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

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Abstract

This paper provides a broad replication of Calderón et al. (2015). We address some complex and relevant issues, namely functional form, non-stationary variables and cross-sectional dependence. In particular, by adopting the CCE framework, we consider both parametric - static and dynamic - and non-parametric specifications, thus allowing for different degrees of flexibility. Contrary to Calderón et al. (2015), we find a lack of significance of the infrastructure index, with an estimated elasticity very close to zero for all estimates. Moreover, by employing the data-driven model selection procedure proposed by Gioldasis et al. (2021), it is found that non-parametric specifications provide the best predictive performance and that CCE models always overperform with respect to traditional panel data methods that employ cross-sectional demeaning to account for cross-sectional dependence.

Keywords: Cross-sectional dependence; factor models; moving block bootstrap; non-parametric regression; spline functions; public capital hypothesis.

JEL classification: C23; C5; O4.

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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 an important factor underlying the productivity slowdown in the US during the 1970s and 1980s. This view is often referred to as the "public capital hypothesis".

Although the empirical framework adopted by Aschauer (1989) is consistent with the endogenous growth models that were developed by Barro (1990) and others, from an empirical point of view, doubts have been cast with respect to the effectiveness of infrastructure to stimulate productivity. Indeed, the subsequent literature shows very mixed results (Holtz-Eakin, 1994; Henderson and Kumbhakar, 2006; Musolesi, 2011; Kortelainen and Leppänen, 2013; Ma et al., 2020; Moussa, 2020). As for econometric estimation and testing, relevant issues raised by this literature are those of functional form, non-stationary variables, spurious regression and cointegration. In particular, the problem of non-stationarity and spurious regression has often been addressed, both with time series (Aaron, 1990; Munnell et al., 1990; Schultze, 1990; Tatom, 1991; Pereira and Flores, 1999; Pereira, 2000; Everaert, 2003) and panel data (Canning and Pedroni, 2004; Kawaguchi et al., 2009).

Within this strand of the literature and in the framework of large panel data, Calderón et al. (2015) adopt a panel cointegration approach. They first specify the relationship linking production to infrastructure capital using a Cobb -Douglas production function with constant returns to scale. They then embed this specification into an auto-regressive distributed lag (ARDL) specification. After cross-sectional demeaning to account for unobserved factors, they implement the pooled mean group (PMG) estimator of Pesaran et al. (1999), finally finding a significant effect of infrastructure capital on productivity over the long -run, thus reinforcing Aschauer's findings.

This paper aims to provide a broad replication of Calderón et al. (2015) by exploiting recent advances in panel data econometrics, specifically, with respect to *i)* handling cross-sectional dependence (CSD), *ii)* allowing flexible functional forms, and *iii)* performing model selection.

In order to handle CSD as a result of unobservable common factors (Ertur and Musolesi, 2017), we follow Pesaran (2006), who developed a class of estimators known as common correlated effects (CCE) estimators. This approach is now widely used because it is easy to implement, it remains consistent in a variety of situations that are likely to occur, such as the presence of both weak and strong cross-sectional dependence (Chudik et al., 2011) or the existence of nonstationary factors (Kapetanios et al., 2011), and contrary to Bai (2009), it doesn't require the *a priori* knowledge of the number of unobserved common factors. These features make it a flexible instrument to use in different settings.

Within the CCE framework, we consider alternative models - allowing for different degrees of flexibility - that have recently been proposed in the literature. We first consider the static model by Pesaran (2006). Then we move to a dynamic specification, the so -called cross-sectionally augmented distributed lag (CS-DL) approach of Chudik et al. (2016), and finally, we consider more flexible semi-parametric (additive) and non-parametric CCE estimators, which were proposed by Su and Jin (2012) and were recently adopted by Gioldasis et al. (2021).

Allowing for different degrees of flexibility, and in particular considering semi- and non-parametric specifications, is of great empirical relevance. As argued by Henderson and Kumbhakar (2006), the estimation of restrictive parametric specifications, such as the the Cobb -Douglas function, may lead to inconsistent results because of a possible functional misspecification bias, thus a non-parametric kernel estimator is implemented (see also Kortelainen and Leppänen, 2013). Similarly, Ma et al. (2020) use spline functions to handle possible complex functional forms.

However, because of the high degree of uncertainty surrounding the data generating process (DGP) (see, among others, Hansen, 2005), it can be crucial to perform model selection. Indeed, while flexible models are appealing because of their ability to handle complex functional forms, sometimes parsimonious models can be preferable because of their efficiency gains (see, Baltagi et al., 2002, 2003). To do so, we adopt the procedure recently proposed by Gioldasis et al. (2021), who extend the data-driven model-selection procedure proposed by Racine and Parmeter (2014) to a large panel data framework by using moving block bootstrap resampling techniques in order to preserve cross-sectional dependence in the bootstrapped samples.

2. Model specification and estimation procedure

Calderón et al. (2015) specify the following aggregate production function:

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

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) exploit balanced panel data from 88 countries observed over 1960 - 2000 period and assume constant returns to scale (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:

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

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

2.1 Modeling cross-sectional dependence

Cross-sectional dependence can be due to unobserved common factors such as economy-wide shocks that affect all countries (Sarafidis and Wansbeek, 2012). The errors e_{it} are then assumed to have the following common factor structure:

$$e_{it} = \gamma_i^{'} \mathbf{f}_t + \varepsilon_{it}, \tag{3}$$

in which $\mathbf{f}_t$ is an $m \times 1$ vector of unobserved common factors with associated country-specific factor loadings γ_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. Eq. (2) can be thus rewritten as

$$y_{it} = \alpha_i' \mathbf{d}_t + \beta^{'} \mathbf{x}_{it} + \gamma_i^{'} \mathbf{f}_t + \varepsilon_{it} \tag{4}$$

where α_i are individual fixed effects as $\mathbf{d}_t = d_t = 1$, $\mathbf{x}_{it} = [k_{it}, z_{it}, S_{it}, l_{it}]'$ and $\beta = [\zeta, \eta, \vartheta, \psi]'$.

In such a framework, Pesaran (2006) suggests the CCE estimation procedure (for a detailed discussion, see, e.g., Ertur and Musolesi, 2017).

2.2 Alternative specifications

In addition to the implementation of the standard static pooled CCE estimator (CCEP) proposed by Pesaran (2006), we consider three different specifications, all based on the CCE framework, allowing for different degrees of flexibility.

First, like Calderón et al. (2015) we embed the production function into a dynamic framework and consider the dynamic extension of Chudik et al. (2016), who suggest the adoption of a CS-DL approach for panels with a moderately large T $(30 \leq T \leq 50)$. The main advantage of this approach, which does not include lags of the dependent variable, is that it is robust along a number of relevant specifications, allowing the possibility of unit roots in regressors and/or factors and the presence of weak cross-sectional dependence in the idiosyncratic errors. As discussed by Raissi et al. (2018), CS-DL exhibits a better small sample performance relative to the panel ARDL approach (CS-ARDL) when T is moderate, as in our case. Even when it suffers from biases induced by possible feedback effects, as argued by Chudik et al. (2013), its performance in terms of RMSE is better than that of the CS-ARDL estimator. Formally, we consider the following specification:

$$y_{it} = \alpha_i' \mathbf{d}_t + \beta' \mathbf{x}_{it} + \sum_{l=0}^{p-1} \delta_l' \boldsymbol{\Delta} \mathbf{x}_{it-l} + \gamma_i' \mathbf{f}_t + \varepsilon_{it} \tag{5}$$

where, given a selected truncation lag order p, differenced explanatory variables are added as further covariates, and the unobserved factors $\mathbf{f}_t$, included into the auxiliary regression function, are proxied with contemporary and lagged cross-sectional averages of the explanatory variables $\mathbf{x}_{it}$. [1]

Second, we address the issue of specifying the production function by adopting a more general approach built on Su and Jin (2012). We generalize Eq. (2) allowing for a non-parametric relationship between the dependent variable and the regressors, while the common factors enter the model in a parametric way, or

$$y_{it} = \alpha_i' \mathbf{d}_t + g(\mathbf{x}_{it}) + \gamma_i' \mathbf{f}_t + \varepsilon_{it},$$

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

[1] See Chudik et al. (2016) for further details about CS-ARDL and CS-DL models. According to Chudik et al. (2016), the truncation lag p in the auxiliary regression is the same for both the differenced explanatory variables and the lagged cross-sectional averages and can be set equal to the integer part of $T^{1/3}$.

condition is necessary:

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

Thus, in the framework of CCE based models, we consider two alternative non-parametric specifications. The first one (ADD) assumes an additive structure of $g(.)$, as follows:

$$y_{it} = \alpha_i + g_k(k_{it}) + g_z(z_{it}) + g_S(S_{it}) + g_l(l_{it}) + \gamma_i^{'}\mathbf{f}_t + \varepsilon_{it}, \tag{6}$$

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.,

$$y_{it} = \alpha_i + g(k_{it}, z_{it}, S_{it}, l_{it}) + \gamma_i^{'}\mathbf{f}_t + \varepsilon_{it}. \tag{7}$$

Relaxing additivity may involve the curse of dimensionality issue, but at the same time, it may allow detecting relevant interaction effects, which are not allowed in the additive specification.

To estimate the non-parametric component of the model, we follow Gioldasis et al. (2021) and employ penalized regression splines (PRS). In particular, we use thin plate regression splines (TPRS), which were introduced by Wood (2003) and have some optimality properties. Since our explanatory variables have different units, in the case of the non-additive specification we avoid isotropy by considering a tensor product basis (Wood, 2006). The smoothing parameter is selected by restricted maximum likelihood estimation (for a discussion, see, for example, Reiss and Todd Ogden, 2009). Finally, note that because of the relatively short time dimension, we restrict our analysis to homogeneous models where β and $g(.)$ are assumed to be constant across cross-sectional units.

3. Results

As a preliminary step, we check for the presence of CSD and unit roots. As detailed in Appendices A and B, 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).

3.1 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.[2] 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 1).

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; Pinilla et al., 2003, 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, which are obtained using both the PMG and the FE model, indicate that estimating (2) without imposing CRS greatly affects the estimated technological parameters, which are somehow rather implausible from an economic point of view. 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.

[2] 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.

===== Insert Table 1 =====

3.2 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 non-parametric specifications. The results are as follows.

===== Insert Table 2 =====

All estimates based on the parametric models (Table 2) 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 Appendix E, 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 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 2 reports the standard errors obtained by using the non-parametric 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 thus compare different methods to calculate the standard errors of the CCEP and the CS-DL and the main result is that the infrastructure index remains insignificant in most cases (see Appendix C).

When moving to the non-parametric 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). 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.[3]

===== Insert Figure 1 =====

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

[3]The computation of standard errors and confidence bands takes advantage of the underlying parametric representation of spline approximations (Gioldasis et al., 2021).

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).

3.3 Model selection

We compare the above specifications using the data-driven model-selection procedure proposed by Gioldasis et al. (2021). It is a pseudo-Monte Carlo experiment that consists of a combination of the panel moving block bootstrap (MBB) scheme proposed by Gonçalves (2011) and the time-series selection procedure introduced by Racine and Parmeter (2014). Using an MBB scheme is useful in order to preserve cross-sectional dependence in the bootstrapped samples. According to block resampling and supposing the time series has length $T = b \times l$, b nonoverlapping blocks, each of length l, are generated, with l sufficiently large in order to preserve in each block the dependence present in the original dataset. With MBB, we allow the blocks to overlap, thus obtaining a total of $T - l + 1$ overlapping blocks. Specifically here, given a time horizon of 41 years and in order to provide equal block lengths and to preserve the dependence structure of the dataset, we drop off one year and fix the length of the blocks to ten years. Thus, we have $40 - 10 + 1 = 31$ 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).[4] This procedure is replicated a number of times $S = 1000$ in order to obtain an $S \times 1$

[4] Given a bootstrapped sample (y^*_{it}, x^*_{it}), $i = 1, \ldots, N$, $t = 1, \ldots, T$, the ASPE of model L is defined as:

$$ASPE^L = \frac{1}{n \times T_E} \sum_{i=1}^{n} \sum_{t=T_T+1}^{T} (y^*_{it} - \hat{g}^L_{T_T}(x^*_{it}))^2$$

where T_T (resp. T_E) is the number of observations in the training (resp. evaluation) sample. The vector of $\hat{g}^L_{T_T}(x^*_{it})$, $i = 1, \ldots, N$, $t = T_T + 1, \ldots, T$, denotes the predictions on the evaluation sample, using the estimate of $g^L(.)$ on the training sample, i.e., $\hat{g}^L_{T_T}(.)$.

vector of ASPEs for each model.

For the purpose of comparing the predictive performances of the different models, we consider the empirical distribution of the ASPEs on a one-year horizon and represent them using boxplots.

===== Insert Figure 2 =====

In the upper panel of Figure 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 consider all of the the different CCE specifications. A first clear result is that all CCE specifications provide a huge improvement in terms of out-of-sample predictive performance with respect to the traditional models. A second relevant result is that among the CCE specifications, the non-parametric ones exhibit the best performance. This result is strongly consistent with Gioldasis et al. (2021) and provides additional evidence supporting the use of flexible models when estimating a production function. Interestingly, the dynamic (CS-DL) specifications show the worst performance among the CCE- based models and, in particular, we observe an increasing loss in terms of predictive ability by increasing the number of lags.

4. Conclusions

This paper provides a broad replication of Calderón et al. (2015) by exploiting recent advances in panel data econometrics. Specifically, we handle cross-sectional dependence and the presence of non-stationary factors by considering CCE-based models. We consider both parametric and non-parametric models. The latter may avoid a functional misspecification bias but could suffer from the curse of dimensionality problem. Given the classic efficiency-bias trade-off and the huge uncertainty surrounding the true DGP, we also perform model selection by employing a data-driven model-selection approach that was recently proposed by Racine and Parmeter (2014) and generalized to panel data by Gioldasis et al. (2021). Contrary to Calderón et al. (2015), we find a lack of significance of the infrastructure index, with an estimated elasticity very close to zero for all specifications. The results also indicate that non-parametric specifications exhibit the best predictive performance and that CCE models always overperform with respect to traditional panel data methods that employ cross-sectional demeaning to account for cross-sectional dependence.

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		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

Table 1: Estimation results on demeaned variables and CRS test

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%.

	CCEP	CS-DL	CS-DL	CS-DL	ADD	NONADD
		0 lags	1 lag	2 lags	edf (p-value)	
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

Table 2: Estimation of the production function: alternative CCE parametric and non-parametric specifications

Note: The displayed standard errors (SEs) for the CCEP model and the CS-DL models correspond to the non-parametric 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%.
The elasticity of scale represents the sum of the parameters referred to as log(capital), log(infrastructure), and log(labor), i.e. $\zeta + \eta + \psi$.

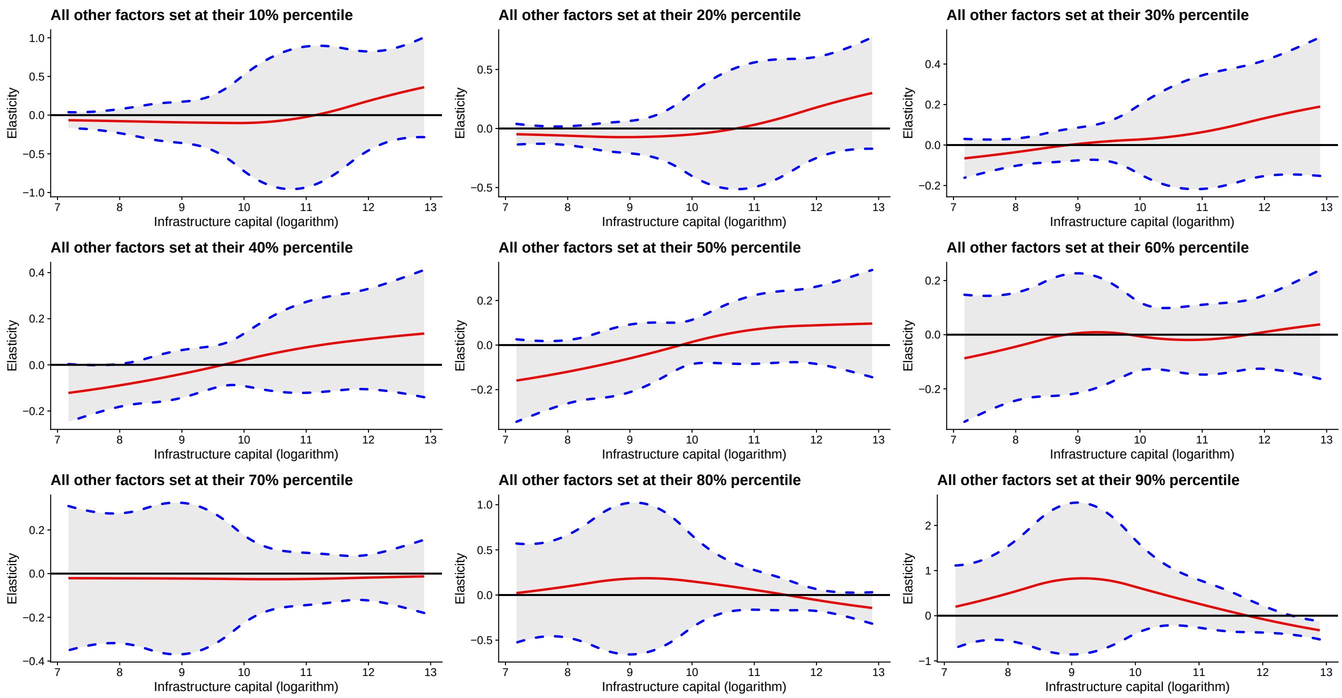

Figure 1: Estimated infrastructure elasticities

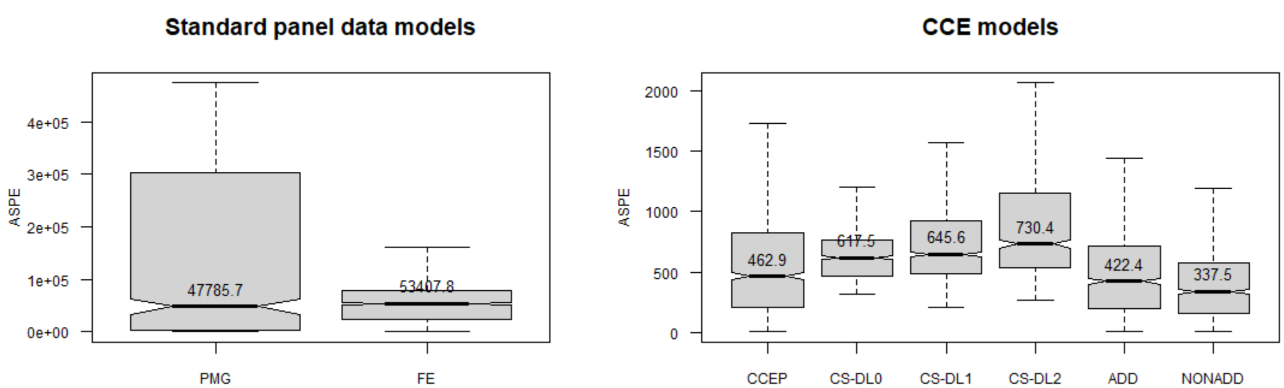

Figure 2: Out-of-sample average square prediction error (ASPE) box plots for different models on a 1-year horizon: the pooled mean group model (PMG), the two-way fixed effects model (FE), the common correlated estimator in its pooled version (CCEP), the cross-sectional augmented distributed lags (CS-DL0,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

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

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A. Assessing cross-sectional dependence

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 α in the range [0, 1], as the exponent of CSD proposed by Bailey et al. (2016a). The value of α in the range [0, 1/2] indicates different degrees of weak CSD , whereas α 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 $0 \leq \alpha < 1/4$. 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 weak CSD, suggesting that the exponent of cross-sectional dependence, α, is in the range [1/4, 1].

===== Insert Table 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 α=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.

B. Panel unit root tests

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:

$$y_{it} = D_{it} + \zeta_{it}^{'}\mathbf{f}_t + v_{it}$$

where D_{it} is the deterministic component with individual effects and, eventually, individual trends. $\zeta_{it}^{'}\mathbf{f}_t$ 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 non-stationarity derives from a non-stationary common component, a non-stationary idiosyncratic component, or the non-stationarity 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).

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 non-stationarity of the idiosyncratic components for all variables. The rejection of the non-stationarity of the idiosyncratic component does not imply that the series are stationary, as some of the common factors may be non-stationary. To determine how many of these factors are non-stationary, 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 non-stationary 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 non-stationary and that this property is the result of multiple non-stationary common factors combined with stationary idiosyncratic components. This result is fully consistent with Ertur and Musolesi (2017) and Gioldasis et al. (2021) and, moreover, as proven by Kapetanios et al. (2011), the CCE approach remains valid in this scenario.

===== Insert Table 2 =====

C. Alternative standard errors for parametric CCE models

For inference purposes, following Millo (2019), we compare three different methods to estimate the standard errors (SEs) of CCEP and CS-DL models. We first consider the non-parametric 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.

===== Insert Table 3 =====

The main result (see Table 3) 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 significant at the usual significance levels. Moreover, consistent with the replication study by Millo (2019), the non-parametric variance estimator always produces higher standard errors with respect to the alternative aforementioned procedures.

D. Further checks on residuals

To provide additional insights on the estimated models, we also perform diagnostic checks on the residuals, specifically focusing on the issue of cross-sectional dependence. 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 5. 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.[1] 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

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

be interpreted with care because as pointed out by Bailey et al. (2016a) the exponent α is identifiable only if $\alpha > 1/2$, while for values of $1/2 < \alpha < 2/3$, the identification of α is difficult, albeit theoretically possible.

===== Insert Table 5 =====

E. 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 Appendix is to examine the effects of telephone lines, paved roads, and electricity, taken separately, on productivity.

===== Insert Table 4 =====

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 not considered here because according to our results it underperformed with respect to all the others models.

The results in Table 4 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 characterized by an estimated elasticity very close to zero. Moreover, relaxing the linearity assumption with the ADD model gives further information and suggests the presence of a functional misspecification bias (see also Figure 1, where the estimated elasticities are depicted while the estimated smooth functions are available upon request). First, as for telephone, it is shown that the estimated elasticity ranges approximately from 0.2 to 0.6 and increases with the level of such a variable. Second, paved roads becomes significant but with a clear nonlinear pattern. In particular, threshold effects now appear as roads seem to have a positive effect to stimulate productivity only for a very low level of such an input, with and estimated elasticity of about 0.8. These results have also interesting economic implications.

===== Insert Figure 1 =====

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	$\hat{\alpha}$	$\hat{\alpha}^*_{0.05}$	$\hat{\alpha}^*_{0.95}$	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

Table 1: Pesaran's (2015) CD test

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

	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

Table 2: PANICCA Test

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.

	$\hat{\alpha}$	$\hat{\alpha}^*_{0.05}$	$\hat{\alpha}^*_{0.95}$	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

Table 5: Exponent of CSD and Frees' test on residuals

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

		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

Table 3: Alternative standard errors (SEs) for the CCEP and CS-DL models

Note: NP= non-parametric 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%.

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

Table 4: Alternative estimates with disaggregated data for infrastructure

Note: The displayed standard errors (SEs) for the CCEP model correspond to the non-parametric 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%.
The elasticity of scale represents the sum of the parameters referred to as log(capital), log(labor), log(roads), log(electricity) and log(telephone).

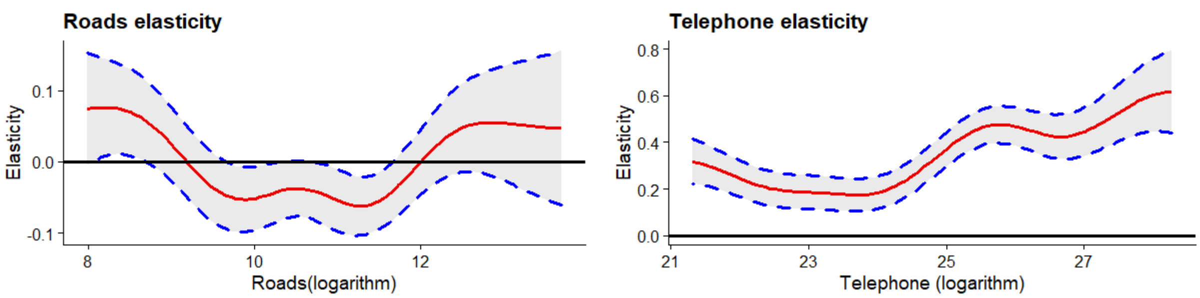

Figure 1: Estimated elasticities of the significant components of infrastructure in the ADD model