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Romp, Willem Eduard

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Chapter 6

Public Capital and Private Productivity: The Long-Run Effect

6.1 Introduction

The previous chapter showed that estimates of the impact of infrastructure investment on economic growth differ substantially depending on the countries and time period covered, the level of aggregation and the econometric methodology employed. This chapter attempts to arrive at a set of robust estimates of the output elasticity of public capital using internationally comparable aggregate and industry data for a considerable number of developed countries and a substantial number of years. State-of-the-art econometric methods are used to counter many of the criticisms raised against earlier studies. In particular, the pooled mean group estimator (PMG) that is used allows for the identification of the long-run effect of infrastructure on productivity.

As discussed in the previous chapter, many studies use growth rates to identify the effect of infrastructure on productivity, thereby destroying the long-run relationship, while infrastructure investment mostly consists of projects with long dur-

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This chapter is based on joint work with Robert Inklaar and Jan Egbert Sturm, 'Public Capital and Private Productivity: In search of the long-run effect', mimeo.

ations and long-run effects.[1] The PMG estimator proposed by Pesaran et al. (1999) avoids this problem by identifying the long-run relationship between variables in an error-correction framework. In cross-country and cross-industry estimates, efficiency gains are possible by restricting the parameter of interest to be equal across countries and/or industries. However, the PMG estimator only restricts the long-run parameter to be the same across countries or industries, while allowing for heterogeneity in the adjustment to this long run. In recent years, this estimator has been successfully applied in a number of studies on various issues, such as the effect of information and communication technologies (ICT) on growth (O'Mahony and Vecchi, 2005), the influences of human capital on growth (Bassanini and Scarpetta, 2002), and the impact of foreign direct investment (FDI) on growth (Ruschinski and Sturm, 2004).

The PMG estimator is first used to test the effect of infrastructure on productivity in an aggregate dataset for 21 OECD countries. However, one concern is that heterogeneity in the short-run adjustment may not be sufficient to arrive at robust elasticity estimates because of differences in the effect of infrastructure across industries. Indeed, a number of recent industry studies find such differences.[2] Furthermore, the impact of infrastructure may vary systematically across industries depending on the amount of transport equipment used by an industry. Fernald (1999) was the first to use this idea by postulating an industry production function with transport services as an input, rather than public capital. Transport services in turn depend on both the amount of transport equipment owned and the amount of public capital. His specification allows for heterogeneity across industries and at the same time tests whether more vehicle intensive sectors benefit more from extra public investment then less vehicle intensive sectors.

This chapter contains estimates of the impact of infrastructure based both on aggregate and industry data. Even though data and econometric methodology are state-of-the-art and counter many, if not all, criticisms raised in this literature, stable output elasticity estimates are elusive. Indeed, the estimated parameters vary wildly between equally plausible econometric specifications and range between -2 and 2. The aggregate estimates tend to be more stable, but even here, output elasticities range between 0.04 and 1.13. While it is hard to discount cross-country variation, the cross-specification variation we find suggests extreme sens-

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[1] An exception is the work by Canning and Pedroni (1999). They find that imposing a common long-run effect across industries and types of public capital is not justified. However, this is not surprising given their sample of both developed and developing countries.

[2] See e.g. Fernald (1999), Mamatzakis (1999a), Pereira and Andraz (2003) and Pereira and Roca-Sagales (2001).

itivity to conceptually innocuous specification choices. Overall, this suggests that production function estimates of the impact of infrastructure are not well-suited to be used for infrastructure policy recommendations.

This chapter continuous as follows. In the next section we describe our theoretical framework and the estimation procedure in more detail. The data are discussed in Section 6.3 and Section 6.4 summarises the empirical results. Section 6.5 offers some concluding remarks.

6.2 Methodology

6.2.1 Basic production function framework

The starting point of our analysis is an industry specific long-run production function with public capital (G) as a third input besides private capital (K) and labour (L) and Hicks neutral technology (U)

$$Y_i = U_i F^i \left(K_i, L_i, G\right). \tag{6.1}$$

Assuming a Cobb-Douglas production function and taking natural logarithms gives

$$y_i = u_i + \alpha_{Ki} k_i + \alpha_{Li} l_i + \alpha_{Gi} g + \epsilon_i, \tag{6.2}$$

where lowercase variables denote the logs. The data is given for time periods $t = 1 \ldots T$ and industries $i = 1 \ldots N$ (time subscripts are omitted). The parameter u_{it} is a proxy for the state of technology. The parameters α_K, α_L and α_G are the elasticities of the input factors, and ϵ_{it} is a time-sector specific error term. If we postulate constant returns to private inputs (capital and labour), i.e. $\alpha_K + \alpha_L = 1$, we get the well-known equation (see Equation (5.6) in Section 5.3 on page 155)

$$y_i - k_i = u_i + \alpha_{Li}(l_i - k_i) + \alpha_{Gi} g + \epsilon_i \tag{6.3}$$

We use a constant and a time trend as a proxy for technology. In this chapter we are only interested in the long-run effects of public capital, so we interpret this equation as a long-run production function. The estimation procedure that we use, the pooled mean group estimator, is specifically developed for this purpose so capacity utilisation correction terms as used by e.g. Aschauer (1989) are not necessary. Equation (6.3) is the most common model in the literature; various authors (e.g. Aschauer, 1989 and Kamps, 2006) have estimated this equation at a macroeconomic or state level. However, to our knowledge, we are the first to use this particular specification at the industry level.

If we assume cost minimisation and price taking in factor markets, we can replace the output elasticity of labour (α_L) by the observed input share of labour, s_L

$$y_i - (1 - s_{Li})k_i - s_{Li}l_i = u_i + \alpha_{Gi}g + \epsilon_i. \tag{6.4}$$

As explained in the previous chapter, estimating the output effect of public capital using Equation (6.3) or (6.4) is problematic, in particular due to the non-stationarity of the dependent and independent variables, forcing most authors to estimate in first differences. However, the PMG estimator also generates consistent estimates if the series are I(1). This allows us to estimate (6.3) and (6.4) in levels.

6.2.2 Inter-industry heterogeneity

Equations (6.3) and (6.4) suffer from one major drawback. To use the cross section dimension of the data to gain efficiency, we have to assume equal long-run public capital parameters; that is, the α_G parameter is equal for all countries and/or industries. This restriction is unlikely to hold. For example the transport and storage sector will probably benefit more from extra public capital than an industry like financial intermediation.[3] To allow for heterogeneity between sectors we use the production framework proposed by Fernald (1999). This method allows for different output elasticities of infrastructure across industries, but assumes that this variation is perfectly correlated with the amount of transport equipment owned by each industry. This restriction allows us to obtain a more efficient estimator of the sector-specific output elasticity of public capital without unduly restricting the output elasticity.

In Fernald's model, public capital does not enter the production function directly as a separate input, but via transport services (T). Transport services are produced within the sector and depend on the stock of vehicles (V) and available public capital. Again we assume that technological process is Hicks-neutral, so we can write the long-term production function as

$$Y_i = U_i F^i \left(K_i^N, L_i, T(V_i, G) \right), \tag{6.5}$$

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[3] In this chapter, public capital and infrastructure capital are used interchangeably as most public capital consists of infrastructure capital (see Section 5.2.3, page 152). Results based on different capital measures are discussed below.

with K^N non-vehicle capital. As before, price taking in factor markets and cost minimization are assumed as well as constant returns to private production factors. Under these assumptions, the output elasticity of, for example, vehicles is equal to the cost share of vehicles

$$s_{v,i} = \frac{dY}{dV_i}\frac{V_i}{Y_i} = \frac{dY}{dT}\frac{dT}{dV_i}\frac{V_i}{Y_i}. \tag{6.6}$$

Ultimately we are interested in the output elasticity of transport capital G. Using the separability in the production function allows us to rewrite this elasticity as

$$\frac{dY}{dG}\frac{G}{Y_i} = \frac{dY}{dT}\frac{dT}{dG}\frac{G}{Y_i} = \left[\frac{dT/dG}{dT/dV}\frac{G}{V_i}\right]\left[\frac{dY}{dT}\frac{dT}{dV}\frac{V_i}{Y_i}\right] = \phi_i s_{v,i}. \tag{6.7}$$

The parameter ϕ is the output elasticity of transport capital relative to the output elasticity of vehicles. This parameter links the unobserved output elasticity of public capital to the observed cost share of vehicles. We assume that the production function that transforms vehicles and infrastructure capital into transport services is of a Cobb-Douglas type with the same coefficients for all sectors

$$T(V_i, G) = A_i V_i^{\beta_V} G^{\beta_G}. \tag{6.8}$$

Substituting the first derivatives of T with respect to V and G in (6.7) shows that ϕ can be written as

$$\phi_i = \frac{dT/dG}{dT/dV} GV = \frac{\beta_G}{\beta_V}, \tag{6.9}$$

which implies that ϕ is the same in all sectors. Note that in Equation (6.9) only the output elasticities had to be assumed constant across sectors, while the transformation technology A may differ across industries.

Returning to the original production function and postulating a Cobb-Douglas specification with industry-specific technology, the production function in log levels becomes

$$y_i = u_i + \alpha_{Ki} k_i^N + \alpha_{Li} l_i + (\alpha_{Ti}\beta_V) v_i + (\alpha_{Ti}\beta_G) g + \epsilon_i. \tag{6.10}$$

Equation (6.10) closely resembles Equation (6.2), except that (private) capital is split between vehicle (v) and non-vehicle capital (k^N). However, if we replace output elasticities of the private inputs by observed, industry-specific shares that are constant over time and use Equation (6.9) we get

$$y_i - s_{Ki}k_i^N - s_{Li}l_i - s_{Vi}v_i = u_i + \phi(s_{Vi}g) + \epsilon_i. \tag{6.11}$$

The term within brackets on the right hand side is fully observable and the transport services technology A is absorbed into the general technology term due to the Cobb-Douglas production function specification. The key point to note about Equation (6.11) is that the estimated coefficient ϕ is constant over industries, allowing us to pool all series and estimate the one coefficient efficiently. However, a constant ϕ implies a different impact of public capital across industries, but this effect is assumed to vary depending on the amount of vehicle capital. Fernald (1999) originally proposed this identification scheme, although he estimated Equation (6.11) in first differences. Denoting the left hand side of (6.11) by mfp (multifactor productivity) and its first difference by Δmfp we get

$$\Delta mfp_i = \phi(s_{Vi}\Delta g) + \epsilon_i. \tag{6.12}$$

Equation (6.12) links sector specific multifactor productivity growth to public investment. There is a causality problem since higher productivity growth possibly leads to higher public investment. A simple correction (Fernald (1999, pp 622-3) for details) is to de-mean the series, i.e. to estimate

$$\Delta mfp_i - \overline{\Delta mfp} = \phi(s_{Vi} - \bar{s}_V)\Delta g + \epsilon_i. \tag{6.13}$$

Under the assumption that only higher average productivity growth has a potential effect on public investment, the estimator of ϕ using Equation (6.13) will be consistent.[4]

6.2.3 Estimation procedure

There are various ways to estimate the panel equations (6.3), (6.4), (6.11) and (6.13). One way, used by Fernald (1999), is the Seemingly Unrelated Regression (SUR) proposed by Zellner (1962). SUR allows the contemporaneous error covariances to be freely estimated, but it neglects further similarities between sectors. The main drawback, however, is that the number of series (N) must be smaller than the length

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[4] Equation (6.13) is a simplified version of Fernald's (1999) estimated equation. His more complex equation also allows for different cyclicality of the industries, i.e. it allows industries to be more responsive to aggregate productivity shocks. However, our more restrictive representation does capture the main idea and does not change the interpretation and sign of the key parameter ϕ.

of each series (T). In our industry level analysis we have 22 years of data on 24 industries per country and 31 years of data for 21 countries on the macro level. Clearly we cannot use SUR estimation directly. Fernald solves this problem by grouping comparable sectors or by selecting only a subset, thereby reducing the number of series. While this is likely to improve estimation efficiency, it reduces cross-section variation. Reducing the cross-sectional dimension and thus variation is strange if one considers that identification in Fernald's model depends on this variation.

Another approach is to estimate a fixed effects panel data model. The main problem with this approach is that these models only allow for different intercepts while all other coefficients are assumed to be constant across all series, both in the short run as in the long run. Especially in Equations (6.3), (6.4) this assumption is troublesome, because it is violated on theoretical grounds since the coefficients of the inputs are all industry-specific.

As a third option we could estimate a separate equation for each industry and examine the distribution of the estimated coefficients across series (countries or industries). The mean of the estimates, often called the Mean Group (MG) estimator will then be of particular interest. However, this procedure does not take into account that some of the parameters might the same across groups and one could obtain a more efficient estimator by using this extra information.

We will use an intermediate procedure proposed by Pesaran et al. (1999) and referred to as the Pooled Mean Group (PMG) estimator. This estimator, based on a maximum likelihood approach, constrains the long-run coefficients to be identical, but allows the short-run coefficients and error variances to differ across industries, thereby allowing for short-run heterogeneity between sectors. As long as the variables are I(0) or I(1), the PMG estimators are consistent and the asymptotic distribution of the PMG estimator can be derived.

To illustrate the PMG method, we start with the long-run relationship in Equation (6.4). If all variables are I(1)[5] and cointegrated, then the error term in the estimating equations is stationary. Instead of estimating the long-run relationships directly, the PMG estimates the error equation of the autoregressive distributed lag (ARDL) representation. For notational convenience we derive the equations here with one lag in the dependent and explanatory variables for all series. In the actual

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[5] Kamps (2006) investigates whether these series are actually I(1) on a macro level for 22 OECD series. If each series is tested individually, he comes to the conclusion that this is probably not true. However, unit root tests do suffer from low power to discriminate between unit root and near unit root processes, especially for small samples. Panel unit root tests do not reject the null hypothesis that the variables are I(1).

estimation procedures, we allow the lags to differ between series and between the dependent and explanatory variables (see Pesaran et al., 1999 for a more general discussion). The ARDL equation is

$$mfp_{it} = \lambda_1 mfp_{i,t-1} + \delta_{i,0} g_{it} + \delta_{i,1} g_{i,t-1} + \beta_i + \gamma t + \epsilon_{it}, \tag{6.14}$$

with the left hand side

$$mfp_i = y_i - (1 - s_{Li}) k_i - s_{Li} l_i \tag{6.15}$$

and where we have imposed a sector specific intercept β and a time trend γt. Rewriting gives the equivalent, but notationally more convenient error correction equation

$$\Delta mfp_{it} = (1 - \lambda_1) mfp_{i,t-1} + (\delta_{i,0} + \delta_{i,1}) g_{it} - \delta_{i,1} \Delta g_{it} + \beta_i + \gamma t + \epsilon_{it}, \tag{6.16}$$

This error correction equation implies the following long-run relation

$$mfp_{it} = \frac{\delta_{i,0} + \delta_{i,1}}{1 - \lambda_1} g_{it} + \beta_i' + \gamma' t + \epsilon_{it}. \tag{6.17}$$

Imposing equal parameters in the long run gives

$$\frac{\delta_{i,0} + \delta_{i,1}}{1 - \lambda_1} = \phi, \tag{6.18}$$

so the ratio of the error correction parameters are restricted to be equal across series. The PMG estimator is the likelihood maximising value of θ. Estimating a restricted version of (6.16) instead of the long-run Equation (6.3), (6.4), (6.11) and (6.13) directly allows the parameters to differ across series in the short run. Another advantage of (6.16) over the non-dynamic estimating equations is that including lagged variables solves problems of possible autocorrelation.

Tests of homogeneity of error variances and short-run or long-run slope coefficients can be easily carried out using Likelihood Ratio tests, since – like fixed effects estimators – the PMG estimator is a restricted version of the set of industry-specific estimators. Although it is common to use pooled estimators without testing the implied restrictions, in case of cross country studies, the Likelihood Ratio tests has a tendency to reject the restrictions at conventional significance levels.[6] In

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[6] Pesaran et al. (1999) explain this by pointing at possibly omitted group specific variables that are correlated with the regressors causing the group specific estimates to vary wildly. When estimating

our industry-level application, the LR test also rejects the null hypothesis of equal long-run coefficients.

Pesaran et al. (1999) suggest using a Hausman (1978) type test instead of a Likelihood ratio test. The MG estimator provides consistent estimates of the mean of the long-run coefficients, though these will be inefficient if slope heterogeneity holds. Under long-run slope homogeneity, the pooled estimators are consistent and efficient. Therefore, the effect of heterogeneity on the means of the coefficients can be determined by a Hausman-type test applied to the difference between the MG and the PMG or the fixed effects estimators.

6.3 Data

Our data are annual. The macro level data cover the period 1960–2001, the industry level data start in 1979. The national public and private capital data are taken from Kamps (2006). He provides international comparable capital stock estimates for 22 OECD countries (see the first column of Table 6.1 for a complete list).[7] The capital stock estimates are calculated using the perpetual inventory method, assuming geometric depreciation. Kamps' concept of public capital includes all capital, not just infrastructure. This dataset has the main advantage that the capital estimates are constructed in a consistent manner, so diverging results for different countries are not caused by merely different concepts of public capital. To be certain that this broad definition of public capital does not influence the results, we also collected data specifically on infrastructure investment for the six countries for which we have industry data. For this set of countries (except Australia), we also gathered data on road length as an admittedly crude, but very straightforward measure of infrastructure.[8]

For data on output, and industry specific capital and labour, we rely on the GGDC database (Inklaar et al., 2006). The second column of Table 6.1 presents the 24 industries included in our analysis.[9] Unfortunately, the industry level data is not

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equations for a large number of groups it is not possible to include all group specific variables. However, if the coefficients are really the same and the bias inducing correlations are not systematic, then pooled estimation will be appropriate.

[7] We excluded Switzerland from the original 22 country dataset due to data availability, leaving 21 countries.

[8] This data is available upon request.

[9] The original dataset covers 26 industries. We exclude two of them; petroleum and coal products and non-market services. The first because value added of this sector is mainly driven by the exogenous oil price, the second because of measurement problems with the output of this sector and because public capital is included in the estimation of output in this sector by the statistical offices.

available for all countries in the macroeconomic dataset for the full sample. Due to limited data availability, we had to restrict our industry level analysis to the time period 1979–2001 and to a subset of six countries, i.e. the Netherlands, Germany, France, the UK, Australia and the United States. We used hours worked as a proxy for labour input and value added as the measure of output. The capital data is divided into growth rates for six types of capital assets, one of which is transport equipment. These six specific capital growth rates are aggregated using the two-period average share of each asset type in total nominal capital compensation (see Inklaar et al., 2006 for details).

$$\Delta \ln K_t = \sum_j \bar{V}^K_{j,t} \Delta \ln K_{j,t},$$

where $\bar{V}^K_{j,t}$ is the two-period average share of asset type j in total nominal capital compensation. This aggregate capital growth rate is finally used to construct a private capital services index.

Of particular interest is the transport capital input or vehicle share, since this is used to calculate the output elasticity of public capital in equations (6.11) and (6.13). Table 6.2 shows this vehicle share per industry per country. The average input share is 2.7%, and similar for all countries, except Australia (4.23%). Australia also has a different distribution over industries. For example, the transport and storage sector, in most other countries the most vehicle intensive sector by far, has only a vehicle share of 5%. In contrast, the construction sector in Australia spends 13.2% of inputs on transport capital, far more than the same sector in the other countries.

6.4 Results

For all estimations we use a three-stage estimation procedure. In the first stage, we determine the optimal number of lags for each series chosen by the Schwarz-Bayesian information criterium (SBC) subject to a maximum lag order of three. All results are robust for alternative selection criteria like Akaike's Information Criterium (AIC) and the Hanna-Quinn Information Criterium (HQ). In the second, stage we search for a suitable initial value of the public capital coefficient. If any output elasticities of other inputs are included in the estimating equation, we fix them temporarily to their observed cost shares. With the other output elasticities fixed, we use a grid search over the relevant domain to obtain an initial value for the public capital parameter in the optimisation algorithm. For the basic estimating

Table 6.1. Countries and industries included in the empirical analysis

Countries	**Industries**
Australia[1]	Agriculture, forestry & fishing
Austria	Mining & quarrying
Belgium	Food products
Canada	Textiles, clothing & leather
Denmark	Wood products
Finland	Paper, printing & publishing
France[1]	Chemical products
Germany[1]	Rubber & plastics
Greece	Non-metallic mineral products
Iceland	Metal products
Ireland	Machinery
Italy	Electrical & optical equipment
Japan	Transport equipment
Netherlands[1]	Furniture & misc. manufacturing
New Zealand	Electricity, gas & water
Norway	Construction
Portugal	Wholesale trade
Spain	Retail trade
Sweden	Hotels and restaurants
United Kingdom[1]	Transport & storage
United States[1]	Communications
	Financial intermediation
	Business services
	Social & personal services

[1] Included in the industry level analysis

equations (6.3) and (6.4) we search over the interval from -0.10 to 0.50; this covers most point estimates of the public capital output elasticity reported in other studies (see Table 5.2 on page 171). For the extended estimating equations (6.11) and (6.13) the interpretation of the public capital coefficient is different, the product of this coefficient and the vehicle share gives the output elasticity of public capital. The average vehicle share is 2.72% so we use the interval from -4 to 18.[10]

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[10] Other studies using the PMG estimator (e.g. Pesaran et al., 1999; O'Mahony and Vecchi, 2005) use the mean group estimator as initial values in the optimisation step. This has the drawback that the mean group estimator might be very far from the likelihood maximising value and that the optimisation algorithm (usually of the Gauss-Newton type) might get stuck at a local maximum. Our grid search prevents this.

Table 6.2. Transport share per industry (%).

Industries	All countries	Netherlands	France	Germany	UK	Australia	USA
Agri., forestry & fishing	6.99	2.56	0.74	0.60	2.90	14.37	9.96
Mining & quarrying	3.00	0.26	0.67	0.71	1.54	3.17	3.91
Food products	1.60	1.72	0.77	1.40	1.75	3.60	1.61
Textiles, clot. & leather	0.60	0.67	0.44	0.65	1.37	1.96	0.43
Wood products	1.54	1.19	1.74	1.04	3.54	3.67	1.30
Paper, print. & publishing	1.43	0.85	1.43	1.30	1.14	3.70	1.39
Chemical products	1.28	0.42	3.34	0.96	1.12	4.66	1.05
Rubber & plastics	0.99	0.62	2.82	1.22	0.91	4.04	0.40
Non-metallic mineral prod's	1.75	1.94	1.20	1.55	2.18	3.83	1.67
Metal products	0.94	0.89	1.79	0.99	0.67	3.69	0.57
Machinery	0.97	1.01	0.93	0.95	2.21	2.36	0.78
Electrical & optical equip.	0.48	0.23	0.85	0.69	1.17	0.47	0.28
Transport equipment	0.68	1.74	0.65	1.07	0.22	1.71	0.53
Furniture & misc. man.	0.78	0.68	1.01	1.10	2.88	1.85	0.41
Electricity, gas & water	1.89	0.30	2.19	1.44	0.76	2.38	2.09
Construction	6.87	3.39	4.46	4.63	8.99	13.17	7.42
Wholesale trade	4.37	5.91	3.12	4.12	8.79	4.35	4.13
Retail trade	1.39	2.29	0.36	1.07	2.42	2.98	1.39
Hotels and restaurants	1.00	1.41	0.22	0.63	1.18	3.24	1.02
Transport & storage	10.85	17.34	10.89	4.45	12.99	5.06	12.57
Communications	3.28	0.89	1.10	1.20	0.94	3.48	4.11
Financial intermediation	1.47	1.01	0.57	1.08	3.64	4.92	1.22
Business services	7.20	9.96	8.62	15.59	4.85	4.53	4.97
Social & personal services	1.58	0.87	0.38	1.41	2.80	3.26	1.61
Average	2.19	2.42	2.09	2.08	2.96	4.19	2.70

Note: the table shows the share of transport equipment capital compensation in value added, averaged over the period 1979-2001.

In the final stage we use a Newton optimisation algorithm to maximise the likelihood function, using the cost shares of the private inputs and the likelihood maximising coefficient of public capital from the second stage as initial values. Naturally we do not restrict the estimated coefficients in any way. In particular, we do not restrict the public capital coefficient to the interval used in stage two.

6.4.1 Output elasticities: country estimates

Table 6.3 shows the country-level estimates of the output elasticities of public capital. The first specification is Equation (6.3). It is the most restrictive, assuming constant returns to private inputs and a common output elasticity of private capital, labour and public capital for all countries. The first row in each block shows the estimation results with all 21 countries included. The estimated output elasticity of public capital is 0.56, with an asymptotic t-value of 5.87 (between brackets). The pooled error correction is -0.11 and also highly significant (t=-5.07). The mean group elasticity estimate is higher, 0.90, with a much higher variance, but still significantly different from zero at the usual significance levels. The last column gives the p-value of the Hausman test. It clearly shows that we have to reject the null hypothesis of equal long-run coefficients. In this specification it is mostly due to wildly varying private input coefficients (not shown).

The second row in the first block shows the estimates if we only include relatively small countries (all countries except the US, UK, France, Germany and Japan). The pooled mean group estimate is lower than the estimate for all countries; however, the mean group estimate is higher, 1.28. Again, the Hausman test shows that we must reject the null hypothesis of equal long-run parameters. The third and fourth row show the estimation results for a pool with only the five large countries and for the 15 European countries. Finally, the last row for each specification shows the estimation results for the six countries that are included in the industry-level analysis.

The second specification shows the same Equation (6.3), but we allow private input coefficients to vary by country. The output elasticity estimates vary between 0.64 and 1.13, although this might seem ridiculously high from an economic viewpoint, they are within the range found in other studies. The Hausman test gives no reason to reject the null hypothesis, mainly because the coefficient of labour is not restricted to be equal among countries in the long run.

Finally, the third specification shows the estimation results for Equation (6.4). Here we fix the private input coefficients to their observed cost shares. The estimated output elasticities all lie within the expected range, varying from 0.04 for the large countries to 0.15 for the small countries. All estimates, except for the large country group, differ from zero at a 5% significance level. As with the previous specification, none of the Hausman tests give reason to reject the null hypothesis of equal coefficients.

The estimated output elasticities in Table 6.3 vary considerably, especially between the various specifications, but also across the subsets of countries. Figure 6.1 shows this variation, the markers indicating the point estimates and the lines the 95% confidence intervals. As mentioned before, specifications 1 and 2 both generate relatively high output elasticities. Given the fairly stringent assumptions about output elasticities of private inputs, this might point to a misspecification. The vertical lines also indicate that the high estimates have high standard errors; the lower, more realistic estimates have smaller confidence intervals. Overall, the country-level estimates cover the entire range of estimates reported in other studies. Furthermore, the estimates based on specification 3 cover the range of estimates found in most modern, sophisticated studies. However, this range of 5-15 percent is still fairly wide and there is no independent information to verify whether the cross-country variation is reasonable.

6.4.2 Output elasticities: industry estimates

Basic estimation results

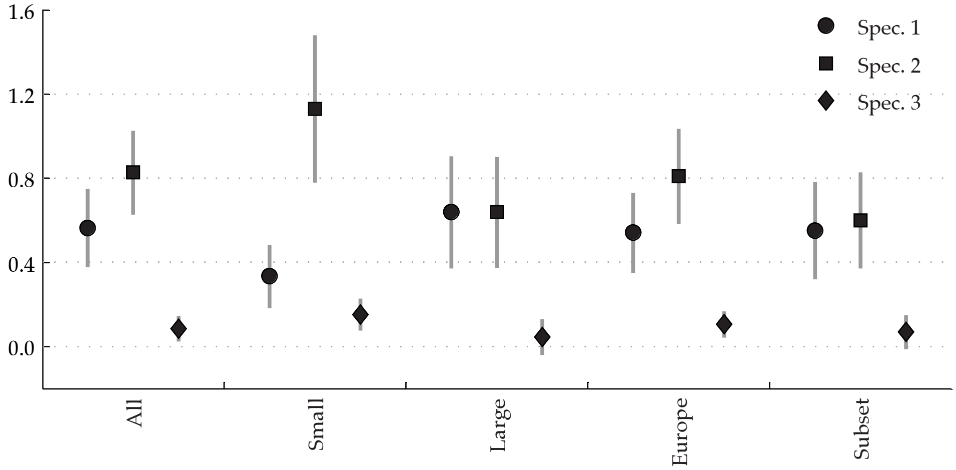
Table 6.4 shows the estimation results based on the same specifications as above. The first line for each specification shows the results for the complete industry panel. With all 24 industries in the six countries included, this estimation is more or less comparable to the 'Subset' group from Table 6.3. Comparing these lines from Table 6.3 and Table 6.4 shows positive estimates in Table 6.3 and negative coefficients in Table 6.4, raising questions about the robustness of the results. Furthermore, the country results in Table 6.4 show a range of output elasticity estimates of -2.38 to 1.53, depending on the country and the specification. This spread is very substantial compared to the spread for the country-level estimates from Table 6.3 of 0.04 to 1.13. A possible explanation is that within a country, some sectors benefit considerably more from public capital than others and restricting the public capital output elasticity to be equal across industries is not justified. However, the joint Hausman tests suggest this is not the case. Only five of the 18 tests reject the null hypothesis of equal long-run parameters and two of them are rejected not because

Table 6.3. Country-level estimates of the output elasticity of public capital

	Pooled Mean Group		Mean Group		Hausman
	Output elasticity	Error correction	Output elasticity	Error correction	p-val
Specification 1 (common labour elasticity)					
All	0.56 (5.87)	-0.11 (-5.07)	0.90 (2.94)	-0.22 (-7.05)	2.9%
Small	0.33 (4.33)	-0.19 (-5.57)	1.28 (3.20)	-0.24 (-5.68)	2.9%
Large	0.64 (4.67)	-0.16 (-2.04)	0.59 (1.35)	-0.18 (-2.27)	0.4%
Europe	0.54 (5.53)	-0.13 (-4.31)	1.16 (3.56)	-0.25 (-6.80)	0.3%
Subset	0.55 (4.66)	-0.17 (-2.48)	0.82 (4.77)	-0.24 (-4.52)	10.2%
Specification 2 (country specific labour elasticity)					
All	0.83 (8.12)	-0.18 (-5.80)	0.90 (2.94)	-0.22 (-7.05)	81.0%
Small	1.13 (6.30)	-0.17 (-4.61)	1.28 (3.20)	-0.24 (-5.68)	66.8%
Large	0.64 (4.73)	-0.19 (-2.56)	0.59 (1.35)	-0.18 (-2.27)	91.5%
Europe	0.81 (6.97)	-0.22 (-6.59)	1.16 (3.56)	-0.25 (-6.80)	24.8%
Subset	0.60 (5.11)	-0.24 (-4.97)	0.82 (4.77)	-0.24 (-4.52)	8.3%
Specification 3 (labour elasticity equal to cost share)					
All	0.08 (2.71)	-0.18 (-7.63)	-0.01 (-0.07)	-0.22 (-8.42)	46.2%
Small	0.15 (3.83)	-0.20 (-5.40)	-0.03 (-0.21)	-0.21 (-5.62)	23.7%
Large	0.04 (1.03)	-0.20 (-3.05)	-0.09 (-0.45)	-0.22 (-3.03)	47.7%
Europe	0.11 (3.32)	-0.20 (-6.35)	0.00 (0.03)	-0.23 (-6.70)	42.6%
Subset	0.07 (1.66)	-0.23 (-4.25)	0.04 (0.26)	-0.27 (-4.34)	84.0%

Notes: t-values are in parentheses. ‘Hausman p-val’ is the probability from testing whether the pooled mean group and mean group coefficients are equal across countries. Specification 1 corresponds to Equation (6.3) with a constant labour elasticity across industries (omitted from the table). Specification 2 corresponds to Equation (6.3) with varying labour elasticity across industries (omitted from the table). Specification 3 corresponds to Equation (6.4)

Figure 6.1. Estimated output elasticity of public capital in a panel of 22 countries, with 95% confidence intervals



Notes: 'Small' excludes US, UK, France, Germany and Japan, 'Large' only covers those countries. 'Europe' includes the 15 (old) EU member countries and 'Subset' includes Australia, France, Germany, Netherlands, UK and US. Spec. 1 corresponds to Equation (6.3) with a constant labour elasticity estimate across countries, Spec. 2 corresponds to Equation (6.3) with varying labour elasticity estimate across countries (omitted from the table). Spec. 3 corresponds to Equation (6.4).

of unequal public capital elasticities, but because of unequal labour elasticities.[11]

The results for France are quite sensitive to the inclusion of the sectors 'food products' and 'furniture and misc. manufacturing'. Without these two sectors, the public capital output elasticity estimates for the first and third specification are 0.18 and 0.26, still relatively high, but not as high as 1.29 and 1.52. Also the results for the UK are sensitive to the exclusion of two outliers. Dropping 'food products' and 'machinery' for the UK changes the first and second results to -0.28 and -0.02. Despite the large impact on the estimates of certain industries in certain countries, there is little reason to exclude these industries systematically. As in the case of the country-level estimates, the large variation of estimates across countries and specifications raises doubts about the usefulness of these estimates.

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[11] The Hausman test p-values for equal public capital coefficients are 0.35 and 0.63 for all countries and the UK in the first specification. The Hausman test p-values for equal labour coefficients are 0.02 and 0.01.

Table 6.4. Industry-level estimates of the output elasticity of public capital

	Pooled Mean Group		Mean Group		Hausman
	Output elasticity	Error correction	Output elasticity	Error correction	p-val
Specification 1 (common labour elasticity)					
All countries	-0.23 (-2.87)	-0.55 (-16.46)	-3.73 (-1.00)	-0.80 (-16.64)	6.6%
Netherlands	-0.37 (-1.59)	-0.64 (-7.32)	0.28 (0.30)	-0.99 (-6.69)	76.7%
France	1.29 (5.23)	-0.39 (-4.62)	0.17 (0.10)	-0.85 (-5.14)	2.8%
Germany	0.12 (1.21)	-0.69 (-6.28)	0.42 (0.52)	-0.89 (-8.42)	86.4%
UK	-0.52 (-3.01)	-0.45 (-5.16)	-0.15 (-0.18)	-0.65 (-6.28)	2.4%
Australia	-2.38 (-4.31)	-0.48 (-7.44)	-22.55 (-1.01)	-0.56 (-9.38)	14.5%
USA	-0.66 (-4.62)	-0.79 (-8.56)	-0.55 (-0.58)	-0.89 (-10.71)	16.0%
Specification 2 (country specific labour elasticity)					
All countries	-0.04 (-0.84)	-0.71 (-16.93)	-3.73 (-1.00)	-0.80 (-16.64)	32.5%
Netherlands	-2.18 (-13.51)	-0.80 (-5.70)	0.28 (0.30)	-0.99 (-6.69)	0.9%
France	-1.10 (-5.78)	-0.75 (-4.90)	0.17 (0.10)	-0.85 (-5.14)	47.2%
Germany	0.25 (2.63)	-0.79 (-7.15)	0.42 (0.52)	-0.89 (-8.42)	83.1%
UK	0.06 (0.98)	-0.57 (-5.28)	-0.15 (-0.18)	-0.65 (-6.28)	79.4%
Australia	-1.75 (-3.69)	-0.58 (-9.01)	-22.55 (-1.01)	-0.56 (-9.38)	35.1%
USA	-0.70 (-5.04)	-0.82 (-9.58)	-0.55 (-0.58)	-0.89 (-10.71)	87.9%
Specification 3 (labour elasticity equal to cost share)					
All countries	-0.36 (-4.05)	-0.50 (-18.29)	-0.72 (-1.01)	-0.57 (-19.24)	61.0%
Netherlands	0.21 (0.83)	-0.52 (-8.83)	1.58 (1.94)	-0.65 (-8.57)	7.7%
France	1.53 (8.07)	-0.34 (-4.37)	1.22 (0.44)	-0.50 (-5.96)	91.0%
Germany	0.34 (2.41)	-0.57 (-7.53)	0.59 (0.98)	-0.62 (-8.48)	67.1%
UK	-0.84 (-4.83)	-0.42 (-7.04)	-3.14 (-1.70)	-0.49 (-7.81)	21.2%
Australia	-2.14 (-4.37)	-0.51 (-8.40)	-1.64 (-1.12)	-0.57 (-10.38)	71.9%
USA	-1.65 (-7.57)	-0.54 (-5.95)	-2.96 (-1.50)	-0.62 (-7.25)	50.4%

See notes table 6.3 for definitions.

Extended estimation results

The previous subsection showed that allowing for heterogeneity between industries within a country increases the variation in estimates across countries and specifications. Although the Hausman tests do not reject equal public capital coefficients in general, it might help if we allow for heterogeneity between sectors regarding the effect of public capital. Table 6.5 shows the estimation results for equations (6.11) and (6.13). The estimated coefficient of interest in these equations is ϕ, which can be multiplied by the average transport equipment share to find the corresponding output elasticity of public capital as in the previous tables. Specification 4 in Table 6.5 shows the results of Equation (6.11), the relation in levels. The last column shows the implied output elasticities of public capital and they are within the range of estimates in Table 6.4. Specification 5 shows the results of the estimating Equation (6.13), Fernald's equation in growth rates, de-meaned to account for possible reverse causality. The point estimate for ϕ for the USA, 9.17, lies well within the range reported by Fernald (1999), although we used a slightly different specification and a different estimation procedure. Also the results for Australia, the UK, and Germany are within the expected interval, although the implied output elasticities are relatively high, especially for the UK, Australia, and the USA. The estimate for the Netherlands is very low, -21.9, implying an output elasticity of -0.53. Moreover, this result does not seem to be driven by outliers. While in Table 6.4, the Hausman tests did not reject equality of output elasticities across industries, the Hausman tests in Table 6.5 also do not reject equality of ϕ across industries. So while Fernald's (1999) identification scheme is attractive on conceptual grounds, there are no statistical reasons to prefer either model.

The results in Tables 6.3–6.5 do not support even the most general conclusions about the impact of public capital on private productivity, since the output elasticity estimates range from negative to positive across specifications. As a further robustness check, we also collected data on infrastructure investment, rather than the broader category of public capital, and road length. However, these alternative capital measures only reinforce the finding that very few robust conclusions can be drawn from this type of regression analysis.

Although the detailed results are available upon request, we will use the estimated coefficients from these regressions, as well as the earlier ones to illustrate the more general conclusion about the robustness of output elasticity estimates of public and infrastructure capital. The previous tables have shown a large range of estimates, both across countries and across different specifications. We have no in-

Table 6.5. Extended industry level output elasticity estimates

	Pooled Mean Group				Hausman	Output
	$\hat{\phi}$		Error correction		p-val	elasticity
Specification 4, Fernald (1999) in log levels						
All countries	-10.90	(-3.39)	-0.49	(-18.03)	63.2%	-0.24
Netherlands	-9.31	(-1.38)	-0.52	(-8.66)	14.1%	-0.23
France	0.65	(0.07)	-0.38	(-5.97)	29.9%	0.01
Germany	26.27	(2.96)	-0.57	(-7.82)	32.8%	0.55
UK	-30.54	(-4.05)	-0.42	(-6.56)	14.7%	-0.90
Australia	-35.52	(-3.40)	-0.51	(-8.46)	79.2%	-1.49
USA	-64.60	(-4.42)	-0.52	(-6.30)	27.0%	-1.74
Specification 5, Fernald (1999) in growth rates						
All countries	1.93	(0.69)	-1.03	(-39.35)	7.3%	0.04
Netherlands	-21.85	(-2.95)	-0.99	(-18.12)	54.2%	-0.53
France	-2.93	(-0.30)	-0.94	(-19.41)	31.7%	-0.06
Germany	3.06	(0.56)	-1.04	(-20.34)	14.0%	0.06
UK	7.49	(0.99)	-0.94	(-13.18)	17.8%	0.22
Australia	4.61	(0.72)	-1.13	(-20.18)	96.0%	0.19
USA	9.17	(1.50)	-1.14	(-13.15)	3.3%	0.25

Notes: t-values are in parentheses. 'Hausman p-val' is the probability from testing whether the pooled mean group and mean group coefficients are equal across countries. Specification 4 corresponds to Equation (6.11) and Specification 5 corresponds to Equation (6.13).

dependent information to verify whether the cross-country variation in estimates is reasonable or not, but the cross-specification variation can be used, since each specification attempts to uncover the same underlying parameter, namely the output elasticity of public capital.[12]

Table 6.6 illustrates this cross-specification variability. The first row, 'country-level', is based on the elasticity estimates from Table 6.3. For each country group, the average across specifications is first subtracted to focus on the variation across specifications. From this set of 15 parameters, the 25th and 75th percentile is determined to get a relatively robust measure of the spread of the distribution and the inter-quartile range is determined.[13] So for a given country group, a change in

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[12] In specifications 4 and 5 in Table 6.5, the output elasticity is not estimated directly, but is derived given the average share of transport capital in value added.

[13] There is overlap in country coverage between the different estimates, as for example, the 'all countries' as well as the 'small' and 'large' countries parameters are included. If anything, this is likely to reduce the inter-quartile range, since the 'all countries' parameter is a (weighted) average of the 'small' and 'large' parameter.

Table 6.6. Cross-specification variation in estimates of the output elasticity of public capital

	Inter-quartile range
Country-level	0.56
Industry-level, specifications 1–3	0.49
Industry-level, specifications 1–5	
Only public capital	0.62
Public capital, infrastructure and roads	0.75

Notes: The inter-quartile range compares the 75th to the 25th percentile of the parameters. The average across specifications for each country (group) is subtracted to put the estimates on a comparable basis. For the final row, this average is different for the definitions of capital. The first figure is based on the parameters in Table 6.3, the second on Table 6.4 and the third on Tables 6.4 and 6.5.

specification could change the elasticity estimate substantially, by 0.56 when moving from the 25th to the 75th percentile. While Figure 6.1 showed that specifications 1 and 2 gave systematically higher elasticity estimates than specification 3, the industry-level parameter estimates are more randomly distributed across specifications. In all cases, relatively minor changes in specification can lead to radically different elasticity estimates. Different specifications can be used to defend the thesis that public capital has no impact on output at all or the same impact as labour.

6.5 Concluding remarks

The studies surveyed in the previous chapter reached very different conclusions about the effect of public capital on productivity. Given the large differences across studies in methodology, data, country and time coverage, this chapter has examined the effect of public capital in a production function framework, using state-of-the-art econometric methodology and two data sets covering a broad range of countries, industries and years. In particular, we use the pooled mean group estimator (PMG) to find the long-run effect of public capital on productivity. Even within this framework, reliable estimates remain elusive, The question arises whether this type of analysis is ever likely to yield estimates that are useful for informing infrastructure investment decisions.

A number of different specifications are tested using country-level and industry-level data. Estimates vary wildly across specifications and country groups and individual countries (using industry data). The cross-country variation is hard to discount, as no independent information is available to confirm whether this variation is reasonable or not. However, the cross-specification variation raises more fundamental questions about using production function estimates to gauge the impact of infrastructure on productivity. In all cases, the regressions aim to find the same underlying output elasticity of public capital and there are no a priori reasons to discount certain specifications entirely. While some would prefer some specifications over others, such as allowing for country-specific output elasticities of labour, this does not seem like a solid basis for drawing radically different conclusions based on the same data and econometric methodology.

And the conclusions are indeed radically different: simply moving from one specification to another for a given country or country group may increase the elasticity estimate by as much as 0.6.[14] In comparison, in most (value added) production function estimates, the output elasticity of labour is about 0.6. Furthermore, it seems unlikely that advances in data or econometrics will improve this situation. Already, the industry data cover about a quarter of century and 24 industries. Furthermore, the longer country-level dataset (more than 40 years) does not fare much better than the industry estimates. The conclusion then has to be that public capital is not important enough for productivity to yield more than the occasional spurious correlation.

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[14] Moreover, this range is not based on the extreme estimates but on the 25th and 75th percentiles of the estimates.