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Abstract

This paper assesses the productivity effects of infrastructure's operations and maintenance (O&M) spending by state and local governments in the 48 contiguous U.S. states over the period 1978-2000. We explicitly account for transboundary spillovers of capital and O&M spending and follow a semiparametric methodology that allows us to estimate state-specific output elasticities. We find strong evidence that in all 48 states the cross-state spillover effects of O&M outlays on productivity exceed their within-state impacts and are substantially higher than the spillover effects of capital expenditures.

Keywords

Total factor productivity growth, infrastructure, operations and maintenance expenditures, spillovers, semiparametric estimation.

JEL classification: C14, E22, E62, H76, O11, O47, R11.

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1 Introduction

The productive role of public infrastructure investment in the U.S. economy has attracted considerable research over the past two decades.[1] Early literature (e.g. Aschauer, 1989; Munnell, 1990a,b) found very large returns, implying that a substantial part of the productivity slowdown of the 1970s and 1980s was due to a shortfall in infrastructure investment. Subsequent studies, based on state-level production functions, pointed out a number of econometric issues and changed the picture dramatically by concluding that total public infrastructure has an insignificant impact on output, a finding that has come to be known as the '*public capital productivity puzzle*' (Evans and Karras, 1994; Holtz-Eakin, 1994; Baltagi and Pinnoi, 1995; Garcia-Milà et al., 1996). Another strand of research has investigated the extent to which state infrastructure provides productivity benefits beyond the narrow confines of each state's borders (Holtz-Eakin and Schwartz, 1995; Boarnet, 1998; Boisso et al., 2000; Cohen and Paul, 2004; Pereira and Andraz, 2004; Sloboda and Yao, 2008). A state's output can be positively affected by other states' public infrastructure when benefits are diffused, for instance, through manufacturer-supplier networks, reduction of travel time and logistics costs.[2]

Even though the literature on the U.S. public infrastructure-productivity nexus is extensive, it has not accounted for the operation and maintenance (O&M) spending which is required for the repair and safe operation of the existing infrastructure stock. The nation-wide figures provided by the Congressional Budget Office (2010) report for public spending on transportation and water infrastructure over the period 1956-2007 show that *'a little more than half of total spending for such infrastructure has been used for operation and maintenance'*.[3] State and local governments (SLGs) account for close to 90% of O&M expenditures, while a significant share of capital expenditure by SLGs is financed by federal grants and loan subsidies (close to 50% before the mid-1980s and about one-third since then) according to the Congressional Budget Office (2007; 2010). Moreover, since the late 1970s real infrastructure spending by SLGs has been growing at a faster annual rate than the corresponding federal outlays and has accounted

[1] See Gramlich (1994), Sturm et al. (1998), and Romp and de Haan (2007) for literature surveys.

[2] Hulten and Schwab (1997, p.157) offer some typical examples: *'...an interstate highway in Illinois does offer some benefits to the residents of other states, a sewage treatment plant in Maryland that reduces water pollution in the Chesapeake Bay benefits people in a wide region'.* Note that the possibility of public capital having negative spillovers in the local area because economic activity may be drawn to the zone with the infrastructure investment and away from otherwise equivalent areas has also been theorized in the literature (see Boarnet, 1998).

[3] Transportation and water infrastructure has been typically considered in the public capital productivity literature following Munnell (1990b), with the main analyzed components including highways and streets, water and sewer facilities, and other buildings and structures.

for about 75% of total public sector spending on infrastructure. These stylized facts provide strong motivation for an empirical assessment of the productivity impact of O&M outlays by SLGs in addition to the widely-explored, traditional effect of capital spending.

The aim of the present study is to explore empirically the direct and spillover effects of O&M spending on total factor productivity (TFP) growth among the 48 contiguous U.S. states. We use a new state-level dataset for capital and O&M spending on water and transportation infrastructure, which we have assembled for the period 1978-2000 based on the Census Bureau's SLG Finances series. The budgetary nature of the dataset stands in contrast to the approach typically followed in the literature, which has mainly used (often controversial) estimates of public capital stocks, and allows us to pursue a topic left unexplored in previous studies, namely the assessment of the productivity impacts of O&M outlays and a comparison of them with the corresponding ones for capital spending. Our econometric analysis employs a semiparametric varying-coefficient specification, which offers observation-specific estimates of output elasticities, in line with recent developments in the literature that have emphasized the importance of parameter heterogeneity and nonlinearities in the growth process (see e.g. Masanjah and Papageorgiou, 2004; Henderson et al., 2012).

Our empirical findings indicate, first, that interstate spillovers are significantly positive and exceed within-state impacts for O&M (and capital) spending, implying that there is a substantial wedge between the aggregate and own-state rates of return. Second, the spillover effect of O&M spending is found to be much higher (up to eight times on average) than the corresponding impact of capital spending. These results remain highly robust when we take an alternative approach via local GMM estimation to address concerns about potential endogeneity. We further robustify inference through a battery of sensitivity tests, including an alternative measurement of the spillover variables.

Our paper is close in spirit to Henderson and Kumbhakar (2006), who attributed the *'public capital productivity puzzle'* to neglected nonlinearities in the production process and recovered statistically significant returns to public capital via a nonparametric approach, yet without considering the potential spillover effects of public spending.[4] Notably, there is only scant

[4]Earlier results by Fernald (1999) also underscored the existence of nonlinearities in the production function. In a similar vein, Aschauer (1999) found that, whereas linear estimates of production functions deliver an infrastructure effect that disappears when state effects are introduced, allowing for nonlinearity delivers robust effects. In addition, Duggal et al. (1999) specified a technological growth rate as a nonlinear function of infrastructure and demonstrated that the impact of infrastructure on the U.S. economy is not constant. More recently, Égert et al. (2009) used thresholds models in a Bayesian-averaging framework and found that the growth impact of infrastructure investment is highly nonlinear, varying across OECD countries and over time. Similarly,

evidence on the productive impact of public spending on capital maintenance. Kalaitzidakis and Kalyvitis (2005) used nation wide data from the Canadian 'Capital and Repair Expenditures' survey and found that Canada would benefit from a fall in total expenditure on both public capital and maintenance and that the aggregate share of maintenance in total expenditures should be lower. Other studies examining the role of O&M spending (e.g. Tanzi and Davoodi, 1997; Ghosh and Gregoriou, 2008) have confirmed that capital maintenance is an important determinant of growth, but have used only proxies due to the lack of reliable and consistent data. More recently, Kalyvitis and Vella (2011) have estimated, using the national-level data from the Congressional Budget Office (2007), a negative effect of federal infrastructure outlays on infrastructure and a positive one of state and local outlays (particularly O&M).[5] In none of these studies are the spillover effects of public capital maintenance taken into account. The present paper contributes to the literature by offering a state-level analysis of the productive impacts of public capital maintenance, which highlights the interregional productivity spillovers of O&M outlays among U.S. states, in comparison to the standard capital outlays employed in related literature.

Our finding that the interregional spillover effects of infrastructure expenditure can be higher than the direct ones may not seem so surprising given that the financing cost and the associated distortive consequences of taxation are borne by other states in this case. But how can one explain the differences in the magnitudes of the spillover effects between capital and O&M outlays? A possible explanation may be related to the lack of central intervention by the federal government in the case of O&M spending, since O&M is almost exclusively locally financed, while federal grants account for a significant share of state and local capital spending on infrastructure. The main conclusion thus is that failure to internalize the spillovers associated with O&M spending through central intervention may suggest an underprovision of it in the U.S. states during the period under investigation, since SLGs might be 'too small to think big enough', creating a collective action problem. Given the central importance of infrastructure spending in recent fiscal stimulus packages, like the American Recovery and Reinvestment Act of 2009, and the discussion on the potential efficacy, need for, and impact of a National

Colletaz and Hurlin (2008) found strong threshold effects in the relationship between output and public capital using a Panel-Smooth-Threshold model.

[5] Earlier evidence on the productivity impact of public capital maintenance in the U.S. comes mainly from case studies or cost-benefit analyses concentrated on highways. An exception is Pinnoi (1994), who provided production function estimates suggesting that state and local expenditures on highway maintenance are productive with respect to the private and non-agricultural non-manufacturing sectors. See Section 4 for more details on studies with data for highways.

Infrastructure Bank these results seem to have timely policy implications.

The rest of the paper is organized as follows. Section 2 outlines the methodology, Section 3 describes the data and Section 4 presents the estimation results along with a variety of robustness checks. Finally, Section 5 concludes the paper.

2 Methodology

In this section we sketch out the main elements of our empirical analysis, namely the theoretical basis with respect to the productive impact of public O&M spending, our empirical specification, and the estimation approaches taken.

2.1 Theoretical foundations of the productive impact of public O&M spending

While the rationale regarding the capital component is straightforward, since capital expenditure add new capacity to the existing infrastructure network, the channel through which O&M expenditures can contribute to private production deserves some comment. Public O&M spending serves two purposes: first, it counters depreciation (see e.g. Rioja, 2003; Kalaitzidakis and Kalyvitis, 2004; Dioikitopoulos and Kalyvitis, 2008; Agénor, 2009); second, it affects the service flow of the existing stock and in a production function should be multiplied by the service flow of the existing stock to get an effective service flow (in the same way that electricity expenditures can be entered multiplicatively with capital to proxy for utilization).

In what follows, we relate both types of infrastructure expenditure to productivity rather than the infrastructure capital stock as is usually done in the literature. This approach is taken here for two reasons. First, conventional estimates of infrastructure stocks are based on constant depreciation schemes, i.e. unrelated to maintenance spending, which neglect the strand of literature mentioned above. Second, our main purpose is to disentangle the productive impacts of the two types of infrastructure outlays on a comparative basis, which would not be possible using measures of public capital stocks instead of flows. Our empirical setup therefore relies on Barro (1990)-style models with government spending as an input to the production process. Devarajan et al. (1996) further specified two types of government spending - one more productive than the other - as production inputs and, in a similar spirit, Pinnoi (1994) in his empirical study separated the effect of services from highways and streets in the production function into capital and maintenance outlays. More recently, Hashimzade and Myles (2010) have developed a multi-country extension of the Barro model of productive public expenditure to account for the presence of infrastructural externalities between countries in the production function.

2.2 The empirical model

We work in a standard growth-accounting framework by assuming a general production function with the following inputs: capital, K, labor, L, own-state capital and O&M spending, G and M, and capital and O&M spending by other states, S_G and S_M:

$$Y = F\left(K,\ L,\ G,\ M,\ S_G,\ S_M,\ t\right) \tag{1}$$

where t is a time trend generally interpreted in this literature as an exogenous technology index and S_G and S_M form transboundary spillover indices.[6]

More specifically, we assume that states $N = \{1, 2, ..., n\}$ belong to a network. Let ϕ_{ij} be a relationship between two states i and j. The interpretation of such links may be attributed, for instance, to trade between them. It is assumed first, that $\phi_{ij} > 0$ if there is a link from node j to node i and $\phi_{ij} = 0$ otherwise, second, that $\phi_{ij} \neq \phi_{ij}$, and third, that $\phi_{ii} = 0$ (directed and weighted network). This notation allows us to represent the network with an adjacency matrix, Φ, of which the $ij - th$ entry is ϕ_{ij} and the main diagonal contains zeros.[7] The two spatial externality variables are then defined by a summary statistic of the capital and O&M spending of a state's neighbors in the network, i.e. the aggregate measures of outlays of all neighboring states linked to region i:

$$S_{Git} \equiv \sum_{j=1}^{N} \phi_{ij} \frac{Y_{it}}{Y_{jt}} G_{jt} \tag{2}$$

$$S_{Mit} \equiv \sum_{j=1}^{N} \phi_{ij} \frac{Y_{it}}{Y_{jt}} M_{jt} \tag{3}$$

The presence of the output multiplicative factor in (2)-(3) is justified by the fact that a state j with a high level of economic activity presumably constitutes overly large portions of the

[6] Holtz-Eakin and Schwartz (1995) and Sloboda and Yao (2008) have included spillover variables in production functions, while Cohen and Paul (2004) have included a similar spillover index of highway stocks as an input to a cost function. In a different context, the literature that views innovation efforts as a major source of technological progress has extensively studied the effects of international R&D spillovers on productivity growth (see e.g. the seminal paper by Coe and Helpman, 1995).

[7] If the network is undirected, then the matrix Φ is symmetric ($\phi_{ij} = \phi_{ij}$). If the network is unweighted, then $\phi_{ij} = 1$ if there is a link between nodes i and j. As described in the next section, we proxy ϕ_{ij} with data on commodity flows across states to account for different degrees of interstate dependence.

spillovers, S_{Git} and S_{Mit}, for a small state i. Thus, by multiplying region $j\prime s$ spending by the ratio of state $i\prime s$ output to its own output, which is a relatively small number, the size effects in the measures of S_G and S_M are neutralized (see Cohen and Paul, 2004).

Differentiating (1) with respect to time, dividing by Y, and rearranging terms yields:

$$\frac{\dot{Y}}{Y} - \theta_K \frac{\dot{K}}{K} - \theta_L \frac{\dot{L}}{L} = \frac{\dot{A}}{A} + \theta_G \frac{\dot{G}}{G} + \theta_M \frac{\dot{M}}{M} + \theta_{S_G} \frac{\dot{S}_G}{S_G} + \theta_{S_M} \frac{\dot{S}_M}{S_M} \tag{4}$$

where the $\theta's$ correspond to output elasticities and $\frac{\dot{A}}{A}$ is the exogenous rate of technological progress.

Next, we define a Törnqvist index of TFP growth, based on the private factors, K and L, to discretely approximate the left-hand side of (1). According to the definition of this index, the growth rates are equal to the difference in the natural logarithms of successive observations of the components and the weights are equal to the mean of the factor shares of the components in the corresponding pair of years:

$$g_{TFP_{it}} \equiv \Delta \ln Y_{it} - \bar{s}_{YK_{it}} \Delta \ln K_{it} - \bar{s}_{YL_{it}} \Delta \ln L_{it} \tag{5}$$

where $\bar{s}_{YQ_{it}} \equiv 0.5 \left(s_{YQ_{it}} + s_{YQ_{it-1}} \right)$ for $Q = K, L$ and $i = 1, ..., N$ denotes the state and $t = 1, ..., T$ denotes the year, given that the output elasticities of capital and labor equal the observed income shares, s_{YK} and s_{YL}, in a perfectly competitive environment.

In order to account for the potential impact of the relative size of the two spending components, in the right-hand side of (1) we model the unobserved contributions of capital and O&M expenditures as unknown functions of the O&M share in total own-state spending ('O&M share' henceforth), i.e. $\theta_G(Z)$, $\theta_M(Z)$, $\theta_{S_G}(Z)$, $\theta_{S_M}(Z)$, where $Z \equiv \frac{M}{G+M}$. Given that capital and O&M outlays are imperfect substitutes, the 'O&M share' is expected to have a nonlinear relationship with growth (see Figure 1 in Kalaitzidakis and Kalyvitis, 2005), and is therefore treated here as a source of potential parameter heterogeneity. This approach will also allow us to evalute how the output elasticities of infrastructure outlays change when the composition between capital and O&M expenditures is altered and to investigate which range of the existing 'O&M shares' among states is associated with the highest elasticities.

Combining all the above, yields our estimated equation:

$$\begin{aligned} g_{TFP_{it}} &= \underbrace{\alpha_0 + \sum_{i=1}^{N-1} \alpha_i D_i + bt}_{linear\ part} + \theta_G \left(Z_{it}\right) \Delta \ln G_{it} + \theta_M \left(Z_{it}\right) \Delta \ln M_{it} \\ &\quad + \theta_{S_G} \left(Z_{it}\right) \Delta \ln S_{G_{it}} + \theta_{S_M} \left(Z_{it}\right) \Delta \ln S_{M_{it}} + u_{it} \end{aligned} \tag{6}$$

where the exogenous rate of technological progress is modelled as a function of state-specific dummy variables, D_i, and a time trend, capturing respectively idiosyncratic and time-related exogenous shifts in technology. Equation (6) allows the growth of both own-state and other states' spending on infrastructure capital and O&M to influence TFP growth nonlinearly by introducing heterogeneity in the marginal effects.[8]

2.3 Estimation approach

The estimation approach we follow is based on the semiparametric smooth-coefficient model (SSCM henceforth) proposed by Li et al. (2002) as a flexible specification for studying a general regression relationship with varying coefficients (see e.g. Fan and Zhang, 1999; Cai et al., 2000a,b). The SSCM lets the marginal effect of the variable(s) of interest be an unknown function of an observable covariate and hence introduces parameter heterogeneity. This specification traces nonlinearities in the estimated relationships, offering the advantage of more flexibility in functional form than parametric counterparts, as the coefficient functions are unspecified. Furthermore, by allowing coefficients to depend on other variables it does not suffer from the 'curse of dimensionality' problem to the extent of a purely nonparametric specification, which also typically requires larger sample sizes. Li et al. (2002) illustrated the application of the SSCM by estimating the production function of the nonmetal-mineral-manufacturing industry in China. More recent applications include e.g. Chou et al. (2004), Stengos and Zacharias (2006), and Jansen et al. (2008).

Due to the presence of the linear part, (6) forms a partially linear varying-coefficient specification, in which the growth of both own-state and other states' spending on infrastructure

[8]Notice that defining TFP based on the private factors (the well-known Solow residual) and relating it to government services, which dates back to Aschauer (1989) and Hulten and Schwab (1991), allows us here to obtain a more parsimonious - in terms of number of parameters - specification than in the case of the corresponding production function. Note also that in our model we include government capital and O&M spending as additional production inputs, which implies that g_{TFP} represents a biased index of technological change that will be affected by changes in the growth rates of G, M, S_G, S_M. Cost-function specifications have also been used in the literature, but in a limited number of studies, since historical price data is typically available only for manufacturing firms.

capital and O&M is allowed to influence TFP growth nonlinearly by introducing heterogeneity in the marginal effects. We employ a standard kernel density estimator with Gaussian kernel and choose the bandwidth using cross validation. The three-step process we follow is described in detail in the Appendix (see also Chou et al., 2004).

One issue of concern that may arise when estimating (6) is related to the presence of the spillover variables. Specifically, if each state government knows that the expenditures of other states can matter for their own productivity, then one might expect that these productivity spillovers can induce strategic interactions ('budget spillovers') among localities (see e.g. Case et al., 1993; Baicker, 2005), which would lead to endogeneity problems in the estimation. To overcome this hazard, we also augment the analysis with local generalized method of moments (LGMM) estimation, proposed in a dynamic panel data context by Tran and Tsionas (2010). LGMM can be considered an extension to the Li et al. (2002) model by allowing for some or all the regressors to be correlated with the error term and for the possibility that the latter is serially correlated.[9] Following the literature discussing the choice of optimal instruments in the context of semiparametric panel data models (see Baltagi and Li, 2002; Tran and Tsionas, 2010), we use the density-weighted kernel estimates of { $E(g_{TFP_{it-1}} \mid Z_{it-1})$, $E(g_{TFP_{it-2}} \mid Z_{it-2})$, $E(\Delta \ln G_{it} \mid Z_{it})$, $E\Delta \ln G_{it-1} \mid Z_{it-1})$, $E(\Delta \ln M_{it} \mid Z_{it})$, $E(\Delta \ln M_{it-1} \mid Z_{it-1})$, $(\Delta \ln S_{G_{it}} \mid Z_{it})$, $E(\Delta \ln S_{G_{it-1}} \mid Z_{it-1})$, $E(\Delta \ln S_{M_{it}} \mid Z_{it})$, $E(\Delta \ln S_{M_{it-1}} \mid Z_{it-1})$} as instruments for {$g_{TFP_{it-1}}$, $\Delta \ln G_{it}$, $\Delta \ln M_{it}$, $\Delta \ln S_{G_{it}}$, $\Delta \ln S_{M_{it}}$}, given that the 'O&M share', Z_{it}, should mainly be related to factors such as the age of the infrastructure stock, demographic trends, weather conditions, natural events, and geography, which are viewed as exogenous. Furthermore, to mitigate the effects of possible cross-sectional dependence we transform all the individual series of the data into deviations from their cross-section means at each point in time t, which is a standard procedure for samples with relatively small time dimension.[10]

[9] By including the lagged dependent variable as a regressor this specification also accounts for the dynamic nature of TFP growth. Note that we have investigated the possibility of serial correlation in our baseline estimation, but the corresponding coefficient did not turn out to be statistically significant.

[10] Spatial econometrics (see e.g. Anselin, 1988) have been widely employed in the literature to deal with spatial interactions. However, given the complexity of nonparametric estimation methods, spatial approaches have only been used in this framework to a very limited extent so far.

3 Data

Our sample covers the 48 contiguous U.S. states over the period 1978-2000, with a total of 1104 observations.[11] A brief description of the data (measured in millions of 2000 U.S. dollars) follows; further details about the data sources and the method of construction of all the variables used in the estimations are provided in the Data Appendix.

We obtain data on SLG expenditures from the 'Rex-Dac' database, which is an internal file of the U.S. Census Bureau. This database is an archive of nearly all the data collected in the periodic censuses of governments and annual surveys of government finances since 1977 (plus 1972).[12] Following the classification in the Congressional Budget Office (2010) report, for O&M and capital expenditures on water and transportation infrastructure, M and G, we consider data on 'current operations' and 'capital outlay' respectively, for the following five infrastructure types: aviation, highways and roads, mass transit, water supply and wastewater treatment, and water transportation, which also cover the core sectors of public infrastructure routinely used in related literature. 'Current operations' comprises direct expenditure for the retribution of officers/employees and for supplies, materials, and contractual services, apart from any amounts for capital outlay. It also includes repair and maintenance services to maintain required standards of compliance for the intended use. 'Capital outlays', on the other hand, are costs associated with: (i) construction, i.e. production, additions, replacements, or major structural alterations to fixed works, by contract or government employees (ii) purchase of land, existing structures, and equipment. Capital expenditures include purchases of new assets as well as major improvements/alterations to existing assets.[13]

Spillover variables for each state, S_G and S_M, are constructed as weighted sums of capital and O&M spending in other states given by (2) and (3). Different states are weighted, first, by commodity flows across states to reflect different degrees of interstate dependence and, second, by information on the relative sizes of state-level economic activity.[14] This weighting scheme

[11] In line with the literature, Alaska, Hawaii, and the District of Columbia are excluded from the sample.

[12] The database of 1,300 finance items is spread across eight data tables. Data become available annually from 1977 onwards, while there are no state-level statistics available for local governments (i.e. counties, municipalities, townships, special districts and school districts) for 2001 and 2003, because the corresponding surveys were redesigned to provide only national estimates. This restricts our sample to the period 1978-2000.

[13] For a detailed description of what exactly constitutes the two main spending categories, see U.S. Census Bureau, *Government Finance and Employment Classification Manual*, Table 5.1: 'Description of Character and Object Categories' (source: http://www2.census.gov/govs/pubs/classification/2006_classification_manual.pdf). For a definition of each type of infrastructure, see Appendix B of Congressional Budget Office (2010).

[14] Because no corresponding time series is available for the commodity flows data, we use an average of the data for 1993 and 1997, which also eliminates potential endogeneity concerns. This approach was first used by Cohen and Paul (2004) to approximate network effects of highway infrastructure and was subsequently followed

is justified by the fact that a state with a high level of economic activity, such as New York, presumably constitutes large portions of S_G and S_M for a relatively small state, such as Rhode Island. Thus, by multiplying New York's infrastructure spending by the ratio of Rhode Island's gross state product to its own gross state product, which is a relatively small number, the size effects in the construction of S_G and S_M for Rhode Island are neutralized. The weight that each state j has on state i in S_G and S_M is proxied by the share of the value of goods shipped from state i to state j, α_{ij}, in the total value of goods shipped from state i to all other states, $\sum_{i \neq j} \alpha_{ij}$, i.e. $\phi_{ij} \equiv \alpha_{ij} / \sum_{i \neq j} \alpha_{ij}$. The above weighting strategy aims to capture the different degrees of economic ties and geographic connections between states by avoiding the oversimplifying assumption that each dollar spent by other states has equal interregional spillover effects on any targeted state.[15]

Finally, to construct the state-by-year TFP index we use data on output, capital and labor for the private non-farm sector. Output, Y, is defined as the real GDP, and labor, L, is defined as the total number of workers. Estimates of state-level capital stocks, K, are from Garofalo and Yamarik (2002).

Table A1 presents data averages by state for the TFP-growth index (our dependent variable) and for the regressors used in the estimations. On average TFP increased over the 1978-2000 period in all states. Connecticut and Massachusetts experienced the largest productivity growth rates of about 1.8% and 1.7% respectively, while, at the opposite end of the scale, the productivity-growth rate for Montana was close to zero. Between 1978 and 2000 capital spending grew positively in most states at a mean rate of 1.8%. For nine states (IL, LA, ME, MD, MT, NH, ND, VT, and WV) the average growth rates of capital expenditure were negative. In contrast, O&M spending grew positively in all the states at a mean rate of around 2.9%. Table A1 also reports the average level of the 'O&M share', which shows considerable variability across states, ranging from 35% (WY) to 65% (MI), and exhibits the highest standard deviation (6.25%) of all the variables used in our baseline specification.

in part by Sloboda and Yao (2008). We test below the sensitivity of our results to the use of these weights by employing an alternative computation of the spillover variables, which maintains only the information on the relative economic activity in the weighting procedure. Further, we show that our results hold for a sample of highway data since this weighting scheme was first applied in the case of highways.

[15] Preliminary estimations were performed simply using equal weights in the construction of S_G and S_M. The output elasticities of own-spending were found to be positive, but small (amounting on average to 0.010 and 0.006 for G and M, respectively), while the output elasticities of spending by other states were found to be negative (amounting on average to -0.011 and -0.082 for S_G and S_M). However, we believe these initial estimates, which differ substantially from the results reported below, can be very misleading as they fail to account for the different degrees of economic and geographic interrelations between states.

4 Estimation results

In this section, we present our empirical findings for the semiparametric model outlined in Section 2 by focusing on the output elasticities estimated with respect to own-state capital and O&M outlays, as well as capital and O&M outlays by other states, $\theta_G(\cdot)$, $\theta_M(\cdot)$, $\theta_{S_G}(\cdot)$, $\theta_{S_M}(\cdot)$, respectively. We also perform a variety of checks to address potential concerns about the robustness of our results.

4.1 Main findings

As a benchmark, we initially estimate the model treating the θ's as constants, i.e. by assuming that the estimated relationships are linear. The first column of Table 1 gives the results from a specification that does not account for spillover effects. As can be readily seen, we obtain statistically insignificant estimates for the output elasticities of both capital and O&M outlays on public infrastructure. This result is in line with the existing literature on the 'public capital productivity puzzle' in the U.S., which has stated that once either state or both state and time effects are controlled for, the resulting estimates of the marginal productivity of public capital are not significantly different from zero (see, among others, Holtz-Eakin, 1994; Baltagi and Pinnoi, 1995; Garcia-Milà et al., 1996). In the second column of Table 1, we run a similar linear regression but accounting for spillover effects. We again obtain insignificant estimates for both intrastate effects, whereas the coefficients for the corresponding cross-state spillover effects turn out to be positive and statistically significant.

Given that neglected nonlinearities can be important in assessing the productive impact of public infrastructure (e.g. Henderson and Kumbhakar, 2006), we next proceed to semiparametric estimation of (6). The estimated coefficients are observation-specific, meaning that output elasticities with respect to capital and O&M spending are derived for each state and time period. We depict the semiparametric smooth coefficients along with the upper and lower limit of the 95% bootstrap confidence interval in Figure 1. For comparison purposes, we also plot the estimated parameters from the parametric linear specification (depicted by the dashed lines). The effects from the semiparametric regression are estimated conditional upon the 'O&M share' and the graphs clearly suggest that the functions are non-constant in the range of the state variable, exhibiting non-linear patterns.[16]

[16] We have also estimated the model parametrically by specifying the varying coefficients as a second-degree polynomial of Z_{it} (based on the graphs). The coefficients on the quadratic terms turned out to be statistically

In detail, the upper diagrams of Figure 1 plot pointwise estimates of the output elasticities with respect to states' own capital and O&M outlays, $\theta_G(Z_{it})$ and $\theta_M(Z_{it})$ respectively. Both graphs indicate that the estimated elasticities are positive for a range of medium-to-high (exceeding 50%) levels of the 'O&M share' and are maximized when the 'O&M share' is around 55%-60%. The general picture seems to point towards the existence of 'output elasticity hills' for intrastate infrastructure outlays, in line with the nonlinearities and the 'growth hills' for US state expenditures found by Bania et al. (2007) based on Barro-style models. The lower diagrams of Figure 1 similarly plot output elasticities with respect to capital and O&M outlays by other states, $\theta_{S_G}(Z_{it})$ and $\theta_{S_M}(Z_{it})$ respectively, and show that both cross-state spillover effects are positive for all sample points. In addition, the plotted results indicate that $\theta_{S_G}(Z_{it})$ and $\theta_{S_M}(Z_{it})$ initially decline and then start to increase above a certain level of the 'O&M share', with these convex relationships implying that for low and high levels of the 'O&M share' the productivity spillover effects are relatively higher. Overall, the graphic analysis suggests that for medium levels of the 'O&M share' within-state effects appear positive and cross-state spillover impacts take their lowest values, while for lower/higher levels of the 'O&M share' within-state effects are negative and spillover effects take their highest values. This evidence seems to imply substitutability between own-state infrastructure outlays and other states' outlays.

To examine the effects by state, we calculate the average output elasticities for each state, along with the corresponding standard errors. The results are reported in Table 2, in which states are grouped into broad census regions to allow for a comparative regional analysis. The state-specific estimates indicate that the elasticities of own-state O&M spending lie between -0.027 (NE) and 0.0004 (NY), whereas the corresponding elasticities of capital spending range between -0.022 (WY) and 0.0034 (IN). Figure 2 offers the corresponding geographical representation. Darker colors on the maps represent larger values for the estimated elasticities. Higher intrastate effects of public infrastructure spending are found mostly in the states located in the Midwest and Northeast (e.g. IN, OH, NY). This is in line with the finding in the public infrastructure literature that productivity effects are larger in the 'snowbelt' states (see e.g. Hulten and Schwab, 1991; Aschauer, 2001). On the other hand, interstate spillover effects are more pronounced in the 'sunbelt' states and, in particular, in the West and South (e.g. CA, GA, NM, TX), which generally consist of more agricultural and sparsely populated regions.

significant for θ_G, θ_{S_G} and θ_{S_M}, with t-statistics -1.89, 2.50 and 2.30, respectively, which indicates that the use of the SSCM is justified.

The general picture is summarized by the means of the observation-specific elasticities, which are statistical significant and amount to -0.017 and -0.002 for O&M and capital expenditures, respectively, implying that, ceteris paribus, a 1% increase in O&M (capital) spending corresponds, on average, to a 0.017% (0.002%) fall in output.[17] In contrast, the output elasticities of other states' expenditures are much greater in magnitude, ranging from 0.37 (MO) to 0.46 (MI) for O&M spending, and are always statistically significant. The corresponding effects of capital spending are also positive and statistically significant, but are much lower in magnitude ranging from 0.033 (OH) to 0.095 (WY). Our estimates imply that a 1% increase in O&M (capital) spending by other states corresponds, on average, to a 0.39% (0.046%) increase in output.

Furthermore, in Table 3 we present the results from a LGMM estimation with cross-sectionally demeaned data, which accounts for the possibility of strategic interactions among local governments that would lead to endogeneity problems in our regression. We find that the estimated magnitudes are very close to our baseline estimation: intrastate effects turn out to be small (-0.0008 and 0.0095 for capital and O&M, on average), while spillover effects are much larger (0.087 and 0.337 for capital and O&M, respectively). Since the two approaches yield very similar results, we feel confident that our baseline specification does not suffer from endogeneity bias and so in the rest of the empirical analysis we will focus on the baseline approach.

In sum, two broad conclusions can be drawn from the empirical findings presented in this section. First, productivity spillovers of O&M (and capital) outlays by other states are significantly positive and exceed the corresponding impacts of within-state outlays. Second, the spillover effect of O&M spending, for which no previous comparable estimates exist in the literature, is found to be much higher (on average up to eight times) than the corresponding spillover impact of capital spending.

Our results for the low (and in some cases negative) intrastate effects of infrastructure expenditures may naturally raise the question of why state governments commit to these expenditures, which is not new, though, in the 'public capital productivity puzzle' literature. From a fiscal federalism perspective, a possible explanation might be that a large proportion of these expenditures on infrastructure are financed by the federal government through matching grants and loan subsidies to states and localities. As mentioned in the Introduction, the

[17] Negative estimates for the productivity effect of public capital have been previously reported in the literature (see e.g. Evans and Karras, 1994; Holtz-Eakin and Schwartz, 1995). In addition, Pinnoi (1994) estimated negative output elasticities with respect to highway capital outlay and maintenance for some sectors of economic activity and U.S. regions. Positive, but small, mean effects (0.006 and 0.009 for capital and O&M, respectively) were estimated without including the spillover variables. The detailed results by state are presented in the Appendix.

nation wide data available show that this share ranged between 30% and 50% over the period considered. But how can one explain the particularly high estimates for the impact of the O&M spillover? A key factor might be associated with the fact that O&M is almost exclusively locally financed. As a result, a given state can enjoy the productivity gains from the better maintained infrastructure network in the neighboring states without participating in the cost, which is not the case for capital spending co-financed through federal grants from local contributions. Hashimzade and Myles (2010) show theoretically that in the presence of positive infrastructure externalities among economies the provision of infrastructure will be inefficiently low unless there is intervention by a supranational body to coordinate policies of the individual governments by internalizing the externality. In our context, the lack of intervention by the central government to share the cost of local maintenance policies may therefore suggest the possibility of under-provision.

4.2 Sensitivity analysis

To assess the robustness of our main findings, we perform a battery of sensitivity tests. First, we attempt to control for the influence of other variables that may affect state productivity growth (see Reed, 2009) to ensure that our results do not suffer from omitted-variables bias. We therefore include in the linear part of (6) the state unemployment rate to account for cyclical effects, as well as the following public-sector variables: 'federal employees' (defined as the log of federal employees per capita), 'S&L employees' (defined as the log of state and local employees per capita), 'federal revenue' (defined as the intergovernmental revenue received by SLGs from the federal government as a share of personal income) and 'tax burden' (defined as total state and local tax revenues as a share of personal income). Additionally, we control for various characteristics of the population with the following variables: 'working population' (defined as the percentage of the population between 20 and 64 years of age), 'non-white' (defined as the percentage of population that is non-white) and 'female' (defined as the percentage of the population that is female). The estimation results, reported in column (2) of Table 4, show no significant change in the average coefficients. Moreover, the coefficients on the additional controls generally have the expected signs, with those on 'working population', 'federal employees', 'S&L employees', and 'federal revenue' being statistically significant.[18]

[18] A correlation matrix of the additional controls is available upon request. Data are obtained from the Census Bureau's 'Rex-Dac' database for all public-sector variables, from the Bureau of Labor Statistics, Local Area Unemployment Statistics for the state-level unemployment rate, and from Pjesky (2006) for the population

Another robustness check is then to use a more general coefficient function that includes a second state variable, namely the share of other states' O&M spending in the sum of the two spillover indices, $\frac{S_M}{S_G+S_M}$. The average coefficients presented in column (3) of Table 4, remain practically unchanged.

Further, we drop the commodity flow weights in the computation of the spillover variables and keep only the information on relative economic activity to investigate whether our results are driven by the use of these weights. The estimation results, reported in column (4), demonstrate that the estimates obtained are again not substantially different from our baseline findings (reported in column (1)).

Finally, we run the regression for a subsample consisting of highway-spending data. We focus on highways and roads for two reasons. First, they form the largest component of transportation infrastructure, which is believed to make the economy more efficient by reducing the amount of time and energy necessary to cover distances between firms, consumers, and employees. Given their network characteristics, they have so far dominated the literature investigating the spillover effects question in the context of public infrastructure (e.g. Holtz-Eakin and Schwartz, 1995; Boarnet; 1998; Cohen and Paul, 2004). Second, some cost-benefit studies have emphasized the productive impacts of maintenance expenditures on highways, yet without taking into account their spillover effects.[19] To assess the significance of our results for O&M spending on highways we report in column (5) of Table 4 the estimates obtained by running the regression for highways and streets. Our main findings continue to hold, with the output elasticity of O&M spending by other states being somewhat lower but still considerably higher than the corresponding effect of capital spending.

5 Concluding remarks

Based on a novel set of data for the 48 contiguous U.S. states over the period 1978-2000, this paper has aimed to disentangle the productivity impacts of capital and O&M spending on

characteristics, available until 1999. We have also experimented with other control variables, like the size of the population and the degree of expenditure decentralization, but they did not turn out to be statistically significant. Finally, using the shares of total earnings earned in federal, state and local governments instead of the number of federal, state and local employees produced essentially the same results.

[19]For instance, the Congressional Budget Office (1988) has indicated that the return to projects designed to maintain the average condition of the federal highway system could be as high as 30%-40%. In a similar vein, there has been some evidence, based on data from the Federal Highway Administration, suggesting that beyond a certain point maintenance and management of existing infrastructure become more attractive than investment in additional capacity; for instance, road-resurfacing projects have cost-benefit ratios that are nearly double compared with projects that add new lanes (Congressional Budget Office, 1998).

public infrastructure by explicitly accounting for cross-state spillover effects. To this end, we have used a semiparametric smooth-coefficient approach to account for potential nonlinearities and parameter heterogeneity. Our findings have documented that interstate spillover impacts are significantly positive and exceed direct impacts for both types of spending. Importantly, the cross-state spillover effect of O&M outlays was estimated to be considerably high. These results were found to be robust to a battery of sensitivity tests, including for the endogeneity of public spending.

By answering some empirical questions unresolved up to now, this study has opened the door to new research issues. For instance, the paper has highlighted the lack of intervention by the federal government in the case of O&M spending as a potential key factor associated with its under-provision in the presence of infrastructural externalities among states. In this vein, the paper has not investigated politico-economic factors that shape infrastructure policy (see e.g. Kemmerling and Stephan, 2002; Cadot et al., 2006). Further work in this area could therefore look into political factors as determinants of state and local infrastructure spending, and of its allocation between capital and O&M. Second, in the presence of the positive productivity spillover effects found here, a natural question that arises is whether states respond to increased capital and O&M spending in neighboring states by decreasing their own outlays ('budget spillovers') or engage in expenditure competition to attract new economic activity (see e.g. Taylor, 1992). We leave these topics for future research.

A Data Appendix

Capital and O&M spending on public infrastructure: To construct capital spending data on water and transportation infrastructure at the state level, we used the following series from the 'Rex-Dac' database: 'Air Trans-Cap Outlay' from Table Rex 2 for aviation, 'Total Highways-Cap Out' from Table Rex 3 for highways and roads, 'Sewerage-Cap Outlay' and 'Water Util-Cap Outlay' from Table Rex 5 for water supply and wastewater treatment, 'Water Trans-Cap Outlay' from Table Rex 5 for water transportation, and 'Transit Util-Cap Outlay' from Table Rex 5 for mass transit. Similarly, to construct O&M spending data on water and transportation infrastructure we used the following series: 'Air Trans-Current Oper (E01)', 'Total Highways-Cur Op', 'Sewerage-Current Oper (E80)', 'Water Util-Cur Oper (E91)', 'Water Trans-Cur Oper (E87)', and 'Transit Util-Cur Oper (E94)'. The estimates for G and M were obtained by summing the respective expenditure amounts over the above infrastructure components. Data series were adusted to express spending in real (or constant) dollars.

Spillovers of capital and O&M spending on public infrastructure: The data on the value of goods shipped from state of origin to state of destination, used for constructing the relevant weights, come from the 1993 and 1997 Commodity Flows Surveys, U.S. Bureau of Transportation Statistics.

Output: Real GDP by state for the private non-farm sector comes from the BEA. The series was discontinued in 1997 due to the industry classification system change from SIC (Standard Industrial Classification) to NAICS (North American Industry Classification System). To calculate output growth rates, we exploited both versions of the data for 1997 to be consistent with industry definitions.

Labor: Private non-farm employment as a measure of labor was obtained from the BEA.

Income shares of labor and capital: Labor income shares, s_{YL}, were calculated at the U.S. state level following the procedure proposed by Gollin (2002). First, the wage and salary income of employees was imputed as labor income. Then the average labor income of employees was calculated and the same average labor income was imputed to the self-employed. The sum of the measured labor income of employees and the imputed labor income of the self-employed was used as a measure of total labor income. Dividing total labor income by total income provided an estimate of the labor income share at the state level. State-level data on total income, employees' wages, and the income of the self-employed for the private non-farm business sector are available from the BEA. Given the labor share, the share of capital, s_{YK}, was then determined residually as $1 - s_{YL}$.

B Appendix: Semiparametric smooth coefficient model

Our estimated equation can be written more concisely as:

$$g_{TFP,it} = W_{it}'\alpha + X_{it}'\beta\left(Z_{it}\right) + u_{it} \tag{A1}$$

where $W_{it} \equiv (1, D_i, t)'$, $\alpha \equiv (\alpha_0, \alpha_i, b)'$, $X_{it}' \equiv (\Delta \ln G_{it},\ \Delta \ln M_{it},\ \Delta \ln S_{G,it},\ \Delta \ln S_{M,it})$, $\beta\left(Z_{it}\right) \equiv \left(\theta_G\left(Z_{it}\right), \theta_M\left(Z_{it}\right), \theta_{S_G}\left(Z_{it}\right), \theta_{S_M}\left(Z_{it}\right)\right)'$, and u_{it} satisfies $E\left(u_{it} \mid W_{it}, X_{it}, Z_{it}\right) = 0$.

For the estimation we follow a three-step process (see also Chou et al., 2004). In the first step, all coefficients are assumed to be smoothing functions of Z_{it} and are estimated by applying a local least-squares method with a kernel weight function:

$$\begin{pmatrix} \hat{\alpha}(Z_{it}) \\ \hat{\beta}(Z_{it}) \end{pmatrix} = \left[\sum_{s=1}^{n} XW_s XW_s' k\left(\frac{Z_{it} - Z_s}{h}\right)\right]^{-1} \sum_{s=1}^{n} XW\left(g_{TFPs}\right) k\left(\frac{Z_{it} - Z_s}{h}\right) \tag{A2}$$

where $XW_s \equiv (W_s, X_s)'$, $k(.)$ is a kernel function and h is the smoothing parameter (bandwidth). We use a standard normal (Gaussian) kernel $k(u) = e^{-u^2/2}/\sqrt{2\pi}$ and choose the bandwidth via cross validation. Unlike (A1), the estimator $\hat{\alpha}(Z_{it})$ in (A2) depends on Z_{it} in the first step, ignoring the fact that α is a vector of constant coefficients. Subtracting $X_{it}'\hat{\beta}(Z_{it})$ from both sides of (A1) yields:

$$g_{TFP_{it}} - X_{it}'\hat{\beta}(Z_{it}) = W_{it}'\alpha + X_{it}'\left(\beta(Z_{it}) - \hat{\beta}(Z_{it})\right) + u_{it} \equiv W_{it}'\alpha + \varepsilon_{it} \tag{A3}$$

where $\varepsilon_{it} \equiv X_{it}'\left(\beta(Z_{it}) - \hat{\beta}(Z_{it})\right) + u_{it}$. The next stage is to run a least-squares regression of (A3):

$$\hat{\alpha} = \left(\sum_{it=1}^{n} W_{it} W_{it}'\right)^{-1} \sum_{it=1}^{n} W_{it}\left(g_{TFP_{it}} - X_{it}'\hat{\beta}(Z_{it})\right) \tag{A4}$$

The final step is to use the second-stage linear part estimates, $\hat{\alpha}$, to redefine the dependent variable in (A1), and return to the simple smooth-coefficient environment of Li et al. (2002). Subtracting $W_{it}'\hat{\alpha}$ from both sides of (A1), we get:

$$g_{TFP_{it}} - W_{it}'\hat{\alpha} = W_{it}'\left(\alpha - \hat{\alpha}\right) + X_{it}'\beta(Z_{it}) + u_{it} \equiv X_{it}'\beta(Z_{it}) + \nu_{it} \tag{A5}$$

where $\nu_{it} \equiv W'_{it}(\alpha - \hat{\alpha}) + u_{it}$. The smooth-coefficient functions can then be estimated, as proposed by Li et al. (2002), using a local least-squares method similar to the first step:

$$\hat{\beta}(Z_{it}) = \left[\sum_{s=1}^{n} X_s X_s' k\left(\frac{Z_{it} - Z_s}{h}\right)\right]^{-1} \sum_{s=1}^{n} X_s \left(g_{TFPs} - W_s'\hat{\alpha}\right) k\left(\frac{Z_{it} - Z_s}{h}\right) \tag{A6}$$

For details on the consistency and asymptotic normality of $\hat{\beta}(Z_{it})$, see also Li and Racine (2007).

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Table 1. Parameter estimates of the linear model

Independent variable	without spillovers	with spillovers
year trend	0.0005	0.0007
	(0.0001)	(0.0001)
growth of capital spending ($\Delta \ln G$)	0.005	-0.004
	(0.004)	(0.005)
growth of O&M spending ($\Delta \ln M$)	0.008	-0.016
	(0.009)	(0.011)
growth of capital spillover ($\Delta \ln S_G$)	-	0.052
		(0.012)
growth of O&M spillover ($\Delta \ln S_M$)	-	0.411
		(0.035)
R^2	0.047	0.436
No. of observations	1104	1104

Notes: Estimation method is OLS and standard errors are reported in parentheses. The dependent variable is TFP growth and regressions include a constant, a time trend and state dummies.

Table 2. Average output elasticities by state, 1978-2000 (semiparametric estimates)

State	$\theta_G(Z_{it})$	$\theta_M(Z_{it})$	$\theta_{S_G}(Z_{it})$	$\theta_{S_M}(Z_{it})$	State	$\theta_G(Z_{it})$	$\theta_M(Z_{it})$	$\theta_{S_G}(Z_{it})$	$\theta_{S_M}(Z_{it})$
NORTHEAST					Virginia	0.0010	-0.012	0.037	0.376
					(VA)	(0.001)	(0.003)	(0.002)	(0.002)
Maine	0.0009	-0.007	0.046	0.409	West Virginia	-0.0029	-0.014	0.046	0.385
(ME)	(0.001)	(0.003)	(0.004)	(0.009)	(WV)	(0.001)	(0.003)	(0.003)	(0.003)
New Hampshire	-0.0008	-0.017	0.059	0.427	North Carolina	-0.0012	-0.017	0.040	0.378
(NH)	(0.001)	(0.004)	(0.006)	(0.012)	(NC)	(0.001)	(0.003)	(0.002)	(0.002)
Vermont	-0.0003	-0.015	0.058	0.438	South Carolina	-0.0006	-0.016	0.039	0.380
(VT)	(0.001)	(0.004)	(0.006)	(0.012)	(SC)	(0.001)	(0.003)	(0.002)	(0.003)
Massachusetts	-0.0007	-0.016	0.040	0.376	Georgia	-0.0101	-0.025	0.061	0.392
(MA)	(0.001)	(0.002)	(0.003)	(0.002)	(GA)	(0.001)	(0.001)	(0.004)	(0.002)
Rhode Island	-0.0017	-0.016	0.042	0.382	Florida	-0.0042	-0.019	0.047	0.383
(RI)	(0.001)	(0.003)	(0.003)	(0.003)	(FL)	(0.001)	(0.003)	(0.003)	(0.002)
Connecticut	-0.0007	-0.015	0.040	0.377	Kentucky	-0.0082	-0.026	0.055	0.389
(CT)	(0.001)	(0.003)	(0.003)	(0.002)	(KY)	(0.002)	(0.001)	(0.006)	(0.004)
New York	0.0031	0.0004	0.037	0.388	Tennessee	-0.0062	-0.028	0.048	0.385
(NY)	(0.001)	(0.001)	(0.001)	(0.004)	(TN)	(0.001)	(0.001)	(0.002)	(0.001)
Pennsylvania	-0.0021	-0.010	0.059	0.438	Mississippi	-0.0001	-0.020	0.035	0.372
(PA)	(0.001)	(0.003)	(0.004)	(0.007)	(MS)	(0.001)	(0.002)	(0.001)	(0.001)
New Jersey	0.0026	-0.005	0.035	0.379	Alabama	0.0021	-0.013	0.034	0.371
(NJ)	(0.0004)	(0.002)	(0.001)	(0.003)	(AL)	(0.001)	(0.002)	(0.001)	(0.001)
					Oklahoma	-0.0004	-0.021	0.036	0.374
MIDWEST					(OK)	(0.001)	(0.002)	(0.001)	(0.001)
					Texas	-0.0044	-0.020	0.047	0.381
Wisconsin	0.0027	-0.005	0.035	0.380	(TX)	(0.002)	(0.002)	(0.004)	(0.003)
(WI)	(0.001)	(0.002)	(0.001)	(0.003)	Arkansas	0.0023	-0.008	0.035	0.379
Michigan	-0.0037	-0.025	0.074	0.461	(AR)	(0.001)	(0.002)	(0.001)	(0.003)
(MI)	(0.001)	(0.003)	(0.005)	(0.010)	Louisiana	-0.0044	-0.022	0.046	0.382
Illinois	0.0025	-0.002	0.038	0.388	(LA)	(0.002)	(0.002)	(0.004)	(0.003)
(IL)	(0.001)	(0.002)	(0.001)	(0.004)					
Indiana	0.0034	-0.006	0.033	0.374	WEST				
(IN)	(0.001)	(0.002)	(0.001)	(0.002)					
Ohio	0.0031	-0.008	0.033	0.372	Idaho	-0.0068	-0.020	0.054	0.386
(OH)	(0.001)	(0.002)	(0.001)	(0.001)	(ID)	(0.001)	(0.002)	(0.003)	(0.002)
North Dakota	-0.0038	-0.021	0.045	0.382	Montana	-0.0071	-0.026	0.052	0.385
(ND)	(0.001)	(0.002)	(0.003)	(0.003)	(MT)	(0.001)	(0.001)	(0.003)	(0.002)
South Dakota	-0.0026	-0.023	0.040	0.377	Wyoming	-0.0220	-0.022	0.096	0.414
(SD)	(0.001)	(0.001)	(0.003)	(0.002)	(WY)	(0.002)	(0.001)	(0.006)	(0.006)
Nebraska	-0.0055	-0.027	0.046	0.384	Nevada	-0.0113	-0.023	0.065	0.393
(NE)	(0.001)	(0.001)	(0.002)	(0.002)	(NV)	(0.001)	(0.001)	(0.004)	(0.003)
Kansas	0.0006	-0.017	0.035	0.373	Utah	-0.0060	-0.025	0.049	0.383
(KS)	(0.001)	(0.002)	(0.001)	(0.002)	(UT)	(0.001)	(0.001)	(0.004)	(0.002)
Minnesota	-0.0016	-0.023	0.037	0.375	Colorado	-0.0007	-0.017	0.039	0.375
(MN)	(0.001)	(0.001)	(0.001)	(0.002)	(CO)	(0.001)	(0.002)	(0.002)	(0.002)
Iowa	-0.0011	-0.023	0.036	0.373	Arizona	-0.0111	-0.020	0.067	0.391
(IA)	(0.001)	(0.001)	(0.001)	(0.001)	(AZ)	(0.002)	(0.001)	(0.006)	(0.004)
Missouri	0.0017	-0.015	0.033	0.370	New Mexico	-0.0070	-0.020	0.062	0.411
(MO)	(0.001)	(0.002)	(0.001)	(0.001)	(NM)	(0.001)	(0.002)	(0.004)	(0.008)
					Washington	-0.0016	-0.021	0.039	0.375
SOUTH					(WA)	(0.001)	(0.002)	(0.002)	(0.002)
					Oregon	0.0023	-0.012	0.033	0.371
Delaware	-0.0032	-0.016	0.046	0.382	(OR)	(0.001)	(0.002)	(0.001)	(0.002)
(DE)	(0.002)	(0.003)	(0.004)	(0.003)	California	-0.0004	-0.002	0.047	0.417
Maryland	-0.0037	-0.016	0.047	0.393	(CA)	(0.001)	(0.001)	(0.002)	(0.004)
(MD)	(0.001)	(0.003)	(0.003)	(0.004)					

Notes: Estimation method is the partially linear semiparametric smooth coefficient approach. See also Table 1.

Table 3. Descriptive statistics of the estimated coefficients, LGMM with demeaned data

Independent variable	Mean	Std Dev	Variance	Minimum	Maximum
lagged TFP growth ($g_{TFP_{it-1}}$)	-0.0133	0.1259	0.0159	-0.3171	0.1981
growth of capital spending ($\Delta \ln G$)	-0.0008	0.0136	0.0002	-0.0254	0.0197
growth of O&M spending ($\Delta \ln M$)	0.0095	0.0448	0.0020	-0.1227	0.0857
growth of capital spillover ($\Delta \ln S_G$)	0.0871	0.0812	0.0066	-0.1066	0.2988
growth of O&M spillover ($\Delta \ln S_M$)	0.3371	0.2048	0.0420	0.1210	0.8467
No. of observations	1008				

Notes: The dependent variable is TFP growth. Details on the instruments are provided in Section 2.

Table 4. Baseline results and sensitivity analysis

Independent variable	(1)	(2)	(3)	(4)	(5)
Nonlinear part: Average Coefficients					
growth of capital spending	-0.002	-0.003	-0.004	-0.008	-0.007
($\Delta \ln G$)	(0.00021)	(0.00021)	(0.00027)	(0.00021)	(0.00032)
growth of O&M spending	-0.017	-0.021	-0.019	-0.029	-0.016
($\Delta \ln M$)	(0.00038)	(0.00047)	(0.00050)	(0.00056)	(0.00032)
growth of capital spillover	0.046	0.050	0.056	0.083	0.049
($\Delta \ln S_G$)	(0.00059)	(0.00060)	(0.00099)	(0.00051)	(0.00083)
growth of O&M spillover	0.388	0.375	0.361	0.354	0.291
($\Delta \ln S_M$)	(0.00085)	(0.00074)	(0.00154)	(0.00121)	(0.00099)
Linear part					
year trend	0.0007	0.0012	0.0006	0.0003	0.0003
	(0.00008)	(0.0002)	(0.00008)	(0.00008)	(0.00009)
unemployment rate	-	-0.001	-	-	-
		(0.039)			
federal employees	-	0.651	-	-	-
		(0.201)			
state and local employees	-	-1.240	-	-	-
		(0.260)			
federal revenue	-	0.372	-	-	-
		(0.139)			
tax burden	-	-0.051	-	-	-
		(0.085)			
working population	-	0.267	-	-	-
		(0.084)			
non-white	-	0.026	-	-	-
		(0.031)			
female	-	-0.006	-	-	-
		(0.331)			
No. of observations	1104	1056	1104	1104	1104

Notes: The table presents coefficients obtained from the estimation of eq. (6). Column (1) reports the baseline results. In column (2) a number of variables are employed as additional controls. In column (3) a second state variable is used, namely the O&M share in the sum of the two spillover indices. In column (4) the spillover variables included in the regression have been computed by weighting different states only with information on relative economic activity. In column (5) the regression is run for highways and roads. The dependent variable is TFP growth. All regressions include a constant and state dummies. Standard errors are reported in parenthesis.

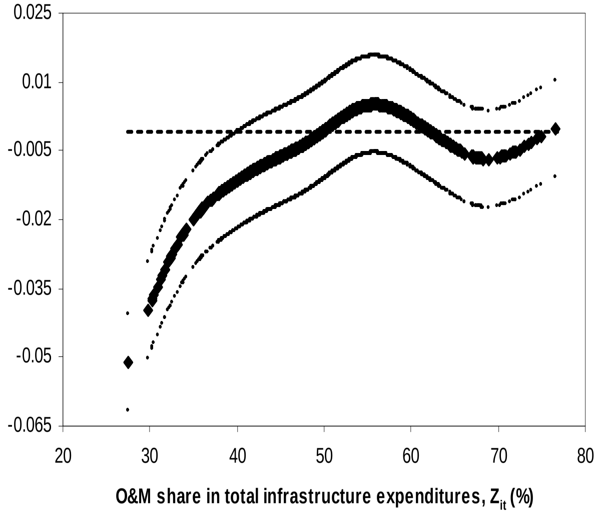
Table A1. Data averages by state (%, 1978-2000)

State	Growth rate of					Level of	
	Total Factor Productivity	own-state spending Capital	own-state spending O&M	spillovers Capital	spillovers O&M	output share of labor	O&M share in total spending
	(TFP)	(G)	(M)	(S_G)	(S_M)	(s_{YL})	$\left(\frac{M}{G+M}\right)$
Alabama (AL)	0.75	1.25	2.20	1.38	2.44	63.67	52.65
Arizona (AZ)	0.98	4.34	5.71	4.94	5.68	66.05	41.76
Arkansas (AR)	0.69	0.56	2.22	1.73	2.78	64.32	55.00
California (CA)	1.17	4.01	4.39	2.94	3.73	68.95	61.82
Colorado (CO)	0.93	2.10	4.37	3.78	4.70	72.92	50.09
Connecticut (CT)	1.79	3.02	1.94	2.94	3.09	68.68	50.49
Delaware (DE)	1.42	2.49	2.78	3.01	3.78	73.65	48.70
Florida (FL)	1.04	3.10	5.44	3.69	4.54	59.73	47.22
Georgia (GA)	1.33	2.84	3.19	3.65	4.80	69.79	41.99
Idaho (ID)	0.96	0.65	3.45	2.55	3.32	64.48	44.58
Illinois (IL)	0.88	-0.08	2.49	1.32	2.11	69.09	57.57
Indiana (IN)	0.65	1.11	2.63	1.14	2.26	69.67	54.78
Iowa (IA)	0.68	1.31	0.95	0.55	1.62	63.47	49.61
Kansas (KS)	0.51	1.10	3.53	1.45	2.37	64.25	51.48
Kentucky (KY)	0.26	1.60	2.77	0.74	1.83	64.98	44.42
Louisiana (LA)	0.45	-0.35	1.82	0.51	1.62	63.57	47.00
Maine (ME)	0.89	-0.50	1.69	1.89	2.18	66.57	60.07
Maryland (MD)	0.89	-0.58	3.46	1.95	3.21	58.44	51.07
Massachusetts (MA)	1.71	5.30	1.54	2.45	3.35	72.44	50.06
Michigan (MI)	0.16	0.77	2.57	0.70	1.60	71.02	65.15
Minnesota (MN)	0.97	1.93	2.05	2.44	3.10	71.49	49.04
Mississippi (MS)	0.79	0.58	1.94	1.05	2.17	58.83	50.40
Missouri (MO)	0.73	1.50	2.90	1.22	2.45	69.89	51.92
Montana (MT)	0.005	-1.15	1.43	0.48	1.11	60.97	44.34
Nebraska (NE)	0.80	0.73	1.29	1.51	2.41	65.37	45.63
Nevada (NV)	0.75	7.21	6.39	5.48	6.31	72.65	41.06
New Hampshire (NH)	1.53	-1.52	2.35	4.22	4.14	64.84	61.30
New Jersey (NJ)	1.22	2.26	3.71	2.47	2.82	64.62	55.77
New Mexico (NM)	0.83	2.80	5.20	2.28	3.23	61.61	50.51
New York (NY)	1.20	2.89	1.49	1.63	2.57	68.01	58.22
North Carolina (NC)	1.24	2.33	5.16	2.97	3.83	68.57	50.07
North Dakota (ND)	0.24	-0.19	1.09	0.55	0.85	61.13	48.11
Ohio (OH)	0.61	1.82	2.09	0.74	1.85	69.78	54.09
Oklahoma (OK)	0.15	2.52	2.24	0.87	2.00	64.46	50.18
Oregon (OR)	0.80	2.46	2.13	2.17	3.04	68.10	53.01
Pennsylvania (PA)	0.96	0.96	1.99	0.97	1.82	66.38	63.64
Rhode Island (RI)	1.56	1.27	2.30	2.54	2.04	64.25	50.27
South Carolina (SC)	1.11	5.27	4.13	2.26	3.51	64.84	51.14
South Dakota (SD)	1.08	2.47	1.00	2.15	2.78	58.29	48.14
Tennessee (TN)	0.90	2.37	2.05	2.25	3.43	69.67	45.02
Texas (TX)	0.52	3.09	3.99	2.68	3.77	70.92	46.78
Utah (UT)	0.61	3.87	5.18	3.35	4.36	69.99	45.44
Vermont (VT)	1.13	-0.46	3.41	2.83	2.88	68.51	64.08
Virginia (VA)	1.28	0.73	4.10	2.92	4.04	62.80	52.11
Washington (WA)	0.95	2.82	3.29	3.12	3.97	67.65	49.05
West Virginia (WV)	0.34	-0.19	0.94	-0.85	0.25	61.88	49.96
Wisconsin (WI)	0.55	3.04	1.49	1.28	2.37	67.12	55.77
Wyoming (WY)	0.17	1.94	2.62	0.12	1.18	63.65	35.66
Mean	0.86	1.82	2.86	2.06	2.90	66.29	50.96
Std. Dev.	0.41	1.76	1.37	1.28	1.22	4.00	6.25

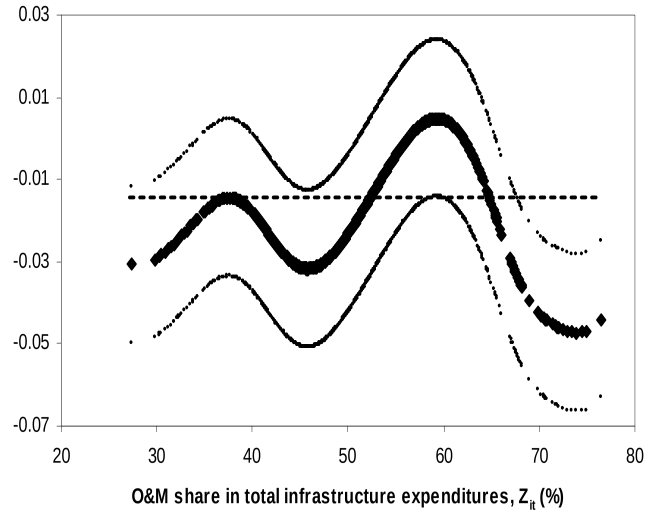
Table A2: Average output elasticities by state in the absence of spillovers, 1978-2000

State	$\theta_G(Z_{it})$	$\theta_M(Z_{it})$	State	$\theta_G(Z_{it})$	$\theta_M(Z_{it})$
NORTHEAST			Virginia	0.0078	0.0144
			(VA)	(0.0012)	(0.0022)
Maine	0.0106	0.0144	West Virginia	0.0046	0.0107
(ME)	(0.0006)	(0.0055)	(WV)	(0.0014)	(0.0025)
New Hampshire	0.0098	0.0006	North Carolina	0.0057	0.0102
(NH)	(0.0006)	(0.0066)	(NC)	(0.0012)	(0.0022)
Vermont	0.0119	-0.0012	South Carolina	0.0063	0.0118
(VT)	(0.0009)	(0.0083)	(SC)	(0.0012)	(0.0022)
Massachusetts	0.0057	0.0104	Georgia	-0.0015	0.0002
(MA)	(0.0014)	(0.0019)	(GA)	(0.0008)	(0.0005)
Rhode Island	0.0055	0.0108	Florida	0.0022	0.0068
(RI)	(0.0013)	(0.0022)	(FL)	(0.0014)	(0.0022)
Connecticut	0.0063	0.0111	Kentucky	0.0029	0.0027
(CT)	(0.0013)	(0.0023)	(KY)	(0.0012)	(0.0009)
New York	0.0114	0.0253	Tennessee	-0.0001	0.0013
(NY)	(0.0003)	(0.0008)	(TN)	(0.0008)	(0.0003)
Pennsylvania	0.0088	0.0131	Mississippi	0.0066	0.0082
(PA)	(0.0004)	(0.0047)	(MS)	(0.0008)	(0.0013)
New Jersey	0.0103	0.0204	Alabama	0.0090	0.0142
(NJ)	(0.0004)	(0.0019)	(AL)	(0.0008)	(0.0018)
			Oklahoma	0.0064	0.0080
MIDWEST			(OK)	(0.0008)	(0.0015)
			Texas	0.0034	0.0054
Wisconsin	0.0104	0.0210	(TX)	(0.0012)	(0.0016)
(WI)	(0.0006)	(0.0019)	Arkansas	0.0098	0.0187
Michigan	0.0086	-0.0092	(AR)	(0.0006)	(0.0019)
(MI)	(0.0006)	(0.0063)	Louisiana	0.0035	0.0055
Illinois	0.0107	0.0233	(LA)	(0.0012)	(0.0016)
(IL)	(0.0005)	(0.0015)			
Indiana	0.0106	0.0198	WEST		
(IN)	(0.0006)	(0.0016)			
Ohio	0.0102	0.0177	Idaho	-0.0004	0.0032
(OH)	(0.0006)	(0.0018)	(ID)	(0.0013)	(0.0019)
North Dakota	0.0037	0.0059	Montana	-0.00002	0.0009
(ND)	(0.0011)	(0.0018)	(MT)	(0.0009)	(0.0007)
South Dakota	0.0043	0.0049	Wyoming	0.0042	-0.0020
(SD)	(0.0009)	(0.0010)	(WY)	(0.0024)	(0.0006)
Nebraska	0.0006	0.0025	Nevada	-0.0021	-0.0008
(NE)	(0.0009)	(0.0008)	(NV)	(0.0011)	(0.0006)
Kansas	0.0075	0.0109	Utah	0.0015	0.0020
(KS)	(0.0008)	(0.0018)	(UT)	(0.0010)	(0.0009)
Minnesota	0.0050	0.0060	Colorado	0.0060	0.0097
(MN)	(0.0008)	(0.0010)	(CO)	(0.0012)	(0.0019)
Iowa	0.0059	0.0060	Arizona	0.0015	0.0010
(IA)	(0.0006)	(0.0010)	(AZ)	(0.0013	(0.0013)
Missouri	0.0085	0.0119	New Mexico	0.0014	0.0023
(MO)	(0.0007)	(0.0014)	(NM)	(0.0014)	(0.0027)
			Washington	0.0052	0.0067
SOUTH			(WA)	(0.0010)	(0.0013)
			Oregon	0.0092	0.0145
Delaware	0.0044	0.0093	(OR)	(0.0006)	(0.0016)
(DE)	(0.0014)	(0.0023)	California	0.0096	0.0245
Maryland	0.0044	0.0107	(CA)	(0.0003)	(0.0011)
(MD)	(0.0012)	(0.0027)			

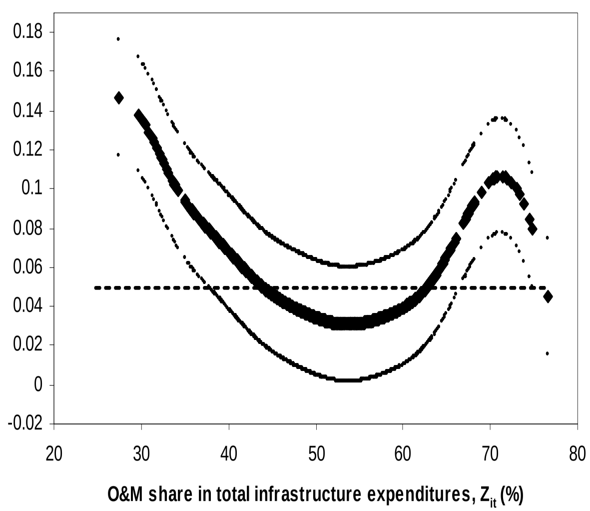
Notes: See Table 2 of the paper.



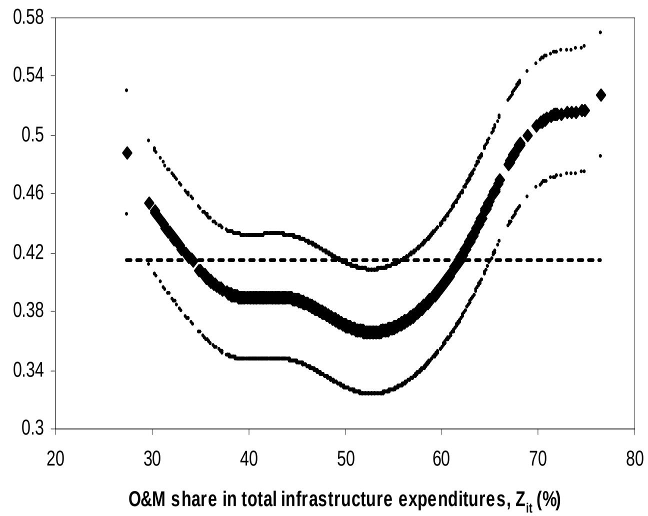
(a) Output elasticity of own-state capital spending, $\theta_G(Z_{it})$



(b) Output elasticity of own-state O&M spending, $\theta_M(Z_{it})$

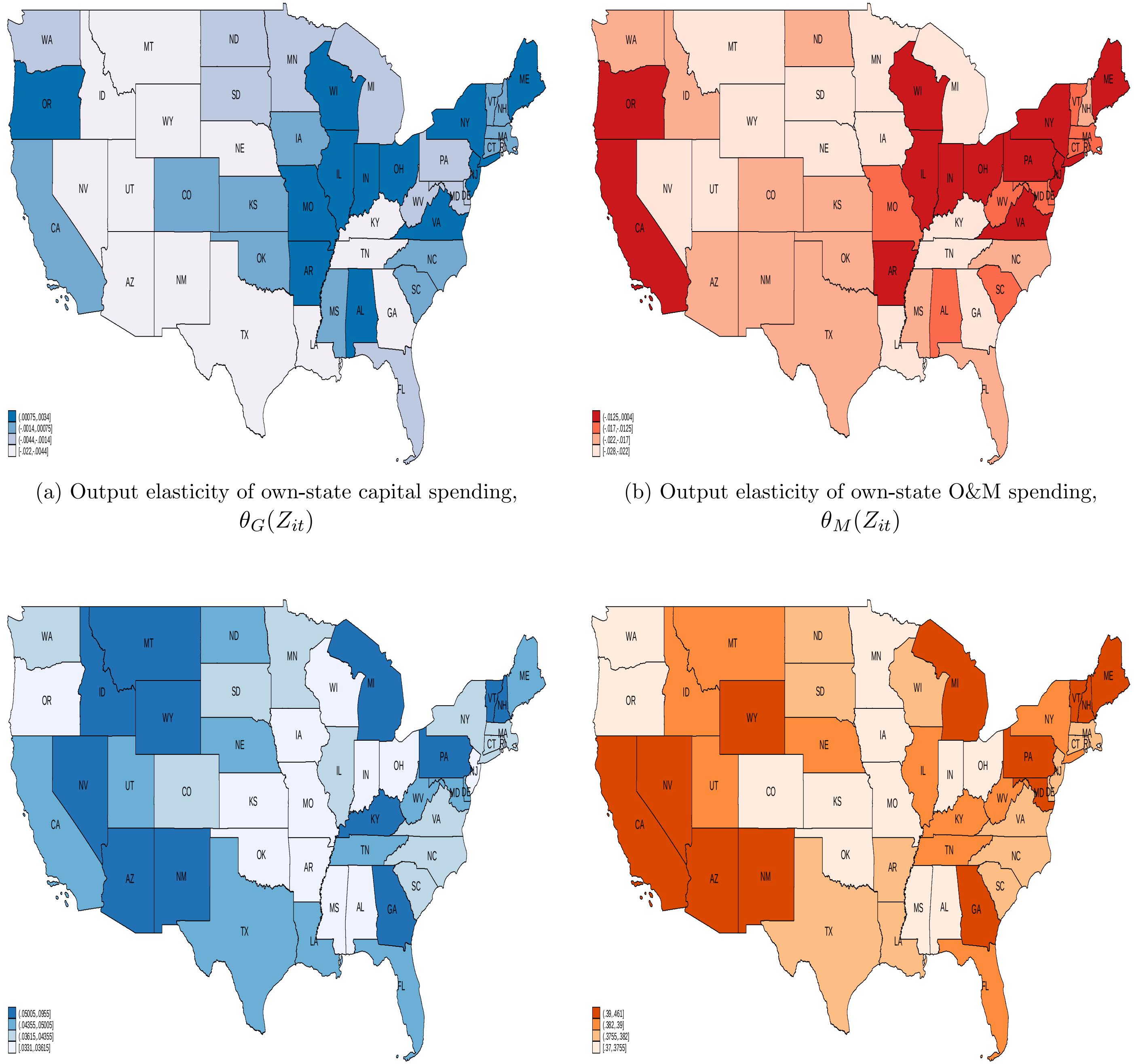


(c) Output elasticity of capital spending by other states, $\theta_{S_G}(Z_{it})$



(d) Output elasticity of O&M spending by other states, $\theta_{S_M}(Z_{it})$

Figure 1: Coefficient estimates for the nonparametric part of the model



(a) Output elasticity of own-state capital spending, $\theta_G(Z_{it})$

(b) Output elasticity of own-state O&M spending, $\theta_M(Z_{it})$

(c) Output elasticity of capital spending by other states, $\theta_{S_G}(Z_{it})$

(d) Output elasticity of O&M spending by other states, $\theta_{S_M}(Z_{it})$

Figure 2: Geographical representation of the average semiparametric estimates by state