structure to Table 10.[37] The most striking observation from these tables is that the results presented earlier remain robust to the inclusion of the states.

6.3 Error-correction model

It is well acknowledged that investment in infrastructure is a domain in which the lagged effects are usually expected. Also, we do not rule out observing some differences between the long-run effects and the patterns of short-run dynamics in response to changes in infrastructure provision. To shed more light on this issue, the study stresses the importance of further investigations within a dynamic framework.

[37]These 10 tables are available directly from the author.

To proceed, (6) and (9) have to be re-specified as an error-correction model (ECM). There are different approaches proposed in the literature to estimate such a model. One example is the 'classical' Engle and Granger (1987) two-step method (EGTSM). In EGTSM, the long-term parameters are first estimated by running a static regression in the levels of variables. Second, the dynamics are estimated using the error-correction term, which is the residual from the static regression. Thus, EGTSM is a quite straightforward method and it has typically been applied in cases where all the series are integrated of the order one.[38] Difficulties with EGTSM arise when the series are integrated of different orders.

A substantial literature in applied economics and other social sciences advocates the usage of the single-equation error-correction model (SEECM) over EGTSM. An interesting debate on this issue was raised during 1992-1993 (for example, see Durr 1993; Beck 1993; Williams 1992; and DeBoef 2001). Recently, Keele and DeBoef (2005) have revisited this issue and shown that the empirical properties of ECM are maintained even when stationary data are used. Another advantage of SEECM is that unlike the EGTSM in which the parameters of the equilibrium equation are estimated separately from the parameters of the error-correction mechanism, SEECM captures both the equilibrium and error-correction features of the cointegrated system (Phillips and Loretan 1991). A general notation of the SEECM is given by:[39]

$$\begin{aligned}\Delta \ln MFP_{st} &= \mu_s + \eta_t + \lambda_s t + \phi_s(\ln MFP_{s,t-1} - \sigma_{1s} \ln G_{s,t-1} \\ &\quad - \sum_{i=1}^{n} \sigma_{2is} Z_{is,t-1}) + \beta_{1s} \Delta \ln G_{st} + \sum_{i=1}^{n} \theta_{1is} \Delta Z_{ist} + \epsilon_{st} \ . \end{aligned} \tag{16}$$

The term in parentheses is the error-correction mechanism. It represents the proportion of the disequilibrium in MFP in one period which is corrected in the next period, and captures the adjustment towards long-run equilibrium. On the other hand, $\Delta \ln G_{st}$ captures the short-run effects of public infrastructure. Therefore, shocks to public infrastructure have two effects on a change in MFP. Some portions of the shocks might immediately affect MFP in the next time period, so that $\Delta \ln MFP_{st}$ responds to $\Delta \ln G_{s,t-1}$. Moreover, a shock to $\ln G_{st}$ will disturb the equilibrium between MFP and public infrastructure and hence drive MFP on a long-run movement to a new level that reproduces the equilibrium state with the new level of infrastructure. The parameter ϕ_s reflects the speed of return to equilibrium after a disturbance. Obtaining a significantly negative value for ϕ_s from an empirical application is usually used as evidence of series cointegration. Finally, the parameter σ_{1s} estimates the long-run effect of $\ln G$ on $\ln MFP$. Such effects will be distributed over future time periods according to the rate of adjustment.

[38]Under EGTSM, higher orders of integration are allowed for under the definition of cointegration, but all the variables are required to be from the same order.

[39]A complete description on how SEECM is derived from an autoregressive lag model is provided in ppendix A.2.

6.3.1 State-by-state results

This part presents the results of applying the ECM regression with time-series for each individual state. We have seen with the DOLS estimator that results from state-by-state regressions are not very compelling. Results on the estimated elasticities of MFP have the unexpected negative sign in four states, and the expected positive sign in the other four states but with an extremely large size. With the ECM, the performance of state-by-state regressions is even more unsatisfactory. As can be seen in Table 11, the long-run elasticity estimates not only have implausible sizes, but in many cases they do not have the expected sign that is suggested by theory. In addition, the general behaviour of the adjustment coefficient is not in line with what is anticipated from a cointegrating relationship.

To discuss these results in more detail, let us start first with NSW where we find only two specifications with a negative and strongly significant adjustment coefficient which - in such cases - supports the result from the cointegration test performed earlier for this state. Across these two specifications the average estimated long-run elasticity is 0.66. This magnitude is considerably higher than the one found earlier with the DOLS regression. Similar to NSW, VIC has only two specifications in which the adjustment coefficient is negative and significant. In one of these two cases the long-run elasticity of public infrastructure is positive and strongly significant with a magnitude of 0.41. This result contradicts the finding from the DOLS where all specifications show a negative effect. On the other hand, for QLD none of the models has a significant negative adjustment coefficient, and such an outcome opposes the finding by Engle & Granger's (1987) cointegration test. Even with no evidence on cointegration, there are two cases with a positive and very high elasticity of infrastructure with an average of 0.90. In SA, there is strong evidence of cointegration in two specifications because the adjustment coefficient is negative and highly significant. However, the long-run elasticity is extremely large with an average of 2.90; this result validates the finding from the DOLS. No specification for WA suggests cointegration; however, the estimated elasticity is significant and positive with an average of 0.80.

Similar to the outcome from the DOLS, the results for TAS appear unacceptable although the adjustment coefficient is significantly negative in two of the specifications. NT is the only state in which the cointegration relationship found support across the four specifications; nevertheless, only Model 1 shows a significant estimate for the infrastructure elasticity parameters. This result is inconsistent with the finding from the DOLS. In the ACT results are mixed. While Model 3 reflects a cointegrating relationship with a significantly negative infrastructure elasticity, Model 4 reflects cointegration with a significantly positive elasticity.

Looking at the dynamics of productivity and infrastructure, with the exception of the NT and ACT, the coefficient on public infrastructure in the short-run is always significant and negative. This suggests that even though public infrastructure has a strongly positive effect on productivity in the long-run, in the short-term this relationship is not established. More discussion on this particular behaviour will be provided below. Results on the control variables are not compelling either. On many occasions, the long and short-run coefficients do not have the expected signs. To conclude, using an ECM finds virtually no support from either the

Table 11: State-by-state error-correction model estimation results (1990 – 2009)

Dependent variable: $\Delta \ln MFP$	NSW				VIC				QLD			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Adj. coeff.	-0.817***	-0.159	-0.095	-0.590***	-0.333**	-0.146	-0.133	-0.291*	-0.073	0.162	0.056	0.121
	(0.130)	(0.187)	(0.239)	(0.123)	(0.151)	(0.101)	(0.129)	(0.158)	(0.078)	(0.115)	(0.151)	(0.127)
LR coeffs.												
$\ln G$	0.404***	0.160**	0.757***	0.923***	-0.067	0.514***	0.383***	0.405***	-0.214***	0.714***	-0.083	1.135***
	(0.006)	(0.065)	(0.098)	(0.081)	(0.045)	(0.514)	(0.089)	(0.114)	(0.039)	(0.041)	(0.112)	(0.102)
Openness	-	-	-	-1.752***	-	-	-	1.736***	-	-	-	-3.748***
				(0.279)				(0.488)				(0.774)
CU	0.625***	-	-	-	0.948***	-	-	-	-0.487	-	-	-
	(0.077)				(0.131)				(0.334)			
ln HK	-	0.648**	-	-	-	-0.640***	-	-	-	-1.142***	-	-
		(0.252)				(0.131)				(0.156)		
U	-	-	0.065***	-	-	-	0.016***	-	-	-	-0.146***	-
			(0.018)				(0.003)				(0.025)	
SR coeffs.												
$\Delta \ln G$	-0.699*	-0.419	-0.358	-0.452*	-1.104*	-1.931***	-1.754***	-1.602***	-0.149	0.427	-0.050	0.010
	(0.354)	(0.398)	(0.318)	(0.240)	(0.576)	(0.474)	(0.430)	(0.437)	(0.193)	(0.476)	(0.257)	(0.400)
$\Delta Openness$	-	-	-	0.568	-	-	-	-0.354	-	-	-	-0.415
				(0.290)				(0.307)				(0.502)
ΔCU	0.249**	-	-		0.504***	-	-	-	0.761**	-		
	(0.108)				(1.137)				(0.307)			
Δ ln HK	-	-0.179*	-	-	-	-0.133**	-	-	-	0.067	-	-
		(0.095)				(0.047)				(0.097)		
ΔU	-	-	-0.005	-	-	-	-0.003	-	-	-	-0.001*	-
			(0.003)				(0.002)				(0.004)	
Constant	2.252***	0.213	0.071	0.310	1.658	0.734	0.354	0.706	0.446	-1.014	-0.342	-0.008
	(0.349)	(0.995)	(0.732)	(0.379)	(0.940)	(0.866)	(0.772)	(0.924)	(0.285)	(0.756)	(0.437)	(0.351)
D-W	1.74	1.17	1.12	0.94	2.26	2.50	2.49	2.41	1.19	2.40	2.26	1.96
$\bar{R}^2$	0.67	0.16	0.14	0.47	0.63	0.35	0.28	0.29	0.53	0.33	0.35	0.26

Table 11: continued

Dependent variable: $\Delta \ln MFP$	**SA**				**WA**				**TAS**			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Adj. coeff.	-0.201 (0.141)	-0.531*** (0.187)	-0.242 (0.167)	-0.307*** (0.077)	-0.014 (0.210)	0.220 (0.226)	0.219 (0.170)	0.230 (0.162)	-0.131*** (0.020)	-0.136** (0.056)	-0.075 (0.089)	-0.107 (0.032)
LR coeffs.												
$\ln G$	2.142*** (0.117)	2.595*** (0.036)	3.167*** (0.181)	3.149*** (0.166)	-5.945*** (1.349)	0.896*** (0.100)	0.768*** (0.080)	0.727*** (0.076)	-1.285*** (0.111)	-2.141*** (0.240)	-2.503*** (0.178)	-1.663*** (0.166)
Openness	-	-	-	-1.142** (0.483)	-	-	-	0.593*** (0.194)	-	-	-	3.231*** (0.522)
CU	1.094*** (0.117)	-	-	-	-12.200*** (2.430)	-	-	-	1.217*** (0.221)	-	-	-
ln HK	-	-0.141*** (0.025)	-	-	-	-0.348* (0.174)	-	-	-	-0.016 (0.062)	-	-
U	-	-	0.021** (0.008)	-	-	-	-0.010** (0.003)	-	-	-	0.018*** (0.005)	-
SR coeffs.												
$\Delta \ln G$	-0.251 (0.598)	-1.431*** (0.398)	-1.261*** (0.397)	-1.171*** (0.303)	-0.015 (0.328)	0.317 (0.284)	0.327 (0.297)	0.342 (0.264)	-.177 (0.190)	-0.467 (0.281)	-0.555 (0.331)	-0.487* (0.241)
$\Delta Openness$	-	-	-	0.466** (0.170)	-	-	-	-0.219* (0.082)	-	-	-	-0.228 (0.316)
ΔCU	0.669 (0.551)	-	-		0.559* (0.308)	-	-	-	0.694*** (0.168)	-		
Δ ln HK	-	0.239*** (0.063)	-	-	-	-0.015 (0.093)	-	-	-	-0.048 (0.050)	-	-
ΔU	-	-	0.005 (0.007)	-	-	-	-0.002 (0.002)	-	-	-	0.003 (0.006)	-
Constant	-1.042 (1.273)	-3.612*** (0.742)	-2.467* (1.213)	0.310 (0.379)	0.491 (0.539)	-0.411 (1.292)	-0.232 (0.528)	-0.195 (0.452)	1.422** (0.507)	2.030** (0.757)	1.237 (1.126)	1.274 (0.889)
D-W	2.57	3.26	2.54	2.79	1.53	1.89	1.93	1.77	2.10	2.06	2.22	2.06
$\bar{R}^2$	0.76	0.68	0.52	0.51	0.48	0.26	0.26	0.48	0.71	0.28	0.27	0.28

Table 11: continued

	NT				ACT			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Adj. coeff.	-0.457***	-0.729***	-0.629**	-0.750***	-0.518	-0.591	-0.610*	-0.616**
	(0.151)	(0.166)	(0.265)	(0.240)	(0.329)	(0.450)	(0.321)	(0.254)
LR coeffs.								
$\ln G$	0.107***	-0.014	0.022	-0.044	0.145***	-0.227*	-0.127*	0.219***
	(0.045)	(0.036)	(0.111)	(0.050)	(0.046)	(0.105)	(0.061)	(0.024)
Openness	-	-	-	0.102	-	-	-	-0.057
				(0.077)				(0.082)
CU	0.431***	-	-	-	0.278	-	-	-
	(0.090)				(0.214)			
ln HK	-	0.041	-	-	-	0.116	-	-
		(0.036)				(0.486)		
U	-	-	-0.007	-	-	-	0.001	-
			(0.009)				(0.003)	
SR coeffs.								
$\Delta \ln G$	0.865**	1.650***	1.443***	1.699***	1.439	1.859	1.191	2.336***
	(0.318)	(0.429)	(0.297)	(0.346)	(1.058)	(0.709)	(1.165)	(0.383)
Δ Openness	-	-	-	-0.014	-	-	-	-0.122
				(0.081)				(0.068)
Δ CU	0.530***	-	-	-	0.231	-	-	-
	(0.158)				(0.253)			
Δ ln HK	-	-0.014	-	-	-	0.102	-	-
		(0.040)				(0.174)		
Δ U	-	-	0.011**	-	-	-	-0.012	-
			(0.004)				(0.011)	
Constant	1.935**	3.357***	2.932*	3.638**	2.784	3.080	3.211	3.525**
	(0.820)	(0.898)	(1.607)	(1.296)	(1.902)	(3.860)	(1.854)	(1.409)
D-W	2.36	2.14	2.28	2.24	2.33	2.18	2.46	2.45
$\bar{R}^2$	0.70	0.40	0.49	0.43	0.24	0.19	0.20	0.38

Estimations cover the period 1990-2009 except for ACT only up to 2007.
SR and LR stand for short-run and long-run coefficients respectively. CU, U and $\ln HK$ stand for capacity utilisation, unemployment rate and natural logarithms of human capital respectively.
Terms in parentheses correspond to heteroskedasticity and autocorrelation robust Newey-West standard errors.
Terms*,**,*** denote significance at the 10%, 5% and 1% levels respectively.

economic or statistical point of view as it does not provide an adequate approximation of the data generating process on a state-by-state basis. Consequently, as with the case of DOLS, this motivates us to question the behaviour of the model within a panel regression framework.

6.3.2 Panel results

Table 12 indicates that with the control for state fixed-effects, results from ECM are quite insightful as they clearly reflect a well-defined error-correction term across all specifications. This in turn confirms that the series are cointegrated. The estimated value of the adjustment speed indicates a convergence to equilibrium by annual rate ranging from 11 percent to 12 percent, and this finding supports a slow speed of adjustment between productivity reactions and infrastructure changes. On the other hand, the long-term effects of public infrastructure are strongly significant, with values ranging from 0.16 to 0.20 with an average of 0.17. This suggests that an increase in public infrastructure capital stock by 1 percent, ceteris paribus, would result in a 0.17 percent increase in productivity. This estimate is somewhat larger than the 0.12 point estimate from the panel DOLS regressions. Considering the short-run effects of the growth rate of public infrastructure on the growth rate of MFP, the estimated coefficient is always negative and significant; this in line with our findings on a state-by-state basis and the findings of a number of other studies (e.g., Nourzad 1998). The results from panel ECM suggest that over the short term when the initial investments on public infrastructure are not fully operational, benefits from these investments will not be realised by the production sector; consequently, no discernible effects will be observed on productivity. However, over the longer term when the production sector has had enough time to adjust to and absorb benefits from infrastructure investment, positive effects on productivity would rather be expected.[40] Shanks and Barnes (2008) engage in some relevant discussion about the relationship between infrastructure and productivity with reference to Australian experience over the past few decades. Citing Dowrick (1994), the authors mention that between the mid- to the late 1990s, Australia has witnessed a noticeable productivity surge; however, public investment declined rather than increased between the mid-1980s and late 1990s. In addition, during the early to mid-2000s, while there has been a considerable growth in public investment, productivity growth has decreased. In an attempt to explain this apparent lack of positive relationship, Shanks and Barnes (2008) highlight three points which can be summarised as follows. First, the fact that there are lags between expenditure and effects. In other words, the translation of investment in infrastructure into operational assets may not be entirely smooth since, by their nature, infrastructure assets are large and may take many years in creation and construction before they can operate fully. Besides, further lags could exist between the time those assets become operational and the time they practically provide improvement in productivity to their users. Second, due to the fast pace of commercialisation and privatisation during the 1980s and 1990s, there was an observable improvement in the efficiency with which services were provided from the current stock of

[40] Our results on the short-run dynamics may be used to explain why authors like Tatom (1991), who differences the data to remove the unit root while neglecting to model for long-run relationships finds no benefit from public investment in productivity.

Table 12 Panel error-correction estimation results (1990-2007)

Dependent variable: $\Delta \ln MFP$	Model 1	Model 2	Model 3	Model 4
Adjustment coefficient	-0.118***	-0.115***	-0.108***	-0.124***
	(0.020)	(0.015)	(0.020)	(0.019)
Long-run coefficients				
$\ln G$	0.173***	0.205***	0.166***	0.159***
	(0.007)	(0.007	(0.011)	(0.006)
Openness	-	-	-	0.174**
				(0.058)
CU	0.709***	0.269**	0.056	0.245**
	(0.084)	(0.088)	(0.078)	(0.084)
ln HK	-	0.002	-	-
		(0.019)		
U	-	-	-	-
Dispute	0.0001***	-0.0003	-	-
	(0.000)	(0.0002)		
Union	-0.0003***	-	-	-
	(0.004)			
Short-run coefficients				
$\Delta \ln G$	-0.292**	-0.310**	-0.245**	-2.328***
	(0.102)	(0.097)	(0.122)	(0.1043)
Δ Openness	-	-	-	0.001
				(0.066)
Δ CU	0.510***	0.609**	0.632***	4.658***
	(0.083)	(0.105)	(0.092)	(0.104)
Δ ln HK	-	0.029	-	-
		(0.037)		
Δ U	-	-	0.002	-
			(0.001)	
Δ Dispute	-0.0000	-0.000	-	-0.0001***
	(0.000)	(0.000)		(0.000)
Δ Union	-0.0001	-	-	-
	(0.000)			
Wooldridge's	(0.002)	(0.001)	(0.001)	(0.002)
R^2	0.42	0.45	0.47	0.45

a Estimations cover the period 1990-2009 except for ACT only up to 2007.
CU,U and $\ln HK$ stand for capacity utilisation, unemployment rate and natural logarithms of human capital respectively.
Estimates of the intercept are not reported.
Terms in parentheses correspond to heteroskedasticity and autocorrelation robust Driscoll-Kraay standard errors.
Terms*,**,*** denote significance at the 10%, 5% and 1% levels respectively.
The null hypothesis of Wooldridge's test for autocorrelation is: H_o: no first-order autocorrelation.

infrastructure. In other words, even though public spending was constrained, the allocation of existing investments and the eventual provision of services has improved significantly. Third, other important factors apart from infrastructure enhanced Australia's productivity during the 1990s and 2000s, and by doing so have surpassed the beneficial effects of infrastructure.

To finalise the discussion with ECM, a few comments on the performance of other explanatory variables are made as follows. Out of six controls, only capacity utilisation and openness show a significant long-run relationship with productivity. The rest of the variables do not show either long-run or short-run significant effects on productivity.

7 Rate of return of public infrastructure

The coefficients on public infrastructure estimated so far are elasticities, which are somewhat hard to interpret precisely since they are expressed as percentage changes. To evaluate the extent to which public infrastructure impacts productivity, it is more informative to derive the rate of return. In the traditional literature, the general approach to calculating the economic rate of return to capital (which essentially measures the increase in output drawn from employing additional capital) involves the multiplication of the estimated output elasticity with respect to capital by the ratio of output to that capital. Because what has been estimated in the present work is not a production function, it may seem a little complex to compare the MFP-based rates of return derived here with the output-based rates of returns derived by other studies. However, to the extent that the assumptions of constant returns to scale and factors paid according to their marginal products (which are imposed to construct MFP indexes) hold, the estimated MFP and output elasticities (even though they are conceptually different) are likely to be quite similar. Thus, the implied rate of return using our estimates of MFP elasticities is likely to be a close approximation to the output rate of return.

Table 13 presents the rates of return to the public infrastructure which are computed by multiplying the estimated MFP elasticity with respect to public infrastructure by the ratio of output to the stock of public infrastructure. Using the findings on elasticities from our preferred estimator, panel DOLS, which are applied on four different specifications, this table presents a set of four values of implied rates of return. Note that the mean value of value-added output and public infrastructure capital stock over the period 1990-2007 are used to calculate output-capital ratio. With the DOLS method, a range of 0.10-0.13 of elasticities is associated with a range of 51-66 percent rate of return. It is clear that the economic magnitude of this rate is very high and may reflect under-investment in public infrastructure. This observation has important policy implication as it may raise the question of whether capital used in building public infrastructure is allocated efficiently (i.e. up to a level where its marginal product equals the rate of return)

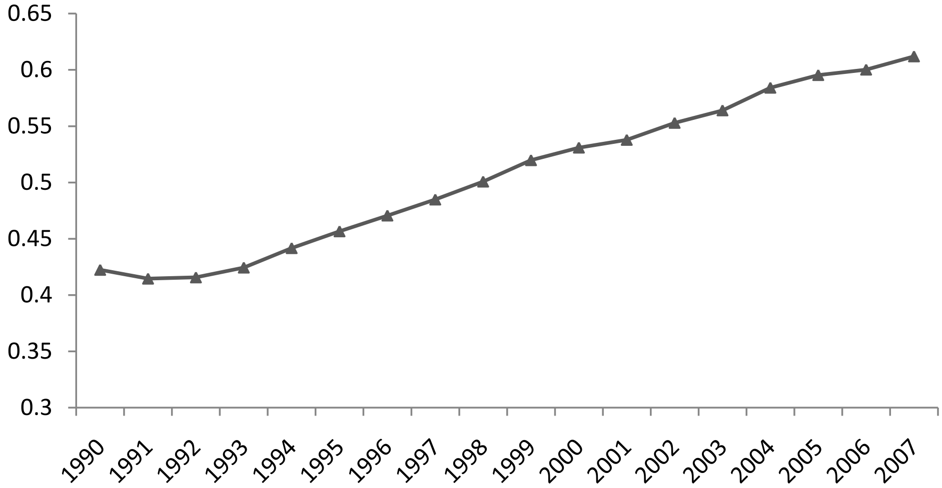
Table 13 Implied rates of return to public infrastructure (1990-2007)

Panel DOLS		
Model	Elasticity (point estimate)	Rate of return
1	0.104	51
2	0.135	66
3	0.124	61
4	0.127	62
Average infrastructure capital stock		159386.7($millions)
Average value added (Y)		785432.6($millions)
Intensity ($\frac{Y}{K}$)		4.9

Rate of return is calculated as infrastructure elasticity multiplied by the ratio of output to infrastructure stock (at mean values).

Figure 3 plots the flow of the gross rate of return. The elasticity used is the average across the four specifications, and the output-capital ratios are calculated in annual terms. As depicted in the figure, the gross rate of return of public infrastructure increases over time. Remember that the observed pattern is derived by two factors. First, the assumption that the average estimated elasticity is constant over time. Second, that the Australian valued-added output has grown faster - with a rate of 79 percent over the period of the study - relative to public infrastructure stock, which has grown by only 23 percent.

Figure 3 Public infrastructure return, 1990-2007



8 Sensitivity test of the returns to scale

As mentioned earlier, the methodology applied by the current study to construct the state level MFP indexes is basically a replication of the ABS method in the estimation of the market sector MFP in the spirit of Solow's (1956) neoclassical model. The two standard assumptions of the neoclassical model of production are perfect competitive markets and constant return to scale (CRS). The satisfaction of these two assumptions implies the existence of allocative and technical efficiency, plus income shares of labour and capital in the state accounts sum to unity.[41] This indicates that the MFP index completely reflects technological progress.[42] However, in practice inefficiencies usually exist because markets are imperfectly competitive, and economies or diseconomies of scale may also exist. Under these violations, the index of MFP may not only reflect the technological change, but may also capture the changes in efficiency and scale economies (Hall 1988, 1990). This stance can bias the estimated coefficients of the variables in the modelling using a MFP equation. For instance, if the true technology is increasing returns to scale, incorporating the CRS assumption can bias the estimates of parameters upward.

[41]The competitive markets and CRS assumptions are usually imposed in the applied work to avoid problems such as the unavailability of independent estimates of input cost shares, and to give more structure to the production function and simplify the interpretation and description.

[42]Recall that MFP is defined as the growth rate of output minus the revenue share-weighted average of the growth rates of inputs. See the Appendix for exact details on the MFP index construction method.

Equivalently, if the true technology is decreasing returns, CRS assumption can bias the estimates of parameters downward.

Using econometric models, previous studies have tested for the assumption of CRS, but the outcomes from these tests are mixed. While some authors find increasing returns (for example see Morrison 1992; Basu and Fernald 1997; and Diewert and Fox 2008 in the U.S.) some others find constant or decreasing returns (e.g., Fox and Nguyen 2007 in Australia). This section of the study aims to test the sensitivity of the results on the effect of public infrastructure on the productivity obtained above to the violation of the CRS assumption.[43] Earlier we demonstrated how the inclusion of a scale variable (measured as a combined index of labour and capital services) in the MFP equation, allows us to account for CRS errors.[44] To pursue the test, we use our preferred estimator, the DOLS, for both state-by-state and panel data regressions, represented by (14) and (15) respectively.

First, to discuss the effect of the alteration of the CRS assumption on the performance of individual states regressions, let us examine Table 14 which presents the results of models that include the scale variable (let us call them non-CRS-based models), and then compare it with Table 9 which presents the results of regressions without the scale variable (i.e. CRS-based models). Generally speaking, results across all the states are considerably affected by relaxing the CRS assumption. In NSW for example, the average magnitude of MFP elasticity has increased to 0.70 compared to 0.41 from CRS-based regression. This difference indicates a downward bias in the earlier result and is explained by the significantly negative coefficient of the scale variable. Similarly, there is evidence of decreasing returns in QLD in which the average magnitude of the estimated elasticity is increased to 0.92 compared to 0.36 from CRS-based regression. Results for SA remain stable, which is also verified by the insignificant coefficient on scale variable across the four specifications. Allowing for decreasing returns to scale in WA has noticeably increased the elasticity of MFP from 0.33, an average across all specifications, to 0.73. By contrast, the economically implausible results for VIC, TAS, NT and ACT (reflected in a significant and negative coefficient on infrastructure) remain even after relaxing the CRS assumption. In sum, results on a state-by-state basis appear to be sensitive to the violation of the CRS assumption and point towards a downward bias in the first set of results; the already poorly performing models over all the states do not show any improvement in terms of the size of estimated MFP elasticities.

The results for the panel DOLS, presented in Table 15, do not show a substantial change with the inclusion of the scale variable when they are compared with the CRS-based results presented in Table 10. There is no evidence of either increasing or decreasing returns to scale since the coefficient on the scale variable remain insignificant across the four specifications. In addition, the size of the coefficient on public infrastructure has slightly increased in three specifications and decreased in the fourth specification. This suggests that the dynamic fixed-effects models find weak evidence against the CRS assumption. Table 15 also presents results for

[43] Note that the analysis presented here does not take into account, or test for, the violation of perfect competition. Some other authors (e.g., Hall 1988, 1990) show that the presence of market imperfections causes MFP to underestimate real productivity growth.

[44] See Section 3 for more details.

Australia's aggregate production function using time-series DOLS. Interestingly, similar to the case of individual states, there is strong evidence of decreasing returns throughout the employed specifications. The almost doubling of elasticities of MFP points to a considerable downward bias in the CRS-based elasticities.

9 Poolability of data

From the overall discussion put forward above, it is quite apparent that our dissatisfaction with the results from a time-series estimation of aggregate production function on one hand and of individual states on the other, has prompted us to put more emphasis on the results from fixed-effects models. Nevertheless, since fixed-effects are based on pooling the data across the states, an important hypothesis that needs to be considered before a decision to pool is the the homogeneity of long-run parameters across the states. This is essentially an inherent assumption with fixed-effects, plus the assumption of intercept heterogeneity. A casual inspection of the state-by-state estimated coefficients in Tables 9 and 11 suggests that the coefficients are not homogeneous. Conventionally, researchers use formal tests (known as poolability tests) to examine the stability of the parameters of pooled cross sections. A typical poolability test is based on the standard form of Wald-test. To evaluate the correctness of pooling T time periods and N cross-sections, a Wald-test for linear restrictions could be extended to N linear regressions and the residual sum of squares of a restricted model then compared with that of an unrestricted model. However, the standard Wald-test is only valid for disturbances that meet the assumptions of homoskedasticity and no serial correlation. If these assumptions are not met, a proper test to perform, as Baltagi (2005) suggests, is that described by Roy (1957) and Zellner (1962) in the context of the Seemingly Unrelated Regression (SUR) model.[45]

Hence, the Roy-Zellner test is applied here to test the null hypothesis that slopes are equal. Interestingly, the test has strongly rejected the homogeneity restrictions across the four specifications. According to the statistical properties, in order to justify pooling, the parameters have to be stable. However, we failed to find the statistical support for the homogeneity assumptions. This seems to be a puzzling outcome indeed: on one hand, results obtained from individual time-series regressions are economically and statistically unsatisfactory, however, when we pool the data across the states and utilise the benefits from applying fixed-effects estimation and enjoy larger degrees of freedom, the results become more credible and robust across estimators, specifications and violation of the CRS assumption. On the other hand, performing formal testing rejects the stability restriction; thus if the prior belief is that homogeneity restrictions are guaranteed only if formal poolability tests are passed, and if results obtained from poolability test have solid grounds, then with the decision to pool we run a risk of obtaining biased estimates.

Nevertheless, although the rejection of the homogeneity restriction leaves us with a dilemma, it comes as no surprise since it is widely documented in previous research that whenever the hypothesis of equal parameters is tested, it is almost always rejected. For example, Rapach

[45] For a review of these and other test procedures, see Baltagi (2005).

Table 14: Sensitivity to scale: state-by-state DOLS estimation results (1990 − 2009)

Dependent variable: $\ln MFP$

	NSW				VIC				QLD			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
$\ln G$	0.711*** (0.036)	0.750*** (0.052)	0.651*** (0.048)	0.666*** (0.045)	-0.874*** (0.060)	-1.144** (0.505)	-1.225*** (0.216)	-1.143*** (0.133)	1.029*** (0.055)	0.963*** (0.066)	0.801*** (0.058)	0.876*** (0.086)
Openness	-	-	-	0.019 (0.221)	-	-	-	0.795*** (0.136)	-	-	-	-0.068 (0.859)
CU	0.548*** (0.118)	0.408*** (0.091)	0.582*** (0.168)	0.513*** (0.081)	0.830*** (0.071)	1.443*** (0.154)	1.410*** (0.141)	0.897*** (0.161)	-0.042 (0.394)	0.680** (0.261)	1.157*** (0.282)	0.639 (0.518)
ln HK	-	-0.063 (0.064)	-	-	-	-0.150 (0.259)	-	-	-	-0.082 (0.117)	-	-
U	-	-	0.002 (0.168)	-	-	-	0.005 (0.004)	-	-	-	0.011* (0.005)	-
Union	0.001 (0.001)	-	-	-	-0.001*** (0.000)	-	-	-	0.001** (0.000)	-	-	-
Scale	-0.003*** (0.000)	-0.004*** (0.000)	-0.003*** (0.000)	-0.003** (0.001)	-0.006**** (0.001)	-0.007* (0.003)	-0.007*** (0.001)	-0.007*** (0.002)	-0.005*** (0.000)	-0.005*** (0.000)	-0.003*** (0.001)	-0.004*** (0.000)
Constant	1.515*** (0.137)	1.766*** (0.159)	1.840*** (0.144)	1.827*** (0.162)	9.492*** (0.323)	11.238** (3.723)	10.909*** (1.140)	10.522*** (0.712)	0.201 (0.289)	1.089** (0.473)	1.066*** (0.244)	(0.244)
D-W	1.99	1.88	1.80	1.73	2.43	1.96	1.76	1.28	1.27	1.57	1.65	0.97
$\bar{R}^2$	0.99	0.99	0.99	0.98	0.99	0.97	0.98	0.99	0.98	0.98	0.98	0.97

	SA				WA				TAS			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
$\ln G$	1.317*** (0.379)	2.840*** (0.063)	2.627*** (0.575)	2.788*** (0.165)	0.408 (0.306)	1.027*** (0.147)	0.796*** (0.161)	0.375 (0.363)	-0.877*** (0.119)	-0.519 (0.417)	-2.535*** (0.286)	-1.738*** (0.278)
Openness	-	-	-	0.088 (0.492)	-	-	-	-0.274 (0.385)	-	-	-	1.524* (0.772)
CU	0.861*** (0.218)	0.893*** (0.246)	0.937 (0.820)	1.418*** (0.218)	-0.839*** (0.231)	-1.702*** (0.187)	-1.428*** (0.230)	-0.945 (0.359)	0.315 (0.220)	1.471*** (0.414)	0.718** (0.316)	0.745* (0.377)
ln HK	-	0.012 (0.057)	-	-	-	-1.341*** (0.150)	-	-	-	0.400*** (0.049)	-	-
U	-	-	-0.011 (0.020)	-	-	-	-0.030*** (0.004)	-	-	-	0.045*** (0.011)	-
Union	-0.002*** (0.001)	-	-	-	-0.001** (0.000)	-	-	-	-0.001*** (0.000)	-	-	-
Scale	0.004 (0.001)	0.003 (0.002)	0.000 (0.008)	0.006 (0.008)	-0.001 (0.001)	-0.002*** (0.000)	-0.003*** (0.001)	0.001 (0.001)	0.003*** (0.000)	0.003 (0.001)	0.015*** (0.002)	0.008*** (0.001)
Constant	-1.389 (1.956)	-8.944 (0.529)	-7.510* (3.608)	-8.945*** (0.728)	3.035** (1.363)	5.837*** (0.431)	1.566** (0.663)	3.014* (1.538)	8.812*** (0.501)	5.036** (2.187)	14.350*** (1.114)	11.606*** (1.335)
D-W	2.40	2.10	1.31	1.45	1.16	2.56	2.08	1.30	2.49	1.64	2.21	1.42
$\bar{R}^2$	0.99	0.98	0.98	0.98	0.92	0.96	0.99	0.80	0.98	0.92	0.93	0.88

Table 14: continued

	NT				ACT			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
$\ln G$	-0.292** (0.128)	-0.478*** (0.081)	-0.619*** (0.179)	-0.541*** (0.077)	-0.804*** (0.455)	-0.973*** (0.157)	-1.032*** (0.112)	-1.236*** (0.122)
Openness	-	-	-	-0.128 (0.099)	-	-	-	0.155*** (0.025)
CU	0.659*** (0.135)	0.774*** (0.124)	0.752*** (0.172)	0.924*** (0.175)	0.901*** (0.163)	1.261** (0.406)	1.058*** (0.328)	1.083*** (0.120)
ln HK	-	-0.002 (0.070)	-	-	-	0.066 (2.77)	-	-
U	-	-	0.014** (0.006)	-	-	-	-0.012* (0.005)	-
Union	-0.004 (0.003)	-	-	-	-0.004*** (0.000)	-	-	-
Scale	-0.001** (0.000)	-0.002*** (0.000)	-0.002*** (0.001)	-0.002*** (0.003)	-0.007*** (0.000)	-0.006*** (0.001)	-0.008*** (0.001)	-0.008*** 0.001
Constant	6.198*** (0.589)	7.010*** (0.459)	7.541*** (0.829)	7.383*** (0.395)	9.154*** (0.448)	9.408*** (1.631)	10.226*** (0.632)	11.021*** (0.642)
D-W	1.89	1.50	1.77	1.53	1.92	0.74	1.22	1.21
$\bar{R}^2$	0.73	0.80	0.77	0.72	0.97	0.87	0.93	0.96

Estimations cover the period 1990-2009 except for ACT only up to 2007.
Heteroskedasticity and autocorrelation robust Newey-West standard errors in parentheses.
Terms*,**,*** denote significance at the 10%, 5% and 1% levels respectively.

Table 15: Sensitivity to scale, DOLS estimates (8 states, 1990-2007)

Dependant variable: $\ln MFP$

Panel A	**Model 1**		**Model 2**		**Model 3**		**Model 4**	
	DFE	DTS	DFE	DTS	DFE	DTS	DFE	DTS
$\ln G$	0.115	2.498	0.167	1.597	0.074	2.172	0.106	1.888
	(0.009)	(0.027)	(0.000)	(0.051)	(0.072)	(0.002)	(0.042)	(0.000)
Openness	-	-	-	-	-	-	0.227	0.4461
							(0.379)	(0.557)
CU	0.271	0.942	0.453	1.611	0.189	0.857	0.580	0.834
	(0.385)	(0.002)	(0.135)	(0.002)	(0.546)	(0.008)	(0.166)	(0.000)
ln HK	-	-	0.138	0.265	-	-	-	-
			(0.212)	(0.117)				
U	-	-	-	-	-0.046	0.001	-	-
					(0.000)	(0.978)		
Dispute	-0.0005	-	-0.001	-	-	-	-0.001	-
	(0.032)		(0.000)				(0.003)	
Union	-0.001.0	0.001	-	-	-	-	-	-
	(0.060)	(0.609)						
Scale	-0.001	-0.006	-0.001	-0.003	-0.001	-0.005	-0.001	-0.005
	(0.229)	(0.060)	(0.143)	(0.003)	(0.342)	(0.053)	(0.135)	(0.008)
R^2(adjusted/within)	0.63	0.98	0.65	0.98	0.79	0.97	0.62	0.98
Durbin-Watson	-	1.69	-	1.79	-	1.66		1.57
Wooldridge's	(0.0003)	-	(0.000)	-	(0.000)	-	(0.0004)	-

Panel B	**Model 1**			**Model 2**			**Model 3**			**Model 4**		
	FE	TE	Trend	FE	TE	Trend	FE	TE	Trend	FE	TE	Trend
$\ln G$	0.136	0.136	0.130	0.124	0.124	0.129	0.150	0.150	0.130	0.144	0.144	0.131
	(0.000)	(0.000)	(0.000)	(0.000)	((0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Within R^2	0.96	0.96	0.95	0.95	0.95	0.94	0.95	0.95	0.94	0.96	0.96	0.94
Wooldridge's	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0002)	(0.000)	(0.000)	(0.0001)	(0.000)	(0.000)	(0.000)
State-fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed-effects	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
State time trend	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes

DFE stands for panel dynamic OLS with fixed-effects regression. DTS stands for dynamic OLS with time series regression.
Numbers in parentheses are p-values.
p-values on the coefficients from DFE correspond to heteroskedasticity and autocorrelation robust Driscoll-Kraay standard errors.
p-values on the coefficients from DTS correspond to heteroskedasticity and autocorrelation robust Newey-West standard errors.
The null hypothesis of Wooldridge's test for autocorrelation is: H_o: no first-order autocorrelation
R^2 corresponding to time series adjusted R^2 and fixed-effects within R^2.
Panel B presents result from DFE only; results on the control variables are not reported.

and Wohar (2004) find a similar result from their long-run monetary model of exchange rate determination over the post-Bretton Woods period. The authors obtain poor results on the monetary model from applying country-by-country regressions. However, they find considerable support for the monetary model using panel procedures. When Rapach and Wohar (2004) apply formal tests for poolability, they do not find statistical support for the homogeneity assumptions. Another relevant study is that of Baltagi, Griffin and Xiong (2000) who investigate cigarette demand for a panel of the United States. Their obtained estimates from the panel regression found support from the theory, while a Wald test rejects the null hypothesis that the slope coefficients are the same across states. A third example, is Pesaran, Shin and Smith (1999) who estimate a panel model to examine consumption and energy demand functions. In line with our results, they find that some individual countries have long-run income elasticities that are at odds with theory, while their pooled mean group estimates (which assume homogeneity of the long-run coefficients) are more sensible in terms of theory. Again, the formal tests reject the homogeneity restrictions.[46]

The problem of poolability has drawn sizeable attention in the literature. One response to the conundrum of researchers with the frequent rejection of homogeneity restriction is a recent work by Westerlund and Hess (2011). In their paper, the authors criticise the standard poolability test based on the Wald approach and propose a new test based on the Hausman (1978) principle. Westerlund & Hess have applied their new test on models such as Rapach and Wohar (2004) mentioned above, and interestingly they find statistical support for poolability.

On the other hand, a strand of literature argues against the homogenous estimators and emphasises that if the cross sections are heterogeneous, pooling the data could lead to inconsistent or maybe misleading results. One prominent example is Pesaran and Smith (1995) who argue that an average of the individual state regressions can lead to consistent estimates of the parameters as long as N and T tend to infinity. This procedure is known in the literature as the mean group (MG) and entails estimation of equations such as (16) for each state separately, and then calculate the averages of the individual coefficients.[47]
We have subjected our data to the MG estimator. Across four specifications none of the long-run elasticities of infrastructure is significant or has acceptable size. A likely reason justifing such poor performance of MG with our data is the small number of time-series observations, while MG requires an infinitely large T. However, Baltagi et al. (2000) obtain an identical outcome even with their relatively large T. 'Even with a relatively long time series, heterogeneous models for individual states tend to produce implausible estimates with inferior forecasting properties' (Baltagi et al. 2000, p. 125).

Another concern with the MG is that although it counts for the heterogeneity between cross sections, since it is derived from a fully heterogeneous model where no restrictions are imposed on the cross section parameters, it does not take into consideration that certain coefficients may be the same across cross sections. Pesaran, Shin and Smith (1999) have considered the weakness

[46] Some other examples of studies that report rejection of the poolability test are Baltagi (1981), Stephan (2003), and Steiner (2009)

[47] See Pesaran and Smith (1995) for a complete description of the MG estimator.

of the MG estimator and they propose an alternative procedure called the pooled mean group (PMG) estimator. The PMG is described as an intermediate between the traditional pooled estimators and the MG, and basically allows the short-run coefficients to differ across cross sections (as the MG estimator) while pooling the data, and constrains the long-run coefficients to be the same (as fixed-effect estimator); however it also requires a large T. To acquire more evidence, we have also implemented the PMG procedure. Interestingly, the results from PMG are also at odds with the theory. Hence, the failure to find economically plausible and statistically significant results from the heterogeneous panel estimators provides a good reason to support the results from the homogenous fixed-effects models.

In sum, the debate on poolability and homogeneity restriction is an ongoing issue. The poolability tests have been highly criticised on the grounds that they exclusively evaluate the validity of the hypothesis of stable parameters while not taking into account the advantage of the small variance of the restricted model from the pooled data rather than the unrestricted model. Even with the frequent rejection of the homogeneity restriction, a large number of studies document that the performance of pooled models, such as fixed and random-effects which posit homogeneous parameters, outperform both heterogeneous panel and individual time-series models. To this end, our conclusion is that although one should be careful when interpreting the results, there is a strong rationale to favour fixed-effect cointegrated estimates over individual state estimates.

10 Granger-causality tests

One of the contributions of this study is to shed some light on the understanding of the direction of causality between infrastructure and productivity. The widely cited Engle and Granger (1987) shows that, if two variables are cointegrated, there will be a causal relationship at least in one direction. The earlier aggregate production function approach is highly debated on the basis that the estimation of production function implicitly assumes public infrastructure causes productivity or output growth. However, the direction of causation could be in the reverse direction. As a country becomes wealthier through achieving a higher rate of output growth, it may have a tendency to spend more on infrastructure projects. This is referred to in the literature as reverse causality. Considering the relationship between infrastructure and productivity, there are three cases one can consider. Unidirectional causality that runs from infrastructure to output; unidirectional causality that runs from output to infrastructure; or bidirectional causality that runs from both directions. The cointegration analysis outlined above does not tell us much about the direction of causality or whether it is unidirectional or bidirectional, therefore a formal test for causality is required.

Some previous studies have applied the standard Granger-causality test (Granger 1969) to detect the direction of causal relationship. In short, the Granger-causality test states that a variable X Granger causes another variable Y if Y can be better predicted by the lagged values of both X and Y than by the lagged value of Y alone. This test could be performed by applying a standard Wald test on the coefficients of the lagged changes of X. However, Engle and Granger (1987) demonstrate a general duality between cointegration and the vector error-correction model (VECM) and assert that, if variables are cointegrated, then the standard Granger causality test is misspecified. Alternatively, one should apply the causality test within an error-correction framework which enables the researcher to distinguish and test for long-run and short-run causality.

For further demonstration, a starting point is the following bivariate VECM:

$$\begin{aligned}\Delta \ln MFP_{s,t} &= \alpha_o + \phi_1 \varrho_{s,t-1} + \sum_{j=1}^{p} \lambda_{1j} \Delta lnKG_{s,t-j} \\ &+ \sum_{j=1}^{q} \delta_{1j} \Delta lnMFP_{s,t-j} + \epsilon_{1s,t}, \end{aligned} \tag{17}$$

$$\begin{aligned}\Delta \ln G_{s,t} &= \beta_o + \phi_2 \varrho_{s,t-1} + \sum_{j=1}^{p} \lambda_{2j} \Delta lnKG_{s,t-j} \\ &+ \sum_{j=1}^{q} \delta_{2j} \Delta lnMFP_{s,t-j} + \epsilon_{2s,t}, \end{aligned} \tag{18}$$

where $\varrho_{s,t-1}$ is one lagged error-correction term.

With VECM, sources of causality can be identified through three different channels: (i) channel 1, known as short-run Granger causality (or weak causality). This is tested by the significance of the coefficients of each explanatory variable by a joint Wald test. Thus, if the lagged values of changes in $\ln G$ ($\Delta \ln G_{t-1}$, $\Delta \ln G_{t-2}$,..., $\Delta \ln G_{t-j}$) in the $\ln MFP$ equation are significantly different from zero, and the lagged values of changes in $\ln MFP$ ($\Delta \ln MFP_{t-1}$, $\Delta \ln MFP_{t-2}$,..., $\Delta \ln MFP_{t-j}$) in the $\ln G$ equation are not different from zero, then infrastructure Granger-causes MFP in the short-run. However, if the lagged changes in $\ln MFP$ in the $\ln G$ equation are significant as well, then there is bidirectional Granger causality between MFP and infrastructure. (ii) channel 2, known as long-run Ganger causality, can be assessed by testing the significance of the error-correction coefficients ,ϕ_1 and ϕ_2 in (17) and (18) respectively. The test can be conducted by t-test. Therefore if $\phi_2 = 0$, then $\ln G$ is said to be weakly exogenous in the sense of Engle, Hendry, and Richard (1983). If $\phi_1 = 0$, then $\ln MFP$ is said to be weakly exogenous. (iii) channel 3, known as strong Granger causality, tests whether both channel 1 and channel 2 sources of causation are jointly significant.

Before discussing the results of the causality test, let us first differentiate between the concepts of weak exogeneity, strict exogeneity and Granger causality. Weak exogeneity is a minimal requirement for endorsing the estimation of and inference on the parameters of a regression model. It implies that no information is lost (with respect to the parameters of interest) when one conditions on a variable without explicitly modelling the variable. On the other hand, Granger causality implies that the exogenous variable cannot be usefully forecasted or is not Granger-caused by the other variables in the system (Strauss and Wohar, 2004). Put in a different way, public infrastructure Granger causes productivity if we can forecast productivity from the future values of public infrastructure. Finally, weak exogeneity of a variable in conjunction with Granger-causality in the short-run establishes strong exogeneity for that particular variable. In other words, $\ln G$ is strongly exogenous in (17), if all $\delta_{2i} = 0$ and $\phi_2 = 0$. By contrast, $\ln MFP$ is strongly exogenous in (18), if all $\lambda_{1i} = 0$ and $\phi_1 = 0$.

Table 16 reports the results of the short and long-run single-equation Granger-causality test. The p-values in the first three columns correspond to tests examining the direction of causation from infrastructure to productivity, while the last three columns relate to the causation from productivity to infrastructure. Short-run causality is tested by the significance of the joint Wald test of the lagged dependent variables (the test considers from 1 to 5 lags). Long-run causality is tested by the joint significance of both the error-correction terms and joint Wald test.

First, considering the causality from infrastructure to productivity, it is evident from the p-values reported in the table that there is not enough evidence on the short-run causality; however, the evidence on the long-run causality is very strong. Second, regarding the tests on causality that run from productivity to infrastructure, the insignificance of all tests indicates insufficient evidence of both short and long-run causality. Thus, from these tests one can deduce that while productivity does not Granger causes infrastructure, the predictive effect of infrastructure on productivity can be established only in the long-term.

11 Conclusion

By how much does investment in public infrastructure affect productivity? Mixed evidence is found in the previous literature. To shed light on this important question, which is tied to serious policy implications, this study has aimed to present a comprehensive analysis of the relationship between public infrastructure and productivity in the Australian context.

With the conundrum of the incredibly high effect of infrastructure obtained from aggregate regressions, there is a consensus among economists that disaggregate analysis should be applied. Using region or state data in modelling the relationship between productivity and infrastructure is assumed to result in more plausible outcomes. Researchers in this line establish two hypotheses. The first emphasises the infrastructure spillovers to productivity which are not captured by aggregate studies. To examine this conjecture, the study applies time-series regressions at both national and state-levels. Our new results support the findings of earlier studies which suggest impractically high estimates of infrastructure effects. In particular, the average estimated elasticity from regressions across the national level is found to be 0.70. This outcome confirms the argument on the innate inability of time-series analysis to capture infrastructure spillovers to productivity, which renders it inadequate for providing clear evidence to guide policy formulation.

The second hypothesis argues that with the existence of states-specific effects which correlate with the level of investment in infrastructure, estimation using pooling across states or aggregate national data without accounting for these characteristics will conceal the real effect of public infrastructure on productivity. To test for this hypothesis, the study applies a panel technique which controls for the state-fixed-effects. Interestingly, the panel regression yields estimates which are much lower in value and reasonably in line with economic theory. More precisely, the

Table 16: Granger causality test results

	$H_o: \Delta \ln MFP_t \longleftarrow \Delta \ln G_t$			$H_o: \Delta \ln MFP_t \longrightarrow \Delta \ln G_t$		
	Source of causation (independent variable)					
	Short run	**Long run**		**Short run**	**Long run**	
lags	Wald F-statistics $\Delta \ln G_t$ lags	t-Statistics ϱ_{t-1}	Joint Wald F-statistics $\Delta \ln G_t$ lags & ϱ_{t-1}	Wald F-statistics $\Delta \ln MFP_t$ lags	t-Statistics ϱ_{t-1}	Joint Wald F-statistics $\Delta \ln MFP_t$ lags & ϱ_{t-1}
5	2.67(0.027)	-6.03 (0.000)	8.91(0.000)	0.87(0.505)	0.84(0.402)	0.90(0.499)
4	2.50(0.048)	-5.13 (0.000)	7.88(0.000)	1.09(0.368)	0.75(0.455)	1.06(0.385)
3	3.27(0.024)	-5.77 (0.000)	9.21(0.000)	1.76(0.161)	1.01(0.315)	1.67(0.163)
2	1.80 (0.171)	-5.52(0.000)	10.49(0.000)	0.64(.531)	1.39(0.166)	1.14(0.335)
1	0.34 (0.561)	-4.93 (0.000)	12.43(0.000)	0.43(0.512)	1.63(0.107)	1.58(0.210)

P-value in parentheses.

average estimated elasticity is found to be 0.12 which is robust to a range of sensitivity tests.

The analysis completed in this study has applied a number of econometric techniques. These are time-series, Dynamic OLS, and error-correction model. Each of these techniques is used to implement both individual and panel regressions. The comparison of results on infrastructure effect obtained from applying these methods supports the performance of panel DOLS.

The noticeable improvement in the estimation outcome, which is realised by moving from time-series to fixed-effects models, reflects the ability of disaggregated analysis in making the links between infrastructure and productivity more apparent. Thus, although one should be careful when interpreting the results, there is a strong rationale for favouring fixed-effect cointegrated estimates over aggregate time-series estimates.

Appendix

Estimating states' multifactor productivity

Economists and statistical agencies traditionally motivate the computation of productivity using Solow's growth accounting approach (Solow 1956) which centres on accounting for the contribution to the growth of output made by the growth of factor inputs (usually capital and labour) and attribute any growth unaccounted for to technological progress. To demonstrate this approach, let us start with a production function defined in terms of capital (K), labour (L) and the level of technological progress (A) which changes over time (t). (A) is also called Hicks-neutral or disembodied technological change:

$$Y = F(L, K, t) = A(t)f(K, L). \tag{A1}$$

Taking the logarithmic differential of (A1), (A2) indicates that the output growth is equal to the sum of the growth rate in labour and capital weighted by their output elasticities plus the technological progress:

$$\frac{\dot{Y}_t}{Y_t} = \frac{\dot{A}_t}{A_t} + \frac{\partial F}{\partial L}\frac{L_t}{Y_t}.\frac{\dot{L}_t}{L_t} + \frac{\partial F}{\partial K}\frac{K_t}{Y_t}.\frac{\dot{K}_t}{K_t}. \tag{A2}$$

These output elasticities are the only variables which are not directly observable. However, when the production process is assumed to have constant returns to scale and perfect competition in both output and input markets, input will be paid its marginal product, which in turn is equal to the input price relative to the output price. Thus, (A2) can be rewritten as:

$$\frac{\dot{Y}_t}{Y_t} = \frac{\dot{A}_t}{A_t} + s_{Lt}\frac{\dot{L}_t}{L_t} + s_{Kt}\frac{\dot{K}_t}{L_t}, \tag{A3}$$

where

$$s_{Lt} \equiv \frac{w_t L_t}{p_t Y_t},$$
$$s_{Kt} \equiv \frac{r_t K_t}{p_t Y_t},$$

and w_t, r_t and p_t denote the prices of labour, capital and output respectively. As shown in (A3), the factor income shares are equal to the respective output elasticity under perfect competition. In addition, $s_{Lt} + s_{Kt} = 1$ due to the assumption of constant returns to scale.

Now rearranging as in (A4) shows that technological progress can be calculated as the residual of output growth minus the growth in labour and capital weighted by their income shares:

$$\frac{\dot{A}_t}{A_t} = \frac{\dot{Y}_t}{Y_t} - s_{Lt}\frac{\dot{L}_t}{L_t} - s_{Kt}\frac{\dot{K}_t}{L_t}. \tag{A4}$$

(A4) is expressed in continuous time, and the last two terms on the right hand side of the equation form a Divisia index number of the total input growth. Considering two discrete points of time approximation, t and $t-1$, and by using average income shares of labour and capital, (A4) becomes:

$$\ln(\frac{A_t}{A_{t-1}}) = \ln(\frac{Y_t}{Y_{t-1}}) - \bar{s}_L \ln(\frac{L_t}{L_{t-1}}) - \bar{s}_K \ln(\frac{K_t}{K_{t-1}}), \tag{A5}$$

where

$$\bar{s}_L \equiv \frac{1}{2}(s_{Lt} + s_{Lt-1}),\ \textit{and}$$
$$\bar{s}_K \equiv \frac{1}{2}(s_{Kt} + s_{Kt-1}).$$

Given data on output, inputs and factor income shares at any two points of time, the rate of growth in MFP can be directly estimated using (A5).

The productivity estimates can be derived wholly based on the index number theory, without using the production function and the associated assumptions. Earlier, we defined productivity as the ratio of volume measure of output over the volume measure of input, $MFP = Y/Q_{K,L}$, so at some level of aggregation these volume measures are derived using index numbers. There are many index number formulae that can be used to derive the volume input and output measures. Generally speaking, the Tornqvist index given by (A6) is a preferred measure in productivity analysis (see Diewert 1992):

$$Q^{0,1}_{K,L} = \prod_{i=l,k}\left(\frac{q_i^1}{q_i^0}\right)^{\frac{1}{2}(s_i^0+s_i^1)}, \tag{A6}$$

where q_i^t is the quantity of labour and capital input at period t; s_i^t is the labour and capital income share at period t; and $t = 0, 1$.

To construct annual indexes of MFP for each of the states; annual data on output, labour and capital inputs, and their income shares are required for each state. Below we outline the construction methods and the sources of these data.

Output

The output measure is the state gross value-added (GVA) which is measured as chain-volume and sourced from ABS (State Accounts cat. no. 5220.0).[48]

Capital

Official ABS estimates for net capital stock (NCS) are available only for Australia as a whole. Accordingly, states capital stocks are constructed using the perpetual inventory method (PIM) represented by the following formula:

$$K_{st} = K_{s,t-1}(1 - \delta_{st}) + I_{st}, \tag{A7}$$

where K_{st} is the value of net capital stock in state s in the current period, $K_{s,t-1}$ is the value of net capital stock in the previous period, I_{st} is the value of gross fixed capital formation (GFCF), and δ_{st} is the rate of depreciation.

The ABS publishes estimates of chained volume measure GFCF at state level from the year 1985 (cat. no. 5206.0). These estimates are disaggregated into private and public sector investments. The private sector investment is further disaggregated into five types of assets: dwellings, non-dwellings constructions, machinery and equipment, livestock and three types of intangible fixed assets: artistic originals; mineral exploration; and computer software. This study measures private capital as the sum of machinery and equipment and non-dwelling construction.[49]

Typically, when following the PIM method, researchers are faced with a difficulty in finding a benchmark value of capital stock, $K_{s,o}$, to start the accumulation process. One traditional solution is to allocate the national capital stock to the states. Different methods are proposed to estimate the share of each state in the aggregate capital stock. For example, Holtz-Eakin (1993), who presents estimates of capital stock for the U.S. states and local government, assumes that the share of capital stock in each state is equal to its share of total current expenditure in the benchmark year. In Australia, Louca (2003) has used nominal aggregate values of investment for a few years preceding the initial year. Some authors have criticised the method of calculating the state share based on the share of national gross investment during a benchmark period. For example, Haughwout (2002) argues that this method introduces the possibility of systematic measurement error into the public capital measure, since investments made during the benchmark period may correlate with factors other than historical investment patterns. In an attempt to address the previous problems, a recent work forwarded by Mikhailitchenko, Nguyen and Smith (2006) has developed estimates for the Australian states over the period

[48] Gross state product (GSP) and GVA are constructed by income approach. Although there is detailed data on final demand, there is a lack of data on the changes in inventories by state and inter-state trade. This renders it impossible to construct estimates of these measures using the expenditure approach.

[49] No further disaggregation by asset types is available for public GFCF, hence, we measure public capital as the total of all assets.

1984/85-2003/04.[50] These authors accumulate the past investment flows in each state after they have been adjusted for depreciation to estimate the states' shares. More detail on their approach, which is adopted in this study, is included in the text below.

Besides the method of allocating the national capital stock across the states, another method which is also widely used to estimate the benchmark capital stock is based on information on the average growth rate of investment flow over the period of study, the depreciation rate and the value of investment in the initial period (see Fox and Kohli 1998 for example). An elaboration on this procedure is presented below.

For the purpose of precision, this study adopts the two methods outlined above to estimate two values of benchmark and, consequently, two series of capital stock for each state. Such an exercise is useful for testing the sensitivity of the resultant MFP indexes to different series of capital stock.

The approach of Mikhailitchenko et al. (2006) can be summarised in two phases. First, because the official ABS data for national NCS are published for private and public sectors combined, we use the available data on the national private and public GFCF to split the national NCS into private and public components for the year 1989. The the procedure is described by the following steps:

1. Apply an appropriate depreciation factor to each year's investment flow in private and public machinery and equipment and non-dwelling constructions separately. An homogenous depreciation rate which is equal to the corresponding national rate is assumed for the two sectors for each type of assets.[51]

2. Accumulate the depreciation-adjusted investment data for the two types of assets obtained from the step above over the period 1960-1989.

3. Using the cumulative sum of the depreciation-adjusted investment in the private and the public sectors obtained from the step above, the share of private machinery and equipment in the total machinery and equipment is computed. A similar calculation is made for private non-dwelling constructions.

4. The private sector shares for the two types of assets obtained above are applied to the total of all assets of national NCS to yield estimates for national private NCS for the year 1989 corresponding to each asset type.

5. Apply an analogous procedure to estimate national public NCS for 1989.

[50] It worth mentioning that Levtchenkova and Petchey (2000), Louca (2003), and Mikhailitchenko et al. (2006) are, according to our knowledge, the only attempts made to estimate capital stock data at state level, but unfortunately their series do not cover recent years. This lack of data represents a stumbling block for research and analysis at state level for both academics and government agents.

[51] To estimate the depreciation rate, we follow Otto and Voss (1996) and the Productivity Commission (2007) in which the depreciation rate, δ_t, is defined as the ratio of consumption of fixed assets (COFA) at period t to the national net capital stock NCS at period $t-1$ and is permitted to vary through time, i.e. $\delta_t = \frac{COFA_t}{NCS_{t-1}}$. There is enough information to estimate the depreciation rates corresponding to each asset type, but this can be calculated only for the economy as whole; consequently, δ_t is assumed to be homogenous across the states. This homogeneity assumption may cause one limitation of this procedure since it does not take into account the different industry structures, vintages and asset mixes across the states.

In phase 2, we allocate the 1989 national private and public NCS estimated in phase 1 among the states. To calculate a share for each state, we again use the method of Mikhailitchenko et al. (2006) in which the GFCF flows in each year before 1989 are adjusted for depreciation and then accumulated by state. The states' shares of the 1989 national NCS are then calculated on the basis of the relative sizes of these cumulative sums of depreciation-adjusted investments. Mikhailitchenko et al. (2006) point out that as earlier and earlier years are involved in the process, the approximation becomes more and more reliable. However, since the data available to us on chained volume GFCF only start in 1986, the state private and public GFCF values are summed by state over the period 1986 to 1989. Each state's share of the 1989 national private and public NCS is then computed as the proportion between the state cumulative sum mentioned above and the national total of all state sums. Finally, the obtained shares are applied to the estimates of the national private and public NCS calculated in phase 1.

In the second method, the benchmark value of capital stock is computed based on the assumption that the average growth rate, g, of the observed total GFCF for each state adequately describes its annual growth rate for the indefinitely long preceding unobserved series. To illustrate this method, rewrite (A7) as:

$$K_t = I_{t-1} + (1-\delta)I_{t-2} + (1-\delta)^2 I_{t-3} + (1-\delta)^3 I_{t-4}. \tag{A8}$$

If investment growth rate is constant, say, γ then,

$$I_t = I_{t-1} + (1+\gamma). \tag{A9}$$

Substituting (A9) into (A8) and setting time to a base period t^* results in the following equation:

$$K_{t^*} = \frac{I_t^*}{(\gamma+\delta)}, \tag{A10}$$

where δ is treated as a constant figure is equal to to 5 percent following Fox and Kohli (1998) which is considered to be a good approximation of the annual rate of depreciation.

Labour

It is widely agreed that the number of hours worked is the best indicator of the labour input to the production process if, for instance, it is compared with the number of workers. The ABS publishes monthly and quarterly estimates for actual and usual hours worked at state level. These estimates principally relate to the hours worked in the survey reference week, i.e. the week prior to the survey interview.[52] A problematic feature of these estimates is that they relate only to a single week rather than the entire month, thus they cannot be aggregated across time to produce, for example, the corresponding quarterly or annual estimates. This, perhaps, represents a barrier for any analysis across time. Since our estimation of MFP indexes requires annual measures for labour input, it is indeed necessary to construct annual flow measures for

[52] See cat. nos. 6291.0.55.001, 6291.0.55.003 and ABS (2006c) for more information.

each of the states.[53]

Starting from 2006 and with the release of the 2005-06 system of national accounts, the ABS started producing estimates of hours worked on a national level following a new method based on the methodology currently used by Statistics Canada. These new estimates are considered to be an improvement in the quality of the estimates of Australian hours worked because the old method does not adjust for the effects of public holidays, school holidays and other non-random events which tend to reduce hours actually worked and result in an upward bias in the estimates (ABS 2006*a*). The problem of the upward bias manifests itself clearly in the case of international comparisons. Guided by the estimates obtained from the old method and published by the Organisation for Economic Co-operation and Development (OECD), Australians appear to work longer hours than workers in other comparable countries. Using the new method of estimating the level of hours worked, there is a reasonably large fall in the total number of hours worked compared to the previous method.

The ABS's new method proves to be more accurate in capturing the impact of public and school holidays, hence removing the upward bias; nevertheless, implementing it for each of the states is indeed a long-term procedure which may not fit the time-frame of this study. The good news is that, according to an ABS information paper, although applying the new method has a noticeable effect on the total number of hours worked when compared with the old method, this effect tends to be very slight on the productivity measures:

> "*Using the new method of estimating the level of hours worked, there is a reasonably large fall in the total number of hours worked but the index of total hours worked shows little change when compared to the previous method. Thus there is little impact on annual productivity growth rates or on the identification of peaks in productivity growth cycles*" ABS (2006*b*, p. 12).

Figure A1 below compares the ABS's market sector multifactor productivity using the old and new methods. Using data on a quarterly measure of hours worked by state and industry (division level) which is published in the SuperTable E03 (publication 6291.0.55.003 - Labour Force), we estimate the states' total hours worked by applying the previous ABS method which is summarised by the following steps:

1. take the average of total hours worked in the four mid-quarter months to estimate the number of hours worked per week.

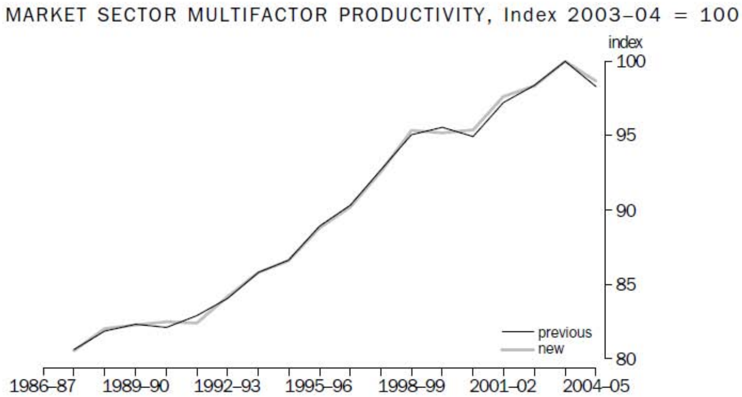
2. divide by seven to estimate the number of hours worked per day.

3. multiply by 365.25 to estimate the total annual or by 91.31 to estimate the quarter hours worked during the year.[54]

[53] At the time the data used to estimate the states' MFP indexes in this study were constructed, and the the regression analysis completed, no monthly aggregates estimates of hours worked were published on the state level. Interestingly, the ABS has recently started to publish new monthly aggregates by individual states (see cat. no. 6202.0). As clarified below, although the previous method used by the ABS and adopted here to construct our annual measure is deemed to result in upward biased estimates, fortunately no major effect occurs in the corresponding productivity indexes.

[54] Being tempted by the ABS's new release on the states' aggregates of hours worked, we have subjected our

Figure A1 The effect of the new method on market sector MFP



Source: Information paper, ABS, cat. no. 5204.0.55.003.

Income shares

In the ABS national accounts, total income = gross operating surplus (GOS) + gross mixed income (MI) + compensation of employees (COE) + taxes less subsidies on production and imports. The gross mixed income includes both capital and labour components and needs to be split to obtain labour and capital income shares. Employing the published data on COE and GOS for each state, we derive capital and labour shares in MI as $COE/(COE + COS)$ and $COS/(COE + COS)$ respectively. Next, these shares are applied to the MI to split capital and labour income shares in MI. In the following step, capital's income share is computed as (GOS +capital component in MI)/(total income), while labour's income share is computed as (COE + labour component in MI)/(total income).

Derivation of error-correction model (ECM)

The starting point for ECM here is autoregressive distributed lag ARDL(1,1,..,1) given by:

$$\begin{aligned} \ln MFP_{st} &= \mu_s + \alpha_s \ln MFP_{s,t-1} + \beta_{os} \ln G_{st} + \beta_{1s} \ln G_{s,t-1} \\ &\quad + \theta'_{os} Z_{st} + \theta'_{1s} Z_{s,t-1} + \epsilon_{st}, \end{aligned} \tag{A11}$$

where all notations are as described in the text.

The short-run effects of public infrastructure measure, $\ln G$, on the productivity measure, $\ln MFP$, is estimated by β_{os} and β_{1s}, which give the immediate effect of a change in $\ln G$ at a given point of a time. The long-run equilibrium is given by the unconditional expectations of the expected value of $\ln MFP$. Thus, let $\ln MFP^*_{st} = E(\ln MFP_{st})$, $\ln G^*_{st} = E(\ln G_{st})$, and $Z^*_{st} = E(Z_{st})$ for all t. If in the long-run all processes move together without error, they will

computations of MFP indexes and the consequent regression analysis to these measures. Interestingly, all the estimated results are found to be quite robust.

converge to the following equilibrium:

$$\begin{aligned}\ln MFP^*_{s,t} &= \alpha_{os} + \alpha_{1s}\ln MFP^*_{st} + \beta_{os}\ln KG^*_{st} + \beta_{1s}\ln G^*_{st} \\ &\quad + \theta'_{os}Z^*_{st} + \theta'_{1s}Z^*_{st}. \end{aligned} \tag{A12}$$

Solving $\ln MFP$ in terms of $\ln G$ and Z results in the following equation:

$$\begin{aligned}\ln MFP^*_{st} &= \frac{\alpha_{os}}{1-\alpha_{1s}} + \frac{\beta_{os}+\beta_{1s}}{1-\alpha_{1s}}\ln G^*_{st} + \frac{\theta_{os}+\theta_{1s}}{1-\alpha_{1s}}Z^*_{st} \\ &= k_{os} + k_{1s}\ln G^* + k'_{2s}Z^*, \end{aligned} \tag{A13}$$

where $k_{os} = \alpha_{os}/(1-\alpha_{1s})$; $k_{1s} = (\beta_{os}+\beta_{1s})/(1-\alpha_{1s})$; and $k'_{2s} = (\theta_{os}+\theta_{1s})/(1-\alpha_{1s})$. k_{1s} and k'_{2s} represent the long-run multipliers of G_{st} andZ_{st} respectively with respect to $\ln MFP_{st}$. However, the ARDL specification does not allow us to distinguish between short- and long-run effects (see Banerjee et al. 1993). Thus, through some simple transformations, the ARDL can be rewritten in the form of ECM where the short-run effects of changes in X are allowed to differ from the long-run effects. To see this we follow Keele and DeBoef (2005). Consider the ARDL (1,1,..,1) in A11, first we take the first difference of $\ln MFP$ to yield:

$$\Delta \ln MFP_{st} = \alpha_o + (\alpha_1 - 1)\ln MFP_{s,t-1} + \beta_o \ln G_{st} + \beta_1 \ln G_{s,t-1} + \epsilon_{st}. \tag{A14}$$

Next, add and subtract $\beta_{os}\ln G_{s,t-1}$ from the right hand side:

$$\begin{aligned}\Delta \ln MFP_{st} &= \alpha_o + (\alpha_{1s} - 1)\ln MFP_{s,t-1} + \beta_o \Delta \ln G_{st} \\ &\quad + (\beta_o + \beta_1)\ln G_{s,t-1} + \epsilon_{st}. \end{aligned} \tag{A15}$$

Then add and subtract $(\alpha_1 - 1)\ln G_{s,t-1}$ from the right hand side to produce the generalised error-correction model (GECM):

$$\begin{aligned}\Delta \ln MFP_{st} &= \alpha_{os} + \phi_s(\ln MFP_{s,t-1} - \sigma_{1s}\ln G_{s,t-1} - \sigma'_{2s}Z_{s,t-1}) \\ &\quad + \beta_s \Delta \ln G_{ts} + \theta'_s \Delta Z_{s,t} + \epsilon_{st}, \end{aligned} \tag{A16}$$

where $\phi_s = (\alpha_{1s} - 1), \sigma_{1s} = (\beta_{os} + \beta_{1s})$, and $\sigma_{2s} = (\theta_{os} + \theta_{1s})$.

(A16) as it is visible has nonlinear coefficients and obviously cannot be estimated using the OLS. One option is to use the nonlinear least square, however, with a panel structure it is problematic to model non-linear fixed-effects.[55] Fortunately, as Keele and DeBoef (2005) among others demonstrate, it is possible to rewrite the above non-linear specification of single equation

[55] In general, including panel-specific dummies to control for fixed-effects in non-linear models results in inconsistent estimates. For some non-linear models, the fixed-effect term can be removed from the likelihood function by conditioning on a sufficient statistic, for example, applying the conditional fixed-effects logit model.

ECM (SEECM) in the following more convenient form of ECM:

$$\begin{aligned}\Delta \ln MFP_{st} &= \gamma_o + \phi \ln MFP_{s,t-1} + \gamma_1 \Delta \ln G_{st} + \delta'_{oi} \Delta Z_{st} \\ &\quad + \gamma_2 \ln G_{s,t-1} + \delta'_{1i} Z_{s,t-1} + \epsilon_{st},\end{aligned} \tag{A17}$$

while the interpretation of the coefficients remain the same.

Since SEECM is a reparametrisation of ARDL, Keele & DeBoef (2005) suggest that we can instead estimate the following representation :

$$\begin{aligned}\Delta \ln MFP_{st} &= \alpha_{os} + \phi_s \ln MFP_{s,t-1} + \eta_{1s} \Delta \ln G_{ts} + \eta'_{2s} \Delta Z_{s,t} \\ &\quad + \sigma_{1s} \ln G_{s,t-1} + \sigma'_{2s} Z_{s,t-1} + \epsilon_{st},\end{aligned} \tag{A18}$$

where $k_1 = \sigma_{1s}/\phi_s = (\beta_{os} + \beta_{1s})(\alpha_{1s} - 1)$.

A disadvantage of the above model is that it does not provide standard errors of the long-run parameters directly. Therefore, we need to apply Bewley transformation to obtain interpretable t-statistics such as follows:

$$\begin{aligned}\ln MFP_{st} &= \varphi_o + \vartheta_1 \Delta \ln MFP_{st} + \delta_{1o} \ln G_{st} + \delta_{11} \Delta \ln G_{st} \\ &\quad + \delta'_{2o} Z_{st} + \delta'_{21} Z_{st} + \mu_{st}.\end{aligned} \tag{A19}$$

However, $\Delta \ln MFPst$ in (A19) above correlates with the error term, μ_{st}, which could point to an endogeneity problem. To resolve the latter problem of endogeneity, the Instrumental Variable (IV) regression can be applied with the instrument $\Delta \widehat{\ln MFP}$ estimated from the following regression:

$$\begin{aligned}\Delta \ln MFP_{st} &= \alpha_o + \alpha_1 \ln MFP_{s,t-1} + \alpha_{2o} \ln G_{st} + \alpha_{21} \Delta \ln G_{st} \\ &\quad + \alpha_{3o} Z_{st} + \alpha_{21} Z_{st} + \mu_{st}.\end{aligned} \tag{A20}$$

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