Nonparametric Estimation of R&D International Spillovers

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Abstract

We revisit the issue of international technology diffusion within the framework of large panels with strong cross-sectional dependence by adopting a method which extends the Common Correlated Effects (CCE) approach to nonparametric specifications. Our results indicate that the adoption of a nonparametric approach provides significant benefits in terms of predictive ability. This work also refines previous results by showing threshold effects, nonlinearities and interactions, which are obscured in parametric specifications and which have relevant policy implications.

Keywords: large panels; cross-sectional dependence; factor models; nonparametric regression; spline functions; international technology diffusion.

JEL classification: C23; C5; F0; O3.

1 Introduction

With the development of endogenous growth theory since the nineties, there has been an increasing interest in international R&D spillovers. A pioneering empirical work by Coe and Helpman (1995), recently revisited by Coe et al. (2009) – henceforth CH and CHH, respectively – relates total factor productivity (TFP) to both domestic and foreign R&D and, assuming that technology spills over across countries through the channel of trade flows, constructs foreign R&D capital stock as the import-share-weighted average of the domestic R&D capital stocks of the trading partners. Subsequent studies consider other factors as channels of international spillovers, such as foreign direct investment, bilateral technological proximity, patent citations between countries, language skills or geographic proximity.

Recent studies extend the literature on international R&D spillovers by accounting for relevant methodological issues such as cross-sectional dependence and non-stationarity (Coe et al., 2009; Lee, 2006; Ertur and Musolesi, 2017) within a parametric framework.

This paper aims at revisiting the issue of international R&D spillovers using nonparametric methods. This could be relevant from both an economic and a methodological perspective. First, from an economic and poliy oriented perspective, it may allow to test the validity of the main results provided in the literature, especially with respect to the possible existence of nonlinearities, threshold effects, non-additive relations, etc., as nonparametric approaches have been shown to provide new and useful insights in topics very closely related to the present one (Ma et al., 2015; Maasoumi et al., 2007). Second, nonparametric approaches, which are recently developing also in the context of panel data (Rodriguez-Poo and Soberon, 2017; Parmeter and Racine, 2018), have been shown to significantly improve the predictive ability of parametric models in many cases (Racine and Parmeter, 2014; Ma et al., 2015; Delgado et al., 2014), even if this is not assured ex ante because of the curse of dimensionality problem of nonparametric specifications and the bias-efficiency trade-off, which generally arises when comparing parametric and nonparametric models. Therefore, it could be of interest to compare parametric and nonparametric models in the present framework.

The econometric analysis is conducted using annual country-level data for 24 OECD countries from 1971 to 2004. This dataset is also used, among others, in Coe et al. (2009) and in Ertur and Musolesi (2017) and this allows for a comparability with previous studies. The analysis is based on the nonparametric approach by Su and Jin (2012), which allows for a multifactor error structure and extends the approach by Pesaran (2006). Such an approach combines the flexibility of sieves with the ability of factor models to allow for cross-sectional dependence and to account for endogeneity due to unobservables, whereby the explanatory variables are allowed to be correlated with the unobserved factors. Following Su and Jin (2012), the nonparametric component is estimated using sieves, and particularly splines. Specifically, we adopt a regression splines framework, which provides computationally attractive low rank smoothers. We also employ penalized regression splines, as they combine the features of regression splines and smoothing splines, and have proven to be useful empirically in many aspects (Ruppert et al., 2003) while their asymptotic properties have been studied in recent years. The choice of the knots is avoided by using knot-free bases for smooths (Wood, 2003). Finally, as far as model selection is concerned, we compare alternative specifications by focusing on their predictive ability and adopt the approach recently proposed by Racine and Parmeter (2014), which is based on a pseudo Monte Carlo experiment and takes its roots on cross validation.

The paper is organized as follows. In section 2 we describe the model specifications that we employ as well as the adopted estimation approach. The comparison among the different model specifications and the results of the estimations, including relevant policy implications, are presented in section 3. Finally, section 4 concludes.

2 Model specification and estimation method

2.1 The classical parametric approach

The standard parametric specification *à la* CH/CHH can be expressed as:

$$\log f_{it} = \alpha_i + \theta \log S_{it}^d + \gamma \log S_{it}^f + \delta \log H_{it} + e_{it}, \tag{1}$$

where e_{it} is the error term, f_{it} is the TFP of country $i = 1, ..., N$ at time $t = 1, ..., T$; α_i are individual fixed effects, S_{it}^d and S_{it}^f are domestic and foreign R&D capital stocks, respectively; H_{it} is a measure of human capital. Foreign capital stock S_{it}^f is defined as the weighted arithmetic mean of S_{jt}^d for $j \neq i$, that is $S_{it}^f = \sum_{j \neq i} \omega_{ij} S_{jt}^d$, where ω_{ij} represents the weighting scheme. We adopt the same definition proposed by Lichtenberg and van Pottelsberghe de la Potterie (1998), which has been previously adopted in many other papers (Coe et al., 2009; Lee, 2006; Ertur and Musolesi, 2017), incorporating information on bilateral imports.

All the existing literature adopts parametric specifications that are variants of (1). Most of the previous studies follow some of the advances in panel time series econometrics over the last two decades. In particular, given the large T dimension of our panel, the likely existence of nonstationarity and cross-sectional dependence (Lee, 2006; Kao et al., 1999; Ertur and Musolesi, 2017) has been investigated.[1] Recently, Ertur and Musolesi (2017) highlight the presence of strong cross-sectional dependence in the data. Further, they use unit roots tests decomposing the panel into deterministic, common and idiosyncratic components (see, e.g. Bai and Ng, 2004) to identify the source of possible nonstationarity. They finally find that the series under investigation are nonstationary and that this property relies on the existence of nonstationary unobserved common factors rather than on idiosyncratic components. Under this scenario, Kapetanios et al. (2011), provide both analytical results and a simulation study according to which the cross-sectional averages augmentation by Pesaran (2006) remains valid.

[1] Another issue, which is out of the scope of this study, questions the homogeneity of the parameters implicit in the use of a pooled estimator in favor of heterogeneous regressions.

In the following, for ease of exposition, we employ the notation:

$$y_{it} = \alpha_i + \beta' \mathbf{x}_{it} + e_{it}, \tag{2}$$

where $y_{it} = \log f_{it}$, $\mathbf{x}_{it} = [\log S^d_{it}, \log S^f_{it}, \log H_{it}]'$ and $\beta = [\theta, \gamma, \delta]'$.

2.2 A nonparametric model with a multifactor error structure

We adopt the method proposed by Su and Jin (2012), who consider a panel data model that extends the multifactor linear specification proposed by Pesaran (2006). Specifically, Su and Jin (2012) consider the following model, which allows for a nonparametric relation between the dependent variable and the regressors, while the common factors enter the model parametrically:

$$y_{it} = \alpha_i' \mathbf{d}_t + g\left(\mathbf{x}_{it}\right) + e_{it}, \tag{3}$$

where $\mathbf{d}_t$ is an $l \times 1$ vector of observed common effects, α_i is the associated vector of parameters and $\mathbf{x}_{it}$ is defined above. The *"one-way"* fixed effect specification is obtained by simply setting $\mathbf{d}_t = 1$. g is an unknown function to be estimated. For identification purposes, the condition $E(g\left(\mathbf{x}_{it}\right)) = 0$ is imposed. The errors e_{it} have a multifactor structure that is described by:

$$e_{it} = \gamma_i' \mathbf{f}_t + \varepsilon_{it}, \tag{4}$$

where $\mathbf{f}_t$ is an $m \times 1$ vector of unobserved common factors with country-specific factor loadings γ_i. Combining (4) and (3), we obtain the following:

$$y_{it} = \alpha_i' \mathbf{d}_t + g\left(\mathbf{x}_{it}\right) + \gamma_i' \mathbf{f}_t + \varepsilon_{it}. \tag{5}$$

The idiosyncratic errors ε_{it} are assumed to be independently distributed over $(\mathbf{d}_t, \mathbf{x}_{it})$, whereas the unobserved factors $\mathbf{f}_t$ can be correlated with the observed variables $(\mathbf{d}_t, \mathbf{x}_{it})$. This correlation is allowed by modeling the explanatory variables as linear functions of the observed common factors $\mathbf{d}_t$ and the unobserved common factors $\mathbf{f}_t$:

$$\mathbf{x}_{it} = \mathbf{A}_i' \mathbf{d}_t + \mathbf{\Gamma}_i' \mathbf{f}_t + \mathbf{v}_{it}, \tag{6}$$

where $\mathbf{A}_i$ and $\mathbf{\Gamma}_i$ are $l \times 3$ and $m \times 3$ factor loading matrices, and $\mathbf{v}_{it} = (v_{i1t}, v_{i2t}, v_{i3t})'$. Following Pesaran (2006), Su and Jin (2012) proxy the unobservable factors $\mathbf{f}_t$ in (5) by the cross-sectional averages $\bar{\mathbf{z}}_t = N^{-1} \sum_{j=1}^{N} \mathbf{z}_{jt}$, where $\mathbf{z}_{it} = [y_{it}, \mathbf{x}_{it}']'$. They estimate the nonparametric part of the model using sieves. It is worth noting that the most common examples of sieve regression are polynomial series expansions and splines.

2.3 Alternative specifications

Consider (5) for $\mathbf{d}_t = 1$, that is $y_{it} = \alpha_i + g\left(\mathbf{x}_{it}\right) + \gamma_i' \mathbf{f}_t + \varepsilon_{it}$. We are interested in three different specifications. As a benchmark, the parametric specification is obtained for $g\left(\mathbf{x}_{it}\right) = \beta' \mathbf{x}_{it}$.

The estimation is performed applying the common correlated effects pooled (CCEP) approach by Pesaran (2006). Then, we consider two specifications where $\mathbf{x}_{it}$ enter the model nonparametrically. The first specification assumes an additive structure of g, as follows:

$$\log f_{it} = \alpha_i + \phi(\log S^d_{it}) + \xi(\log S^f_{it}) + \psi(\log H_{it}) + \gamma_i' \mathbf{f}_t + \varepsilon_{it}, \tag{7}$$

where ϕ, ξ and ψ are unknown univariate smooth functions of interest. The second specification assumes a non-additive structure of g, particularly:

$$\log f_{it} = \alpha_i + g(\log S^d_{it}, \log S^f_{it}, \log H_{it}) + \gamma_i' \mathbf{f}_t + \varepsilon_{it}. \tag{8}$$

2.4 Spline modeling

Su and Jin (2012) estimate the nonparametric component of the model using sieves, and particularly splines, as they typically provide better approximations (see, *e.g.*, Hansen, 2014). Following Su and Jin (2012), we adopt a regression splines (RS) framework. We also employ penalized regression splines (PRS), as they combine the features of both regression splines, which use less knots than data points but do not penalize roughness, and smoothing splines, which control the smoothness of the fit through a penalty term but use all data points as knots. PRS have proven to be useful empirically in many aspects (see, e.g. Ruppert et al., 2003) and, in recent years, their asymptotic properties have been studied and then connected to those of regression splines, to those of smoothing splines and to the Nadaraya - Watson kernel estimators (Claeskens et al., 2009; Li and Ruppert, 2008).

Specifically, for both RS and PRS, we use thin plate regression splines (TPRS), which are a low rank eigen-approximation to thin plate splines. Thin plate splines are somehow ideal smoothers (see Wood, 2017) but are not computationally attractive because they require the estimation of as many parameters as the number of data points. TPRS avoid the problem of knot placement that usually complicates modeling with RS or PRS and more generally have some optimality properties, as they provide optimal low rank approximations to thin-plate splines, while they also are computationally efficient (see Wood, 2003). Since our explanatory variables have different units, in the case of the non-additive specification (8), we avoid isotropy by considering a tensor product basis, which is constructed by assigning TPRS as the basis for the marginal smooth of each covariate and then creating their Kronecker product. The tensor product smooths are invariant to the linear rescaling of covariates, and for this reason, they are appropriate when the arguments of a smooth have different units (Wood, 2006). Finally note that in the PRS framework, the smoothing parameter is selected by the restricted maximum likelihood (REML) estimation, which, relative to other approaches, is less likely to develop multiple minima or to undersmooth at finite sample sizes (see, e.g. Reiss and Todd Ogden, 2009).[2]

[2]The nonparametric specifications are estimated by the R package mgcv.

3 Results

3.1 Model comparison

To compare the aforementioned specifications, we perform a pseudo Monte Carlo experiment. In particular, along the lines depicted by Racine and Parmeter (2014), Ma et al. (2015) and Delgado et al. (2014), using similar macro panel data variables related to economic growth, the observations are randomly shuffled at 90% into training points and at 10% into evaluation points. Each model is fitted according to the training sample. Then, the average out-of-sample squared prediction error (ASPE) is computed using the evaluation sample. The above steps are repeated a large number of times $B = 1000$, so that a $B \times 1$ vector of prediction errors is created for each model.[3]

The method is linked to cross validation (CV), in the original formulation of which a regression model fitted on a randomly selected first half of the data was used to predict the second half. The division into equal halves is not necessary. For instance, a common variant is the leave-one-out CV, which fits the model to the data excluding one observation each time and then predicts the remaining point. The average of the prediction errors is the CV measure of the error. As highlighted in Racine and Parmeter (2014), the method can provide significant power improvements over existing single-split techniques.

Figure 1 presents the box-and-whisker plots of the ASPE distributions for the different specifications. A first relevant result is that the median that corresponds to the parametric model is the largest among the different specifications, while the non-additive penalized model has the smallest median. In particular, the median ASPEs of the non-additive penalized model relative to the other models – the parametric, the additive unpenalized, the additive penalized and the non-additive unpenalized – is 0.6023, 0.9284, 0.9409 and 0.8278, respectively. A second interesting result is that the penalized regression modeling has a smaller median ASPE than its unpenalized counterpart for both additive and non-additive specifications. However, although when imposing an additive structure, the two approaches provide quite similar performances, the gain in terms of predictive ability from using PRS over RS is extremely pronounced when estimating the non-additive specification, which typically suffers more from the curse of dimensionality problem. Also, it is worth noting that within the RS framework, the additive specification provides a better performance than the non-additive one.

Next, figure 2 shows the empirical distribution functions of the ASPEs for each model. Clearly, the ASPE of the non-additive penalized model is stochastically dominated by the ASPE of any of the remaining models. This indicates that the non-additive penalized model outperforms all others in terms of predictive ability. It is also evident that the parametric model underperforms with respect to the nonparametric ones.

Finally, we compare the different specifications using the test of revealed performance (TRP)

[3]See also Baltagi et al. (2003) who contrast the out-of-sample forecast performance of alternative parametric panel data estimators.

proposed by Racine and Parmeter (2014).[4] The results of these paired t-tests are presented in Table 1. In all cases, the null hypothesis that the difference in means of the ASPEs is zero is rejected. Thus, the tests complement the above presented results, indicating that this difference is statistically significant in all cases.

3.2 Estimation results

In this subsection, we present the main estimation results and specifically focus attention on the nonparametric specifications. We only consider PRS, since they outperform their unpenalized counterparts. We first provide the results obtained using the additive specification (7) because, due to the additive structure, the results are directly comparable to those ones of the parametric specifications adopted in previous studies. Then, we present the results of the non-additive specification (8), which, according to our findings, provides the best performance. Specifically, we focus on the interaction between domestic and foreign R&D.

The results concerning the nonparametric part of the additive penalized specification are presented in figure 3. The three graphs depict the estimated univariate smooth functions, which all appear to be highly significant, with extremely low p-values associated with the Wald test (Wood, 2012) that the function equals zero. It is worth mentioning that because the response as well as the explanatory variables are in logs, the slope of the estimated smooth functions represents the estimated elasticity. The first plot shows the effect of domestic R&D on TFP. It appears that for low values of R&D, where data are sparse and large confidence interval bands are present, the relation is flat. Then, for intermediate values of domestic R&D, the function is monotonic increasing, with a steep rise in approximately the last two deciles. The policy implications resulting from the above are clear: an increase in domestic R&D has an effect on productivity only above a threshold, thus suggesting that a critical mass of investments in R&D is crucial for R&D to become effective. After this threshold, the estimated output elasticity becomes positive and increases even more for very high levels of domestic R&D. This can be seen as a refinement of the results of the existing empirical literature on R&D spillovers, which is based on parametric models and generally distinguishes between G7 and non-G7 countries. Indeed, Ertur and Musolesi (2017), employing the CCE approach, show that the estimated output elasticity of domestic R&D is positive and significant for G7 countries, while it is non-significant for non-G7 countries. Similar results are also found by Coe et al. (2009), who adopt the dynamic OLS for cointegrated panels, and by Barrio-Castro et al. (2002), who use a standard fixed effects approach.

The second graph shows the effect of foreign R&D on TFP. Again, for low levels of the variable, data are scarce, making it difficult to identify a clear pattern. Then, the relation is positive and roughly concave for intermediate values, while it becomes flat for high levels of foreign R&D. The

[4] The TRP involves estimating the distribution of the true errors for the different models and testing whether their expectations are statistically different. The true error is associated with out-of-sample measures of fit, contrasted to the apparent error, which is associated with within sample measures. Typically, the latter is smaller than the former and frequently overly optimistic (see e.g. Efron, 1982).

results show that an increase in foreign R&D affects TFP positively, but only up to a certain level. They complement previous empirical literature such as Coe et al. (2009), who indicate that trade-related foreign R&D is a significant determinant of TFP. More specifically, our findings improve the results of Ertur and Musolesi (2017), among others, who find a small, positive and significant effect of R&D on TFP in non-G7 countries, but no significant effect in the case of the G7. Nevertheless, in all previous studies, the linearity assumption obscures the fact that the output elasticity of foreign R&D is not constant but varies with respect to the different levels of foreign R&D. Indeed, looking at the bottom panel of figure 3, it can be seen that the estimated elasticity constantly decreases over the range of foreign R&D up to a level where it becomes not significantly different from zero.

The third graph in figure 3 depicts the effect of human capital on TFP. It again shows scarce data and large confidence bands for low levels. Then, the relation between human capital and TFP is approximately flat for intermediate values, while for high values, it seems to be monotonic increasing, with a steep rise in approximately the last two deciles. In terms of policy perspectives, the results suggest a threshold that occurs at very high levels of human capital, above which the estimated elasticity becomes positive. Investing in human capital becomes effective only after a certain level is reached. These findings add new insights to Ertur and Musolesi (2017), who find no significant effect of human capital on TFP for both G7 and non-G7 countries and explain their result on the grounds that the quantity of education no longer has a significant effect when omitted variable bias is addressed. We find confirmation of such results for most of the domain of human capital, but we also show that allowing for nonlinearity in the relation between human capital and TFP is crucial in order to highlight a positive effect for the highest levels of human capital.

Next, we turn to the estimates of the non-additive specification. Also, in this case, the estimated (multivariate) smooth function appears to be highly significant. In particular, we focus on the effect of the interaction between domestic and foreign R&D on TFP. The results are presented in figure 4, which shows the impact on TFP for a level of human capital fixed to the first, fifth (the median) and ninth decile. As depicted in the first graph, for low levels of human capital and irrespective of the level of domestic R&D, foreign R&D has almost no effect on TFP. In terms of policy implications, these findings suggest that foreign R&D spillovers cannot be effective if the level of human capital in a country remains low. Moreover, the effect of domestic R&D on TFP seems not to be linked to the level of foreign R&D, which implies an additive pattern when the level of human capital is low. Similar to the additive model presented above, there is a threshold above which domestic R&D becomes effective.

The second and third graphs in figure 4 show the effect on TFP when human capital is fixed to the median and to the ninth decile, respectively. The results in both graphs suggest a complementarity between domestic R&D and foreign R&D. For low levels of domestic R&D, the effect of foreign R&D on TFP is low, and vice versa. Domestic R&D becomes more effective when the levels of both domestic and foreign R&D are increasing. This is also true for foreign

R&D. These findings have interesting policy implications; in countries with intermediate or high levels of human capital, investments in R&D are not very effective if the level of foreign R&D is low. Further, the benefits of foreign R&D spillovers cannot be exploited unless both human capital and domestic R&D are above a critical mass. The above results contrast with results from some previous studies such as in Coe et al. (2009), who report that their estimations considering interactions between human capital and domestic and foreign R&D do not yield correctly signed and significant results.

4 Concluding remarks

This paper revisits the analysis of international technology diffusion by adopting the approach proposed by Su and Jin (2012), which extends the multifactor linear specification proposed by Pesaran (2006) to nonparametric specifications. We first show that a shift from a parametric to a nonparametric framework provides a significant improvement in terms of predictive ability. Moreover, it is also documented that penalized regression splines perform significantly better than their unpenalized counterparts, especially in the case of a non-additive model. Turning to the estimation results, our findings suggest the presence of threshold effects and nonlinearities. Then, the estimation of a non-additive specification provides further insights into the interactions among explanatory variables without imposing any parametric restrictions and definitively indicating that a critical mass of human capital is necessary to benefit from R&D spillovers and to observe an interactive effect between domestic and foreign R&D. In general, our findings strongly highlight that the presence of nonlinearities and complex interactions is an important feature of the data; these are obviously hidden within a parametric framework and have relevant implications for policy. Finally, it is worth mentioning that a further extension of the present study may account for heterogeneity across countries. This work is outside the realm of the nonparametric estimations presented in this paper and could be accomplished, for instance, by resorting to Bayesian modeling (Kiefer and Racine, 2017) to address the curse of dimensionality problem raised by heterogeneity.

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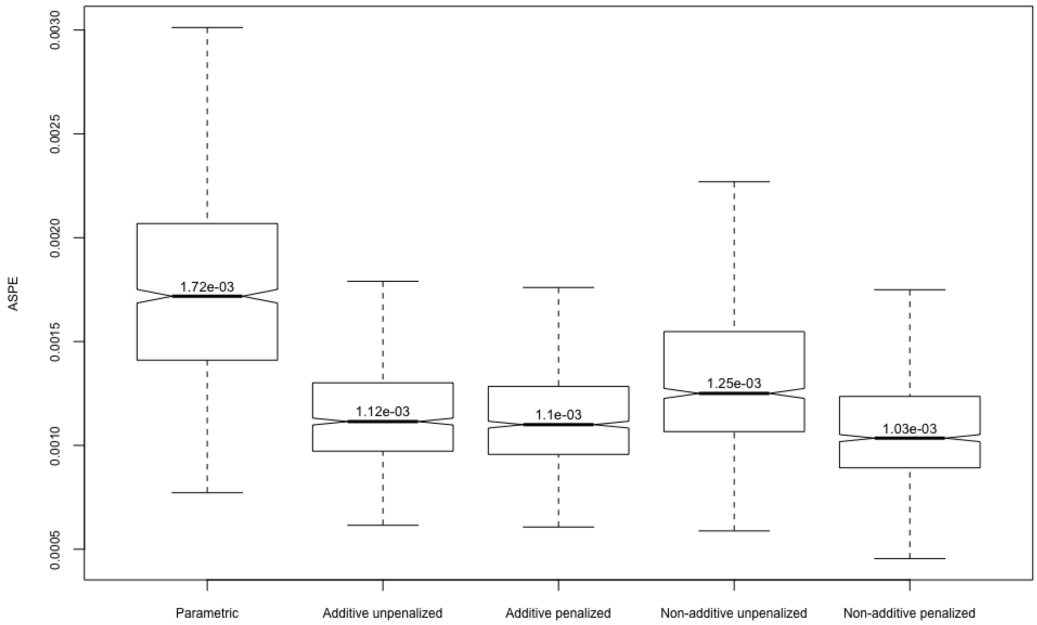

Figure 1: Out-of-sample average square prediction error (ASPE) box plots for different factor models: the parametric, the additive and the non-additive.

TABLE 1 - Paired t-tests of factor models

models	Additive unpenalized	Additive penalized	Non-additive unpenalized	Non-additive penalized
Parametric	43.683***	45.461***	27.042***	47.992***
Additive unpenalized		9.849***	-18.493***	13.138***
Additive penalized			-20.492***	10.697***
Non-additive unpenalized				32.642***

Null hypothesis: The true difference in means of the ASPEs of the compared models is zero.
The training sample is 90% of the data-sample; number of resampling iterations B: 1.000
Classification of p-value: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

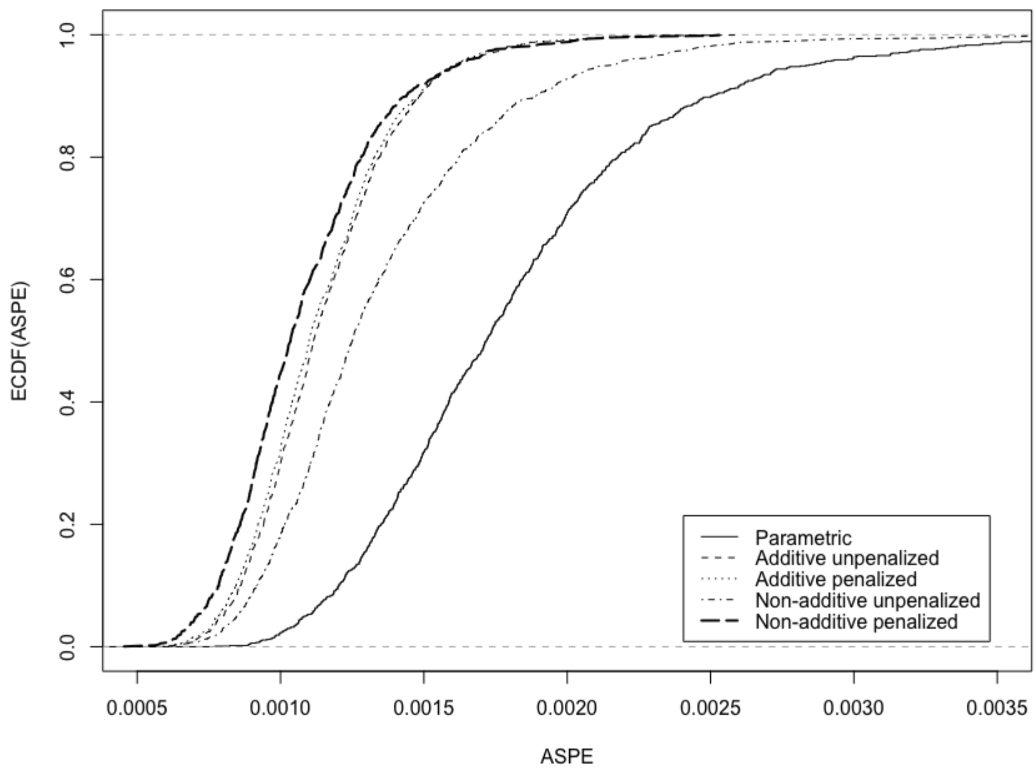

Figure 2: Empirical Cumulative Distribution Functions (ECDFs) of the ASPE for different factor models: the linear, the additive and the non-additive models for the OECD data.

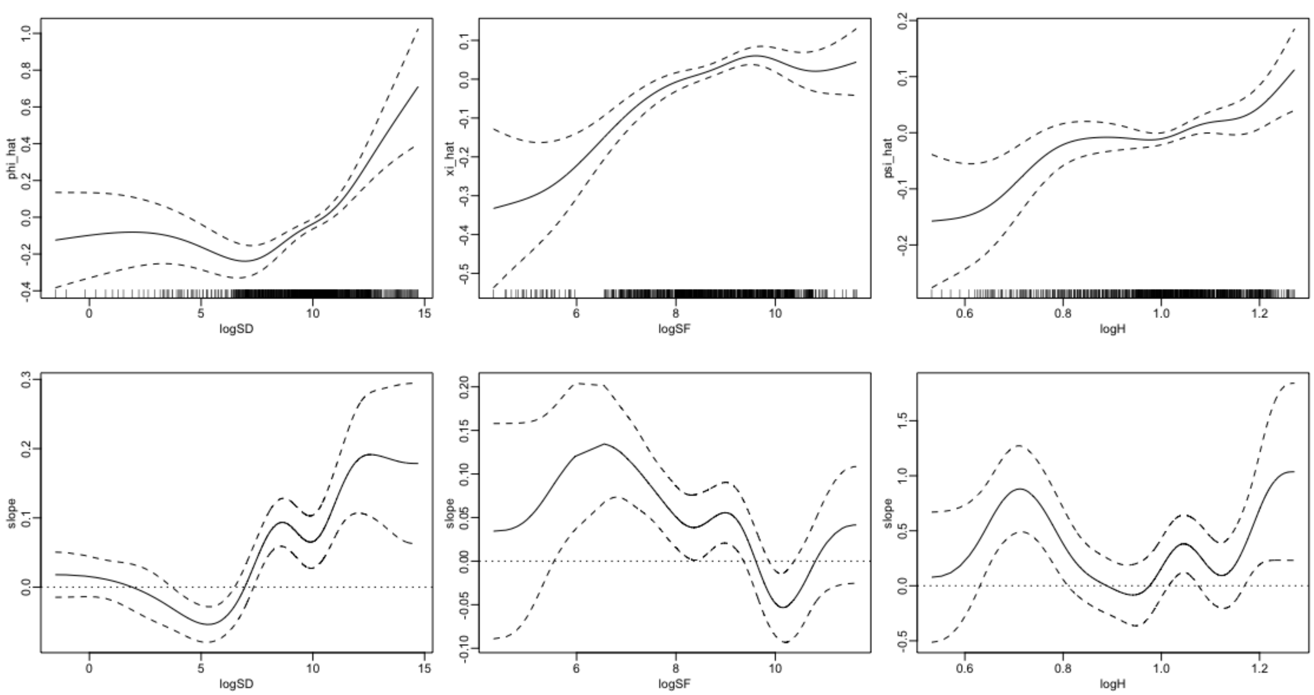

Figure 3: Additive Model. Estimated smooths (top panel) and corresponding derivatives (bottom panel) for the additive penalized regression model. Component smooths are shown with confidence intervals obtained by computing a Bayesian posterior covariance matrix.

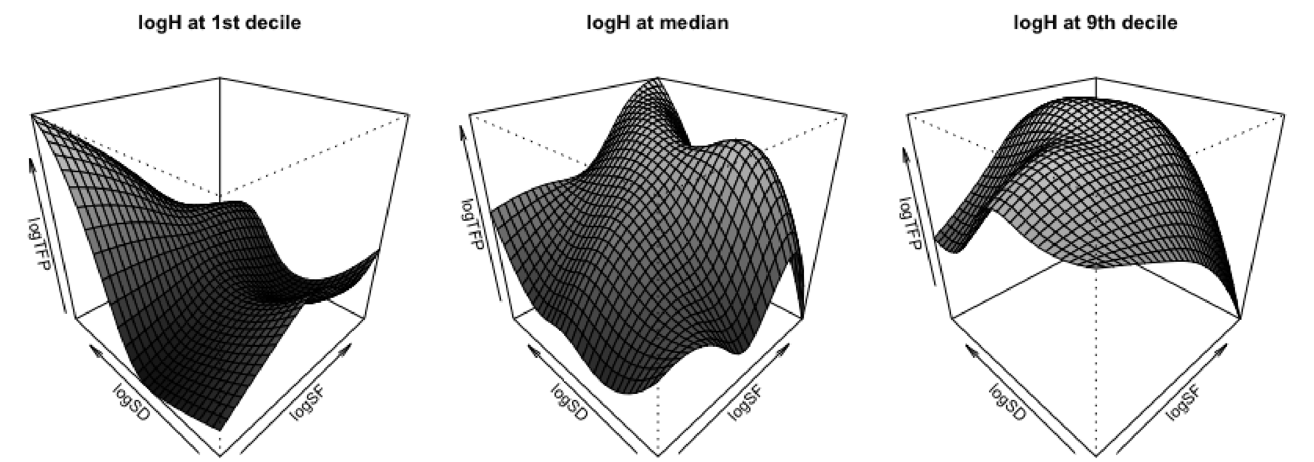

Figure 4: Non-additive model. The effect of domestic and foreign R&D on TFP for different levels of human capital. The log of human capital is fixed to the first, fifth and ninth decile, respectively.