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Is infrastructure capital really productive? Nonparametric modeling and data-driven model selection in a cross-sectionally dependent panel framework

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Abstract
This paper examines the contribution of infrastructure to aggregate productivity. We address some complex and relevant issues, namely functional form, nonstationary variables and cross-sectional dependence. We adopt the CCE framework and consider both parametric and nonparametric specifications, thus allowing for different degrees of flexibility. We also employ a data-driven model selection procedure based on moving block bootstrap to choose among alternative specifications. It is found that nonparametric specifications provide the best predictive performance and that CCE models always overperform with respect to traditional panel data methods. Furthermore, we find a lack of significance of the infrastructure index, with an estimated elasticity very close to zero for all estimates.

Keywords Cross-sectional dependence · factor models · moving block bootstrap · nonparametric regression · spline functions · public capital hypothesis

JEL classification C23 · C5 · O4

1 Introduction

Since the seminal paper by Aschauer (1989), there has been increasing interest in assessing the effect of public infrastructure capital on productivity. Specifically, Aschauer (1989) identified the decline in infrastructure investment as a key factor underlying the productivity slowdown in the US during the 1970s and 1980s. This perspective-often referred to as the "*public capital hypothesis*"-is theoretically grounded in the endogenous growth literature, in which public capital is modeled as a productive input alongside private capital and labor.

Among the most influential frameworks, Barro (1990) introduced a model where productive government spending enters the aggregate production function, potentially sustaining long-run growth by enhancing the productivity of private inputs. Subsequent contributions, including Futagami et al. (1993) and Greiner and Semmler (2000), emphasized the role of public capital in raising the marginal productivity of private investment, thereby fostering self-sustaining growth. At the same time, the literature has identified channels through which public capital may have neutral or adverse effects. As reviewed by Agénor (2010) and Durlauf et al. (2005), infrastructure investment can operate through: (i) a direct productivity effect, lowering production costs and raising total factor productivity; (ii) a complementarity effect, enhancing returns to labor and private capital; and (iii) a crowding-out effect, where public investment displaces private capital or is financed via distortionary taxation. The latter may prevail when infrastructure is funded through excessive borrowing or inefficient taxation, potentially raising interest rates, limiting credit access, or discouraging private investment. Moreover, if misallocated, plagued by inefficiencies, or

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poorly maintained, infrastructure spending may have little or even negative impact on performance (Pritchett, 2000). These considerations suggest that the growth effects of public capital are highly context-specific, depending on the level and quality of existing infrastructure, financing methods, and the institutional environment.

These theoretical considerations offer a natural explanation for the highly mixed findings reported in the empirical literature (Henderson and Kumbhakar, 2006; Holtz-Eakin, 1994; Kortelainen and Leppänen, 2013; Ma et al. 2020; Musolesi, 2011). On the methodological front, key concerns include the appropriate functional specification, the presence of nonstationary variables, risks of spurious regression, and issues of cointegration. These challenges have been addressed using both time-series methods (Aaron, 1990; Everaert, 2003; Munnell et al. 1990; Pereira, 2000; Pereira and Flores, 1999; Schultze, 1990; Tatom, 1991) and panel data approaches (Canning and Pedroni, 2004; Kawaguchi et al. 2009).

This persistent ambiguity, often referred to as the "*public capital puzzle*", suggests that the inconclusiveness may stem not only from differences in country experiences, but also from methodological shortcomings. Traditional approaches often rely on restrictive parametric models and impose assumptions such as cross-sectional independence, which are difficult to justify in macro-panel settings. These limitations call for more flexible and dependence-robust panel estimators.

Recent empirical contributions have attempted to address some of these limitations. For instance, Calderón et al. (2015) employ a panel cointegration framework using an autoregressive distributed lag (ARDL) model and the pooled mean group estimator of Pesaran et al. (1999), reporting significant long-run effects of infrastructure capital. However, even these more refined methods may fall short when the data-generating process (DGP) includes unobserved common shocks or nonlinear relationships.

In this paper, we aim to advance the econometric analysis of the infrastructure-productivity nexus by addressing two fundamental challenges: (i) cross-sectional dependence (CSD) and (ii) functional form misspecification. Both are key sources of model uncertainty, defined as uncertainty about the DGP (see Cui et al. 2025 for a review of relevant definitions and classifications). One way to address this uncertainty is to select among alternative models that aim to approximate the underlying relationship. Given sampling variability and the inherent complexity of economic mechanisms, it is unlikely that any single specification - parametric or nonparametric, even when allowing for CSD - can fully capture the true DGP. We therefore adopt a model selection strategy aimed at identifying the least inaccurate specification among a set of competing alternatives. Model performance is assessed based on predictive accuracy, that is, the ability to forecast new data generated by the same process that produced the estimation sample. The goal is thus to reduce model uncertainty, specifically in the form of model selection uncertainty, which arises when choosing among competing specifications in the absence of full knowledge of the true DGP (Cui et al. 2025).

From a macroeconomic perspective, CSD is a pervasive feature of international panel datasets and particularly relevant in studies on infrastructure capital and productivity. It reflects exposure to global shocks, such as commodity price volatility, financial crises, or common technological trends, as well as policy synchronization and regional development programs that induce coordinated investment across countries (Calderón and Servén, 2004; Fernald, 1999; Laborda and Sotelsek, 2019). These considerations motivate the use of econometric models capable of capturing unobserved common factors.

Furthermore, a substantial body of empirical research has shown that infrastructure investment may generate spatial productivity spillovers, whereby public capital in one country or region affects economic outcomes in adjacent areas. Studies such as Cohen and Morrison Paul (2004), Boarnet (1998), Ezcurra et al. (2005), and Holtz-Eakin and Schwartz (1995) provide robust evidence that these spillovers operate through mechanisms such as reductions in transport costs, improvements in connectivity, and integration of regional supply chains.

To address these sources of dependence, we adopt the Common Correlated Effects (CCE) estimator proposed by Pesaran (2006). A relevant feature of the CCE estimator is that it remains consistent under a wide array of dependence structures, including both strong dependence, driven by a limited number of pervasive latent factors, and weak dependence (Chudik et al. 2011). Although the CCE approach does not explicitly model spillover effects -such as those captured by including foreign R&D as an additional explanatory variable (Ertur and Musolesi, 2017), or by employing spatial econometric models (Baltagi, 2011)- it remains consistent in the presence of weak CSD in the error term, beyond the dependence accounted for by the common factors. This robustness is empirically relevant, as it preserves the validity of the estimator in the presence of those spillover effects that, although not directly modeled, are likely to manifest as weak or spatial-type residual interdependence across cross-sectional units (see Soberon et al. 2025, 2024 for recent contributions and detailed discussion). Furthermore, the CCE is also robust to nonstationary unobserved components (Kapetanios et al. 2011) and avoids the need to estimate the number or structure of latent factors, as is required in principal component-based approaches (Bai, 2009). These robustness properties render CCE particularly suitable for macro-panel applications where global shocks, weak/spatial residual interdependencies, nonstationary latent factors, and country-specific heterogeneity coexist.

Within the CCE framework, we consider a range of model specifications that vary in their degree of functional flexibility. We begin with the static model proposed by Pesaran (2006), then proceed to a dynamic specification, the cross-sectionally augmented distributed lag (CS-DL) model of Chudik et al. (2016), and finally incorporate more flexible semi and nonparametric estimators introduced by Su and Jin (2012) and recently applied in a macro-panel data context by Gioldasis et al. (2023).

Allowing for flexible functional forms is a substantively important modeling choice, particularly in the context of infrastructure-productivity relationships that may exhibit complex, nonlinear features. Marginal returns to infrastructure, for instance, may be subject to threshold effects, becoming significant only after a critical mass of investment is reached (Berg et al. 2022; Creel et al. 2009), or may vary non-linearly depending on the level of complementary inputs such as human capital, financial development, or institutional quality (Bougheas et al. 2000; Calderón and Servén, 2014). These features are difficult to capture with traditional parametric specifications. By contrast, semi and nonparametric methods allow for data-driven estimation of potentially nonlinear and complex functional forms, accommodating structural features such as interaction effects, threshold behavior, and non-monotonic marginal returns, without imposing restrictive parametric assumptions. Empirical support for this approach can be found in studies such as Henderson and Kumbhakar (2006), Kortelainen and Leppänen (2013), and Ma et al. (2020), which use kernel and spline-based techniques to uncover these patterns.

Despite their advantages, flexible estimators may also introduce new challenges. In particular, when the data-generating process is unknown and the sample size is finite, overfitting and reduced efficiency can be problematic. Consequently, choosing the appropriate level of flexibility is a nontrivial task. Striking a balance between model complexity and parsimony becomes essential (see also Baltagi et al. 2003). To address this issue, and given the substantial uncertainty surrounding the DGP (see, among others, Hansen, 2005), we implement a forecasting-based model selection procedure. Specifically, we adopt the approach proposed by Gioldasis et al. (2023), which extends the data-driven method of Racine and Parmeter (2014) to a macro-panel framework. The procedure employs moving block bootstrap resampling to preserve the time-series and cross-sectional dependence structures in the data, allowing us to compare the predictive performance of alternative specifications, parametric, semiparametric, and nonparametric, on out-of-sample forecasts.

This procedure offers a statistically sound framework for selecting among competing model specifications based on their predictive performance. It facilitates the empirical calibration of functional complexity, allowing for the detection of structural nonlinearities while mitigating the risk of overfitting. By relying on forecasting accuracy rather than ex ante functional restrictions, the approach provides a data-driven means of assessing model adequacy in settings where theoretical guidance is limited. More fundamentally, the strategy reflects the recognition that, in macroeconomic applications, the DGP is unlikely to be fully captured by any finite-dimensional parametric model. Candidate specifications are thus evaluated as approximations, with out-of-sample prediction accuracy serving as a criterion for identifying those that best capture the systematic components of the DGP. Semi- and nonparametric models may outperform parametric ones not by recovering the "true" model, but by approximating economically relevant relationships more effectively, particularly in the presence of nonlinearities, threshold effects, or interactions. Although such models can entail higher estimation variance, especially in small samples, the forecasting-based selection procedure addresses this trade-off directly by choosing the degree of flexibility that minimizes out-of-sample prediction error as a proxy for the *true error* (in opposition to the *apparent error* based on in-sample prediction, see Efron, 1982), conditional on the structure and limitations of the available data.

In summary, this paper provides a framework for the consistent estimation of long-run output elasticities with respect to infrastructure capital, explicitly accounting for latent factor structures, nonlinear functional forms, and heterogeneous effects. It also facilitates formal model comparison and the identification of structural features, such as thresholds and interactions, that shape the productivity effects of infrastructure investment. In doing so, it contributes to addressing the long-standing "*public capital puzzle*" by identifying the empirical conditions under which infrastructure investment yields statistically significant and economically meaningful gains in productivity. Finally, note that this paper shares some relevant features with Hou et al. (2025), as they employ a range of parametric, semiparametric, and nonparametric estimators - including CCE-type approaches - to assess the impact of infrastructure capital within an aggregate production function framework. However, while their strategy aims to reconstitute the *puzzle* and to address model uncertainty by comparing results obtained from alternative estimators, we tackle these issues by implementing a data-driven model selection procedure grounded in the principle of minimizing the *true error*. This approach allows us to formally address model selection uncertainty and to identify the most adequate specification among competing alternatives.

2 Specification and estimation of the production function under a latent factor structure

2.1 Infrastructure and the aggregate production function

Infrastructure capital may enter the production function as a distinct input, interacting with private capital and labor. This structural perspective departs from approaches that treat infrastructure as a purely external efficiency factor (Durlauf et al. 2005).

Several growth models suggest that infrastructure may affect returns to scale. Barro (1990) develops a framework in which productive government spending enters the production function multiplicatively with private capital, potentially generating increasing returns at the aggregate level. Subsequent contributions link public capital accumulation to sustained output growth, further supporting this mechanism (Futagami et al. 1993; Greiner and Semmler, 2000). These insights motivate relaxing the constant returns to scale (CRS) assumption and testing it empirically.

Furthermore, infrastructure investment and output dynamics are shaped by global forces. Capital flows, coordinated fiscal policies, and commodity cycles generate cross-country co-movements (Calderón and Servén, 2004; Laborda and Sotelsek, 2019), while network externalities and cross-border infrastructure linkages create spatial spillovers (Fernald, 1999).

These considerations motivate an econometric framework that (i) treats infrastructure as a distinct input, (ii) allows for testing returns to scale, and (iii) accounts for CSD.

2.2 Parametric modeling of the aggregate production function

Calderón et al. (2015), among others, consider the following aggregate production function:

$$Y_{it} = A_{it} K_{it}^{\zeta} Z_{it}^{\eta} (e^{\xi S_{it}} L_{it})^{\psi} \quad (1)$$

where Y is the real gross domestic product (GDP), A is total factor productivity, K and Z denote physical and infrastructure capital, respectively, while the interacted variable $e^{\xi S_{it}} L_{it}$ is "human capital augmented labor", where L represents the labor force and S is human capital. To estimate the model, Calderón et al. (2015) assume CRS, i.e., $\psi = 1 - \zeta - \eta$. They also assume that $\log(A_{it}) = \alpha_i + \omega_t$. They then take logs and add an error term to get an econometric specification.

We depart from Calderón et al. (2015) by estimating the model without assuming CRS and by testing whether this assumption is verified by the data, i.e., by focusing on the following type of econometric specification:

$$y_{it} = \alpha_i + \omega_t + \zeta k_{it} + \eta z_{it} + \vartheta S_{it} + \psi l_{it} + e_{it}, \quad (2)$$

where lower-case letters indicate variables expressed in log form, e.g., $y_{it} = \log(Y_{it})$, and $\vartheta = \xi * \psi$.

2.3 Modeling cross-sectional dependence

Following previous discussion, the error term e_{it} is assumed to follow a common factor structure:

$$e_{it} = \boldsymbol{\gamma}_i' \mathbf{f}_t + \varepsilon_{it}, \quad (3)$$

in which $\mathbf{f}_t$ is an $m \times 1$ vector of unobserved common factors with associated country-specific factor loadings $\boldsymbol{\gamma}_i$. The number of factors, m, is assumed to be fixed relative to the number of countries N and, more specifically, $m << N$. These factors $\mathbf{f}_t$ are supposed to have a widespread effect, as they heterogeneously affect every country in the sample. ε_{it} is an idiosyncratic error term. Equation (2) can be thus viewed as a special case of the more general specification (see, for instance, Chudik et al. 2011):

$$y_{it} = \alpha_i' \mathbf{d}_t + \boldsymbol{\beta}' \mathbf{x}_{it} + \boldsymbol{\gamma}_i' \mathbf{f}_t + \varepsilon_{it} \quad (4)$$

where d_t is a vector of *observed* common factors, α_i is the vector of individual i's responses to these factors, $\mathbf{x}_{it} = [k_{it}, z_{it}, S_{it}, l_{it}]'$ and $\boldsymbol{\beta} = [\zeta, \eta, \vartheta, \psi]'$. In Eq. (2), d_t is simply a scalar whose value is 1, and α_i a fixed effect. In the econometric analysis, we only consider this latter case.

Eq. (4) can be interpreted as a log-linear approximation of a production function with Hicks-neutral and country-specific technical change, where TFP evolves as $\log(A_{it}) = \alpha_i + \boldsymbol{\gamma}_i' \mathbf{f}_t$. In this formulation, α_i captures time-invariant differences in TFP levels across countries, reflecting persistent institutional, structural, or geographical characteristics, while $\mathbf{f}_t$ denotes a vector of unobserved global productivity shocks, such as shifts in the technological frontier, international knowledge diffusion, or synchronized policy reforms. The vector γ_i represents country-specific transmission or absorption capacity (see Eberhardt et al. 2013).

2.4 Parametric CCE estimators

We first consider the implementation of the static pooled CCE estimator (CCEP) by Pesaran (2006). Second, following Calderón et al. (2015), we embed the production function into a dynamic setting and adopt the CS-DL estimator proposed by Chudik et al. (2016), which is designed for panels with a moderately large time dimension ($30 \le T \le 50$).

The dynamic representation is motivated by the production theory literature, which emphasizes that firms may not fully adjust their input levels instantaneously due to frictions such as capital adjustment costs, hiring delays, and information rigidities (see Mairesse and Jaumandreu, 2005, Dobbelaere and Mairesse, 2013). As a result, input-output relationships could be dynamic, and the resulting empirical specification could allow for gradual responses in input choices over time. The CS-DL framework captures these adjustment dynamics by including current and lagged first-differenced inputs, allowing for a distributed lag structure that links short-run parameters to long-run elasticities. Formally, we estimate the following model:

$$y_{it} = \boldsymbol{\alpha}_i'\mathbf{d}_t + \boldsymbol{\beta}'\mathbf{x}_{it} + \sum_{l=0}^{p-1} \boldsymbol{\delta}_l'\Delta\mathbf{x}_{it-l} + \boldsymbol{\gamma}_i'\mathbf{f}_t + \varepsilon_{it} \tag{5}$$

where, for a selected lag order p, the explanatory variables are included in both levels and first differences. The unobserved factors $\mathbf{f}_t$ are proxied through contemporaneous and lagged cross-sectional averages of the regressors. Furthermore, the long-run output elasticities are defined as $\boldsymbol{\theta} = \boldsymbol{\beta} + \sum_{l=1}^{p-1} \boldsymbol{\delta}_l$, where $\boldsymbol{\beta}$ captures the contemporaneous effect of input levels, and $\boldsymbol{\delta}_l$ the impact of lagged input changes. Since $\mathbf{x}_{it-l} = \mathbf{x}_{it} - \sum_{j=0}^{l-1} \Delta\mathbf{x}_{it-j}$, the model embeds a distributed lag structure in both levels and differences, offering an internally consistent mapping between short-run and long-run effects. The static CCEP estimator corresponds to the special case where $\boldsymbol{\delta}_l = \mathbf{0}$ for all $l \geq 1$, implying instantaneous adjustment. However, when adjustment is gradual, static models may fail to recover the true technological parameters, leading to biased estimation (see Bond, 2002).

Finally note that the main advantage of this approach-relative to the CS-ARDL model-is its robustness to unit roots in the regressors and/or unobserved factors, and its ability to handle weak cross-sectional dependence in the idiosyncratic errors. As noted by Raissi et al. (2018), the CS-DL estimator also tends to outperform CS-ARDL when T is moderate. Moreover, it also performs well even in the presence of feedback effects that may induce endogeneity (Chudik et al. 2013).

3 Flexible estimation of production functions

3.1 Rationale for adopting nonparametric specifications

Before introducing the nonparametric specifications, we briefly outline the theoretical and econometric motivations for relaxing functional form assumptions. As previously discussed, this study is grounded in growth and production theories, with a focus here on the specification of the production function and, in particular, on the issue of functional form flexibility. The previous section introduced a parametric formulation based on a log-linear Cobb-Douglas structure, where we deliberately refrained from imposing constant returns to scale, allowing the data to inform this key property.

We now extend the analysis to semiparametric and fully nonparametric models, which progressively relax the assumptions of log-linearity and additivity. This approach is motivated by the literature on flexible functional forms, including Translog and Fourier approximations, which offer greater flexibility than conventional specifications. Foundational contributions include Christensen et al. (1973) on the Translog function, Ivaldi et al. (1996) on empirical comparisons of flexible forms, and Diewert et al. (2025), who provide a contemporary reassessment of these models in macroeconomic applications.

The nonparametric approach adopted here encompasses flexible parametric functional forms and allows for an unrestricted representation of the production technology. This framework facilitates the detection of complex non-linearities and interaction effects among inputs, enabling the estimation of infrastructure's marginal productivity without imposing a restrictive structure. As noted by Ma et al. (2020), spline-based nonparametric methods provide a consistent and robust approach to uncovering intricate relationships in production data when the true functional form is unknown.

3.2 Additive and nonadditive econometric specifications

In this section, we generalize Eq. (2) allowing for a nonparametric relationship between the dependent variable and the regressors, while the common factors enter the model in a parametric way, or

$$y_{it} = \boldsymbol{\alpha}_i'\mathbf{d}_t + g(\mathbf{x}_{it}) + \boldsymbol{\gamma}_i'\mathbf{f}_t + \varepsilon_{it},$$

where $g(.)$ is an unknown smooth continuous function. For identification purposes, the following condition is necessary:

$$E(g(\mathbf{x}_{it})) = 0,$$

which is deemed necessary in this framework due to the inclusion of the intercept term in $\mathbf{d}_t$ (refer to Su and Jin 2012, for detailed explanations). Thus, in the framework of CCE based models, we consider two alternative nonparametric specifications. The first one (ADD) assumes an additive structure of $g(.)$, as follows:

$$y_{it} = \boldsymbol{\alpha}_i'\mathbf{d}_t + g_k(k_{it}) + g_z(z_{it}) + g_S(S_{it}) + g_l(l_{it}) + \boldsymbol{\gamma}_i'\mathbf{f}_t + \varepsilon_{it}, \tag{6}$$

where $g_k(.)$, $g_z(.)$, and $g_S(.)$ are unknown univariate smooth continuous functions of interest. The second one

(NONADD), instead, assumes a non-additive structure of $g(.)$, i.e.,

$$y_{it} = \boldsymbol{\alpha}_i'\mathbf{d}_t + g(k_{it}, z_{it}, S_{it}, l_{it}) + \boldsymbol{\gamma}_i'\mathbf{f}_t + \varepsilon_{it}. \tag{7}$$

From an economic standpoint, the additive specification of the production function implies that the marginal product of each input is independent of the quantities of the other inputs. While this assumption enhances analytical tractability and interpretability, it may prove overly restrictive in the presence of technological complementarities among inputs. In the context of infrastructure, its marginal productivity may be influenced not only by its own stock but also by interactions with other inputs. For instance, the productivity-enhancing effects of infrastructure investment may be amplified in settings characterized by abundant skilled labor or complementary capital, reflecting potential non-separabilities in the underlying technology. The nonadditive specification relaxes separability assumptions and accommodates nonlinear interactions among inputs, offering a more flexible representation at the cost of greater computational complexity and vulnerability to the curse of dimensionality.

3.3 Estimation strategy

Econometric theory underlying the estimation has been developed by Su and Jin (2012). The estimation procedure consists of the following steps. First, following Pesaran (2006) they proxy the unobservable common factors $\mathbf{f}_t$ by the cross-sectional averages $\overline{\mathbf{w}}_t = N^{-1}\sum_{j=1}^{N}\mathbf{w}_{jt}$, where $\mathbf{w}_{it} = [y_{it}, \mathbf{x}_{it}']'$. Second, they approximate the nonparametric part of the model, $g_i(.)$, using sieve approximation.

Sieve approximation proceeds as follows. First, we must choose an infinite sequence of known basis functions, which we denote by $\{\pi_l(x),\ l = 1,\ 2,\ \ldots\}$ and that can approximate any square-integrable function of x very well. Different choices are possible, including spline approximation. Second, the order of approximation must be defined. Let K denote this order, which is a function of N and T. This integer number will tend to infinity as $(N, T) \rightarrow \infty$. Third, under fairly weak conditions we can approximate the unknown function very well by a linear combination of the K first elements of the chosen basis, or $\pi^K(x) = (\pi_1(x), \pi_2(x), \ldots, \pi_K(x))'$, i.e.,

$$g(.) \approx \boldsymbol{\delta}_g'\pi^K(x) \tag{8}$$

Given the above approximations for $\mathbf{f}_t$ and $g(.)$, the following auxiliary regression equation is considered:

$$y_{it} = \boldsymbol{\alpha}_i'\mathbf{d}_t + \boldsymbol{\delta}_g'\pi^K(x_{it}) + \boldsymbol{\psi}_i'\overline{\mathbf{w}}_t + u_{it}. \tag{9}$$

where the term u_{it} includes ε_{it} and two approximation errors, one for the unobservable factors $\mathbf{f}_t$ and the other for the unknown function g(.). The former approximation error is given by $\mathbf{f}_t - \overline{\mathbf{w}}_t$ while the latter is the difference between the unknown function and the sieve approximation. In that auxiliary regression framework, the unknown smooth function is estimated as $\hat{g}(x_{it}) = \hat{\delta}'\pi^K(x_{it})$ where $\hat{\delta}$ is basically a standard CCE pooled estimator. According to Su and Jin (2012), $\hat{g}(x_{it})$ is consistent and asymptotically normal.

3.4 Penalized regression splines and thin plate bases in the CCE framework

This section clarifies the construction and implementation of penalized regression splines (PRS) for estimating the unknown function $g(\mathbf{x}_{it})$ in the CCE framework. We build on Gioldasis et al. (2023), who propose a semiparametric CCE estimator based on PRS, and explicitly formalize how thin plate regression splines (TPRS), as developed by Wood (2003), can be used within this structure. Our aim is to detail the steps and assumptions involved in applying this method to equation (9), ensuring coherence with the CCE structure and improving on the original implementation, where several aspects remained implicit.

PRS combine the computational simplicity of regression splines—which involve relatively few knots—with the smoothness control of smoothing splines, achieved via a penalty on the roughness of the fitted function. Among available spline bases, we adopt TPRS due to their strong theoretical properties and practical advantages. In particular, TPRS provide a low-rank approximation to classical thin plate splines (TPS), which are optimal in terms of smoothing but computationally expensive, as their basis dimension grows with the sample size. TPRS overcome this limitation by eliminating the need for manual knot selection and by adapting naturally to multivariate predictor spaces, making them ideal for high-dimensional panel data structures.

The smoothing parameter governing the strength of the penalty is selected via Restricted Maximum Likelihood (REML), which has been shown to perform well in finite samples and is less prone to undersmoothing or convergence to local minima compared to alternatives such as generalized cross-validation (Reiss and Todd Ogden, 2009). Additionally, in our empirical application, the covariates $\mathbf{x}_{it}$ vary in scale. To accommodate anisotropy and interaction effects in the nonparametric specification of $g(\cdot)$, we adopt tensor product bases (Wood, 2006).

To implement the TPRS-CCE estimator, we express the panel data $\{y_{it},\ \mathbf{x}_{it}\}$ in stacked vector form (stacking first observations over time periods for a given individual and then by the N individual). Let $n = N \times T$ denote the total number of observations. Then, define $\mathbf{y} \in \mathbb{R}^n$, the stacked outcome vector, $\mathbf{x}_i$, the $T \times d$ matrix of covariate values for individual i, and $\mathbf{W}$, the kronecker product of the $N \times N$ identity with the $T \times q$ matrix of observed proxies for unobserved common factors (typically including stacked $\overline{\mathbf{w}}_t$).

We approximate the unknown function $g(\cdot)$ by a smooth estimator $\hat{g} \in \mathcal{H}$, where $\mathcal{H}$ is a Hilbert space of smooth functions, by solving the following penalized least squares problem:

$$\min_{g \in \mathcal{H}, \boldsymbol{\psi}} \left\{ \|\mathbf{y} - \mathbf{g} - \mathbf{W}\boldsymbol{\psi}\|^2 + \lambda J_{md}(g) \right\}, \tag{10}$$

where $\mathbf{g}$ denotes the $n \times 1$ vector of stacked values of function $g(\cdot)$ in each observation $\mathbf{x}_{it}$, $\boldsymbol{\psi}$ the $Nq \times 1$ stacked vector of individual parameters ψ_i. The penalty function which controls the trade-off between data fitting and smoothness of $g(\cdot)$, is defined as

$$J_{md}(g) = \int_{\mathbb{R}^d} \sum_{\nu_1 + \cdots + \nu_d = m} \frac{m!}{\nu_1! \ldots \nu_d!} \left(\frac{\partial^m g}{\partial x_1^{\nu_1} \ldots \partial x_d^{\nu_d}} \right)^2 dx_1 \ldots dx_d,$$

with $m > d/2$ ensuring that the functional defines a proper semi-norm. By the representer theorem (Wahba and Wang, 2019), the penalized spline estimator $\hat{g}$ admits the following finite-dimensional representation:

$$\hat{g}(\mathbf{x}) = \sum_{i=1}^{N} \sum_{t=1}^{T} \gamma_{it} \eta_{md}(\|\mathbf{x} - \mathbf{x}_{it}\|) + \sum_{l=1}^{M} \mu_l \pi_l(\mathbf{x}), \tag{11}$$

where $\eta_{md}(\cdot)$ is a radial basis function whose expression depends on m and d (see Wood, 2003, for details), and $\{\pi_l(\cdot)\}_{l=1}^{M}$ is a basis for the space of polynomials in $\mathbb{R}^d$ of degree less than m (i.e. the space of polynomials for which J_{md} is 0). The number of basis functions associated with such polynomials in is given by $M = \binom{m+d-1}{d}$. The coefficients $\boldsymbol{\gamma} \in \mathbb{R}^n$ and $\boldsymbol{\mu} \in \mathbb{R}^M$ are unknown. Moreover, coefficients $\boldsymbol{\gamma}$ must satisfy the constraint $\mathbf{\Pi}'\boldsymbol{\gamma} = \mathbf{0}$, where $\mathbf{\Pi}_{it,l} = \pi_l(\mathbf{x}_{it})$, to ensure orthogonality to the polynomial space.

Substituting (11) into (10), the problem becomes:

$$\min_{\boldsymbol{\gamma}, \boldsymbol{\mu}, \boldsymbol{\psi}} \|\mathbf{y} - \mathbf{E}\boldsymbol{\gamma} - \mathbf{\Pi}\boldsymbol{\mu} - \mathbf{W}\boldsymbol{\psi}\|^2 + \lambda \boldsymbol{\gamma}'\mathbf{E}\boldsymbol{\gamma}, \text{ subjectto } \mathbf{\Pi}'\boldsymbol{\gamma} = \mathbf{0}, \tag{12}$$

where $E_{it,jt'} = \eta_{md}(\|\mathbf{x}_{it} - \mathbf{x}_{jt'}\|)$.

However, solving this system directly becomes computationally intensive when n is large, as we must estimate a number of paramaters larger than the number of observations. To address this issue, Wood (2003) proposes to leave unchanged the basis of the unpenalized functions, i.e. the matrix Π, and to concentrate on the basis of the γ parameter space. He introduces a low-rank approximation that preserves the essential features of the full basis. Therefore, let $\mathbf{E} = \mathbf{UDU}'$ be the spectral decomposition of $\mathbf{E}$ where $\mathbf{D}$ is a diagonal matrix of eigenvalues of $\mathbf{E}$ arranged from largest to smallest, and $\mathbf{U}$ is a matrix whose ith column corresponds to the ith eigenvalue of matrix $\mathbf{E}$. The best basis of rank k is given by $\mathbf{U}_k$, the first k columns of matrix $\mathbf{U}$, with k greater than M. As usual in spectral decomposition, this rank can be chosen by truncating the eigenvalues of smaller magnitude. Then, given the choice of the truncated basis, $\boldsymbol{\gamma} = \mathbf{U}_k\boldsymbol{\gamma}_k$ (in which case, $\boldsymbol{\gamma}_k = \mathbf{U}_k'\boldsymbol{\gamma}$), and the minimization problem (12) can be approximated by:

$$\min_{\boldsymbol{\gamma}_k, \boldsymbol{\mu}, \boldsymbol{\psi}} \|\mathbf{y} - \mathbf{U}_k\mathbf{D}_k\boldsymbol{\gamma}_k - \mathbf{\Pi}\boldsymbol{\mu} - \mathbf{W}\boldsymbol{\psi}\|^2 + \lambda \boldsymbol{\gamma}_k'\mathbf{D}_k\boldsymbol{\gamma}_k, \text{ subjectto } \mathbf{\Pi}'\mathbf{U}_k\boldsymbol{\gamma}_k = \mathbf{0}, \tag{13}$$

where $\mathbf{D}_k$ is the $k \times k$ diagonal matrix with the top k eigenvalues of $\mathbf{E}$ on its diagonal. Although truncating the basis introduces approximation error, Wood (2003) shows that truncation based on the top k eigenvectors of $\mathbf{E}$ minimizes the change in fitted values associated to any truncation in the basis of the γ parameters.

To sum up, this formulation integrates thin-plate regression splines into the CCE approach. It accommodates cross-sectional dependence via proxies in $\mathbf{W}$, retains flexibility in estimating the unknown nonparametric function $g(\cdot)$ through a penalized spline approximation $\hat{g}(\cdot)$, and remains computationally efficient through basis truncation.

4 Forecasting-driven model-selection procedure based on moving block bootstrap

We compare the aforementioned model specifications using the data-driven model selection procedure proposed by Gioldasis et al. (2023). This approach is a pseudo-Monte Carlo experiment that combines the panel moving block bootstrap (MBB) scheme introduced by Gonçalves (2011) with the time-series selection procedure developed by Racine and Parmeter (2014). The MBB scheme is particularly useful for preserving cross-sectional dependence in the bootstrapped samples. In this process, the time series is assumed to have length $T = b \times l$, wher b represents the number of nonoverlapping blocks and l the length of each block. To ensure that the dependence present in the original dataset is preserved, l is chosen to be sufficiently large. With MBB, we allow the blocks to overlap, thus obtaining a total of $T - l + 1$ overlapping blocks. For this specific analysis, we are working with a time horizon of 41 years. To ensure equal block lengths and maintain the dependence structure, we remove one year, setting the block length to 10 years. As a result, we obtain $40 - 10 + 1 = 31$ blocks.

Once the blocks are defined, following Racine and Parmeter (2014), the data are split into a training sample and an evaluation sample. The different models are then fitted according to the training sample and a measure of model forecasting performance is computed using the evaluation sample. In particular, we focus on the so-called average out-of-sample squared prediction error (ASPE) following Racine and Parmeter (2014). This procedure is replicated a number of times $S = 1000$ in order to obtain an $S \times 1$ vector of ASPEs for each model, allowing for a robust comparison of model performance.

The forecasting-data-driven model-selection procedure then works as follows:

1. Apply MBB to resample from original panel data $\mathbf{z}_{it} = (y_{it}, \mathbf{x}'_{it})'$, $i = 1, \ldots, n$, and $t = 1, \ldots, T$, and call these $\mathbf{z}^*_{it} = (y^*_{it}, \mathbf{x}^{*'}_{it})'$, $i = 1, \ldots, n$, and $t = 1, \ldots, T$.
2. Let the first T_1 years for the n countries form a training sample, i.e., $\mathbf{z}^*_{it}$, $i = 1, \ldots, n$, and $t = 1, \ldots, T_1$, and let the remaining observations, or $\mathbf{z}^*_{it}$, $i = 1, \ldots, n$, and $t = T_1 + 1, \ldots, T$, form an evaluation sample.
3. Consider two competing models A and B. Fit each model to the $n \times T_1$ training observations. Let $\widehat{g}^A_{T_1}(.)$ and $\widehat{g}^B_{T_1}(.)$ denote the estimated models.
4. Generate predictions for evaluation observations, or $\widehat{g}^A_{T_1}(\mathbf{x}^*_{it})$ and $\widehat{g}^B_{T_1}(\mathbf{x}^*_{it})$, $i = 1, \ldots, n$, and $t = T_1 + 1, \ldots, T$. The generation of predictions requires knowledge of factor values, i.e., $\mathbf{f}_t$, $t = T_1 + 1, \ldots, T$. These values are easily obtained using their approximation by cross-sectional averages.
5. Compute the ASPE of each model, i.e.,

$$ASPE^L = \frac{1}{n \times T_1} \sum_{i=1}^{n} \sum_{t=T_1+1}^{T} \left(y^*_{it} - \widehat{g}^L_{T_1}(\mathbf{x}^*_{it})\right)^2, \; L = A, B.$$

6. Repeat this a large number of times, say S times, yielding $(ASPE^A_s, ASPE^B_s)$, $s = 1, \ldots, S$, $s = 1, \ldots, S$.
7. Compare the predictive performance of the two models using their respective ASPE or MAPE empirical distribution functions. For instance, comparison can be achieved using paired-t or dominance tests.

MBB applied to panel data runs as follows:

1. Consider you have one response y_{it} and a $p \times 1$ vector of explanatory variables, or $\mathbf{x}_{it}$, with $i = 1, \ldots, n$, and $t = 1, \ldots, T$.
2. Let $\mathbf{z}_{it} = (y_{it}, \mathbf{x}'_{it})'$, vector whose dimension is $(p + 1) \times 1$.
3. Let $Z_{t,n} = (\mathbf{z}'_{1t}, \mathbf{z}'_{2t}, \ldots, \mathbf{z}'_{nt})'$ whose dimension is $n(p + 1) \times 1$. In fact, we stack all observations for the n individuals at period t.
4. Let l be the chosen length of a block. A block will thus be defined as the matrix $B_{t,l} = \{Z_{t,n}, Z_{t+1,n}, \ldots, Z_{t+l-1,n}\}$. $T - l + 1$ overlapping blocks are generated.
5. MBB resamples $k = T/l$ blocks with replacement from the set of $T - l + 1$ overlapping blocks.

5 Results

In this section, we present the results of our study, which exploit the balanced panel dataset covering 88 countries observed over the 1960-2000 period, as built by Calderón et al. (2015). We begin by examining the presence of cross-sectional dependence and unit roots in the data, followed by testing the restriction of constant returns to scale (CRS). Next, we report the estimation results for various parametric and nonparametric specifications and compare their performance using the previously described model selection procedure. We then assess residual cross-sectional dependence and, finally, provide additional estimation results by disaggregating the infrastructure index.

5.1 Assessing cross-sectional dependence and stationarity of the variables

To assess the presence and degree of cross-sectional dependence (CSD) in the data, we adopt the so-called CD test (Pesaran, 2021). Pesaran (2015) demonstrates that, in the most common cases, the implicit null of the test is weak cross-sectional dependence rather than independence. This is an important result from an empirical perspective because only strong cross-sectional dependence leads to inconsistent estimates, while under weak cross-sectional dependence standard panel estimators will suffer from inefficiency but still remain consistent.

In particular, we define a in the range [0, 1], as the exponent of CSD proposed by Bailey et al. (2016a). A value of a in the range [0, 1/2] indicates different degrees of weak CSD, whereas a in the range [1/2, 1] relates different degrees of strong CSD.

According to Pesaran (2015), in a typical macro-panel data setting and roughly in our case, the implicit null hypothesis of the CD test when T and $N \to \infty$ at the same rate is $0 \leq a < 1/4$. As reported in Table 1, the CD statistics for log(GDP), log(-capital), log(infrastructure), log(labor), and secondary education are equal to 369.824, 341.259, 384.904, 380.814 and 369.920, respectively. They are all highly statistically significant and lead to a strong rejection of the null hypothesis of

Table 1 Pesaran's (2015) CD test

	$\hat{a}$	$\hat{a}^*_{0.05}$	$\hat{a}^*_{0.95}$	CD test	p-value
log(GDP)	1.003	− 0.219	2.224	369.824	0.000
log(capital)	1.003	0.896	1.110	341.259	0.000
secondary education	1.003	0.964	1.042	369.920	0.000
log(infrastructure)	1.003	0.855	1.151	384.904	0.000
log(labor)	1.000	0.804	1.196	380.814	0.000

Note: The a exponent has been computed considering a number of 4 principal components (PCs)

weak CSD, suggesting that the exponent of cross-sectional dependence, a, is in the range [1/4, 1].

More specifically, the exponent of CSD has been computed according to the bias-adjusted estimator derived by Bailey et al. (2016a). All variables have an estimated exponent equal to 1. This result not only confirms the presence of strong CSD, but is also consistent with the factor literature, which typically assumes that all factors have the same cross-sectional exponent of $a = 1$ (Bai and Ng, 2002; Stock and Watson, 2002). Moreover, as also suggested by Bailey et al. (2016b), this result does not exclude the possibility that both weak and strong CSD coexist in the data.

Moving on to the panel unit root test, in order to investigate the stationarity of the series, it may be useful to consider the so-called second-generation tests which allow for CSD. As demonstrated by Pesaran (2007), tests that ignore this issue tend to over-reject the null hypothesis when CSD is present. In their seminal work, Bai and Ng (2004) propose decomposing the panel into deterministic, common and idiosyncratic components as follows:

$$y_{it} = D_{it} + \zeta_i'\mathbf{f}_t + v_{it},$$

where D_{it} is the deterministic component with individual effects and, eventually, individual trends. $\zeta_i'\mathbf{f}_t$ are the unobserved common factors, and v_{it} is the idiosyncratic term. Such a decomposition allows us to consider factors as objects of interest and to determine not only whether the data are stationary but also whether the eventual nonstationarity derives from a nonstationary common component, a nonstationary idiosyncratic component, or the nonstationarity of both components. However, a preliminary issue that arises involves determining how many common factors are necessary to capture the existing cross-sectional dependence. Usually, this choice is made by adopting information criteria (Bai and Ng, 2002). Nevertheless, the practical implementation of such criteria is difficult as they may tend to overestimate the number of factors and the results are known to be sensitive to the maximum number of factors which should be arbitrarily fixed (Ertur and Musolesi, 2017).

Table 2 PANICCA Test

	Idyosincratic component			Nonstationary factors	
	P_a	P_b	$PMSB$	MQ_f	MQ_c
	p-value				
log(GDP)	0	0	0	5	5
log(capital)	0	0	0.0001	5	5
secondary education	0	0	0.0037	5	5
log(infrastructure)	0	0	0.0003	5	5
log(labor)	0	0	0.0009	5	5

Note: The PANICCA test has been performed using the xtpanicca Stata command. For the lag structure of the unit root test, we referred to the Akaike information criterion

We adopt the PANICCA test proposed by Reese and Westerlund (2016) which is a PANIC approach implemented on cross-sectional averages rather than on principal components. This test preserves the asymptotic theory of PANIC but leads to much improved small-sample properties and does not require the preliminary indication of the number of factors.

The results of the PANICCA test are illustrated in Table 2. The statistics P_a, P_b, and $PMSB$ proposed by Bai and Ng (2010) clearly lead to a rejection of the null hypothesis of nonstationarity of the idiosyncratic components for all variables. The rejection of the nonstationarity of the idiosyncratic component does not imply that the series are stationary, as some of the common factors may be nonstationary. To determine how many of these factors are nonstationary, we follow Reese and Westerlund (2016) and consider the MQ_f and MQ_c statistics. The limiting distributions of these statistics are non-standard, and critical values are reported in Bai and Ng (2002) for up to six factors. The results provide a very clear picture. For all variables and regardless of the test used, the number of nonstationary common factors is always equal to the total number of common factors, which given the cross-sectional averages augmentation is equal to five. The application of the PANICCA approach thus suggests that the variables are nonstationary and that this property is the result of multiple nonstationary common factors combined with stationary idiosyncratic components. This result is fully consistent with Ertur and Musolesi (2017) and Gioldasis et al. (2023) and, moreover, as proven by Kapetanios et al. (2011), the CCE approach remains valid in this scenario.

Overall, the results indicate the presence of strong CSD and nonstationarity for all variables and suggest that such nonstationarity is the result of the coexistence of nonstationary factors and stationary idiosyncratic components, thus validating the adoption of the CCE estimation strategy which remains valid in this setting

(Chudik et al. 2011; Kapetanios et al. 2011; Pesaran and Tosetti, 2011).

5.2 Preliminary estimates without assuming CRS

We first estimate variants of Eq. (2) and test the restriction of CRS, that $\zeta + \eta + \psi = 1$, by using the same approach by Calderón et al. (2015), i.e. the PMG estimator with demeaned variables to account for CSD at least partially.[1] We also adopt the two-way fixed effects (FE) model.

Estimation results suggest the existence of decreasing returns to scale, with estimated scale elasticity equals to 0.73. The estimated elasticity of scale is implausibly low, and this result is clearly not consistent with the existence of CRS (see Table 3).

As for the output elasticities with respect to the inputs, the estimated elasticity with respect to capital is 0.465, which is higher than the corresponding estimated value found in Calderón et al. (2015) among many others. However, as argued by Romer (1987), this finding could be consistent with the presence of positive externalities due to investments in physical capital.

The output elasticity with respect to labor is instead implausibly low (0.124) if compared to the empirical findings in the existing literature (see Henderson and Kumbhakar, 2006; Holtz-Eakin, 1994, for further details).

As for the parameter $\xi = \vartheta/\psi$, which represents the contribution of the adopted proxy of human capital to "human capital augmented labor", we find a counter-intuitive and negative estimated parameter ($\widehat{\xi} = -0.049/0.124 = -0.395$), contrasting Calderón et al. (2015) who find an estimated coefficient of 0.17 (see Bils and Klenow, 2000, for further discussion). This finding may suggest misspecification problems and/or that the average years of secondary schooling, S, represent a poor proxy of human capital, as suggested by Hanushek and Kimko (2000) and Ertur and Musolesi (2017).

Finally, as far as the effect of infrastructure capital is concerned, the estimated elasticity of infrastructure capital equals 0.138 and is statistically significant at standard significance levels. This value is consistent with the estimated output elasticities of Aschauer (1989) and Calderón et al. (2015).

In summary, the results obtained using the PMG model suggest that estimating equation (2) without imposing CRS greatly affects the estimated technological parameters, yielding values that appear economically implausible. Similarly, the FE specification produces comparable results, with returns to scale that are implausibly low. These results will be reassessed in the next section after *i)* accounting for CSD using a more suitable multifactor error model and *ii)* allowing for flexible functional forms.

[1] We impose an underlying ARDL (1,1,1,1,1) order since it is one of the different order specifications considered by Calderón et al. (2015) and, moreover, the Stata routine xtpmg does not allow order selection using information criteria.

Table 3 Estimation results on demeaned variables and CRS test

		PMG	FE
	log(capital)	0.465***	0.270***
		(0.012)	(0.010)
	secondary education	− 0.049***	0.056***
		(0.007)	(0.010)
	log(infrastructure)	0.138***	0.234***
		(0.007)	(0.012)
	log(labor)	0.124***	0.160***
		(0.016)	(0.027)
	elasticity of scale	0.727	0.664
CRS test	test-statistics	242.00	182.80
	p-value	0.000	0.000

Note: The PMG model has been estimated using the xtpmg Stata command. The elasticity of scale represents the sum of the parameters referred to as log(capital), log(infrastructure), and log(labor), i.e., $\zeta + \eta + \psi$. The CRS test is an F-test for the FE model and a Wald test, which consists of a χ^2 statistic, for the PMG model. Significance levels: ***1%; **5%; *10%

5.3 Alternative CCE estimates

We now present the estimation results of the different specifications presented in Section 2, first focusing on the parametric specifications, i.e, the CCEP of Pesaran (2006) and the CS-DL of Chudik et al. (2016), and then moving to the two nonparametric specifications. The results are as follows.

All estimates based on the parametric models (Table 4) indicate a lack of significance of the infrastructure index and a magnitude of the estimated coefficient that is very close to zero, ranging from 0.005 to 0.059. This result is at odds with respect to Calderón et al. (2015), but it is not new in the empirical literature. Indeed, Tatom (1991) rejected the public capital hypothesis after controlling for the spurious regression problem, and Holtz-Eakin (1994) found no effect of public capital on productivity after controlling for country specific characteristics. Furthermore, Baltagi and Pinnoi (1995) and Canning and Pedroni (2004) pointed out the important issue of aggregated data in two perspectives. They first suggest looking at the contribution of each single component of public capital. In Section 5.6, we estimate the effects of telephone lines, paved roads, and electricity on productivity, taken separately, rather than considering the synthetic index. Moreover, another possible explanation for the lack of significance of the infrastructure index may be the data aggregation problem as also recently detected by

Table 4 Estimation of the production function: alternative CCE parametric and non-parametric specifications

	CCEP	CS-DL 0 lags	CS-DL 1 lag	CS-DL 2 lags	ADD edf (*p*-value)	NONADD
log(capital)	0.287***	0.274***	0.223**	0.290	8.026***	
	(0.075)	(0.063)	(0.095)	(0.210)	(<2e − 16)	
secondary education	0.189	0.183**	0.190	0.308	5.780***	
	(0.118)	(0.079)	(0.186)	(1.141)	(0.000)	115.1***
log(infrastructure)	0.020	0.059	0.048	− 0.005	1.002	(< 2e − 16)
	(0.041)	(0.037)	(0.043)	(0.135)	(0.320)	
log(labor)	0.730*	0.627	0.265	− 0.024	7.836***	
	(0.409)	(0.405)	(0.311)	(1.292)	(< 2e − 16)	
elasticity of scale	1.037	0.960	0.536	0.261	–	–
obs	3608	3520	3432	3344	3608	3608

Note: The displayed standard errors (SEs) for the CCEP model and the CS-DL models correspond to the nonparametric variance estimator from Pesaran (2006)

The acronym "edf" stands for effective degrees of freedom estimated from generalized additive models. They are used as proxies for the degree of non-linearity in the considered relationship. Specifically, values of edf equal to 1 indicate a linear relationship and values above 1 indicate progressively higher degrees of non-linearity. The reported *p*-values refer to the Wald-type test suggested by Wood (2013). Significance levels: ***1%; **5%; *10%

Elasticity of scale represents the sum of the parameters referred to as log(capital), log(infrastructure), and log(labor), i.e. $\zeta + \eta + \psi$

Feng and Wu (2018), who suggest considering disaggregated firm-level data.

Overall, contrary to the estimates of Calderón et al. (2015), the magnitude of the technological parameters associated with labor, physical capital, and human capital is reasonable and consistent with the main literature (see, for example, Holtz-Eakin, 1994 and Henderson and Kumbhakar, 2006). Capital and labor inputs show respective magnitudes of about 0.28 and 0.73 in the CCE static model. These estimated elasticities are economically plausible and in line with previous empirical findings (see, among others, Eberhardt et al. 2013). The resulting contribution of human capital ξ is positive and equal to 0.259, which is more reasonable if compared to the previous PMG estimate.

As for the CS-DL estimator, we note that the estimates are quite sensitive with respect to the lag order, which ranges from 0 to 2 as in Raissi et al. (2018). This instability could be due to the presence of feedback effects from lagged values of the dependent variable into the regressors, as suggested by Chudik et al. (2013) based on both theoretical results and Monte Carlo simulations, according to which the bias of the CS-DL estimator that arises because of feedback effects may worsen as the number of lags increases. The possibility of feedback effects is supported by previous literature, according to which public infrastructure investments and more generally the level of production inputs could also be induced by economic growth rather than just driving it (see Feng and Wu, 2018). In particular, while the estimates obtained by fixing the number of lags to zero are close to the CCEP ones and are consistent from an economic point of view, when increasing the number of lags the results indicate an implausibly low coefficient of labor. Moreover, these results may be consistent with the belief that addressing the endogeneity of labor is more important than addressing that of capital because labor is a more flexible input than capital (Antonioli et al. 2021).

As far as statistical inference is concerned, it is worth noting that, while Table 4 reports the standard errors obtained by using the nonparametric variance estimator of Pesaran (2006), which is consistent in long heterogeneous panels and performs well in simulations and is often employed, in the homogeneous case with $T/N \to 0$, a sandwich estimator such as the Newey-West procedure may be preferable.

Similar to Millo (2019), we compare three different methods to estimate the standard errors (SEs) of CCEP and CS-DL models. We first consider the nonparametric variance estimator of Pesaran (2006), which is consistent in long heterogeneous panels, performs well in simulations and is often employed (Ertur and Musolesi, 2017). Second, we adopt a Newey-West-type approach (Ditzen, 2018), which may be preferable in the homogeneous case when $T/N \to 0$ (Millo, 2019), and finally add a third alternative known as the fixed-T variance estimator (Westerlund et al. 2019) which consists of a heteroskedasticity-robust covariance matrix estimator.

The main result (see Table 5) is that the synthetic infrastructure index remains insignificant in most cases. The only relevant exception is provided by the CS-DL models with 0 and 1 lag, for which, when using the Newey-West-type variance estimator, the infrastructure index is statistically

Table 5 Alternative standard errors (SEs) for the CCEP and CS-DL models

		log(capital)		secondary education		log(infrastructure)		log(labor)	
CCEP	NP	0.075	0.000***	0.118	0.110	0.041	0.623	0.409	0.074*
	NW	0.039	0.000***	0.059	0.001***	0.021	0.346	0.239	0.002***
	WPN	0.050	0.000***	0.062	0.002***	0.031	0.518	0.327	0.026**
CS-DL (0 lags)	NP	0.063	0.000***	0.079	0.020**	0.037	0.106	0.405	0.122
	NW	0.046	0.000***	0.074	0.014**	0.025	0.019**	0.222	0.005***
	WPN	0.061	0.000***	0.082	0.026**	0.037	0.105	0.357	0.079*
CS-DL (1 lag)	NP	0.095	0.019**	0.186	0.306	0.043	0.263	0.311	0.394
	NW	0.053	0.000***	0.065	0.004***	0.029	0.096*	0.161	0.10*
	WPN	0.080	0.005***	0.078	0.014**	0.042	0.253	0.269	0.324
CS-DL (2 lags)	NP	0.211	0.168	1.141	0.787	0.135	0.970	1.292	0.985
	NW	0.054	0.000***	0.079	0.000***	0.040	0.897	0.190	0.899
	WPN	0.085	0.001***	0.119	0.010***	0.061	0.933	0.353	0.945

Note: NP= Nonparametric variance estimator from Pesaran (2006); NW= Newey West sandwich estimator from Pesaran (2006); WPN=fixed-T variance estimator from Westerlund et al. (2019). For each variable: standard error and p-value for the t-test. Significance levels: ***1%; **5%; *10%.

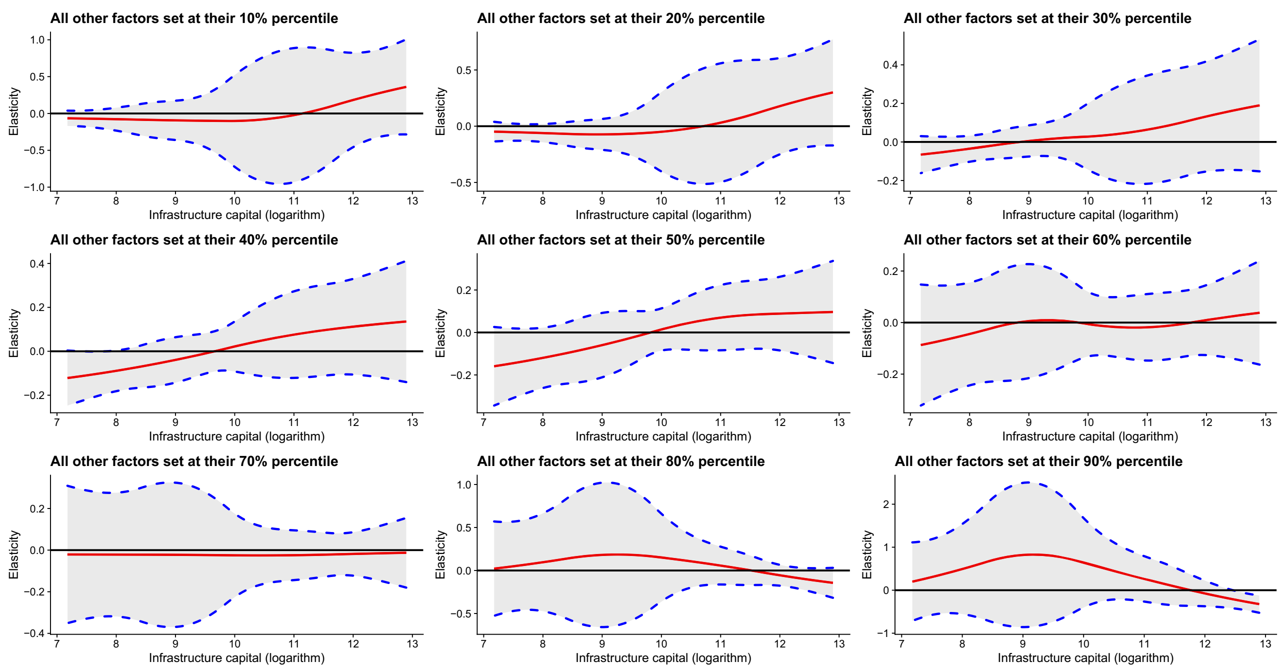

Fig. 1 Estimated infrastructure elasticities

significant at the usual significance levels. Moreover, consistent with the replication study by Millo (2019), the nonparametric variance estimator always produces higher standard errors with respect to the alternative aforementioned procedures.

When moving to the nonparametric specifications, we again find a lack of significance of the infrastructure index. Specifically, on the one hand, for the additive model (ADD) we look at the Wald-type test suggested by Wood (2013) for the significance of the univariate smooth function, which clearly appears to be non-significant at the usual significance levels (p-value=0.32). Figure 1 On the other hand, even though the non-additive specification (NONADD) provides an overall significant smooth multivariate function, we specifically focus our attention on the estimated output elasticity of infrastructure capital as a function of its potential values, the other inputs being fixed to some quantile values.[2]

[2] The computation of standard errors and confidence bands takes advantage of the underlying parametric representation of spline approximations (Gioldasis et al. 2023).

Overall, the estimated elasticity of infrastructure swings around zero and is always not significant, which is fully consistent with the results obtained from the parametric models. More specifically, beyond this overall non-significance, for low levels of all other inputs (until the 50th percentile) we observe an increasing smooth function, with an estimated elasticity that becomes positive and is relatively high in magnitude after a certain threshold. We also observe that the estimated function varies greatly with the value of the other inputs. Overall, these results could be consistent with some previous work suggesting that threshold effects may be at work, as a critical mass of infrastructure may be necessary to become effective (Musolesi, 2011), and that interaction effects among inputs are relevant in the sense that it is necessary to find an appropriate mix of them (Kortelainen and Leppänen, 2013).

5.4 Model selection

We compare the aforementioned model specifications using the data-driven model selection procedure. For this specific analysis, we are working with a time horizon of 41 years. To ensure equal block lengths and maintain the dependence structure, we remove one year, setting the block length to 10 years.As a result, we obtain $40-10+1=31$ blocks. To compare the predictive performances of the different models, we analyze the empirical distribution of the ASPEs over a one-year horizon, presenting the results using boxplots.

In the upper panel of Fig. 2, we focus on standard panel data models that employ cross-sectional demeaning, namely the PMG and the FE. In the lower panel, we instead examine the various CCE specifications. A key finding is that all CCE models significantly outperform the traditional models in terms of out-of-sample predictive accuracy. Another notable result is that among the CCE specifications, the nonparametric models deliver the best predictive performance. This finding strongly aligns with the results of Gioldasis et al. (2023) and provides further support for using flexible models when estimating a production function. Interestingly, the dynamic CS-DL specifications perform the worst among the CCE models, with a noticeable decline in predictive accuracy as the number of lags increases.

5.5 Further checks on residuals

In principle, the residuals of all specifications should exhibit only weak cross-sectional dependence as, in a more or less flexible way, common factors are explicitly accounted for. In doing so, we estimate the exponent of cross-sectional dependence previously discussed and apply Frees' (1995; 2004) test on the residuals of the different models. As discussed in De Hoyos and Sarafidis (2006), Millo (2019), and Juodis and Reese (2021), the standard Pesaran CD test is subject to a bias term of order $\sqrt{T}$ when common time effects or interactive fixed effects are included, thus leading to a potential over-rejection of the null hypothesis of weak cross-sectional dependence. We specifically consider Frees' test because it does not present such a problem, returning unbiased diagnostics. The results of the test are illustrated in Table 6. In particular, while Frees' test leads to a rejection of the null of cross-sectional independence for all specifications, the estimation of the exponent of cross-sectional dependence provides additional interesting insights.[3] The results indicate that i) the residuals of the PMG model clearly exhibit strong cross-sectional dependence, with an estimated exponent at 0.85, and ii) the consideration of CCE models produces a reduction of the estimated exponent, with the NONADD model performing best also in terms of reducing residual cross-sectional dependence, with an estimated exponent equal to 0.45. Finally, note that these results should be interpreted with care because as pointed out by Bailey et al. (2016 a) the exponent a is identifiable only if $a > 1/2$, while for values of $1/2 < a < 2/3$, the identification of a is difficult, albeit theoretically possible.

5.6 Disaggregating the infrastructure index

Following Baltagi and Pinnoi (1995) and Canning and Pedroni (2004), the lack of significance of the synthetic index could be due to the aggregation of different kinds of infrastructure and consequently it can be crucial looking at the contribution of each single component of infrastructure capital on productivity. More specifically, the purpose of this section is to examine the effects of telephone lines, paved roads, and electricity, taken separately, on productivity.

For a sake of simplicity, we compare the results by adopting the CCEP and the ADD model. The NONADD model, despite its appeal, with the inclusion of additional regressors may suffer of the curse of dimensionality problem, its interpretation can be extremely complex, and, more generally, it may require a specific investigation, which is outside the scope of this paper. The CS-DL is not considered here because it underperformed with respect to all the others models.

The results in Table 7 provide additional interesting insights. A first result that appears from the CCEP is that disaggregating the infrastructure index is crucial to find a significant effect of one component of such an index, as it is found a positive and significant effect of telephone lines, with an estimated elasticity equals to 0.07, while both paved roads and electricity are still not-significant and

[3] Following Bailey et al. (2016a), we consider four principal components for the estimation of the exponents.

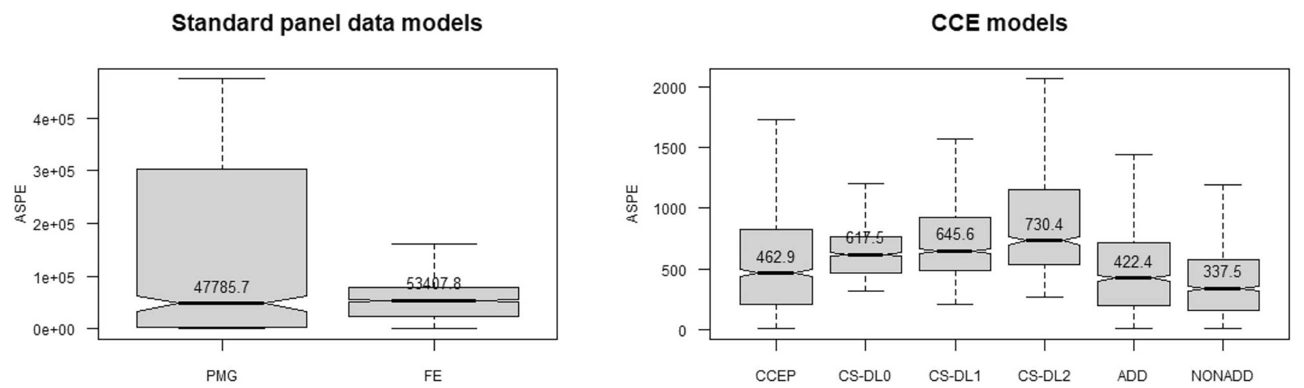

Fig. 2 Out-of-sample average square prediction error (ASPE) box plots for different models on a 1-year horizon: the pooled mean group model (PMG), the two-way fixed effects model (FE), the common correlated estimator in its pooled version (CCEP), the cross-sectional augmented distributed lags (CS-DL0, CS-DL1, and CS-DL2), and the additive (ADD) and non-additive penalized (NONADD) models

Table 6 Exponent of CSD and Frees' test on residuals

	$\hat{a}$	$\hat{a}^*_{0.05}$	$\hat{a}^*_{0.95}$	Frees' test	p-value
PMG	0.856	0.588	1.124	19.301	0.000
CCEP	0.488	0.403	0.572	4.523	0.000
CS-DL0	0.712	0.647	0.778	4.082	0.000
ADD	0.657	0.595	0.719	4.201	0.000
NONADD	0.447	0.373	0.521	3.311	0.000

Note: The a exponent has been computed considering a number of 4 principal components PCs

Table 7 Alternative estimates with disaggregated data for infrastructure

	CCEP	ADD edf (p-value)
log(capital)	0.299***	7.336***
	(0.073)	(< 2e − 16)
secondary education	0.280**	7.389***
	(0.129)	(7.58e − 07)
log(roads)	−0.022	5.282*
	(0.033)	(0.064)
log(electricity)	−0.021	5.956
	(0.023)	(0.161)
log(telephone)	0.069**	4.598**
	(0.029)	(0.002)
log(labor)	0.775	7.439***
	(0.494)	(< 2e − 16)
elasticity of scale	1.1	–
obs	3608	3608

The displayed standard errors (SEs) for the CCEP model correspond to the nonparametric variance estimator from Pesaran (2006)

Acronym "edf" stands for effective degrees of freedom estimated from generalized additive models. They are used as proxies for the degree of non-linearity in the considered relationship. Specifically, values of edf equal to 1 indicate a linear relationship and values above 1 indicate progressively higher degrees of non-linearity. The reported p-values refer to the Wald-type test suggested by Wood (2013). Significance levels: ***1%; **5%; *10%

Elasticity of scale represents the sum of the parameters referred to as log(capital), log(labor), log(roads), log(electricity) and log(telephone).

characterized by an estimated elasticity very close to zero. Moreover, relaxing the linearity assumption with the ADD model gives further information (see also Fig. 3). First, it confirms the CCEP result with respect to telephone, as the estimated smooth component not only remains significant but also presents a rather linear pattern. Second, it suggests the presence of a functional misspecification bias, as paved roads becomes significant but with a clear non-linear pattern. In particular, threshold effects now appear as roads seem to have a positive effect to stimulate productivity only for a very low or a very high level of such an input. This result has also interesting economic implications.

6 Conclusions and policy implications

This paper offers a comprehensive analysis of the role of infrastructure in production, integrating recent advances in panel data econometrics. Specifically, we address cross-sectional dependence and nonstationarity using CCE-based models. Both parametric and nonparametric specifications are considered. While the latter offer greater functional flexibility and mitigate misspecification bias, they come with higher computational cost and increased sensitivity to dimensionality.

Given the classic efficiency-bias trade-off and the uncertainty surrounding the true data-generating process, we employ a data-driven model selection strategy based on Racine and Parmeter (2014) and extended to panel data by Gioldasis et al. (2023).

Our results yield several key insights. First, when using an aggregate infrastructure index, estimated elasticities are

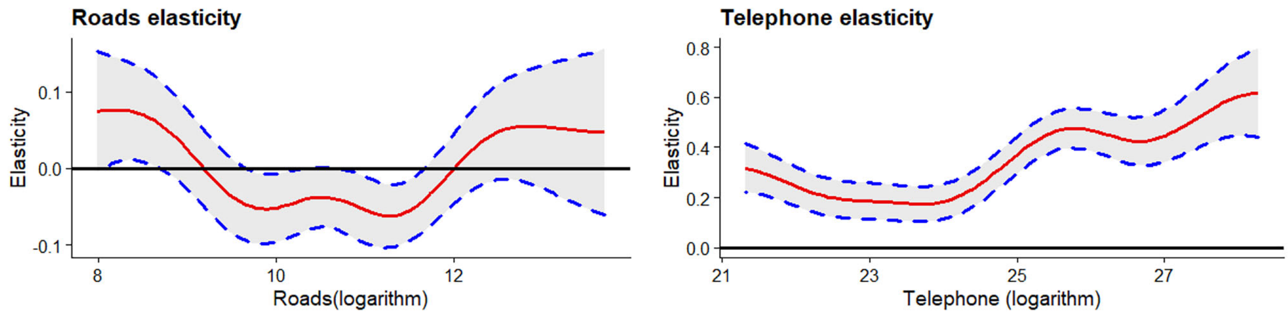

Fig. 3 Estimated elasticities of the significant components of infrastructure in the ADD model

consistently near zero and statistically insignificant in parametric and semiparametric (additive) models. However, fully nonparametric estimation reveals more nuanced patterns. For low levels of infrastructure and other inputs (below the median), the elasticity becomes significantly positive and relatively large beyond a critical threshold. This supports the "critical mass" hypothesis of public capital (Musolesi, 2011), suggesting that infrastructure contributes meaningfully to output only once a sufficient stock is in place. In addition, we find evidence of interaction effects, pointing to complementarities among production factors (Kortelainen and Leppänen, 2013).

Second, disaggregated analysis of infrastructure components - telephone lines, paved roads, and electricity - reveals substantial heterogeneity. Telecommunications infrastructure stands out as a key driver of output growth, with robust and significant effects. This finding is consistent with literature emphasizing the productivity-enhancing role of information and communication technologies (Agénor and Neanidis, 2015; Kellenberg, 2009; Röller and Waverman, 2001).

These results have several policy implications. First, generalized infrastructure spending is unlikely to yield productivity gains unless a critical threshold of capital stock is achieved. Investment strategies should therefore prioritize the attainment of a critical mass of high-quality infrastructure, particularly in settings with low initial endowments. Second, given the heterogeneous productivity effects across infrastructure types, resources should be allocated preferentially to components with higher returns, especially telecommunications. Third, the presence of interaction effects highlights the need for coordinated policy design. Infrastructure initiatives should be integrated into broader development strategies that also involve investment in complementary factors such as human capital and institutional quality. Finally, the findings demonstrate the importance of flexible, data-driven model selection: allowing the data to determine the appropriate functional form improves empirical reliability and enhances the credibility of policy conclusions.

In summary, the evidence supports investment strategies that are both targeted in focus and embedded within comprehensive development frameworks.

Data Availability

No datasets were generated or analysed during the current study.

Author contributions A.M. and M.S. contributed to the conceptualization, writing, econometric methodology (both parametric and nonparametric models, including model selection), and econometric modelling. G.P. contributed to the computational implementation and to the econometric methodology and writing, with a specific focus on dynamic parametric models.

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References

Aaron HJ (1990) Why is infrastructure important? discussion. In *Federal Reserve Bank of Boston Conference Series*, volume 34

Agénor P-R (2010) Public capital, growth and welfare: Analytical foundations for public policy. *Princeton University Press*

Agénor P-R, Neanidis KC (2015) Innovation, public capital, and growth. Journal of Macroeconomics 44:252–275

Antonioli D, Gioldasis G, Musolesi A (2021) Estimating a non-neutral production function. Oxford Economic Papers 73(2):856–878

Aschauer DA (1989) Is public expenditure productive? Journal of monetary economics 23(2):177–200

Bai J (2009) Panel data models with interactive fixed effects. Econometrica 77(4):1229–1279

Bai J, Ng S (2002) Determining the number of factors in approximate factor models. Econometrica 70(1):191–221

Bai J, Ng S (2004) A panic attack on unit roots and cointegration. Econometrica 72(4):1127–1177

Bai J, Ng S (2010) Panel unit root tests with cross-section dependence: A further investigation. Econometric Theory 26(4):1088–1114

Bailey N, Holly S, Pesaran MH (2016) A two-stage approach to spatio-temporal analysis with strong and weak cross-sectional dependence. Journal of Applied Econometrics 31(1):249–280

Bailey N, Kapetanios G, Pesaran MH (2016) Exponent of cross-sectional dependence: Estimation and inference. Journal of Applied Econometrics 31(6):929–960

Baltagi BH (2011) Spatial panels. Handbook of empirical economics and finance: 435–454

Baltagi BH, Bresson G, Griffin JM, Pirotte A (2003) Homogeneous, heterogeneous or shrinkage estimators? Some empirical evidence from French regional gasoline consumption. Empirical Economics 28(4):795–811

Baltagi BH, Pinnoi N (1995) Public capital stock and state productivity growth: Further evidence from an error components model. Empirical Economics 20(2):351–359

Barro RJ (1990) Government spending in a simple model of endogeneous growth. Journal of political economy 98(5):S103–S125

Berg AG, Ostry JD, Zettelmeyer J (2022) Public capital and economic growth: A critical survey. International Monetary Fund Staff Papers 69(1):1–34

Bils M, Klenow PJ (2000) Does schooling cause growth? American economic review 90(5):1160–1183

Boarnet MG (1998) Spillovers and the locational effects of public infrastructure. Journal of Regional Science 38(3):381–400

Bond SR (2002) Dynamic panel data models: A guide to micro data methods and practice. Portuguese economic journal 1:141–162

Bougheas S, Demetriades PO, Morgenroth EL (2000) Infrastructure, transport costs and trade. Journal of International Economics 47(1):169–189

Calderón C, Moral-Benito E, Servén L (2015) Is infrastructure capital productive? A dynamic heterogeneous approach. Journal of Applied Econometrics 30(2):177–198

Calderón C, Servén L (2004) The effects of infrastructure development on growth and income distribution. *Policy Research Working Paper 3400*, World Bank

Calderón C, Servén L (2014) Infrastructure, growth, and inequality: An overview. *Policy Research Working Paper 7034*, World Bank

Canning D, Pedroni P (2004) The effect of infrastructure on long run economic growth. Harvard University 99(9):1–30

Christensen LR, Jorgenson DW, Lau LJ (1973) Transcendental logarithmic production frontiers. The Review of Economics and Statistics 55(1):28–45

Chudik A, Mohaddes K, Pesaran MH, Raissi M (2013) Debt, inflation and growth: Robust estimation of long-run effects in dynamic panel data models. *Cafe research paper*, (13.23)

Chudik A, Mohaddes K, Pesaran MH, Raissi M (2016) *Long-run effects in large heterogeneous panel data models with cross-sectionally correlated errors*. Emerald Group Publishing Limited

Chudik A, Pesaran MH, Tosetti E (2011) Weak and strong cross-section dependence and estimation of large panels

Cohen JP, Morrison Paul CJ (2004) Public infrastructure investment, interstate spatial spillovers, and manufacturing costs. Review of Economics and Statistics 86(2):551–560

Creel J, Monperrus-Veroni P, Saraceno F (2009) Public investment, growth and fiscal constraints: Challenges for the eu new member states. Journal of Policy Modeling 31(6):837–852

Cui G, Wei Y, Zhang X (2025) A review and classification of model uncertainty

De Hoyos RE, Sarafidis V (2006) Testing for cross-sectional dependence in panel-data models. The stata journal 6(4):482–496

Diewert WE, Nomura K, Shimizu C (2025) Estimating flexible functional forms using macroeconomic data. *Empirical Economics*, pages 1–27

Ditzen J (2018) Estimating dynamic common-correlated effects in stata. The Stata Journal 18(3):585–617

Dobbelaere S, Mairesse J (2013) Panel data estimates of the production function and product and labor market imperfections. Journal of Applied Econometrics 28(1):1–46

Durlauf SN, Johnson PA, Temple JRW (2005) Growth econometrics. In Aghion P, Durlauf SN, editors, *Handbook of Economic Growth*, volume 1A, chapter 8, pages 555–677. Elsevier, Amsterdam

Eberhardt M, Helmers C, Strauss H (2013) Do spillovers matter when estimating private returns to R&D? Review of Economics and Statistics 95(2):436–448

Efron B (1982) *The jackknife, the bootstrap and other resampling plans*. SIAM

Ertur C, Musolesi A (2017) Weak and strong cross-sectional dependence: A panel data analysis of international technology diffusion. Journal of Applied Econometrics 32(3):477–503

Everaert G (2003) Balanced growth and public capital: An empirical analysis with I(2) trends in capital stock data. Economic Modelling 20(4):741–763

Ezcurra R, Gil C, Pascual P, Rapun M (2005) Public capital, regional productivity and spatial spillovers. The annals of regional science 39:471–494

Feng Q, Wu GL (2018) On the reverse causality between output and infrastructure: The case of China. Economic Modelling 74:97–104

Fernald JG (1999) Roads to prosperity? Assessing the link between public capital and productivity. American Economic Review 89(3):619–638

Frees EW (1995) Assessing cross-sectional correlation in panel data. Journal of econometrics 69(2):393–414

Frees EW et al. (2004) *Longitudinal and panel data: analysis and applications in the social sciences*. Cambridge University Press

Futagami K, Morita Y, Shibata A (1993) Dynamic analysis of an endogenous growth model with public capital. *The Scandinavian Journal of Economics*, pages 607–625

Gioldasis G, Musolesi A, Simioni M (2023) Interactive r&d spillovers: An estimation strategy based on forecasting-driven model selection. International Journal of Forecasting 39(1):144–169

Gonçalves S (2011) The moving blocks bootstrap for panel linear regression models with individual fixed effects. Econometric Theory 27(5):1048–1082

Greiner A, Semmler W (2000) Endogenous growth, government debt and budgetary regimes. Journal of macroeconomics 22(3):363–384

Hansen BE (2005) Challenges for econometric model selection. Econometric Theory 21(1):60–68

Hanushek EA, Kimko DD (2000) Schooling, labor-force quality, and the growth of nations. American economic review 90(5):1184–1208

Henderson DJ, Kumbhakar SC (2006) Public and private capital productivity puzzle: A nonparametric approach. *Southern Economic Journal*, pages 219–232

Holtz-Eakin D (1994) Public sector capital and the productivity puzzle. *Review of Economics and Statistics*, (76):12–21

Holtz-Eakin D, Schwartz AE (1995) Spatial productivity spillovers from public infrastructure: Evidence from state highways. International Tax and Public Finance 2(3):459–468

Hou Z, Zhao S, Kumbhakar SC (2025) Revisiting the productivity effects of public capital. Empirical Economics 68(3):1233–1264

Ivaldi M, Ladoux N, Ossard H, Simioni M (1996) Comparing fourier and translog specifications of multiproduct technology: Evidence from an incomplete panel of french farmers. Journal of Applied Econometrics 11(6):649–667

Juodis A, Reese S (2021) The incidental parameters problem in testing for remaining cross-section correlation. *Journal of Business & Economic Statistics*, pages 1–13

Kapetanios G, Pesaran MH, Yamagata T (2011) Panels with non-stationary multifactor error structures. Journal of econometrics 160(2):326–348

Kawaguchi D, Ohtake F, Tamada K (2009) The productivity of public capital: Evidence from Japan's 1994 electoral reform. Journal of the Japanese and International Economies 23(3):332–343

Kellenberg DK (2009) Us affiliates, infrastructure and growth: A simultaneous investigation of critical mass. The Journal of International Trade & Economic Development 18(3):311–345

Kortelainen M, Leppänen S (2013) Public and private capital productivity in Russia: A non-parametric investigation. Empirical Economics 45(1):193–216

Laborda L, Sotelsek D (2019) Effects of road infrastructure on employment, productivity and growth: An empirical analysis at country level. Journal of Infrastructure Development 11(1-2):81–120

Ma S, Racine JS, Ullah A (2020) Nonparametric estimation of marginal effects in regression-spline random effects models. Econometric Reviews 39(8):792–825

Mairesse J, Jaumandreu J (2005) Panel-data estimates of the production function and the revenue function: What difference does it make? The Scandinavian Journal of Economics 107(4):651–672

Millo G (2019) Private returns to R&D in the presence of spillovers, revisited. Journal of Applied Econometrics 34(1):155–159

Munnell AH et al. (1990) Why has productivity growth declined? Productivity and public investment. *New England Economic Review*, (Jan):3–22

Musolesi A (2011) On public capital hypothesis with breaks. Economics Letters 110(1):20–24

Pereira AM (2000) Is all public capital created equal? Review of Economics and Statistics 82(3):513–518

Pereira AM, Flores R (1999) Public capital and private sector performance in the United States. Journal of Urban Economics 46(99):300–22

Pesaran MH (2006) Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica 74(4):967–1012

Pesaran MH (2007) A simple panel unit root test in the presence of cross-section dependence. Journal of applied econometrics 22(2):265–312

Pesaran MH (2015) Testing weak cross-sectional dependence in large panels. Econometric reviews 34(6-10):1089–1117

Pesaran MH (2021) General diagnostic tests for cross-sectional dependence in panels. Empirical Economics 60:13–50

Pesaran MH, Shin Y, Smith RP (1999) Pooled mean group estimation of dynamic heterogeneous panels. Journal of the American statistical Association 94(446):621–634

Pesaran MH, Tosetti E (2011) Large panels with common factors and spatial correlation. Journal of Econometrics 161(2):182–202

Pritchett L (2000) The tyranny of concepts: Cudie (cumulated, depreciated, investment effort) is not capital. Journal of Economic Growth 5(4):361–384

Racine J, Parmeter C (2014) Data-driven model evaluation: a test for revealed performance. In Racine JS, Su L, Ullah A, editors, *Handbook of Applied Nonparametric and Semiparametric Econometrics and Statistics*, pages 308–345. Oxford University Press

Raissi MM, et al. (2018) Corporate indebtedness and low productivity growth of Italian firms. *Technical report*, International Monetary Fund

Reese S, Westerlund J (2016) Panicca: Panic on cross-section averages. Journal of Applied Econometrics 31(6):961–981

Reiss PT, Todd Ogden R (2009) Smoothing parameter selection for a class of semiparametric linear models. Journal of the Royal Statistical Society: Series B (Statistical Methodology) 71(2):505–523

Röller L-H, Waverman L (2001) Telecommunications infrastructure and economic development: A simultaneous approach. American economic review 91(4):909–923

Romer PM (1987) Crazy explanations for the productivity slowdown. NBER macroeconomics annual 2:163–202

Schultze CL (1990) The federal budget and the nations economic health. *Setting National Priorities: Policy for the Nineties. Aaron, Henry (ed.). Brookings Institution*

Soberon A, Mazzanti M, Musolesi A, Rodriguez-Poo JM (2025) Efficient estimation of a partially linear panel data model with cross-sectional dependence. Journal of Multivariate Analysis 206:105393

Soberon A, Musolesi A, Rodriguez-Poo JM (2024) A semi-parametric panel data model with common factors and spatial dependence. Oxford Bulletin of Economics and Statistics 86(4):905–927

Stock JH, Watson MW (2002) Macroeconomic forecasting using diffusion indexes. Journal of Business & Economic Statistics 20(2):147–162

Su L, Jin S (2012) Sieve estimation of panel data models with cross section dependence. Journal of Econometrics 169(1):34–47

Tatom JA (1991) Public capital and private sector performance. Review 73:3–15

Westerlund J, Petrova Y, Norkute M (2019) CCE in fixed-T panels. Journal of Applied Econometrics 34(5):746–761

Wood SN (2003) Thin plate regression splines. Journal of the Royal Statistical Society: Series B (Statistical Methodology) 65(1):95–114

Wood SN (2006) Low-rank scale-invariant tensor product smooths for generalized additive mixed models. Biometrics 62(4):1025–1036

Wood SN (2013) On p-values for smooth components of an extended generalized additive model. Biometrika 100(1):221–228