Interactive R&D spillovers: an estimation strategy based on forecasting-driven model selection

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Abstract

This paper proposes an estimation strategy that exploits recent non-parametric panel data methods that allow for a multifactor error structure and extends a recently proposed data-driven model-selection procedure, which has its roots in cross validation and aims to test whether two competing approximate models are equivalent in terms of their expected true error. We extend this procedure to a large panel data framework by using moving block bootstrap resampling techniques in order to preserve cross-sectional dependence in the bootstrapped samples. Such an estimation strategy is illustrated by revisiting an analysis of international technology diffusion. Model selection procedures clearly conclude in the superiority of a fully non-parametric (non-additive) specification over parametric and even semi-parametric (additive) specifications. This work also refines previous results by showing threshold effects, non-linearities, and interactions that are obscured in parametric specifications and which have relevant implications for policy.

Keywords: large panels; cross-sectional dependence; factor models; non-parametric regression; spline functions; approximate model; predictive accuracy; moving block bootstrap; international technology diffusion.

JEL classification: C23; C5; F0; O3.

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1 Introduction

With the development of endogenous growth theory since the nineties, there has been an increasing interest in estimating the effect of research and development (R&D) on growth and productivity (Jones, 1995). At present, however, as also stressed by Keller (2004), while only a few rich countries account for most of the world's creation of new technology, for most countries foreign technology accounts for a large portion of domestic productivity. Studying international technology diffusion, which can be defined as the process by which innovation spreads within and across economies (Stoneman, 1985; Karshenas and Stoneman, 1995), and estimating its impact on domestic productivity are consequently of crucial relevance.

A pioneering empirical work by Coe and Helpman (1995), revisited by Coe et al. (2009)—henceforth CH and CHH, respectively—builds on innovation-driven endogenous growth models (Helpman, 1992) and relates total factor productivity (TFP) not solely to domestic R&D but also to 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 spillover, such as foreign direct investment, bilateral technological proximity, patent citations between countries, language skills, or geographic proximity (Keller, 2002; Potterie and Lichtenberg, 2001; Lee, 2006).

As for econometric estimation and testing, the most relevant issues raised by the literature are those of heterogeneous slope parameters and the non-stationarity of variables (Coe et al., 2009), and more recently, the existence of cross-country dependence arising from the interactions among economic units or from the presence of latent common factors (Ertur and Musolesi, 2017).

To the best of our knowledge, however, the existing literature has adopted parametric specifications and does not provide any attempt to check the ability of the CH/HH specification to correctly approximate the underlying data generating process (DGP) or test whether other specifications may be more suitable, whereas the likely complex relation between research activity and economic performance is often recognized in the closely related literature on the economics of innovation (Griliches, 1998; Hall et al., 2010; Charlot et al., 2014).

This paper aims to contribute to the existing literature by proposing an estimation strategy based on forecasting-driven model selection that exploits recent non-parametric panel data methods and extends existing data-driven model-selection procedures to the case of cross-sectionally dependent panels.

First, we adopt a non-parametric approach to avoid the possible functional form bias that may arise when estimating the standard parametric model. Our econometric approach builds on the non-parametric model by Su and Jin (2012) Pesaran (2006). Following Su and Jin (2012), the non-parametric component is estimated using splines. Specifically, we adopt penalized regression splines as they combine the features of regression splines and smoothing splines and have proven to be empirically useful in many respects (Ruppert et al., 2003), with their asymptotic properties having been studied in depth in recent years (see, for example, Li and Ruppert, 2008).

Second, because of the high degree of uncertainty surrounding the data generating process (DGP)

(Ma et al., 2015; Racine and Parmeter, 2014; de Almeida et al., 2018), we perform model selection by comparing the forecasting performance of some alternative models. Specifically, we compare the forecasting performance of a fully non-parametric specification of the relationship between TFP and domestic R&D, foreign R&D, and human capital with those of two competing specifications: a usual log-log parametric one and a non-parametric additive one.

To do so, we build on a method recently proposed by Racine and Parmeter (2014) that is based on a pseudo-Monte Carlo experiment and has its roots in cross-validation. When performing model selection, it is typically assumed that there exists a finite-dimensional "true model". In contrast, in Racine and Parmeter (2014) fitted econometric models are viewed as approximations, as suggested by Hansen (2005). The goal is then to test whether, when fitted to the same data, one approximate model performs better than another in predicting new data drawn from the same data-generating process. In such a framework, it is common to adopt a sample-splitting mechanism whereby one splits the full sample into two sub-samples, where one sub-sample is used for estimation and the other for out-of-sample evaluation. To avoid that the results reflect a particular division of the data into two sub-samples, the main idea of Racine and Parmeter (2014) is to repeat this process a large number of times using bootstrapping techniques, because this can provide significant power improvements over existing single-split techniques. Drawing from a recent literature focusing on cross-sectional dependence in panels and on factor models (Gonçalves, 2011; Palm et al., 2011; Smeekes and Westerlund, 2019), we extend the data-driven model-choice method proposed by Racine and Parmeter (2014) by considering a moving block bootstrap resampling scheme and assessing performance using the accuracy of forecasts at various time horizons.

The econometric analysis is conducted using new annual country-level data for 24 OECD countries from 1971 to 2014, which extends the time coverage of the data used by CHH and Ertur and Musolesi (2017). Results clearly point to the superiority of a fully non-parametric specification of the relationship between TFP and domestic R&D capital, foreign R&D, and human capital, over parametric and even semi-parametric specifications. The non-parametric specification allows for a richer view of the resulting spillover effects, showing non-linear effects and thresholds not previously detected in the literature and ultimately suggesting the presence of *(non-linear) interactive spillover effects* (non-linearly) increases with the amount of foreign R&D. These effects are illustrated by a detailed comparison of the results obtained with those presented in the literature or obtained by the estimation of usual parametric models.

The paper is organized as follows. Section 2 provides a short literature review focusing on the various channels of technology diffusion and the main econometric issues, highlighting existing research gaps. Section 3 focuses on the econometric methodology, and more specifically on the issues of model specification and estimation. The forecasting-driven model-selection procedure is presented in Section 4. Section 5 describes the data. The out-of-sample comparison of the alternative specifications, as well as the estimation results, are presented in Section 6. Finally, Section 7 concludes, and additional information is provided in the appendices.

2 A critical review of empirical findings and econometric issues

Beyond its plausibility with respect to endogenous growth theory (see, for example, Keller, 2004, p. 762), the influence of the CH/CHH model was due to its versatility in allowing for both the consideration of alternative channels of international technology diffusion and the utilization of modern, large panel data econometric methods. In this section, we first briefly review these two areas of the literature and finally highlight the research gaps that this paper tries to address.

2.1 The uncertain effect of international technological spillovers

As noted by Potterie and Lichtenberg (2001, p. 490), *"International technological spillovers have no widely accepted measures"*. According to Keller (2004), the main channels of international technology diffusion are trade, foreign direct investment (FDI), and language skills. For instance, CHH and Lichtenberg and van Pottelsberghe de la Potterie (1998) use alternative definitions of weights based on imports. Potterie and Lichtenberg (2001) focus on FDI, and Musolesi (2007) adopts a weighting scheme that takes language skills into account. Keller (2002) and Ertur and Musolesi (2017) use geographic proximity, while Spolaore and Wacziarg (2009) suggest genetic distance as a barrier to the diffusion of development.

Most previous studies focus on rent spillovers, which are spillovers that originate solely from economic transactions such as trade and FD, while analyses of technology diffusion originating from knowledge spillovers that are not necessarily embodied in specific economic transactions are rarer (see, for example, Griliches (1979) for a discussion of rent and knowledge spillovers).

As for rent spillovers, the body of literature focusing on trade reports results that are characterized by a high degree of instability of the estimated output elasticity with respect to foreign R&D (see Table A1 of Appendix A), as the estimated elasticity ranges from being non-significant in some cases (Kao et al., 1999; Lee, 2006) to high in magnitude, with some estimates of about 0.2–0.3 (Engelbrecht, 1997; Barrio-Castro et al., 2002; Coe et al., 2009). As Fracasso and Marzetti (2013) note, analyses of spillovers generated by FDI also present conflicting results. For instance, Potterie and Lichtenberg (2001) report that outward FDI flows are conducive to international knowledge spillovers while inward FDI flows do not have a significant effect. This result has been questioned by subsequent papers that obtained the opposite finding (Lee, 2006; Bitzer and Kerekes, 2008).

As for knowledge spillovers that are not necessarily embodied in specific economic transactions, Lee (2006) finds that disembodied channels such as bilateral technological proximity and patent citations between countries have a significant and quite substantial effect in the range of 0.15–0.18. This result is broadly the same as that obtained by Musolesi (2007), who focuses on knowledge spillovers incorporated into language skills.

The empirical literature has often allowed the impact of foreign R&D to differ between G7 and other countries. According to the pioneering CH/CHH studies, the effect of trade-related foreign R&D on TFP is much higher for non-G7 than for G7 countries. The same result can be found in Bitzer and Kerekes (2008), who find that non-G7 countries benefit more from inward FDI than G7 countries. In contrast, Potterie and Lichtenberg (2001) find the opposite result for outward FDI. Ertur and Musolesi (2017) find that richer countries benefit more from geographic spillovers, which are not necessarily embodied in specific economic transactions, than poorer countries, while smaller countries benefit more from rent spillovers originating from trade.

Overall, the literature does not seem to provide robust evidence regarding the magnitude of spillovers on TFP. Moreover, a high variability in the estimates seems to be present i) irrespective of whether spillovers are supposed to originate solely from economic transactions such as trade and FDI or they are knowledge spillovers not necessarily embodied in specific economic transactions, and ii) also when researchers have allowed the effect of foreign R&D to vary between G7 and non-G7 countries. This ultimately suggests that a functional misspecification bias could be present in standard parametric CH/CHH specifications.

2.2 Econometric issues

As far as econometric estimation and testing are concerned, the most relevant issues raised by the existing literature are i) heterogeneous slope parameters; ii) integration-cointegration; and iii) cross-sectional dependence.

Heterogeneous slope parameters. The homogeneity of the slope parameters implicit in the use of a pooled version of the CH/CHH specification (see Eq.(1) below) has been questioned from both an econometric and an economic perspective. Econometrically speaking, when the DGP is characterized by heterogeneous slopes, fixed effects estimators yield consistent estimates of the mean coefficients only when the number of cross-sectional units approaches infinity. From an economic standpoint, and closely related to the present topic, a theoretical justification for heterogeneous slope parameters across countries can be found in the "new growth" literature, which argues that technology differs across countries (Brock and Durlauf, 2001; Durlauf et al., 2001). Concerning international technology diffusion in particular, some studies have challenged the assumption of a common technology by arguing that technologies are specific to particular combinations of inputs (Basu and Weil, 1998). While some previous econometric studies have introduced a certain degree of heterogeneity by allowing the impact of the explanatory variables to differ between G7 countries and others (see, for example, Potterie and Lichtenberg, 2001, p. 762), other studies have instead adopted methods allowing for heterogeneous slopes, such as the mean group estimator (Pesaran and Smith, 1995). Although approaches allowing for slope-specific parameters are conceptually appealing, they may face the problem of parameter estimate instability, caused by the estimation of several parameters with relatively short time series (Baltagi et al., 2002, 2004). In particular, the mean group estimator has asymptotic justification only for $T \to \infty$ and generally suffers from the problem of parameter estimate instability, which can in turn produce non-significant estimates. Moreover, pooled and fully heterogeneous estimators have relative advantages and disadvantages, as *"the truth probably lies somewhere in between. The parameters are not exactly the same, but there is some similarity between them"* (Maddala et al., 1997, p. 91). For this reason, some previous studies have applied the shrinkage estimators described in Maddala et al. (1997) and the hierarchical

Bayes approach (Hsiao et al., 1998). The former can be viewed as a compromise between the unrealistic homogeneity assumption and unstable heterogeneous estimates, while the latter makes use of Markov chain Monte Carlo methods via Gibbs sampling. According to Hsiao et al. (1998), this estimator is asymptotically equivalent to the mean group estimator but performs better for small samples.

Integration–cointegration. The large time dimension of macro panel data makes extremely relevant the adoption of time-series procedures applied to panel data to deal with non-stationarity, spurious regression, and cointegration. In this respect, some of the previous works find evidence of non-stationary variables by applying first-generation tests (Coe et al., 2009), and after having checked for the existence of a valid cointegration relation, they applied estimation methods for cointegrated regression models in panel data, such as the dynamic OLS estimator proposed by Kao and Chiang (2001). Recently, Ertur and Musolesi (2017) provided a more nuanced and thorough picture by adopting second-generation tests decomposing the panel into deterministic, common, and idiosyncratic components (Bai and Ng, 2004), suggesting that while the unobserved idiosyncratic component of the variables under study is stationary, the unobserved common-factors component is non-stationary.

Cross-sectional dependence. In the last decade, with the increasing process of globalization and the growing importance of economic and social interconnections across economic agents, the issue of cross-sectional dependence (CSD) in panel data models has become of crucial relevance from both a theoretical and an empirical point of view. CSD has been typically introduced as a result of a finite number of unobservable (and/or observed) common factors or by the consideration of spatial models. Ertur and Musolesi (2017) focus on the detection of CSD and then on the estimation under CSD. They first find evidence of strong cross-sectional dependence in the data and then estimate the model by using the common correlated effects (CCE) approach as it remains valid in a variety of situations that are likely to occur, such as the presence of both forms of dependence (Pesaran and Tosetti, 2011) or the existence of non-stationary factors (Kapetanios et al., 2011), and it also allows for the estimation of both pooled and heterogeneous specifications.

2.3 Research gaps

In summary, the existing literature has adopted alternative measures of international technological spillover and has focused on various methodological issues, such as allowing for heterogeneous slopes, addressing non-stationary variables, and handling cross-sectional dependence. Although the likely complex relation between research activity and economic performance—pointed out in the related literature on the economics of innovation—and the high degree of instability of the estimated output elasticity with respect to foreign R&D suggest that the traditional CH/CHH parametric specification may suffer from a functional misspecification bias, previous works did not check the ability of this specification to correctly approximate the underlying DGP or test whether more flexible specifications may be more suitable. This is the main purpose of the present work.

3 Model specifications and their estimation

3.1 The classical parametric specification

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

$$\log f_{it} = \alpha_i + \theta \log S^d_{it} + \gamma \log S^f_{it} + \delta \log H_{it} + e_{it}, \tag{1}$$

where f_{it} is the TFP of country $i = 1, ..., N$ at time $t = 1, ..., T$; α_i are individual fixed effects; S^d_{it} and S^f_{it} are domestic and foreign R&D capital stocks, respectively; H_{it} is a measure of human capital; and e_{it} is the error term. Foreign capital stock S^f_{it} is defined as the weighted arithmetic mean of S^d_{jt} for $j \neq i$, that is,

$$S^f_{it} = \sum_{j \neq i} \omega_{ij} S^d_{jt}, \tag{2}$$

where ω_{ij} represents the weighting scheme.

The model in Eq. (1) can be written as a special case of the heterogeneous panel data model,

$$y_{it} = \alpha_i' \mathbf{d}_t + \beta_i' \mathbf{x}_{it} + e_{it}, \tag{3}$$

with $y_{it} = \log f_{it}$. α_i is a constant term as $\mathbf{d}_t = d_t = 1$, $\mathbf{x}_{it} = [\log S^d_{it}, \log S^f_{it}, \log H_{it}]'$ and $\beta_i = \beta = [\theta, \gamma, \delta]'$.

In the general specification (3), it is usually assumed that $\beta_i = \beta + \mu_i$, where the deviations, μ_i, are independently and identically distributed with mean 0. Moreover, these deviations are distributed independently of e_{jt}, $\mathbf{d}_t$, and $\mathbf{x}_{jt}$ for all i, j, and t. In this general specification, $\mathbf{d}_t$ denotes a $l \times 1$ vector of observed common effects (including deterministic terms such as intercepts and seasonal dummies), and α_i is the associated vector of parameters.

CCE estimators Panel data literature dealing with models like (3) with both N and T being large has shown that ignoring cross-sectional dependence can seriously impair the properties of usual panel data estimators (Andrews, 2005; Phillips and Sul, 2007; Sarafidis and Wansbeek, 2012). Cross-sectional dependence can be due to unobserved common factors such as economy-wide shocks (for instance, an oil price increase) that affect all countries, albeit with different intensity. The errors e_{it} are then assumed to have the following common factor structure:

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

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, in particular, $m << N$. 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. Pesaran (2006) considers the case of i.i.d errors, while Pesaran and Tosetti (2011) focus on the more general case of a multifactor error structure and spatial error correlation. Combining (3) and (4), we obtain the following:

$$y_{it} = \alpha_i' \mathbf{d}_t + \beta_i' \mathbf{x}_{it} + \gamma_i' \mathbf{f}_t + \varepsilon_{it}. \tag{5}$$

This model cannot be estimated using traditional panel data estimators due to the unobservability of common factors $\mathbf{f}_t$. Pesaran (2006) suggests the common correlated effects (CCE) estimation procedure to deal with this issue. CCE consists of approximating the linear combination of the unobserved factors by cross-sectional averages of the dependent and explanatory variables and then running standard panel regressions augmented with these cross-sectional averages.

The CCE estimator can be motivated as follows. The idiosyncratic errors ε_{it} in Eq. (4) 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 $\mathbf{v}_{it} = (v_{i1t}, v_{i2t}, v_{i3t})'$. $\mathbf{v}_{it}$ is assumed to be distributed independently of ε_{it} and is allowed to be serially correlated as well as weakly cross-sectionally correlated.

Combining Eqs. (5) and (6), we get the following system of equations:

$$z_{it} = \begin{pmatrix} y_{it} \\ x_{it} \end{pmatrix} = \mathbf{B}_i'\mathbf{d}_t + \mathbf{C}_i'\mathbf{f}_t + \xi_{it}, \tag{7}$$

where

$$\mathbf{B}_i = (\alpha_i \ \mathbf{A}_i) \begin{pmatrix} 1 & 0 \\ \beta_i & \mathbf{I}_3 \end{pmatrix}, \mathbf{C}_i = (\gamma_i \ \mathbf{\Gamma}_i) \begin{pmatrix} 1 & 0 \\ \beta_i & \mathbf{I}_3 \end{pmatrix}, \text{ and } \xi_{it} = \begin{pmatrix} \varepsilon_{it} + \beta_i'\mathbf{v}_{it} \\ \mathbf{v}_{it} \end{pmatrix}.$$

Using sample cross-sectional averages, Eq. (7) can be written as

$$\bar{z}_t = \overline{\mathbf{B}}'\mathbf{d}_t + \overline{\mathbf{C}}'\mathbf{f}_t + \bar{\xi}_t, \tag{8}$$

where

$$\bar{\mathbf{z}}_t = \frac{1}{N}\sum_{i=1}^{N}\mathbf{z}_{it}, \ \overline{\mathbf{B}} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{B}_i, \ \overline{\mathbf{C}} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{C}_i, \text{ and } \ \bar{\xi}_t = \frac{1}{N}\sum_{i=1}^{N}\xi_{it}.$$

Following Pesaran (2006), we can pre-multiply both sides of Eq. (8) by $\overline{\mathbf{C}}$ and solve for $\mathbf{f}_t$. We get

$$\mathbf{f}_t = \left(\overline{\mathbf{C}}\,\overline{\mathbf{C}}'\right)^{-1}\overline{\mathbf{C}}'\left(\bar{z}_t - \overline{\mathbf{B}}'\mathbf{d}_t - \bar{\xi}_t\right). \tag{9}$$

It is possible to show that $\bar{\xi}_t$ converges to 0 in quadratic mean as $N \to \infty$ (Pesaran and Tosetti, 2011). Accordingly, it can be shown that

$$\mathbf{f}_t - \left(\overline{\mathbf{C}}\,\overline{\mathbf{C}}'\right)^{-1}\overline{\mathbf{C}}'\left(\bar{z}_t - \overline{\mathbf{B}}'\mathbf{d}_t\right) \xrightarrow{\text{q.m.}} 0, \text{ as } N \to 0, \tag{10}$$

or put differently, the unobservable common factors, $\mathbf{f}_t$, can be well approximated by a linear combination of observed common factors, $\mathbf{d}_t$, the cross-sectional averages of the dependent variable, $\bar{y}_t$, and those of the country-specific regressors, $\bar{x}_t$. Two alternative estimators have been proposed in the literature: the CCE mean group (CCEMG) estimator and the CCE pooled (CCEP) estimator. It has been shown that CCE estimators yield consistent estimates in a large variety of situations (Chudik et al., 2011; Kapetanios et al., 2011; Pesaran and Tosetti, 2011). Moreover, small-sample properties of CCE estimators have also been investigated in various papers (see, among others, Chudik et al., 2011; Kapetanios et al., 2011; Westerlund and Urbain, 2015). More specifically, these papers compare the small-sample properties of CCE estimators to their competitors, i.e., estimators based on principal components (PCs) (Bai, 2009), and show that although the PC estimates of factors are more efficient than the cross-sectional averages, the CEE estimators of slope coefficients generally perform the best. To conclude, a significant advantage of CCE estimators is that they do not require a priori knowledge about the number of unobserved common factors.

3.2 Alternative non-parametric specifications

Specifications Recently, Su and Jin (2012) considered a panel data model that extends the multifactor linear specification proposed by Pesaran (2006). Specifically, Su and Jin (2012) considered the following panel data model that allows for a non-parametric relation between the dependent variable and the regressors, while the common factors enter the model in a parametric way:

$$y_{it} = \alpha_i^{\prime}\mathbf{d}_t + g_i\left(\mathbf{x}_{it}\right) + \gamma_i^{\prime}\mathbf{f}_t + \varepsilon_{it}, \tag{11}$$

where $g_i(.)$ are unknown smooth continuous functions (heterogeneous case). In the homogeneous case, $g_i(.) = g(.)$ for all $i = 1, 2, \ldots, N$. For identification purposes, the following condition is necessary:

$$E(g_i\left(\mathbf{x}_{it}\right)) = 0.$$

In the empirical framework, we consider two alternative specifications where $\mathbf{x}_{it}$ enter the model non-parametrically. Because of the relatively short time dimension, we restrict our analysis to the homogeneous case where $g_i(.) = g(.)$ (see Su and Jin, 2012, p. 41) and propose two alternative specifications. The first specification assumes an additive structure of $g(.)$, as follows:

$$\log f_{it} = \alpha_i + \phi(\log S_{it}^d) + \xi(\log S_{it}^f) + \psi(\log H_{it}) + \gamma_i^{\prime}\mathbf{f}_t + \varepsilon_{it}, \tag{12}$$

where $\phi(.)$, $\xi(.)$, and $\psi(.)$ are unknown univariate smooth continuous functions of interest.

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

$$\log f_{it} = \alpha_i + g(\log S_{it}^d, \log S_{it}^f, \log H_{it}) + \gamma_i^{\prime}\mathbf{f}_t + \varepsilon_{it}. \tag{13}$$

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

Sieve approximation Su and Jin (2012) extend the CCE approach to the estimation of a heterogeneous panel data model (11). First, following Pesaran (2006) they proxy the unobservable common factors $\mathbf{f}_t$ in (11) by the cross-sectional averages $\overline{\mathbf{z}}_t = N^{-1}\sum_{j=1}^{N}\mathbf{z}_{jt}$, where $\mathbf{z}_{it} = [y_{it}, \mathbf{x}_{it}^{\prime}]^{\prime}$. Second, they approximate the non-parametric part of the model, $g_i\left(.\right)$, 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 (see below). Second, the order of approximation must be defined. Let K denote this order, which is a function of T when estimating the heterogeneous model with $g_i(.)$, or of N and T when estimating the homogeneous model with $g(.)$. This integer number will tend to infinity as $N \to \infty$ (heterogeneous case) or $(N, T) \to \infty$ (homogeneous case). 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.,

$$g_i(.) \approx \delta_{g_i}{}'\pi^K(x) \text{ (heterogeneous case) or } g(.) \approx \delta_g{}'\pi^K(x) \text{ (homogeneous case).} \tag{14}$$

Finally, to estimate δ_{g_i}, we run the following regression:

$$y_{it} = \alpha_i'\mathbf{d}_t + \delta_{g_i}{}'\pi^K(x) + \psi_i'\overline{\mathbf{z}}_t + u_{it}, \tag{15}$$

To estimate δ_g, the regression is

$$y_{it} = \alpha_i'\mathbf{d}_t + \delta_g{}'\pi^K(x) + \psi_i'\overline{\mathbf{z}}_t + u_{it}. \tag{16}$$

Su and Jin (2012) show that the extended CCE estimators of both the heterogeneous and homogeneous regression functions are consistent as N and T tend to infinity and establish the asymptotic normality of these estimators.

Thin plate regression splines Su and Jin (2012) estimate the non-parametric component of the model using Sieves—specifically, splines—as they typically provide better approximations (see, for example, 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 fewer 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 respects (see, for example, 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 (Li and Ruppert, 2008; Claeskens et al., 2009).

In this work, for both RS and PRS we use thin plate regression splines (TPRS), which were introduced by Wood (2003). TPRS 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, they have some optimality properties as they provide optimal low-rank approximations to thin plate splines, while also being computationally efficient (see Wood, 2003). Since our explanatory variables have different units, in the case of the non-additive specification (13) we avoid isotropy by considering a tensor product basis, which is constructed by assigning TPRS as the basis for the marginal smooth function 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 function 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 is less likely to develop multiple minima or to undersmooth at finite sample sizes, compared to other approaches (see, for example, Reiss and Todd Ogden, 2009). Since TPRS have been developed and mostly adopted in statistical science, a more detailed description of them is provided in Appendix C.

4 Forecasting-driven model-selection procedure

To compare the alternative specifications, we perform a pseudo-Monte Carlo experiment. In the case of independent and identically distributed data, Racine and Parmeter (2014) propose a method 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 true error. In the approach by Racine and Parmeter (2014), the observations are randomly shuffled at a given percentage level into training points and into evaluation points. Each model is then fitted according to the training sample, and 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 S, so that a $S \times 1$ vector of prediction errors is created for each model.[1] As highlighted in Racine and Parmeter (2014), the method can provide significant power improvements over existing single-split techniques.

In the context of time series, the performance of a model is usually assessed on its ability to forecast new observations over a given time horizon, and resampling methods are then used to evaluate forecasting performance. Racine and Parmeter (2014) extend their method to time-series data using recent advances in time-series resampling methodology based on block bootstrapping, which was introduced by Carlstein (1986) and developed by Künsch (1989).[2] The main idea underlying block resampling is that individual blocks of observations that are separated far enough in time will be approximately uncorrelated and can be treated as exchangeable. Suppose that the time series has length $T = b \times l$. We can generate b non-overlapping blocks, each of length l. Moreover, if the blocks are sufficiently long each block preserves in the resampled series the dependence present in the original data sequence. The resampling or bootstrap scheme used here, named non-overlapping block bootstrap, is to resample with replacement from the set of b blocks. Moving block bootstrap (MBB) generalizes this scheme by allowing the blocks to overlap (Künsch, 1989). Resampling now involves more blocks: a total of $T - l + 1$ overlapping blocks.

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

[2]Applications of the various types of block bootstrap methods for time series and other models of dependent data (including spatial data) are extensively presented in Lahiri (2003).

Although Racine and Parmeter (2014) do not provide any extension of their method to panel data, for which the random resampling originally proposed for cross-sections has been employed by Ma et al. (2015) and Delgado et al. (2014), they provide enough insights as to the generalization of their method to this type of data. Indeed, block bootstrapping approaches, and more specifically MBB, have been recently generalized to panel data, especially when cross-sectional dependence is present, eventually arising from a multifactor error structure. For instance, Gonçalves (2011) proposed panel MBB, i.e., standard MBB applied to the vector containing all of the individual observations at each point in time (see Appendix D for a complete description). She proved that panel MBB is robust to both serial and cross-sectional dependence of unknown form when applied to the fixed effects estimator. The same year, Palm et al. (2011) presented panel unit root tests that can deal not only with common factors but also with a wide range of other plausible dynamic dependencies. They use MBB to achieve this goal. Recently, Smeekes and Westerlund (2019) extended the work of Palm et al. (2011) to panel predictability tests, also making use of block bootstrapping.

Drawing from the abovementioned literature, we extend the data-driven model-choice method proposed by Racine and Parmeter (2014). As measures of model forecasting performance, we focus our attention on both the average square prediction error (ASPE), which was adopted by Racine and Parmeter (2014), and the mean absolute percentage error (MAPE), which is often recommended for forecasting exercises (see, for example, Bowerman et al., 2005, p. 18, and Hyndman and Koehler, 2006) and has the interesting property of being scale-independent. These two measures are defined as

$$ASPE = \frac{1}{N}\sum_{i=1}^{N}\sum_{f=1}^{F}\left(y_{if}-\widehat{y}_{if}\right)^2, \tag{17}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\sum_{f=1}^{F}\frac{100\times|y_{if}-\widehat{y}_{if}|}{y_{it}}, \tag{18}$$

where F is the forecast horizon. Our 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 (see Eq.(10)).

5. Compute the ASPE and MAPE of each model, i.e.,

$$
\begin{aligned}
ASPE^L &= \frac{1}{n \times T_1} \sum_{i=1}^{n} \sum_{t=T_1+1}^{T} (y_{it}^* - \widehat{g}_{T_1}^L(\mathbf{x}_{it}^*))^2, \; L = A, B, \text{ and} \\
MAPE^L &= \frac{1}{n \times T_1} \sum_{i=1}^{n} \sum_{t=T_1+1}^{T} \frac{100 \times |y_{it}^* - \widehat{g}_{T_1}^L(\mathbf{x}_{it}^*)|}{y_{it}^*}, \; L = A, B.
\end{aligned}
$$

6. Repeat this a large number of times, say S times, yielding $(ASPE_s^A, ASPE_s^B)$, $s = 1, \ldots, S$, and $(MAPE_s^A, MAPE_s^B)$, $s = 1, \ldots, S$.

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.

Appendix D explains how MBB can be applied to panel data, while Appendix E provides further insights about the validity of the proposed forecasting-driven model-selection procedure by reporting a small simulation study.

5 Data

We build a new annual country-level balanced panel dataset covering 24 OECD countries from 1971 to 2014. This dataset is an updated version of the data used by CHH and Ertur and Musolesi (2017), which covers the 1971–2004 period. Consequently, our updated dataset covers a more recent period, which is particularly interesting due to the increasing process of globalization and the likely increase in the interconnections across economies over time. As for the dependent variable (f_{it}), we use TFP at constant prices from Penn World Table version 9.0 (Feenstra et al., 2015). As for the explanatory variables, to build the domestic R&D stock (S_{it}^d) we consider business expenditure on research and development (BERD) flow values, collected from the OECD-STATS database, using total data as source of funds. Missing values are filled, and then the BERD stock is calculated using the perpetual inventory method, assuming the depreciation rate to be 0.05. In taking these steps, we follow CH and CHH. For the human capital variable (H_{it}^d), we build a stock measure using the same method as Ertur and Musolesi (2017), which is grounded on earlier works on the return to schooling, and then assume a log-(piecewise)linear relationship between H and the average number of years of schooling, which were obtained from Barro and Lee (2013). Note that for the last three years of our sample, which are not covered by Barro and Lee (2013), we fill the missing values by linear extrapolation.

Finally, as far as foreign R&D is concerned, we focus on geographic proximity as a channel for technology diffusion. This choice was made not only because it is theoretically consistent (Eaton and Kortum, 2002; Keller, 2002) but mainly because traditional channels of international technology diffusion, such as trade, FDI, or patent activity, might create reverse causality problems when included in econometric specifications as they may depend on the country's technological level and, in turn, may be endogenous with respect to TFP (Hong and Sun, 2011). In contrast, geographic distance is generally considered as exogenous (Keller, 2004, p. 772) and may also proxy some endogenous measures of socioeconomic, institutional, cultural, or linguistic similarity that might enhance the diffusion of technology. Following Keller (2002) and Ertur and Musolesi (2017), we propose a specification of foreign R&D that incorporates the notion that the impact of foreign R&D is a decreasing function of geographic distance from foreign economies. Therefore, the foreign R&D capital stock for each country i is obtained by weighting the domestic R&D capital stocks of every other country $j \neq i$ in the sample using an exponential distance decay function, $\omega_{ij} = \exp(-d_{ij})$, with d_{ij} being the spherical distance between the capitals of countries. Therefore,

$$S_{it}^{f} = \sum_{j \neq i} \exp(-d_{ij}) S_{jt}^{d}. \tag{19}$$

It is also interesting to note that a possible alternative approach that has never been investigated within this literature involves calculating a multidimensional distance by adopting the Mahalanobis method, as proposed by Berry et al. (2010). This method allows summarizing many dimensions and is preferable to other approaches when the alternative measures of cross-national distance are highly correlated, as is often the case. This may provide further interesting insights. However, in this methodological paper, which aims to compare alternative specifications, geographic distance is preferred in light of exogeneity reasons.

Some descriptive statistics are provided in Table 1. One piece of relevant information provided by this table is that both domestic and foreign R&D present between variation that is almost twice the within variation, whereas for both TFP and human capital between and within variation are of the same order of magnitude.

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

In addition, Figure 1 depicts univariate and bivariate plots for a few representative countries: USA, Germany, South Korea, Italy, Spain, and Sweden. The USA and Germany are the global and European leaders, respectively, with respect to technology. South Korea has become one of the most innovative countries in the world over the years, with a massive increase in R&D stock. Italy and Spain are two Southern European countries suffering from under-investment in R&D, and Sweden is a representative Nordic country. Figure 1 shows relevant non-linear and heterogeneous dynamics across countries, which may be considered as a first descriptive indication that flexible non-parametric models could be suitable in such a framework.

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

Appendix B provides some additional insights about the time series properties of the main variables under investigation through application of the PANICCA test by Reese and Westerlund (2016), which is a PANIC approach (Bai and Ng, 2004) based on cross-sectional averages augmentation rather than on principal component estimation. Application of the test confirms the results of Ertur and Musolesi (2017) with an extended dataset and indicates that the variables are non-stationary and that such non-stationarity arises as a result of the combination of a stationary idiosyncratic component with non-stationary common factors.

6 Results

6.1 Model selection

Three empirical specifications are considered:[3]

$$\log f_{it} = \alpha_i + \theta \log S^d_{it} + \gamma \log S^f_{it} + \delta \log H_{it} + \gamma_i^{'} \mathbf{f}_t + \varepsilon_{it}, \quad (20)$$

$$\log f_{it} = \alpha_i + \phi(\log S^d_{it}) + \xi(\log S^f_{it}) + \psi(\log H_{it}) + \gamma_i^{'} \mathbf{f}_t + \varepsilon_{it}, \text{ and} \quad (21)$$

$$\log f_{it} = \alpha_i + g(\log S^d_{it}, \log S^f_{it}, \log H_{it}) + \gamma_i^{'} \mathbf{f}_t + \varepsilon_{it}. \quad (22)$$

Additive and non-additive specifications (21) and (22) are estimated using either regression splines or penalized regression splines.

Traditional in-sample model-selection procedures The traditional approach to select between competing specifications is based on criteria measuring their goodness of fit to observed data, or in other words, their in-sample prediction performances. In this respect, the selection method can be defined in terms of an appropriate information criterion. Information criteria are based on the idea of balancing fit with complexity (Konishi and Kitagawa, 2008).

When focusing on smooth regression models, as in the present case, a possibility is adopting an information criterion based on the conditional likelihood of the model coefficients. Within the exponential family framework, Hastie and Tibshirani (1990) proposed the widely used conditional AIC (Akaike information criterion). Subsequent studies showed that this approach tends to select too much complex models. Recently, Wood et al. (2016) proposed an AIC that overcomes such a problem and, more generally, that avoids neglecting the smoothing parameter uncertainty in the conditional AIC, as well as being easy to compute. Wood (2020) provided further details and, in particular, gave useful insights for obtaining a BIC (Bayesian information criterion).

While both the AIC and BIC can be used to select among nested or non-nested models, they have different properties. The AIC, which was derived as an asymptotic approximate estimate of the Kullback–Leibler information discrepancy, is not strongly consistent but is efficient, while the opposite is true for the BIC (Claeskens et al., 2008).

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

[3] The parametric specification is estimated using a CCEP estimator already coded in R within the package plm, while the non-parametric specifications are estimated by exploiting the R package mgcv. The model selection procedure has been coded by the authors using the R programming language.

The results in Table 2, which are based on the AIC and BIC proposed by Wood et al. (2016) and Wood (2020), provide a very robust picture as both the BIC and AIC rank the models in the same way. Indeed, according to both criteria i) the non-additive penalized model performs above all others, ii) the parametric model—at the other extreme—underperforms with respect to all other models, and iii) penalized models are preferred over non-penalized ones.

Forecasting-driven selection method According to the statistical literature dealing with apparent versus true error (see, for example, Efron, 1982), the true error is associated with out-of-sample measures of fit, in contrast to the apparent error, which is associated with within-sample measures. Typically, the latter is smaller than the former and frequently overly optimistic since a model is mostly selected to best fit the data.

Consequently, we adopt the forecasting data-driven model selection approach previously described, which allows obtaining the entire distribution of the true error for alternative models and thus permits determining which model is closer to the true unknown DGP. As far as the blocks are concerned, we fix the length of the blocks to eleven years. This allows a simple split of our sample of 44 years and also provides blocks that should be long enough to preserve the dependence structure of the original data. Overall, we draw with replacement from $44 - 11 + 1 = 34$ blocks. The number of draws S is fixed to 1000. We consider different out-of-sample performance horizons, and similar to Baltagi et al. (2004) we consider both a one-year and a three-year horizon.

A first relevant result is that the non-additive penalized model has the smallest median for both the ASPE and MAPE. More specifically, for the 1-year horizon the median ASPEs (MAPEs) of the parametric, the additive unpenalized, the additive penalized, and the non-additive unpenalized models are 0.552, 0.634, 0.636, and 0.617 (0.830, 0.913, 0.888, and 0.791), respectively. For the 3-year horizon, these ratios do not change significantly and take the following values: 0.521, 0.656, 0.656, and 0.631 (0.870, 0.978, 0.930, and 0.844). It can be expected that the out-of-sample performance will deteriorate when the horizon increases. Interestingly, it can be noted that when moving from a 1- to a 3-year horizon the median of the ASPEs and MAPEs is almost unaffected, showing a low increase, while the variability increases substantially as the standard deviation almost doubles in all models.

A second interesting result is that when looking at the median, the parametric model is almost always outperformed by the alternative non-parametric specifications, the only exception being the non-additive unpenalized model, which provides the worst results in terms of MAPE. Third, while when we impose an additive structure the penalized regression modeling and its unpenalized counterpart present very similar median ASPEs and MAPEs, when estimating the non-additive specification, which typically suffers more from the curse of dimensionality, an extremely pronounced gain in terms of predictive ability from using PRS over RS is observed.

In order to test whether the above differences across alternative specifications—in terms of their median—are statistically significant, we also performed a paired Wilcoxon test, which is a non-parametric alternative to the paired t-test when comparing paired data. The results of these tests are presented in Table 3. In all cases, when contrasting the non-additive penalized model with the others the null hypothesis that the difference in the medians of the ASPEs/MAPEs is zero is strongly rejected, thus indicating that this difference is statistically significant. The same happens when contrasting the additive models—both penalized and unpenalized—with the standard parametric specification.

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

Next, Figure 2 shows the empirical cumulative distribution functions of the ASPEs (MAPEs) for each model. Clearly, the ASPE (MAPE) of the non-additive penalized model is stochastically dominated by the ASPE of any of the other models. This indicates that the non-additive penalized model outperforms all others in terms of predictive ability. Even if visual differences seem to appear between the distributions for the different competing models in the figures presented above, it is interesting to confirm their existence with a statistical test. The most popular approach for distribution homogeneity testing is based on the Kolmogorov–Smirnov (KS) statistic, which is obtained as the largest discrepancy between the empirical distribution functions by these models (see, for example, Lehmann and Romano, 2006). Below, we use KS test to choose the best model in terms of predictive performance.

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

The first set of results presented in Table 4 are those of the KS tests of equality of the ASPE distributions for the estimated models. These tests clearly conclude with a rejection of the null hypothesis of the equality of distributions for each pair of models, whatever the forecasting time horizon, with the notable exception of generalized additive unpenalized and penalized specifications. The second part of Table 4 reports the results of the KS test of dominance for each forecasting time horizon. We focus on the distribution of the penalized tensor model because this distribution sets itself apart from those of the other models estimated in the figures presented above. We first test whether the distribution of the penalized tensor model dominates the distribution of each of the competing models. Results clearly show that this hypothesis is rejected, whatever the considered competing model and time horizon. We then test the reverse hypothesis, i.e., that the distribution of the penalized tensor model is dominated by the distribution of each of the competing models. Test values do not allow a rejection of this hypothesis. The penalized tensor model therefore appears to be the model that generates the forecasts closest to the observed values, whatever the considered forecasting time horizon, when the quality of the forecasts is measured by the ASPE criterion.

===== Insert Tables 4 and 5 =====

A similar analysis can also be performed using MAPE criterion. The corresponding results are reported in Table 5. The first set of results given in this table shows that there are only significant differences between the distribution of the penalized tensor model and those of its competitors, whatever the forecasting time horizon. Moreover, dominance tests here also clearly conclude that the MAPE distribution of the non-additive penalized model is stochastically dominated by the MAPE distribution of any of the remaining models. The penalized tensor model therefore appears to be the model that generates the forecasts closest to the observed values, whatever the considered forecasting time horizon, when the quality of the forecasts is measured by the MAPE criterion.

To sum up, these results clearly indicate that i) the parametric specification underperforms with respect to the non-parametric penalized models, and ii) there is very robust evidence that the penalized non-additive model outperforms all the others. This is a similar result to Ma et al. (2015), who use a similar macro panel dataset. As far as non-parametric specifications are concerned, PRS perform better than unpenalized RS. The improvement achieved when using PRS is much more pronounced when focusing on the non-additive specification, where RS suffer more from the curse of dimensionality while PRS appear to be extremely efficient. While there are a number of studies comparing alternative spline methods by using Monte Carlo simulations (see, for example, Wood, 2003, 2006; Nie and Racine, 2012), to the best of our knowledge this is the first paper contrasting PRS and RS in terms of their predictive ability, and the results may provide some guidance for future work. The non-additive specification is indeed the best one when using PRS, while with unpenalized RS the best model is the one with additive smooth terms. These results thus suggest adopting a non-parametric, non-additive specification and indicate that PRS are more efficient than their unpenalized counterparts, especially for non-additive specifications when the curse of dimensionality is a concern.

6.2 Estimation results

We now present the estimation results of the non-additive penalized specification, which according to our findings clearly provides the best predictive performance and thus is the most suitable to approximate the underlying DGP.

As a preliminary step, in order to provide a straightforward comparison with previous works such as Ertur and Musolesi (2017), CHH, and others, we also estimate the model exploiting our extended dataset and adopting some parametric estimators that have already been employed in the literature. The results in Table 6 are structured as follows. Column (i) and (ii) report the results obtained by using the pooled CCE by Pesaran (2006), which was employed by Ertur and Musolesi (2017). In column (i), we consider the standard parametric specification, which was previously discussed; in column (ii), we allow the impact of the explanatory variables to differ between the G7 countries and the others, as is sometimes done in the literature. In columns (iii) to (vi), following CHH, Kao et al. (1999), and Lee (2006), we instead focus on panel cointegration estimators. We consider both the pooled fully modified OLS (FMOLS) by Phillips and Moon (1999) and the pooled dynamic OLS (DOLS) by Kao and Chiang (2001), with and without a linear time trend in the deterministic component.

===== Insert Table 6 =====

The results are as follows. When employing the pooled CCE in (i), all of the estimated parameters are close to zero and are not significant at standard significance levels. A similar result was found by Eberhardt et al. (2013) when estimating the effect of R&D within a Griliches-type knowledge capital production function and can be partially explained as a result of an *"omitted time-related factor bias"* that may arise in common panel data models that do not account for common factors. Allowing the impact of the explanatory variables to differ between the G7 countries and the others (model (ii)) provides additional insights and, in particular, may suggest that model (i) suffers from misspecification bias, as it is now found that the coefficient associated with domestic R&D for G7 countries is positive (0.04) and significant at the 10% level. A positive (0.07) and significant effect of foreign R&D for non-G7 countries is also found. Finally, an implausible negative effect of human capital for non-G7 countries is also obtained, with an estimated elasticity equal to -0.31. These results partially contradict the findings of Ertur and Musolesi (2017), who exploited a shorter dataset (1971–2004) and found totally different results for foreign R&D and human capital. Human capital was found to have a positive and significant effect only for G7 countries, while the opposite happened for foreign R&D. Overall, such parameter estimate instability may suggest that the traditional CH/CHH parametric model likely suffers from a *"functional misspecification bias"*. The results obtained adopting panel cointegrated estimators provide similar evidence. Indeed, while the model without a trend provides results that are consistent with CHH and Kao et al. (1999), who adopted the same panel cointegration estimators, the inclusion of a linear trend in the cointegration relation makes all of the estimated parameters close to 0 and statistically non-significant. Including a linear trend seems to be consistent with the time series properties of the data and also makes the estimated specification closer to the factor model. The results do not change significantly when moving from pooled to mean-group estimators.[4]

In order to discuss the results for the preferred non-additive model, we first provide a visual inspection of the estimated smooth function and then focus our attention on the estimated elasticities. Also note that the estimated (multivariate) smooth function appears to be highly significant when adopting the Wald-type test suggested by Wood (2012).[5]

As for the visual inspection of the estimated multivariate function, we depict the joint effects of two variables at a time, fixing the level of the third one to the first, fifth (the median), and ninth deciles. At first glance, looking at Figures 3, 4, and 5 it easy to see that complex interactive effects are a relevant feature of the data that is obscured in parametric specifications.

===== Insert Figures 3, 4 and 5 =====

When focusing on the joint effect of the R&D variables on TFP (see Figure 3), it can be noted that such an interactive effect increases with the level of human capital. As depicted in panel (a), for low levels of human capital and for most of the domain of the R&D variables, the estimated function is flat. Only for high values of foreign R&D does domestic R&D have a positive effect

[4]FMOLS and DOLS estimates were obtained by exploiting Eviews 11. The coefficient covariances were computed using the default settings, and the long-run covariances used a Bartlett kernel and a Newey–West fixed bandwidth. As for the DOLS, leads and lags were selected using the BIC. Finally, note that it was computationally unfeasible to estimate the model with G7 interactions.

[5]Test results are available upon request from the authors.

on TFP. Panels (b) and (c) show the estimated bivariate function when human capital is fixed to the median and to the ninth decile, respectively. The results in both panels suggest a positive and non-linear effect of domestic/foreign R&D on TFP, which seems to increase as human capital moves from the median the ninth decile.

A similar pattern appears for the domestic R&D–human capital bivariate function (see Figure 4), as it clearly increases by increasing the level of foreign R&D. Indeed, when foreign R&D is fixed to the first decile (panel (a)) the estimated function is very flat; it then becomes an increasing function when foreign R&D is fixed to the median or to the ninth decile. However, while panel (b) (foreign R&D fixed at the median) indicates a rather additive effect, panel (c) (foreign R&D fixed at the ninth decile) suggests a more complex non-linear non-additive interactive effect.

Finally, as far as the joint human capital–foreign R&D effect is concerned, a different pattern is observed as the estimated relation (see Figure 5) is always very flat for any level of domestic R&D. Relevant exceptions occur for high levels of foreign R&D, where in some specific regions human capital has a pronounced positive effect on TFP.

We provide a thorough analysis of the estimated elasticities and compare them with both previous results and our parametric estimates in Table 6. As far as domestic R&D is concerned, the literature provides an estimated elasticity that is typically bounded in the range of 0.05–0.2 and also suggests that the effect of domestic R&D on TFP is much higher for G7 than for non-G7 countries (Kao et al., 1999; Coe et al., 2009; Ertur and Musolesi, 2017). While the parametric CCE in Table 6 confirms this finding and our non-parametric results are somehow consistent with it, they are also much richer, as shown in Table 7 and in Figure 6 where we report the estimated elasticity of one domestic R&D as a function of the potential values of this factor, the other two being fixed to some quantile values.[6]. Indeed, the output elasticity of domestic R&D capital stock from the preferred non-additive model ranges between about 0 and 0.21. There are some combinations of factors for which the estimated elasticity is very close to zero and is not significant. This happens for low values of human capital associated with high values of domestic R&D. This pattern can be viewed as consistent with the existence of a minimum level of absorptive capacity, arising from the human capital endowment, that allows a country to benefit from technology. Similarly, the estimated output elasticity of domestic R&D is close to zero and non-significant for high levels of foreign R&D associated with low levels of domestic R&D. In contrast, high values of domestic and foreign R&D in combination with average levels of human capital are associated with an estimated elasticity of about 0.2. We label this situation in which the estimated output elasticity of domestic R&D (non-linearly) increases with the amount of foreign R&D as *(non-linear) interactive spillover effects*, in opposition to standard spillover effects, which generally refer to the direct ceteris paribus effect of foreign R&D on TFP. We also note that for median/high values of human capital, threshold effects appear as a relevant feature of the data since the estimated elasticity is positive (in the range

[6]Standard errors are reported in Table 7, in addition to estimated values of elasticities. Their computation takes advantage of the underlying parametric representation of sieve approximations (see Eq. (14)) and is based on the covariance matrix of estimated parameters $\widehat{\delta}_g$ and derivatives of the elements belonging to the chosen basis $\pi^K(x) = (\pi_1(x), \pi_2(x), \ldots, \pi_K(x))^{'}$. The 90% confidence intervals in Figure 6 are computed in the same way (See Wood, 2017, p. 341, for more details)

of 0.05–0.10) and significant for low values of domestic R&D; it then decreases to around zero and finally increases again for high values of domestic R&D.

===== Insert Table 7 =====

As for the output elasticity of foreign R&D, and as was stressed in Section 2, a high degree of variability is observed when looking at the existing literature. Looking also at the results in Table 6, such variability could be explained as a consequence of functional misspecification bias, and our results from the preferred non-parametric model are consistent with this view. Three main findings arise from Figure 7. First, there are many combinations of inputs for which the estimated elasticity is about 0 and is not statistically significant. This happens, for instance, for median levels of both domestic R&D and human capital (irrespective of the level of foreign R&D). Second, for high levels of both domestic R&D and human capital, the estimated elasticity is always positive and significant, ranging from about 0.1 to 0.2, depending on the level of foreign R&D. Third, there are some combinations of domestic R&D–human capital for which a certain amount of foreign R&D is necessary to observe a significantly positive elasticity. On the one hand, these results are consistent with the existence of a certain level of absorptive capacity arising from domestic technology that is necessary for a country to benefit from foreign technology (see, for example, Xu, 2000) and with theories suggesting that technology that is invented in frontier countries is less appropriate for poorer countries (see, for example, Basu and Weil, 1998). On the other hand, however, they suggest that this arises with complex non-linearities that clearly make the parametric model misspecified and may explain both the high variability in estimates from previous parametric specifications and our own parametric estimates in Table 6.

===== Insert Figures 6, 7, and 8 =====

Finally, as for the output elasticity of human capital, typical approaches not accounting for common latent factors generally conclude in a high and significant estimated elasticity, which is often in the range of 0.5–0.7 (see, for example, CHH). However, Ertur and Musolesi (2017) cast considerable doubt on the idea that the stock of human capital—constructed using the average years of schooling—significantly affects TFP. Their result complements some previous studies on growth that emphasize the key role of the quality of education (see, for example, Hanushek and Kimko, 2000) and finally suggests that the quantity of education no longer has a significant effect when omitted time-related variable bias is addressed. While our parametric results in Table 6 confirm this finding, the non-parametric non-additive model provides further insights, as depicted in Figure 8. Indeed, for low-to-median levels of both R&D variables the estimated elasticity is generally non-significantly different from zero, thus confirming the parametric results. However, for high values of domestic and/or foreign R&D, some locally significant positive effect is documented. In particular, when both R&D variables are high the estimated elasticity presents an interesting non-linear pattern: for low-to-median values of human capital, the estimated function is flat and non-significantly different from zero, but it then increases and becomes positive, high in magnitude, and significant for the last two deciles of human capital. This pattern seems to be empirically consistent with the Korean technological development that has occurred over the last decades.

Overall, this evidence appears to be consistent with the existence of threshold effects, non-linear interactive spillover effects, and complex absorptive capacity effects, and is consistent with the idea of localized technical change, as suggested in the seminal paper by Atkinson and Stiglitz (1969).

7 Concluding remarks

This paper proposes an estimation strategy that exploits recent non-parametric panel data methods and extends a recently proposed data-driven model-selection procedure to the case of cross-sectionally dependent panels. This estimation strategy builds on Su and Jin (2012), who generalize the common correlated effects estimation procedure proposed by Pesaran (2006) in a parametric framework to a more general non-parametric one. Indeed, the choice of a fully non-parametric specification of the function of interest is very appealing as it avoids the specification bias involved in the estimation of more restrictive and possibly misspecified specifications. However, this choice has a cost in terms of the number of observations necessary for sufficient precision of the estimated function—the so-called curse of dimensionality issue. It is therefore relevant to compare different specifications and choose the one with the best performance in any empirical application.

Our estimation strategy is inspired by the data-driven model-selection procedure proposed by Racine and Parmeter (2014) for cross-sectional data and time-series. In line with Efron (1982), competing specifications are evaluated in terms of their performance predicting new observations. We extend this procedure to a large panel data framework by using moving block bootstrap resampling techniques in order to preserve cross-sectional dependence in the bootstrapped samples used when assessing specification performance and by measuring forecasting performance as a tool for selecting among the competing specifications.

This estimation strategy is illustrated by revisiting an analysis of international technology diffusion and exploiting new annual country-level data for 24 OECD countries from 1971 to 2014, which extends the time-coverage of the data used by Coe et al. (2009) and Ertur and Musolesi (2017). Model selection procedures clearly conclude in the superiority of a fully non-parametric (non-additive) specification of the relationship between TFP and domestic R&D capital, foreign R&D, and human capital, over parametric and even semi-parametric (additive) specifications. Moreover, the non-parametric specification allows for a richer view of the resulting spillover effects, showing non-linear effects and thresholds not previously detected in the literature and ultimately suggesting the presence of *(non-linear) interactive spillover effects* (non-linearly) increases with the amount of foreign R&D. In addition, we also document that penalized regression splines perform significantly better than their unpenalized counterparts, especially in the case of a non-additive model, when the curse of dimensionality is a concern. To the best of our knowledge, this is the first paper contrasting penalized and unpenalized regression splines in terms of their predictive ability.

To conclude, it is worth mentioning that further extensions of the present study should account for heterogeneous relations across countries. Given the relatively short time dimension of our sample, such an extension is outside the realm of the non-parametric estimators presented in this paper, where heterogeneity is addressed by adopting a mean group approach, and could be accomplished, for instance, by resorting to Bayesian modeling (Kiefer and Racine, 2017; Parmeter and Racine, 2019) to address the additional curse of dimensionality problem raised by heterogeneity.

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Table 1: Descriptive statistics

Variable		Mean	SD	Min.	Max.
$\log TFP$	Overall	-0.090	0.146	-0.645	0.256
	Between		0.097	-0.308	0.113
	Within		0.110	-0.427	0.218
$\log$ *domestic R&D*	Overall	10.190	2.223	-1.545	14.925
	Between		2.099	3.793	3.793
	Within		0.846	4.851	12.771
$\log$ *foreign R&D*	Overall	11.210	1.109	6.634	14.793
	Between		0.962	8.300	14.137
	Within		0.585	7.420	13.738
$\log$ *human capital*	Overall	1.038	0.141	0.532	1.295
	Between		0.108	0.798	1.236
	Within		0.093	0.741	1.300

Table 2: Traditional in-sample model selection

Model	BIC	Rank (BIC)	AIC	Rank(AIC)
Non-additive penalized	-4267.796	1	-5202.976	1
Additive penalized	-4044.856	2	-4764.583	2
Additive unpenalized	-4028.581	3	-4762.993	3
Non-additive unpenalized	-3941.881	4	-4671.33	4
Parametric	-3851.537	5	-4466.855	5

Notes: BIC and AIC are based on Wood et al. (2016) and Wood (2020).

Table 3: Paired Wilcoxon tests of factor models

	Horizon	Additive unpenalized	Additive penalized	Non-additive unpenalized	Non-additive penalized
ASPE					
Parametric	1-year	394, 916(< 0.001)	412, 761(< 0.001)	370, 720(< 0.001)	464, 626(< 0.001)
	3-year	411, 659(< 0.001)	432, 372(< 0.001)	367, 896(< 0.001)	451, 674(< 0.001)
Additive unpenalized	1-year		294, 332(< 0.001)	164, 042(< 0.001)	459, 080(< 0.001)
	3-year		309, 488(< 0.001)	140, 828(< 0.001)	438, 475(< 0.001)
Additive penalized	1 year			152, 358(< 0.001)	452, 034(< 0.001)
	3 year			127, 792(< 0.001)	427, 726(< 0.001)
Non-additive unpenalized	1 year				473, 174(< 0.001)
	3 year				461, 908(< 0.001)
MAPE					
Parametric	1 year	208, 088(0.020)	220, 794(< 0.001)	196, 197(0.4649)	220, 797(< 0.001)
	3 year	179, 872(0.057)	185, 370(0.007)	169, 856(0.680)	194, 917(< 0.001)
Additive unpenalized	1 year		189, 658(0.8835)	179, 751(0.140)	219, 520(0.000)
	3 year		171, 769(0.4868)	157, 148(0.141)	183, 474(0.015)
Additive penalized	1 year			177, 662(0.079)	213, 788(0.002)
	3 year			152, 699(0.033)	176, 860(0.147)
Non-additive unpenalized	1 year				223, 099(< 0.001)
	3 year				196, 897(< 0.001)

Null hypothesis: The true difference in the medians of the ASPEs/MAPEs of the compared models is zero.
Number of resampling iterations B: 1000.
p-values are between brackets.

Table 4: Kolmogorov–Smirnov test results: $ASPE$

—— Forecasting horizon = 1 year ——				
Two-sided tests				
	Additive unpenalized	Additive penalized	Non-additive unpenalized	Non-additive penalized
Parametric	0.002	< 0.001	0.006	< 0.001
Additive unpenalized	—	0.999	0.061	< 0.001
Additive penalized	—	—	0.020	< 0.001
Non-additive unpenalized	—	—	—	< 0.001
One-sided tests				
H_A: The distribution of $ASPEs$ for the non-additive penalized model is lower than that for:				
	Parametric	Additive unpenalized	Additive penalized	Non-additive unpenalized
Non-additive penalized	< 0.001	< 0.001	< 0.001	< 0.001
H_A: The distribution of $ASPEs$ for the non-additive penalized model is greater than that for:				
	Parametric	Additive unpenalized	Additive penalized	Non-additive unpenalized
Non-additive penalized	≈ 1	0.999	0.996	≈ 1

—— Forecasting horizon = 3 years ——				
Two-sided tests				
	Additive unpenalized	Additive penalized	Non-additive unpenalized	Non-additive penalized
Parametric	< 0.001	< 0.001	0.003	< 0.001
Additive unpenalized	—	0.954	0.055	< 0.001
Additive penalized	—	—	0.020	< 0.001
Non-additive unpenalized	—	—	—	< 0.001
One-sided tests				
H_A: The distribution of $ASPEs$ for the non-additive penalized model is lower than that for:				
	Parametric	Additive unpenalized	Additive penalized	Non-additive unpenalized
Non-additive penalized	< 0.001	< 0.001	< 0.001	< 0.001
H_A: The distribution of $ASPEs$ for the non-additive penalized model is greater than that for:				
	Parametric	Additive unpenalized	Additive penalized	Non-additive unpenalized
Non-additive penalized	≈ 1	≈ 1	≈ 1	≈ 1

Table 5: Kolmogorov–Smirnov test results: $MAPE$

—— Forecasting horizon = 1 year ——

	Additive unpenalized	Additive penalized	Non-additive unpenalized	Non-additive penalized
Two-sided tests				
Parametric	0.573	0.370	0.859	0.008
Additive unpenalized	—	0.954	0.610	0.078
Additive penalized	—	—	0.200	0.069
Non-additive unpenalized	—	—	—	0.069
One-sided tests				
H_A: The distribution of $MAPEs$ for the non-additive penalized model is lower than that for:				
	Parametric	Additive unpenalized	Additive penalized	Non-additive unpenalized
Non-additive penalized	0.004	0.039	0.034	0.034
H_A: The distribution of $MAPEs$ for the non-additive Penalized model is greater than that for:				
	Parametric	Additive unpenalized	Additive penalized	Non-additive unpenalized
Non-additive penalized	0.952	0.845	0.866	0.940

—— Forecasting horizon = 3 years ——

	Additive unpenalized	Additive penalized	Non-additive unpenalized	Non-additive penalized
Two-sided tests				
Parametric	0.573	0.288	0.648	0.005
Additive unpenalized	—	0.999	0.401	0.029
Additive penalized	—	—	0.219	0.020
Non-additive unpenalized	—	—	—	0.015
One-sided tests				
H_A: The distribution of $MAPEs$ for the non-additive penalized model is lower than that for:				
	Parametric	Additive unpenalized	Additive penalized	Non-additive unpenalized
Non-additive penalized	0.023	0.015	0.009	0.007
H_A: The distribution of $MAPEs$ for the non-additive penalized model is greater than that for:				
	Parametric	Additive unpenalized	Additive penalized	Non-additive unpenalized
Non-additive penalized	0.975	0.845	0.845	0.952

Table 6: Parametric estimation results

	CCE	CCE_G7	FMOLS	DOLS	FMOLS_T	DOLS_T
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$\log S^d$	-0.0004		0.071***	0.062***	0.005	0.006
	(0.0056)		(0.0086)	(0.0097)	(0.0102)	(0.0111)
$\log S^f$	0.009		0.013	0.005	-0.030	-0.033
	(0.0122)		(0.0115)	(0.0149)	(0.0186)	(0.0195)
$\log H$	-0.095		0.357***	0.361***	0.225	0.178
	(0.0779)		(0.0680)	(0.0719)	(0.1366)	(0.1431)
$\mathbf{1}_{G7} \log S^d$		0.041*				
		(0.0248)				
$\mathbf{1}_{NOG7} \log S^d$		0.008				
		(0.0060)				
$\mathbf{1}_{G7} \log S^f$		0.039				
		(0.0281)				
$\mathbf{1}_{NOG7} \log S^f$		0.065***				
		(0.0184)				
$\mathbf{1}_{G7} \log H$		0.26				
		(0.2357)				
$\mathbf{1}_{NOG7} \log H$		-0.306**				
		(0.121)				

Notes:

CCE: pooled CCE ; CCE_G7: pooled CCE with G7 interactions;

$1_{G7}=\begin{cases} 1 & \text{if country} \in \text{G7 group} \\ 0 & \text{if country} \notin \text{G7 group} \end{cases}$, and$1_{NOG7}= 1 - 1_{G7}$

FMOLS: fully modified OLS; FMOLS_T: fully modified OLS with linear trend;

DOLS: dynamic OLS; leads and lags selection based on BIC;

DOLS_T: dynamic OLS with linear trend;

***, **, *: significant at the 1%, 5%, and 10% level, respectively; standard errors in brackets.

Appendices

A Summary of previous works

The Table A1 below summarizes some previous works and highlights some relevant methodological aspects.

TABLE A1

Some previous studies on R&D international spillovers

Author	Sample	Technology transfer	Method	COINT	HET	CSD	NL	Foreign R&D
Coe and Helpman (1995)	22 countries, 1971-90	trade	LSDV					.06-.092
Coe et al. (2009)	22 countries, 1971-90	trade	DOLS					.165-.186
	24 countries, 1971-2004	trade	LSDV	x				.185-.206
	24 countries, 1971-2004	trade	DOLS					.206-.213
Kao et al. (1999)	22 countries, 1971-90	trade	BC-OLS					.09-.125
	22 countries, 1971-90	trade	FM-OLS	x				.075-.103
	22 countries, 1971-90	trade	DOLS					.044NS-.056NS
Lichtenberg and Van Pottelsberghe (1997)	22 countries, 1971-90	trade	LSDV					.058-.276
Lichtenberg and Van Pottelsberghe (2001)	23 countries, 1971-90	trade	LSDV					.154
	23 countries, 1971-90	FDI	LSDV					-.06NS-.072
	23 countries, 1971-90	trade	FD					.067
	23 countries, 1971-90	FDI	FD					.006NS-.039
Musolesi (2007)	13 countries, 1981-98	trade	HB					.09
	13 countries, 1981-98	FDI	HB		x			-0.01NS-.004NS
	13 countries, 1981-98	language	HB					.23
Lee (2006)	16 countries, 1981-2000	trade	DOLS					-.02NS-.17
	16 countries, 1981-2000	FDI	DOLS	x				-.017NS-.034
	16 countries, 1981-2000	patents	DOLS					.157-.183
Keller (2002)	14 countries, 1970-95	geography	NLS				x	.843
	14 countries, 1970-95	language	NLS					.565
Engelbrecht (2002)	21 countries, 1971-85	trade	LSDV					.220-.305
Bitzer and Kerekes (2008)	17 countries, 1973-2000	trade	FGLS					.009-.02
	17 countries, 1973-2000	FDI	FGLS					-.016-.012
Barrio-Castro et al. (2002)	21 countries, 1971-85	trade	LSDV					.094-.225
	21 countries, 1966-95	trade	LSDV					0.016-0.106
	21 countries, 1966-95	trade	DOLS					.092-.141
Fracasso and Vittucci (2013)	24 countries, 1971-2004	trade	DOLS		x		x	.107-.126
	24 countries, 1971-2004	geography	NLS					0.016-0.106
Ertur and Musolesi (2017)	24 countries, 1971-2004	geography	CCEP					0.094NS-0.329
	24 countries, 1971-2004	geography	CCEMG	x	x	x		0.240NS-0.510NS
	24 countries, 1971-2004	geography	SEM					0.011-NS-0.22

Notes:

COINT: Integration-Coitegration analysis; HET: Heterogeneous slopes; CSD: Cross-Sectional Dependence; NL: Non-linear models.

LSDV: Least Squares Dummy Variable ; DOLS: Dynamic Ordinary Least Squares; BC-OLS: Bias Corrected OLS; FM-OLS: Fully Modified OLS;

FD: First Difference; HB: Hierarchical Bayes; NLS: Non Linear Least Squares; FGLS: Feasible Generalized Least Squares;

CCEP:Pommon Correlated Effects Pooled; CCEMG: Pommon Correlated Effects Mean Group; SEM: Spatial Error Model; NS: not significant.

B Panel unit roots tests

Some of the previous works find evidence of nonstationary variables by applying first-generation tests (Coe et al., 2009). Recently, Ertur and Musolesi (2017), by adopting the PANIC approach (Bai and Ng, 2004), which decomposes the panel into deterministic, common and idiosyncratic components, not only confirmed that the series are nonstationary but also suggested that that such a nonstationarity arises as a result of a stationary idiosyncratic component combined with nonstationary common factors. Despite providing a thorough investigation of the time series properties of the variables is somehow outside the scope of the paper, it is of some interest to check whether this result holds with this extended dataset, also in light of the results provided by Kapetanios et al. (2011) showing that the CCE approch remains valid when the nonstationarity arises because of nonstationary factors.

We adopt the PANICCA test by Reese and Westerlund (2016), which is a PANIC approach based on cross-sectional averages augmentation rather than on principal component estimation. PANICCA maintains the generality of PANIC as it allows testing for unit roots in both the common and idiosyncratic components of the data, but it has better small samples properties and avoids the determination of the total number of factors, which is usually done by adopting information criteria (Bai and Ng, 2002). Nevertheless, 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).

The results in Table B1 are clear-cut. The statistics proposed by Bai and Ng (2010), denoted P_a and P_b and $PMSB$ provide evidence for 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 we consider the MQ_f and MQ_c statistics. The limiting distributions of these statistics are nonstandard, 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, regardless of the test used, the number of nonstationary common factors is almost always equal to the total number of common factors, which given the cross-sectional averages augmentation is equal to four. 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.

TABLE B1

PANICCA test

	Idiosyncratic component			Nonstationary factors	
	P_a	P_b	$PMSB$	MQ_f	MQ_c
	p-value				
log TFP	0	0	0.008	4	4
log *domestic R&D*	0	0.004	0.07	4	4
log *foreign R&D*	0	0	0.059	4	4
log *human capital*	0	0.003	0.086	4	4

The estimated number of independent stochastic trends is reported (5% level).

C Thin plate regression splines

Consider the generic problem of finding the smooth function g of $y = g(\mathbf{x}) + \epsilon$ from n observations, where $\mathbf{x}$ is a vector of d variables. Thin plate splines (TPS) can be employed to estimate g by finding the function $\hat{g}$ that minimizes the quantity

$$||\mathbf{y} - \boldsymbol{\chi}|| + \lambda J_{md}(\chi), \tag{23}$$

where $\mathbf{y}$ and $\boldsymbol{\chi}$ are n-dimentional vectors of the y_i and $\chi(\mathbf{x_i})$, $i = 1, 2, ..., n$, respectively. $||\cdot||$ is the Euclidean norm. $J_{md}(\chi)$ is a penalty functional that is related to the order m of differentiation in J_{md} and to the dimension d, as described below.

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

It is proven that the function that minimizes the expression above is of the form

$$\hat{g}(\mathbf{x}) = \sum_{i=1}^{n} \delta_i \eta_{md}(||\mathbf{x} - \mathbf{x}_i||) + \sum_{j=1}^{M} \alpha_j \pi_j(\mathbf{x}), \tag{24}$$

under the constraint that $\boldsymbol{T'\delta} = \mathbf{0}$, $T_{ij} = \pi_j(\mathbf{x}_i)$. $\boldsymbol{\delta}$ and $\boldsymbol{\alpha}$ are vectors of unknown parameters and π_j, $j = 1, 2, ..., M$, are $M = \binom{m+d-1}{d}$ are linearly independent polynomials of degree less than m that span the $\mathbb{R}^d$ space. η_{md} is a specific function associated with m and d (see Wood, 2003). Then, (23) translates to minimizing with respect to $\boldsymbol{\delta}$ and $\boldsymbol{\alpha}$

$$||\boldsymbol{y} - \mathbf{E}\boldsymbol{\delta} - \boldsymbol{T\alpha}||^2 + \lambda \boldsymbol{\delta}' \mathbf{E} \boldsymbol{\delta}, \text{ subject to } \boldsymbol{T'\delta} = \mathbf{0}, \tag{25}$$

where $\mathbf{E}$ is the matrix with elements $E_{ij} = \eta_{md}(||\mathbf{x}_i - \mathbf{x}_j||)$, $i, j = 1, 2, ..., n$.

In contrast to typical RS and PRS, the estimation of g using TPS does not require the choice of knots or the selection of basis functions. Moreover, TPS do not impose any restriction in the number of predictor variables and allow some flexibility to the selection of m. Nevertheless, TPS are not computationally attractive because, as implied by (24) and (25), except for the case when $d = 1$, they require the estimation of as many parameters as the number of data points n.

To overcome this computational difficulty, Wood (2003, 2017) starts from the smoothing problem (25) and truncates the space of the components with parameters $\boldsymbol{\delta}$, which are the ones associated with the wiggliness of the spline. Following Wood (2017), let $\mathbf{E} = \mathbf{UDU}'$ be the eigen-decomposition of $\mathbf{E}$, where $\mathbf{D}$ is a diagonal matrix of eigenvalues of $\mathbf{E}$ such that $|D_{i,i}| \geq |D_{i-1,i-1}|$ and $\mathbf{U}$ the corresponding eigenvectors. Denote by $\mathbf{U}_k$ the matrix of the first k columns of $\mathbf{U}$ and by $\mathbf{D}_k$ the upper left $k \times k$ submatrix of $\mathbf{D}$. Restrict $\boldsymbol{\delta}$ to the column space of $\mathbf{U}_k$, so that $\boldsymbol{\delta} = \mathbf{U}_k \boldsymbol{\delta}_k$, where $\boldsymbol{\delta}_k$ is a k-dimensional vector with $k > M$. Then, within the space spanned by $\mathbf{U}_k$, problem (25) is replaced by minimizing

$$||\boldsymbol{y} - \mathbf{U}_k \mathbf{D}_k \boldsymbol{\delta}_k - \boldsymbol{T\alpha}||^2 + \lambda \boldsymbol{\delta}_k' \mathbf{D}_k \boldsymbol{\delta}_k, \text{ subject to } \boldsymbol{T}' \mathbf{U}_k \boldsymbol{\delta}_k = \mathbf{0}. \tag{26}$$

Having fitted (26), the spline is evaluated from (24) after estimating $\boldsymbol{\delta}$ from $\boldsymbol{\delta}_k$.

It is worth to note that while TPS are optimal with respect to minimizing (23), the low rank smoothers resulting from the truncation described above do not inherit such an optimality property. Moreover, this low rank approximation would be ideal only if, for any given $\boldsymbol{\delta}$, it would result in minimum change in the goodness of fit and, simultaneously, in the penalty term. Nevertheless, no single basis can achieve the above for all $\boldsymbol{\delta}$. This fact raises the need to define a way by which (25) is approximated by (26). Wood (2003, 2017) proposes an approach that is associated to minimizing the largest possible change of the goodness of fit, that is $\hat{e}_k = \max_{\boldsymbol{\delta}=\mathbf{0}} \frac{||(\mathbf{E}-\hat{\mathbf{E}}_k)\boldsymbol{\delta}||}{||\boldsymbol{\delta}||}$, as well as minimizing the largest change in wiggliness, that is $\tilde{e}_k = \max_{\boldsymbol{\delta}=\mathbf{0}} \frac{\boldsymbol{\delta}'(\mathbf{E}-\tilde{\mathbf{E}}_k)\boldsymbol{\delta}}{||\boldsymbol{\delta}||^2}$. In these quantities, $\hat{\mathbf{E}}_k = \mathbf{E}\mathbf{U}_k\mathbf{U}_k'$

and $\tilde{\mathbf{E}}_k = \mathbf{U}_k'\mathbf{U}_k\mathbf{E}\mathbf{U}_k\mathbf{U}_k'$. Further, Wood (2003) shows that the choice of $\mathbf{U}_k$ as the truncated basis for $\boldsymbol{\delta}$ minimizes simultaneously both $\hat{e}_k$ and $\tilde{e}_k$. This approximation that also considers the minimization criteria of $\hat{e}_k$ and $\tilde{e}_k$ results in the definition of the TPRS.

D Moving block bootstrap applied to panel data

Moving block bootstrap (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 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.

E MBB forecasting-driven model selection procedure with generated data

This appendix aims to provide further insights about the validity of the proposed MBB-forecasting-driven model selection procedure by applying such a procedure to generated data. We generate three alternative DGPs: linear, additive and non-additive, respectively, all being characterized by both cross-sectional dependence arising from (stationary and nonstationary) common factors and serial error dependence:

$$
\begin{aligned}
y_{it} &= \alpha_i + 0.3x_{1it} + 0.7x_{2it} + \gamma_{1i}f_{1t} + \gamma_{2i}f_{2t} + \varepsilon_{it}, \\
y_{it} &= \alpha_i + 0.01x_{1it}^2 - 0.00007x_{1it}^3 + 0.8\sin(x_{1it}) + 0.1x_{2it} + 0.1x_{2it}^2 - 0.005x_{2it}^3 + \cos(x_{2it}) + \gamma_{1i}f_{1t} + \gamma_{2i}f_{2t} + \varepsilon_{it}, \text{ and} \\
y_{it} &= \alpha_i + x_{1it}^{1.3} * x_{2it}^{0.7} + 0.5\sin(x_{1it}) + 1.5\cos(x_{2it}) + \gamma_{1i}f_{1t} + \gamma_{2i}f_{2t} + \varepsilon_{it}.
\end{aligned}
$$

The error term ε_{it} has been genearated as a first-order autoregressive process:

$$\varepsilon_{it} = 0.8\varepsilon_{it-1} + v_{it}, \text{ with } v_{it} \sim N(0, 0.7).$$

The explanatory variables are generated as linear functions of the individual effects and of common factors:

$$x_{1it} = c_{1i} + a_{11i}f_{1t} + a_{12i}f_{2t} + e_{1it} \text{ and } x_{2it} = c_{2i} + a_{21i}f_{1t} + a_{22i}f_{2t} + e_{2it},$$

where the error terms are supposed to be white noise processes, i.e. $e_{1it} \sim N(0, 0.4)$ and $e_{2it} \sim N(0, 0.6)$.

The first common factor f_{1t} is stationary and is generated as:

$$f_{1t} = t + v_{1t} \text{ with } v_{1t} \sim N(0, 0.3),$$

while the second one, f_{2t}, is supposed to be nonstationary:

$$f_{2t} = \log(t) + v_{2t} \text{ with } v_{2t} = v_{2t-1} + u_t, \text{ and } u_t \sim N(0, 0.1)$$

The individual effects and the factor loadings are drawn from Gaussian distributions as follows:

$$\begin{aligned}
\gamma_{1i} &\sim N(0.8, 1), \\
\gamma_{2i} &\sim N(0.4, 0.4), \\
a_{11i} &\sim N(0.6, 0.8), \\
a_{12i} &\sim N(0.9, 0.5), \\
a_{21i} &\sim N(1, 0.8), \\
a_{22i} &\sim N(0.6, 0.6), \\
c_{1i} &\sim N(80, 1), \\
c_{2i} &\sim N(10, 0.5), \\
c_{3i} &\sim N(0, 0.3), \text{ and} \\
\alpha_i &= c_{1i} + c_{2i} + c_{3i}
\end{aligned}$$

We fix $T = 44$ and $N = 24$ to get the same sample dimension as in the empirical analysis. As in the main analysis, we fix the length of the blocks to eleven years and we draw with replacement from $44 - 11 + 1 = 34$ blocks. The number of draws S is fixed to 1000. Figure A1 shows the ECDFs of the MAPEs (1-year forecast horizon) for each DGP, where, for estimation purposes, we employed the parametric CCE, the semiparametric (additive) CCE approach and the fully non-parametric (non-additive) CCE approach. To significantly reduce the computation time, we only consider PRS.

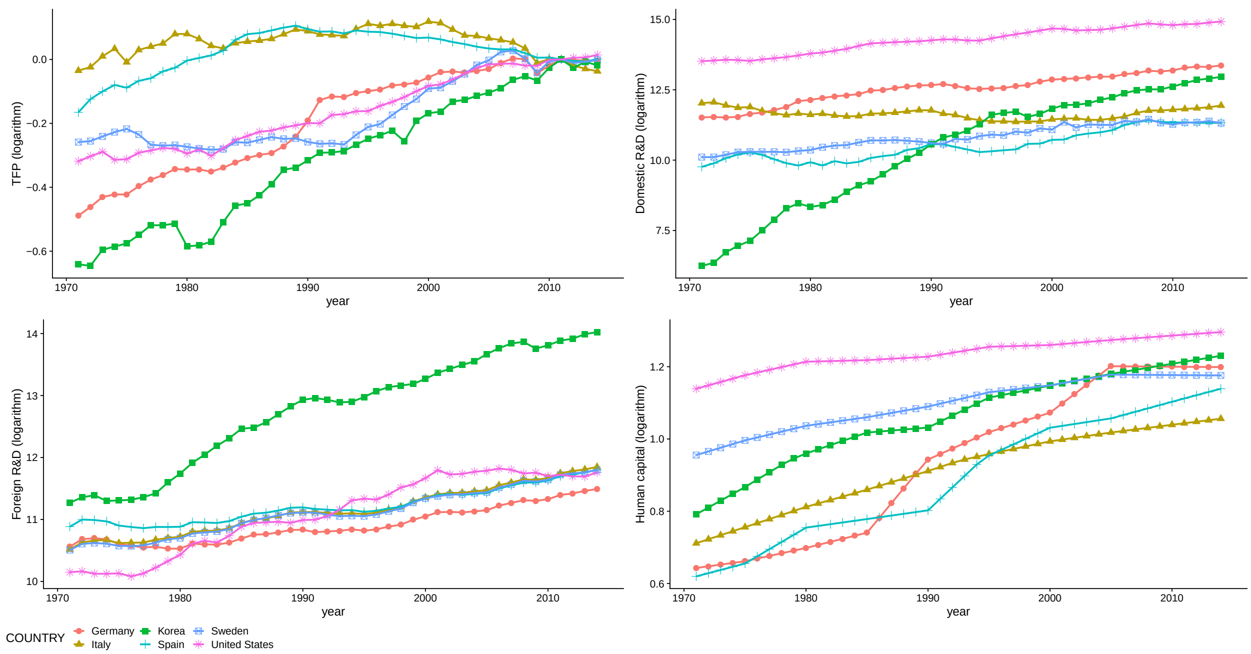
The results are clear-cut and provide evidence regarding how well the model choice procedure performs when selecting the right DGP underlying observed data in presence of non-linearities. Indeed, when the underlying DGP is fully non-parametric (resp. semiparametric) the MAPE of the non-additive (resp. additive) penalized estimator is stochastically dominated by the MAPEs of others models, with the parametric estimator that clearly provides the worst forecasting performances. Moreover, results indicates that the gain in terms of forecasting of employing tensor splines with respect to univariate (additive) splines, when the underlying functional relation is non-additive, is much bigger than the gain that is obtained by using univariate splines rather than tensor splines, when the underlying DGP is additive.

When the underlying DGP is characterized by a linear functional relationship, all three estimators generate very similar forecasting performances. The parametric specification being a special case of the additive semiparametric and fully non-parametric ones, this result is not surprising. Indeed, if the underlying DGP is linear and parametric, the estimator of the function $s(x_1, x_2)$ in the non-linear and non additive specification can be expected to be an additive function with linear components at x_1 and x_2. Therefore, the choice of one of the two non-linear specifications must be completed by a detailed analysis of the additivity and linearity of the resulting estimated functions. Poor performances of the parametric specification when the underlying DGP is either non-linear and additive or non-linear and non-additive could be similarly motivated by the fact that nor the additive semiparametric or the fully non-parametric specifications are special cases of the linear parametric one. Nevertheless, this last issue would deserve a more in-depth analysis.

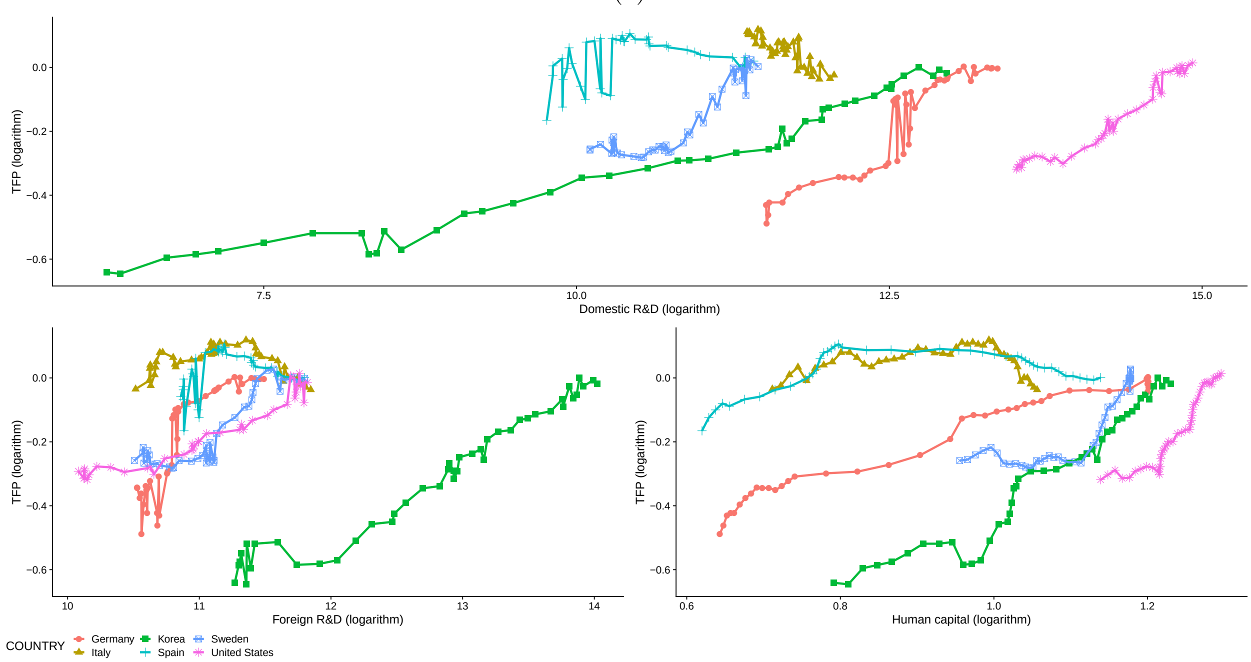
===== Insert Figure A1 =====

Table 7: R&D elasticities

Value of domestic R&D fixed at the 10% quantile				
		Values of Foreign R&D fixed at		
		Q10	Median	Q90
Values	Q10	0.0342**	0.04601***	0.0616
of		(0.0160)	0.0092)	(0.0276)
Human	Median	0.0393***	0.0320***	-0.0193
Capital		(0.0137)	(0.0086)	(0.0170)
fixed	Q90	0.0876***	0.0921***	0.0241
at :		(0.0229)	(0.0215)	(0.0230)
Value of domestic R&D fixed at the median				
		Values of Foreign R&D:		
		Q10	Median	Q90
Values	Q10	0.0083	0.0630***	0.2001***
of		(0.0276)	(0.0185)	(0.0634)
Human	Median	0.0154	-0.0188	-0.0251*
Capital		(0.0210)	(0.0130)	(0.0129)
fixed	Q90	-0.0076	0.0354**	0.0697***
at:		(0.0249)	(0.0194)	(0.0201)
Value of domestic R&D fixed at the 90% quantile				
		Values of Foreign R&D:		
		Q10	Median	Q90
Values	Q10	-0.0176	-0.0564	-0.0114
of		(0.0479)	(0.0499)	(0.1017)
Human	Median	0.1619***	0.1977 ***	0.2128***
Capital		(0.0351)	(0.0316)	(0.0469)
fixed	Q90	0.1459***	0.0572*	0.0125
at:		(0.0377)	(0.0302)	(0.0281)

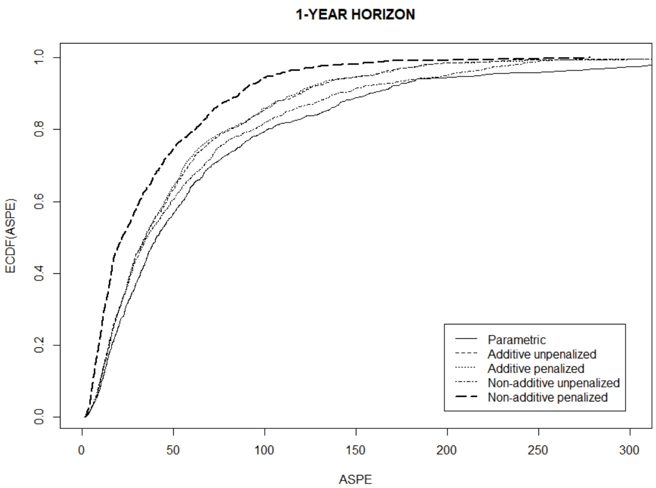


(a)

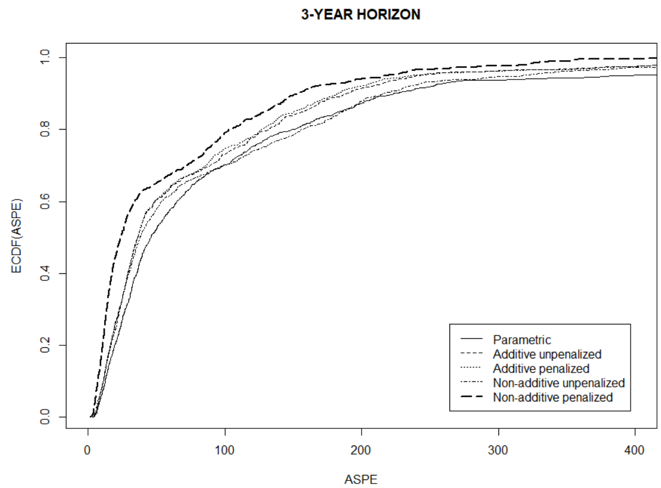


(b)

Figure 1: Univariate (a) and bivariate (b) plots.



(a)



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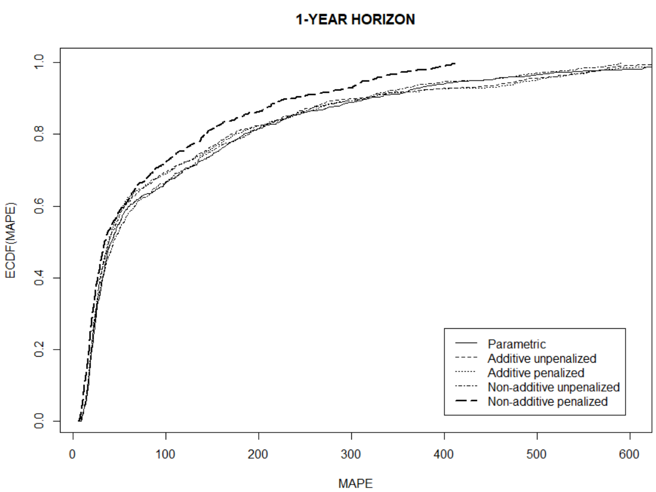
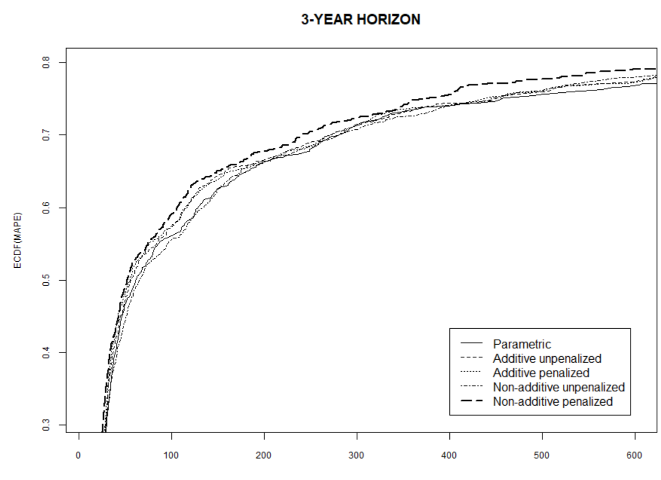


(c)



(d)

Figure 2: Empirical cumulative distribution functions (ECDFs) of the ASPE and MAPE for different factor models: the linear, the additive, and the non-additive models for the OECD data.

Figure 3: TFP as a function of domestic and foreign R&D

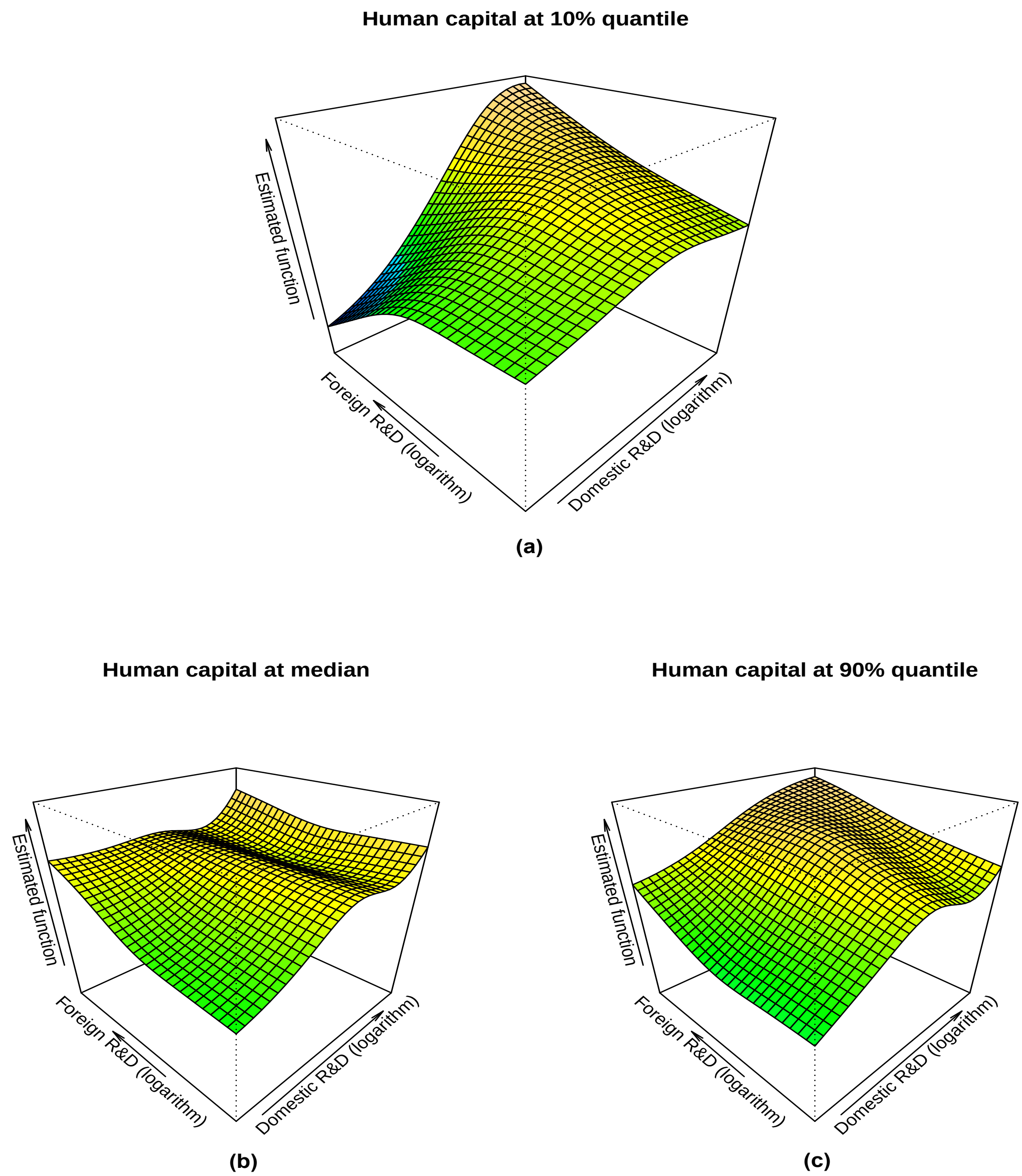


Figure 4: TFP as a function of domestic R&D and human capital

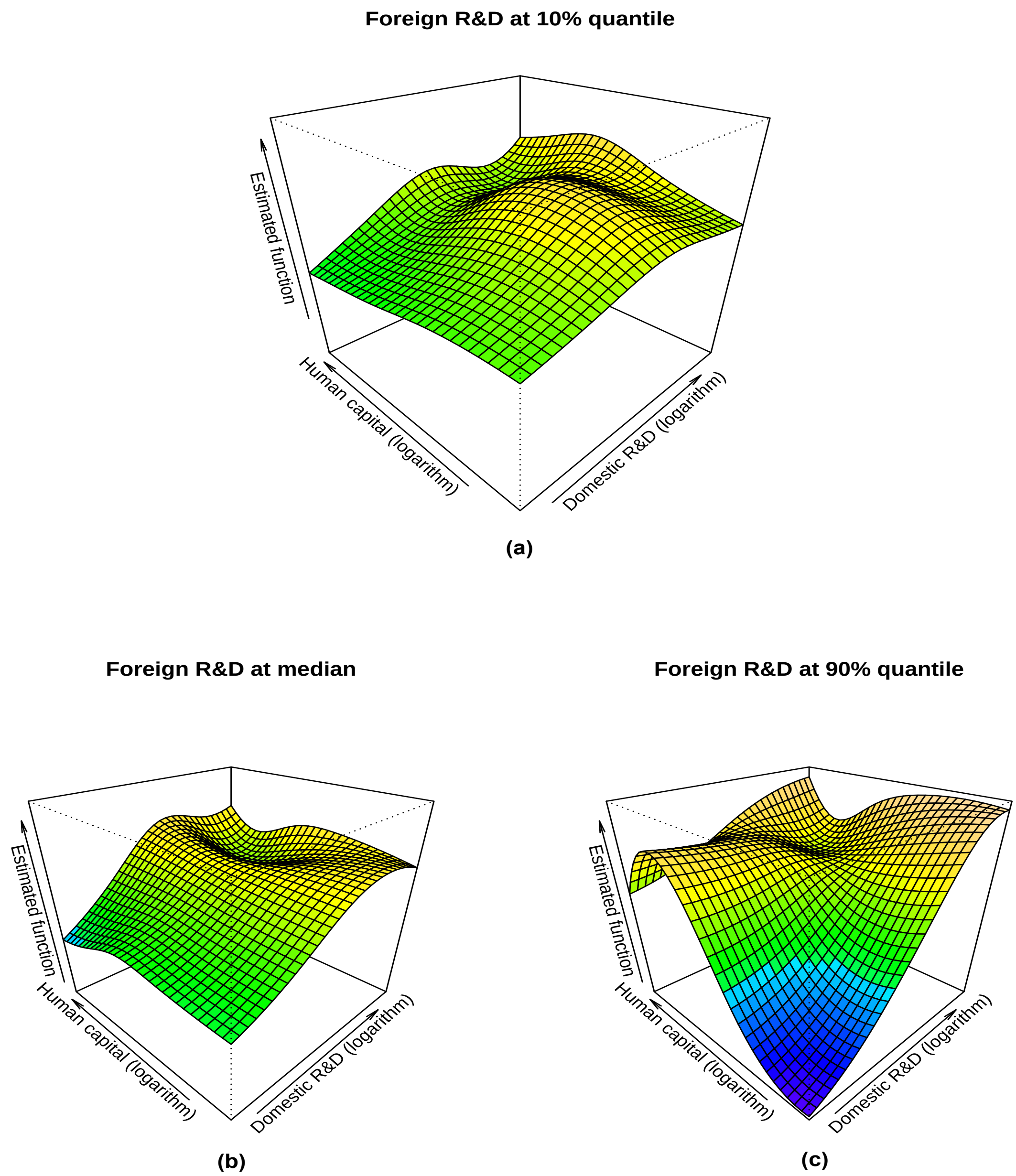


Figure 5: TFP as a function of foreign R&D and human capital

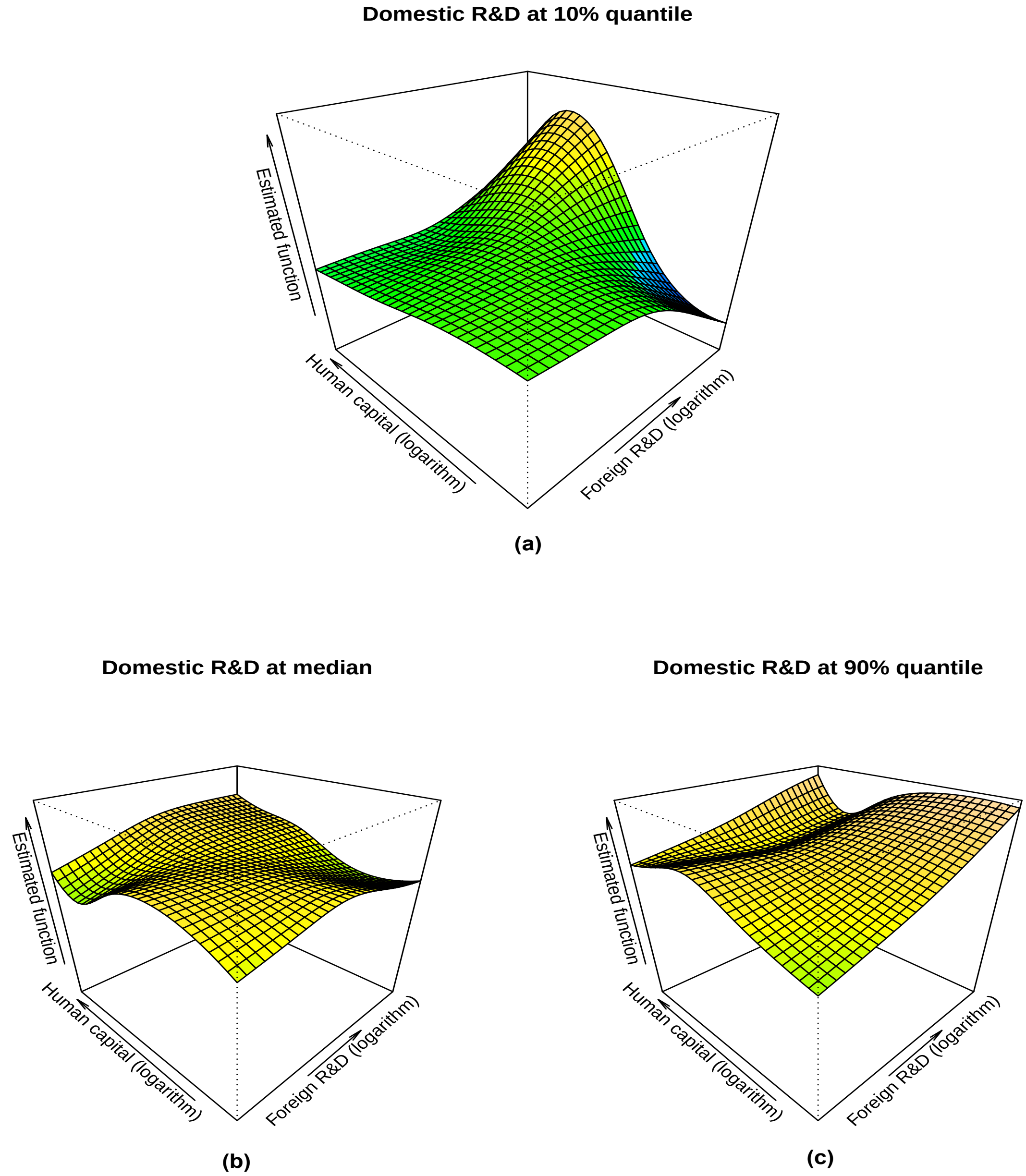


Figure 6: Estimated R&D elasticities

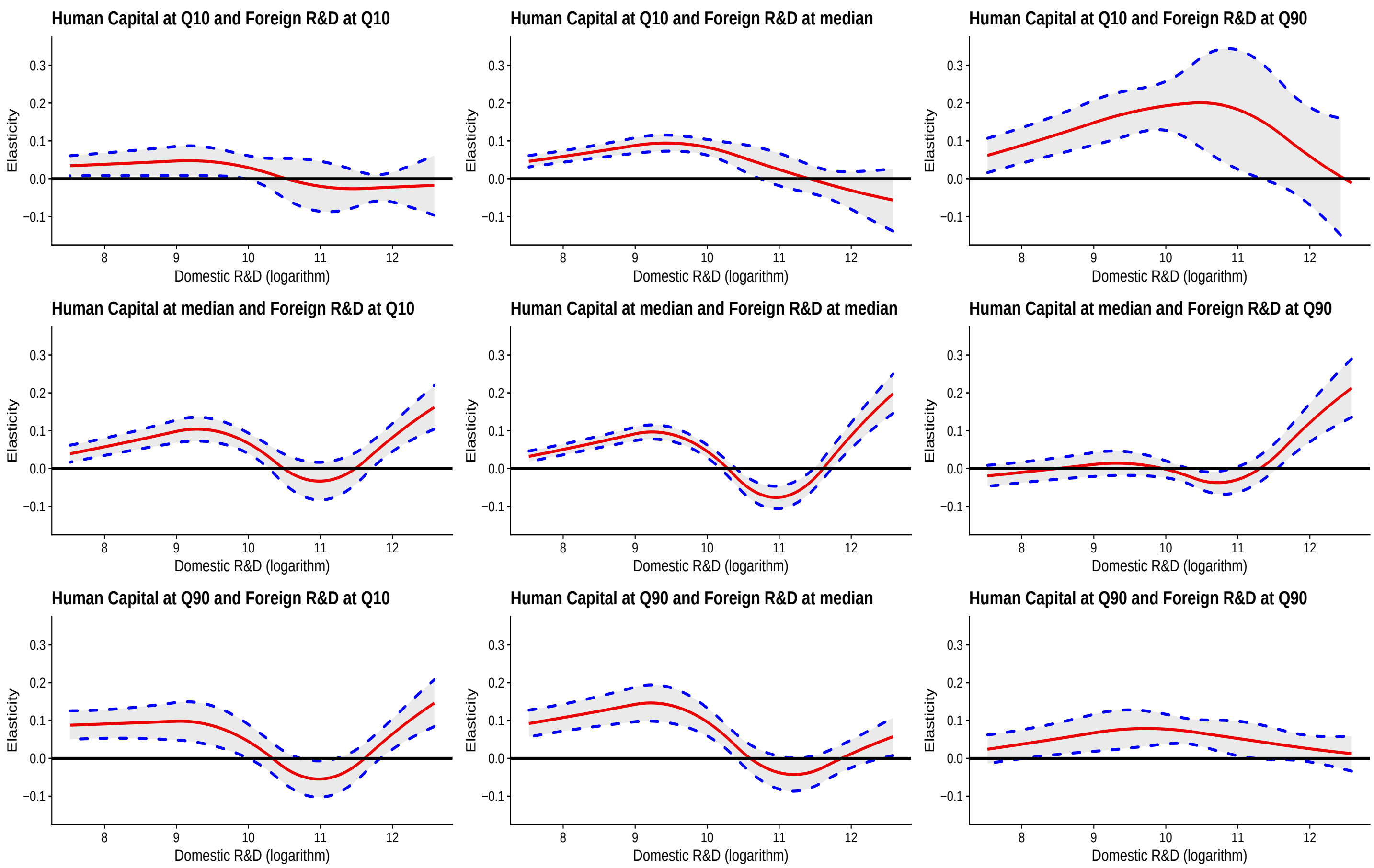


Figure 7: Estimated foreign R&D Elasticities

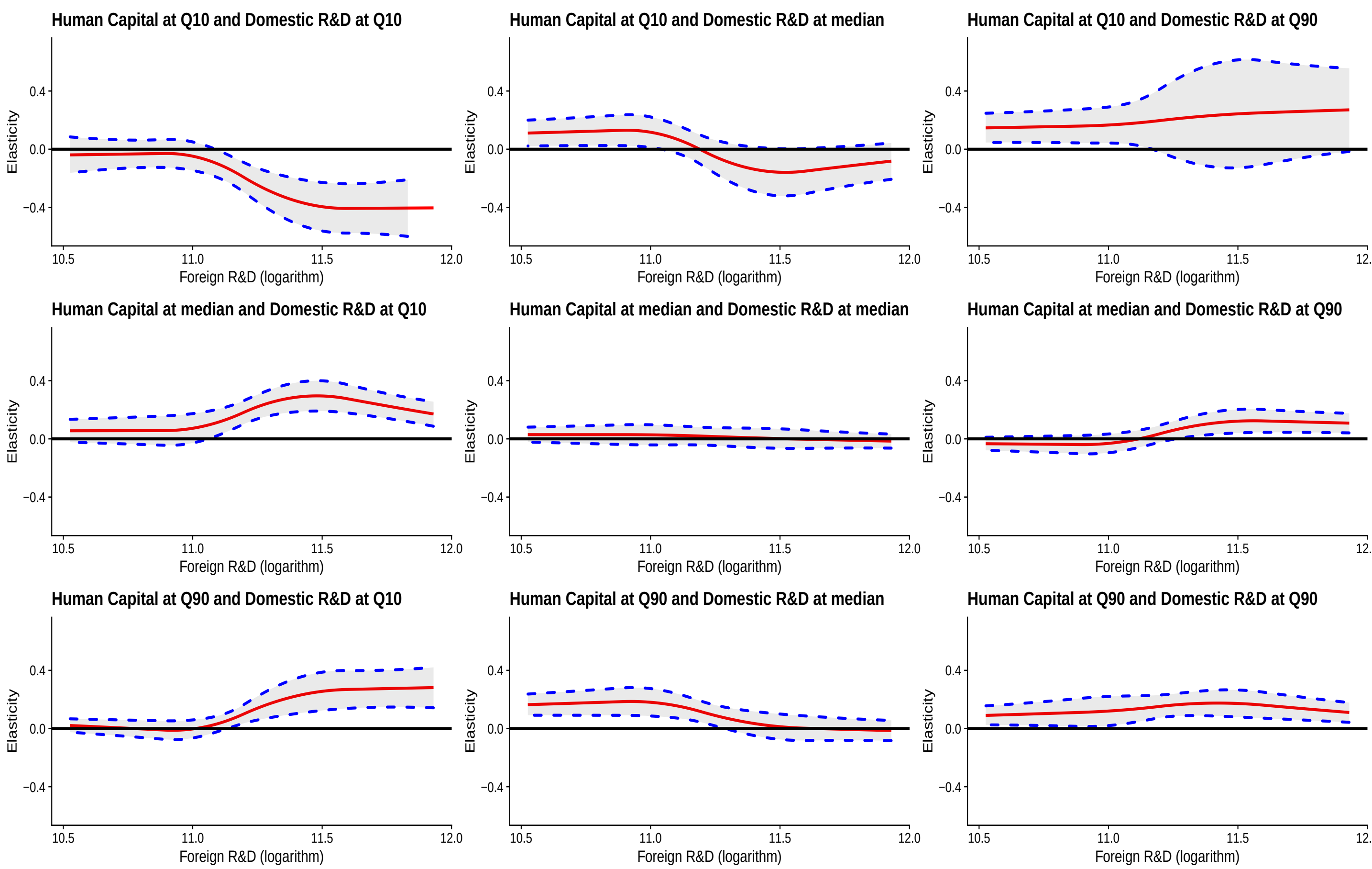
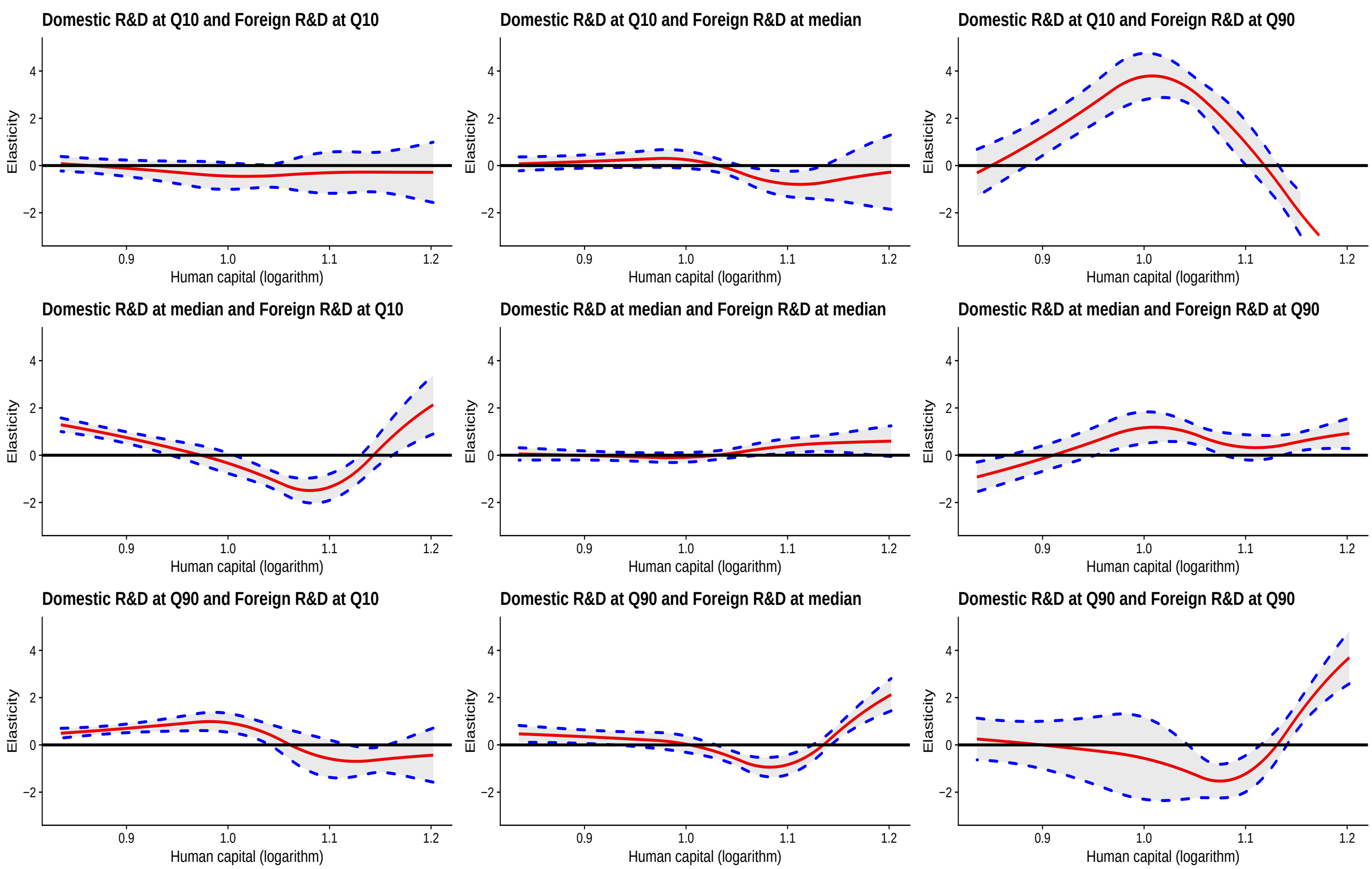
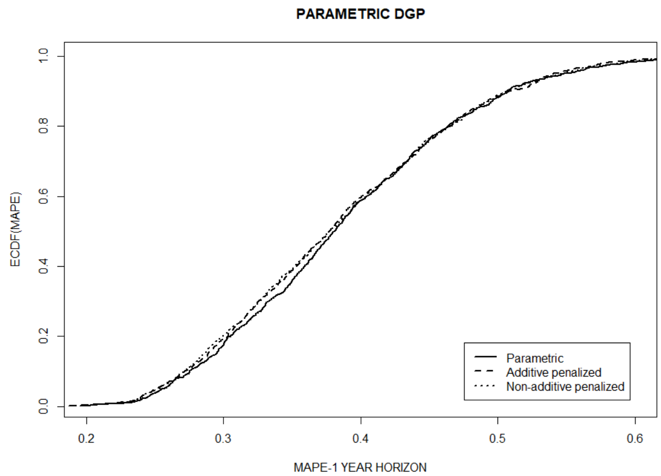
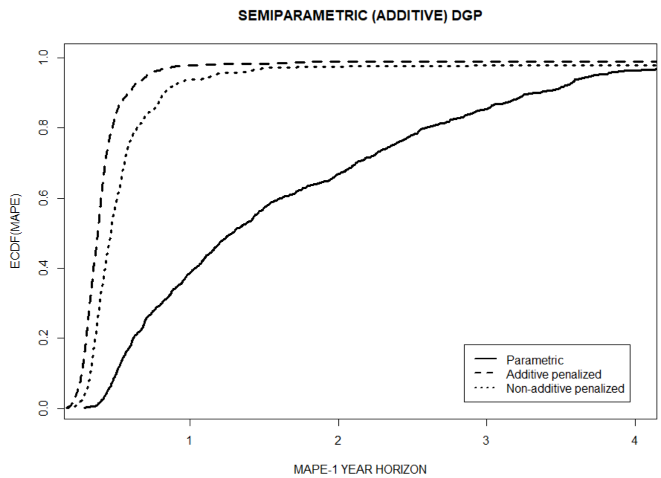


Figure 8: Estimated human capital elasticities





(a)



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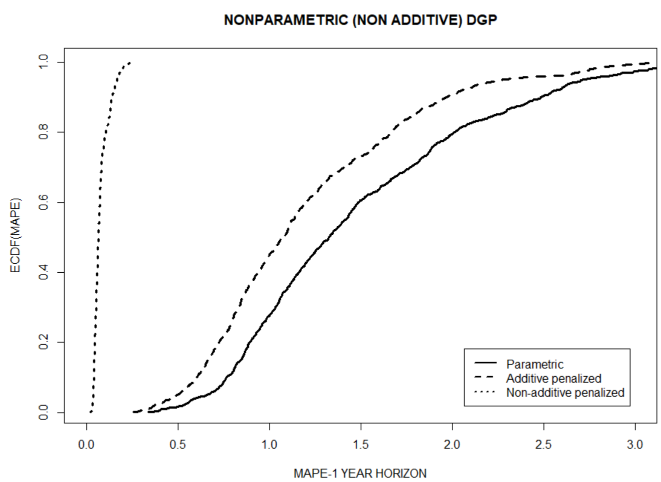

(c)

Figure A1: Empirical Cumulative Distribution Functions (ECDFs) of the MAPE for different DGPs: the linear, the additive and the non-additive generated models.