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International R&D spillovers, absorptive capacity and relative backwardness: a panel smooth transition regression model

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Abstract

We investigate how the country's absorptive capacity and relative backwardness affect the impact of international R&D spillovers on domestic Total Factor Productivity (TFP). To account for nonlinearities, we adopt a Panel Smooth Transition Regression (PSTR) approach, where the country's elasticity of TFP to foreign R&D stock is allowed to change smoothly across various identified extreme values, and this change is related to observable transition variables: human capital (capturing the country's absorptive capacity) and relative backwardness. The results suggest that absorptive capacity is positively associated with international R&D spillovers. In addition, and in contrast with previous results, relative backwardness has a negative and significant impact on them.

Key words: Absorptive capacity, International R&D spillovers, Nonlinear panel, Smooth Transition Regression, Total Factor Productivity

JEL Classification: C23, C24, F43, O30, O47

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1. Introduction

Several empirical and theoretical contributions (e.g. Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991; Aghion and Howitt, 1992; Eaton and Kortum, 1999; Howitt, 2000; Keller, 2004) have shown that the impact of international R&D spillovers on Total Factor Productivity (TFP) is non-negligible. Most studies have in particular focused on the specific channels through which foreign knowledge is transferred across countries and international trade has been identified as an important vehicle (see, for instance, Coe and Helpman, 1995; Coe et al., 1997, 2009; Keller, 1998, 2002; Guellec and Van Pottelsberghe de la Potterie, 2004). Fewer studies have instead looked at the local conditions which make foreign knowledge appropriable and domestically implementable.

In fact, since the seminal work by Cohen and Levinthal (1989), there has been a widely-held consensus that international spillovers depend on the ability of the potential recipient to identify, assimilate and exploit foreign knowledge. Following Cohen and Levinthal, this ability, which mainly depends on whether the labor force has the skills to imitate and learn about foreign innovations, has been called absorptive capacity.[1]

In this paper, we study how absorptive capacity affects the impact of international R&D spillovers on TFP and test the conjecture that the elasticity of TFP to foreign knowledge is not identical across countries and over time, but depends on the absorptive capacity of the receiving country. In so doing, we contribute to the empirical literature on absorptive capacity and, by identifying its role in the way knowledge diffusion influences productivity at the country level, we also add to the literature on international R&D spillovers, which has instead mainly focused on the role of trade and geographical distance in the transmission of knowledge.

In a similar vein, together with the role of absorptive capacity, we investigate also whether relative backwardness of the recipient country impacts on the international transmission of knowledge. From a theoretical viewpoint, countries closer to the technological frontier could either benefit little from the accumulation of knowledge in relatively less developed foreign countries, or make the best out of foreign improvements. This issue has not been fully settled at the empirical level, as indicated by the contrasting conclusions of Crespo-Cuaresma et al. (2004) on the one hand, and Kneller (2005) and Falvey et al. (2007), and this paper contributes to shed light on it.

We are not the first to tackle these issues. By adding an interaction term between human capital and foreign knowledge to a regression *à la* Coe and Helpman (1995), Kwark and Shyn (2006) find that human capital is important for the absorption of foreign knowledge.[2] Among the various empirical findings

[1] This intuition dates back to Abramovitz (1986), who argued that "social capability" affects the different strength of the catching-up processes across countries and over time.

[2] In a similar way, Kneller (2005) investigates the impact of absorptive capacity on international R&D spillovers at the sectoral level in a sample of 12 developed economies over 1972–1992. In his empirical specification, the highest level of productivity in the sample is

that Kwark and Shyn report, however, some clash against well established empirical results and this casts some doubts on theirs.[3] This is most likely due to a specification that does not allow the elasticity of TFP to knowledge to properly reflect nonlinear (country- and time-specific) effects.

To overcome these limitations, we study how absorptive capacity affects the impact of international R&D spillovers on TFP by means of a general nonlinear regression method applied to Coe and Helpman's (1995) specification. The Panel Smooth Transition Regression (PSTR) approach allows to loosen the hypotheses of homogeneity and time-stability of the parameters in a convenient and flexible way: the parameter of interest (i.e, the elasticity of TFP to foreign knowledge) is let free to change smoothly across various identified regimes and the transition across such regimes is related to meaningful observable variable (i.e., a measure of absorptive capacity). This nonlinear technique, albeit only recently extended by González et al. (2005) to panel data models, has been already employed in other economic fields with interesting results—see, for instance, Fok et al. (2005), Fouquau et al. (2008), Béreau et al. (2010), Delatte and Fouquau (2011), or Franses and van Dijk (2000), Deschamps (2008) and Alcidi et al. (2011) for time series applications.

We find that absorptive capacity and relative backwardness are, respectively, positively and negatively related with the impact of the trade-weight measure of foreign knowledge on domestic TFP: trade-related international R&D spillovers, thus, are influenced by the conditions of the recipient countries, even when the latter are OECD countries. As shown, the elasticity of TFP to foreign knowledge varies considerably across countries and over time. Our results also suggest that failing to account for nonlinearities leads to the overestimation of the direct impact of domestic R&D and human capital on TFP.

In order to account for the econometric issues arising from the identification problem in testing the hypothesis of linearity, we adopt state-of-the-art econometric techniques to conduct reliable inference (e.g. González and Teräsvirta, 2006; Hurn and Becker, 2009). Furthermore, to make inference more robust and account for unspecified forms of heteroskedasticity, and serial and simultaneous correlation in the data, we join the Bravo and Godfrey's (2011) double bootstrap method with the panel moving blocks bootstrap recently proposed by Gonçalves (2011). To the best of our knowledge, this approach has never been used before in applied works and represents a further contribution of the paper.

The paper proceeds as follows. Section 2 offers a concise overview of the literature focusing on international R&D spillovers and absorptive capacity. In

adopted as a measure of foreign knowledge, following Benhabib and Spiegel (1994), and three proxies of absorptive capacity are linearly interacted with it. This is in contrast with the literature on R&D spillovers *à la* Coe and Helpman (1995), which we follow, where spillovers depend on foreign R&D stocks. Similar considerations hold for Madsen et al. (2010), where foreign knowledge is not considered.

[3]For instance, when the interaction between human capital and foreign knowledge is added to the specification, the positive and significant elasticity of TFP with respect to the average years of schooling disappears.

Section 3, we illustrate the PSTR model and discuss the methodological issues regarding the tests of (no remaining non) linearity, the model estimation, and the bootstrap methods used to robustify inference. We present and discuss the results in Section 4. Section 5 concludes.

2. International R&D spillovers and absorptive capacity

There is not much dissent in the empirical literature on international R&D spillovers about the fact that both domestic and foreign knowledge—usually measured as capitalized R&D expenses, respectively inside and outside a country (Coe and Helpman, 1995)—affect the country's TFP.

Not all countries, however, can equally exploit foreign knowledge. The impact of international R&D spillovers on the country's TFP is in fact affected by its absorptive capacity. From a theoretical point of view, as argued by Abramovitz (1986) and Keller (1996), the latter most likely depends on the country's stock of human capital for labor skills determine the extent to which foreign knowledge is assimilated. Accordingly, one would expect international knowledge spillovers to have a greater impact on local productivity (or its growth) in the countries where human capital is more abundant.

In a recent paper, Kwark and Shyn (2006) empirically assess whether absorptive capacity affects how international R&D spillovers contribute to countries' TFP growth in the medium-term. They add an interaction term between human capital and foreign knowledge to the usual explanatory variables encompassed in a traditional regression *à la* Coe and Helpman (1995) (though applied to a five-year term panel). They conclude that human capital matters for the transmission of foreign knowledge, but also find that, once the interaction enters the specification, both foreign R&D and domestic human capital have no direct effects on productivity. These findings clash against previous empirical evidence and this casts some doubts on the robustness of the results.

Furthermore, the specification adopted by the authors prevents the detection of any nonlinear impact of absorptive capacity on knowledge spillovers. In fact, nonlinearities are very likely to exist. For instance, there might be a minimum level of human capital necessary for countries to assimilate foreign knowledge. Similarly, the marginal importance of absorptive capacity may not be constant and start diminishing once a certain level is reached.[4] Thus, a more flexible specification allowing the elasticity of TFP to domestic and foreign knowledge to reflect nonlinear effects is in order.

In addressing how absorptive capacity affects the way international knowledge spillovers impact on medium-term output growth, Crespo-Cuaresma et al. (2004) and Falvey et al. (2007) acknowledge the possible presence of nonlinear effects. Accordingly, they adopt a Threshold Regression (TR) model allowing the absorption parameters to change across two regimes, associated with the

[4]Focusing on diverse manufacturing sectors, Girma (2005) finds evidence that the impact of FDI on TFP is affected by absorptive capacity in a nonlinear way.

average years of secondary schooling above or below some critical values. Albeit informative, these studies do not allow to conclude much about the precise impact of absorptive capacity on how international spillovers affect productivity. First, the dependent variable in these studies is the growth rate of GDP per capita, rather than TFP. Second, a TR model is restrictive in so far as it allows the parameters to change only across a limited number of regimes and in a dichotomous fashion. Third, they look at five-year non-overlapping averages, while we consider yearly data. Finally, Crespo-Cuaresma et al. (2004) do not include human capital among the regressors and interact foreign knowledge also with the import penetration ratio.

To take all these observations into account, we apply a Panel Smooth Transition Regression (PSTR) model to Coe and Helpman's (1995) original specification, and include human capital as in Engelbrecht (1997) and Coe et al. (2009). This approach, which nests the TR model adopted by Crespo-Cuaresma et al. (2004) and Falvey et al. (2007), allows to loosen the hypotheses of parameter homogeneity and time-stability in a convenient, parsimonious, and flexible way. In particular, as we shall illustrate in the next section, it allows the parameters of interest to change smoothly across regimes and it relates the transition process to specific variables—in this case, proxies of absorptive capacity and relative backwardness—which vary across countries and over time, thus effectively relaxing parameter homogeneity and parameter stability.

In the literature on catching-up and knowledge transmission, whether relative backwardness affects the impact of knowledge on growth has long been a relevant empirical issue. On the one hand, more developed countries may have little external knowledge to absorb as they are already at the frontier (Gerschenkron, 1962). On the other hand, relative backwardness could make it more difficult to borrow foreign technology, so that it can be interpreted as a form of absorptive capacity (Matthews, 1969). Not only does this entail that the relationship between relative backwardness and growth is theoretically unclear, but also that it is likely nonlinear. As shown by Benhabib and Spiegel (1994), Falvey et al. (2007), and Mancusi (2008), this remains an open empirical issue. Although focusing on a sample of developed countries and looking at productivity rather than medium-term GDP growth rates as done in most of the literature, we exploit the length of our dataset to investigate how relative backwardness impacts on the relationship between knowledge spillovers and TFP. Notably, the nonlinear estimation technique we adopt is sufficiently flexible to detect nonlinear effects, such as those discussed before, of relative backwardness on the international transmission of knowledge.[5]

[5] Our work is close in spirit to Madsen et al. (2010) who develop a cross-country study about the impact of both absorptive capacity and gap from the technological frontier on TFP growth. This notwithstanding, our work differs considerably from theirs, at least in two respects: first, we nest the analysis in the empirical literature on international R&D spillovers, while Madsen et al. (2010) refer to growth convergence models with no role for foreign knowledge; second, our nonlinear estimation strategy is more general and allows for gradual changes in the parameters. The model is also different from Crespo-Cuaresma et al. (2004) for all the reasons illustrated

3. Empirical methodology

3.1. Specification

In their seminal paper, Coe and Helpman (1995) adopt a specification that is now the workhorse of the empirical studies in this strand of the literature:

$$\ln F_{it} = \alpha_i + \beta^d \ln S^d_{it} + \beta^f \ln S^f_{it} + \epsilon_{it} \tag{1}$$

where i is the country index, t is the time index, $\ln F_{it}$ is the log of TFP, S^d_{it} the domestically produced R&D stock, S^f_{it} an import-weighted sum of the R&D stock produced abroad (i.e., $S^f_{it} = \sum_{j\neq i} \frac{M_{ijt}}{\sum_{j\neq i} M_{ijt}} S^d_{jt}$, where M_{ijt} is the import of country i from country j at time t). Engelbrecht (1997) shows that human capital affects domestic productivity and should accordingly be included in the model. Equation (1) is thus modified as follows:[6]

$$\ln F_{it} = \alpha_i + \beta^d \ln S^d_{it} + \beta^h \ln H_{it} + \beta^f \ln S^f_{it} + \epsilon_{it} \tag{2}$$

where H_{it} is human capital, proxied by the average years of schooling in country i at time t.

Such specification imposes that the elasticities (the β's) are constant across countries and over time. Clearly, the simple inclusion of interacting terms between absorptive capacity and foreign R&D stock (as in Kwark and Shyn, 2006) might not address properly nonlinear effects. To this aim, the TR model proposed by Hansen (1999b) might represent a better solution. However, this approach imposes that the values of the coefficients are divided into a small number of classes (one per regime) and that the transition across them, driven by a transition variable being above or below a given threshold, is instantaneous. No gradual variation of the parameters is thus possible.

To relax these limitations, we adopt the PSTR model developed by González et al. (2005) and Fok et al. (2005) following the work of Granger and Teräsvirta (1993) on Smooth Transition Autoregressive (STAR) models. This approach allows the parameters of interest to change smoothly between two (or more) regimes, according to the value of a transition variable with respect to critical location values. This implies that the actual coefficients are not forced to assume the values associated with the extremes, but are let free to vary within them. The adoption of a bounded and continuous function of the transition variable (typically a logistic function) guarantees the gradual variation of the coefficients across the regimes, in contrast with the dichotomous switches in the TR model.[7]

in the Introduction.

[6]Lichtenberg and van Pottelsberghe de la Potterie (1998) observe that, to weight foreign R&D stocks, one should not use import shares, but export ones, i.e. the ratio of bilateral imports over the GDP of the exporting country. As shown by Coe et al. (2009), this modification does neither invalidate nor weakens what found with the specification of equation (1).

[7]Differently from random coefficient models (Hsiao and Pesaran, 2004), PSTR makes the transition across regimes depend on an observable variable.

In this study, we focus on how absorptive capacity and relative backwardness can affect the elasticity of TFP to foreign R&D spillovers and we aim at accounting for possible nonlinear effects neglected in the literature on international R&D spillovers. Accordingly, we estimate a PSTR model to deal with the potential heterogeneity and time-instability of the coefficients and the nonlinear impact of absorptive capacity and relative backwardness on them. Indeed, absorptive capacity, measured as the lagged value of the country's human capital, and relative backwardness, measured as the gap in GDP per capita in PPP with respect to the leading country, are the variables driving the transition across regimes.

Modifying equation (2), we adopt the following specification:

$$\ln F_{it} = \alpha_i + \beta^d \ln S^d_{it} + \beta^h \ln H_{it} + \beta^f_{it} \ln S^f_{it} + \epsilon_{it} \tag{3}$$

where

$$\beta^f_{it} = \beta^f_0 + \sum_{j=1}^{r} \beta^f_j \, g(q^{(j)}_{it}; \gamma_j, c_j) \tag{4}$$

and

$$g(q^{(j)}_{it}; \gamma_j, c_j) = \frac{1}{1 + \mathrm{e}^{-\gamma_j (q^{(j)}_{it} - c_j)}}. \tag{5}$$

Equation (4) shows that the time- and country-varying elasticity of TFP to foreign R&D stock is a weighted average of the coefficients associated with the $r+1$ regimes, with weights given by the equations (5). These weights are logistic functions of a transition variable $q^{(j)}_{it}$ where c_j is a location parameter (i.e., the critical level separating two continguous regimes) and the parameter γ_j (> 0) determines the smoothness of the transition across regimes.

When $\gamma_j \to \infty$, for all j, the r transition functions $g(.)$ become indicator functions and the model reduces to a simple panel TR model. On the contrary, when $\gamma_j \to 0$, the r functions $g(.)$ become constant and the model collapses to a simple panel linear regression model with fixed effects. The procedure provides for the estimation of all the parameters of interest in the model, including any γ_j and c_j, so that no *a priori* identification of the regimes is required.

3.2. Estimation procedure and methodological issues

The first step in the procedure—thoroughly discussed in González et al. (2005)—is to test the linearity of equation (2) against a PSTR model with two regimes ($r = 1$) and a candidate transition variable, that is:

$$\ln F_{it} = \alpha_i + \beta^d \ln S^d_{it} + \beta^h \ln H_{it} + \beta^f_0 \ln S^f_{it} + \beta^f_1 \, g(q^{(1)}_{it}; \gamma_1, c_1) \ln S^f_{it} + \epsilon_{it} \tag{6}$$

If more candidate transition variables $q^{(1)}_{it}$ exist, the procedure is repeated for each of them. The variable that leads to the strongest rejection of the null is selected for the estimation.

Testing the null hypothesis of linearity is a non-standard problem because under the null of linearity there are unidentified nuisance parameters.[8] The identification problem can be solved in two ways. The first approach, proposed by Luukkonen et al. (1988), tests the null $\gamma_1 = 0$ with a m-order Taylor expansion of the nonlinear model around this point. An auxiliary regression is run:

$$\ln F_{it} = \alpha_i + \beta^d \ln S_{it}^d + \beta^h \ln H_{it} + \delta_0 \ln S_{it}^f + \sum_{p=1}^{m} \delta_p \, q_{it}^p \ln S_{it}^f + \nu_{it} \tag{7}$$

where ν_{it} is the sum of the residuals of (3) and the remainder of the series expansion. The null hypothesis ($\delta_1 = \ldots = \delta_m = 0$) can be tested by using a (heteroskedasticity-robust) LM-test statistic. Under the null, the test statistic has asymptotically a χ^2 distribution with m degrees of freedom. In small samples, the authors suggest to use an F-version of the LM test (LM_F) by dividing the latter by the number of restrictions.[9] Usually, a third-order Taylor approximation is chosen ($m = 3$).

The second approach, applied by Hansen (1999a,b, 2000) in the context of TR models, tests the null $\beta_1^f = 0$ and circumvents the identification problem by computing the supremum LR test statistic. Andrews and Ploberger (1994),instead, suggest to use alternative statistics, i.e. AveLM, ExpLM or wLM, that are weighted averages of the (heteroskedasticity-robust) LM-test statistic computed for several combinations of γ_1 and c_1 spanning the parameter space. Given that these statistics have (asymptotically) pivotal but non-standard distributions, which depend also on the moments of the distribution of the nonlinear parameters and whose critical values cannot therefore be tabulated, one has to bootstrap the tests to obtain the critical values.

Hansen's approach has been recently extended to STR models by González and Teräsvirta (2006), Hurn and Becker (2009) and Becker and Osborn (2010). In particular, González and Teräsvirta (2006) study the finite sample properties of Andrews (1993) and Andrews and Ploberger's (1994) test statistics (SupLM, AveLM, ExpLM or wLM) and compare them with the Taylor expansion-based linearity test of Luukkonen et al. (1988) for STR models.[10] They show that AveLM, ExpLM or wLM are always more powerful than SupLM and Taylor expansion-based tests.

Hurn and Becker (2009) and Becker and Osborn (2010) deal with the problem of heteroskedasticity and the related distortions in the size of the test in small samples. Indeed, allowing for heteroskedasticity in nonlinearity tests can be

[8]Linearity follows imposing either $\beta_1^f = 0$ or $\gamma_1 = 0$. When the null is $\beta_1^f = 0$, c_1 and γ_1 are unidentified nuisance parameters. When the null is $\gamma_1 = 0$, the unidentified nuisances are c_1 and β_1^f.

[9]The F-version in our case is approximately F-distributed with m and $(TN - N - m - 3)$ degrees of freedom, where T is the time length of the panel, N the number of units.

[10]In wLM, the weights are proportional to the magnitude of the values of the LM statistic, for the test not to be too heavily influenced by redundant values of γ_1 and c_1, that may have a negative effect on the power of the test.

problematic: on the one hand, neglecting heteroskedasticity may lead to reject the null of linearity when it is not the case but, on the other hand, robustification can remove most of the test power as showed by Lundbergh and Teräsvirta (1998). To cope with this problem, Hurn and Becker (2009) compute heteroskedasticity-robust test statistics and calculate the critical values of the tests using fixed-design wild bootstrap (Gonçalves and Kilian, 2004). They show via simulation that this leads to significant reduction in the distortions of the test.[11]

If the null of linearity is rejected, a two-regime PSTR model is estimated. The estimation is carried out minimizing a concentrated Sum of Squared Residuals (SSR) via Nonlinear Least Squares (NLS). The SSR is concentrated with respect to the fixed effects α_i and the linear coefficients β's applying a standard fixed effects estimator for panel data conditional on a given combination of the nonlinear parameters (c_1 and γ_1). The panel fixed effects estimates are recomputed at each iteration in the nonlinear optimization.[12]

Notably, to select the starting values of the nonlinear coefficients, we do not use a grid search over a limited number of values, as usually done in the literature, because this approach may easily lead to local minima in the estimation. Instead, following the suggestions of González et al. (2005) and González and Teräsvirta (2006), we implement and apply the Simulated Annealing (SA) algorithm proposed by Corana et al. (1987) (see also Goffe et al., 1994, for an application to M-estimation problems).

After the estimation, to test the hypothesis that a two-regime PSTR model adequately captures the nonlinearities in the panel, we follow González et al. (2005) and perform a test of (no remaining) nonlinearity on the following specification:

$$\begin{aligned} \ln F_{it} = \alpha_i + \beta^d \ln S^d_{it} + \beta^h \ln H_{it} + \beta^f_0 \ln S^f_{it} + \beta^f_1\, g(q^{(1)}_{it}; \hat{\gamma}_1, \hat{c}_1) \ln S^f_{it} \\ + \beta^f_2\, g(q^{(2)}_{it}; \gamma_2, c_2) \ln S^f_{it} + \epsilon_{it} \end{aligned} \tag{8}$$

where $q^{(1)}_{it}$, $\hat{\gamma}_1$ and $\hat{c}_1$ are, respectively, the chosen transition variable and estimates of the nonlinear parameters in the already estimated two-regime PSTR model. Proceeding as before, this test of (no remaining) nonlinearity is performed testing $\gamma_2 = 0$ with the LM_F test statistic on the Taylor-based expansion around this point, and testing $\beta^f_2 = 0$ by computing AveLM, ExpLM or wLM.

When the null is rejected for more than one of the alternative candidate transition variables, the tests are also used to choose among them for the additional nonlinear regime. As before, the transition variable actually chosen is the one associated with the lowest p-value/highest value of the test statistic.

Following a sequential procedure, as in González et al. (2005), we generalize the test to a r number of regimes to determine the number of transitions in

[11]The alternative heteroskedasticity-robust bootstrap procedure, discussed in Hansen (1999a) for TR models, is able to preserve the observed heteroskedasticity but it does not exactly reproduce the heteroskedastic pattern of the observed data.

[12]As noted by González et al. (2005), with normally distributed errors this estimation procedure is equivalent to the maximization of a concentrated log-likelihood.

the model. After the estimation of a model with $r+1$ regimes, we perform a nonlinearity test on:

$$\begin{aligned}\ln F_{it} = \alpha_i + \beta^d \ln S^d_{it} + \beta^h \ln H_{it} + \beta^f_0 \ln S^f_{it} + \sum_{j=1}^{r} \beta^f_j \, g(q^{(j)}_{it}; \hat{\gamma}_j, \hat{c}_j) \ln S^f_{it} \\ + \beta^f_{r+1} \, g(q^{(r+1)}_{it}; \gamma_{r+1}, c_{r+1}) \ln S^f_{it} + \epsilon_{it}\end{aligned} \tag{9}$$

where the null is $\gamma_{r+1} = 0$ or $\beta^f_{r+1} = 0$. If it is rejected, we estimate a $(r+2)$-regime PSTR model with the transition variable for the $(r+2)$-th regime leading to the strongest rejection. We continue adding regimes until the first acceptance of the null of no remaining nonlinearity.[13]

In estimating models with more than two regimes, we first search via SA the starting values of the nonlinear parameters for the additional regime keeping constant those of the previously estimated regimes. Then, we let the gradient-based algorithm freely search the entire parameter space for the combination of the nonlinear coefficients that minimizes the concentrated SSR. We are thus also able to check whether the addition of another regime affects the estimates of the nonlinear parameters of the other regimes. Moreover, since it is not desirable for a regime to be estimated with only few observations, we check that the estimated location parameters are within the 5-95 percentiles of the sample values of the associated transition variables and that they are not too close each other, so that each regime can be estimated using at least 5% of all the observations.

3.3. Robust inference

In order to achieve asymptotic refinements and account for the presence of unspecified forms of heteroskedasticity, and serial and simultaneous correlation in the data, we build on the recent contributions of Gonçalves (2011) and Bravo and Godfrey (2011) to estimate the statistical significance of the linear coefficients β's conditional on the nonlinear parameters γ_j and c_j $(j = 1, \ldots, r)$ in a way that, to our knowledge, has never been used. More precisely, to perform the t tests, we join Bravo and Godfrey's (2011) double bootstrap method—that uses (first- and second-level) Moving Blocks Bootstrap (MBB) (Liu and Singh, 1992) and quasi-estimators (Hu and Zidek, 1995)—with the Panel MBB (PMBB) recently put forward by Gonçalves (2011) in the context of large n, large T balanced panels with weak time series dependence (of the mixing type) and (weak or strong) cross-sectional dependence.

In particular, to calculate the p-value of the t statistic for any coefficient β, we first compute the panel fixed-effects estimator $\hat{\beta}$. Using the actual data, we then generate B first-level bootstrap samples by applying Gonçalves's (2011) PMBB, that is applying the standard MBB to all the individual observations

[13] To avoid excessively large models, González et al. (2005) suggest to adjust the initial significance level α of the test, multiplying it by a factor τ $(0 < \tau < 1)$ after every regime addition.

at each point in time. On each bootstrap sample, we compute the bootstrap fixed-effects estimator $\hat{\beta}^*_b$, the quasi-estimator $\tilde{\beta}^*_b$[14] and the discrepancy $(\hat{\beta}^*_b - \hat{\beta})$. For each first-level bootstrap sample, we generate D second-level bootstrap samples by applying PMBB to the first-level sample and compute D quasi fixed-effects estimates $\tilde{\beta}^{**}_{bd}$[15] and their sample variance $\tilde{C}^{**}_b = \sum_{d=1}^{D}(\tilde{\beta}^{**}_{bd} - \bar{\tilde{\beta}}^{**}_b)^2/D$, where $\bar{\tilde{\beta}}^{**}_b = \sum_{d=1}^{D}\tilde{\beta}^{**}_{bd}/D$. Then, we compute the B bootstrap t statistics $t^* = (\hat{\beta}^*_b - \hat{\beta})/\sqrt{C^{**}_b}$. To calculate the bootstrap p-value, we compute the fraction of these statistics greater than $t = \hat{\beta}/\sqrt{C^*}$, with C^* being the variance of the first-level bootstrap quasi-estimator $\tilde{\beta}^*_b$.[16]

For the nonlinear parameters, we instead use the robust quasi-ML sandwich estimator.[17] Contrary to TR models, in STR models the location parameters c_j are asymptotically normally distributed and conventional hypothesis testing is possible.

Finally, we must warn the reader that, for the parameters inducing nonlinearity the standard approach may encounter problems because of identification issues. Indeed, when $\beta^f_j = 0$ $(\gamma_j = 0)$, c_j and γ_j (β^f_j) are not identified, hypothesis testing for β^f_j and γ_j could be therefore not straightforward.[18]

That said, in the next section, we apply these techniques to estimate the possible nonlinear effects of absorptive capacity and relative backwardness on the elasticity of countries' TFP to foreign knowledge.[19]

[14] The quasi-estimator is computed as follows:

$$\tilde{\beta}^*_b = \hat{\beta} + (\dot{\boldsymbol{X}}'\dot{\boldsymbol{X}})^{-1}\dot{\boldsymbol{X}}^{*\prime}_b(\dot{\boldsymbol{y}}^*_b - \dot{\boldsymbol{X}}^*_b\hat{\beta})$$

where $\boldsymbol{X}$ is the $NT \times (3+r)$ matrix of regressors $(\ln S^d_{it},\ \ln H_{it},\ \ln S^f_{it},\ g(q^{(1)}_{it};\hat{\gamma}_1,\hat{c}_1)\ln S^f_{it},\ \ldots,\ g(q^{(r)}_{it};\hat{\gamma}_r,\hat{c}_r)\ln S^f_{it})$, $\boldsymbol{y}$ is the $NT \times 1$ vector $\ln F_{it}$, $\boldsymbol{X}^*_b$ and $\boldsymbol{y}^*_b$ are the series resulting from the first-level bootstrap, and the dot denotes the standard within-transformation needed to remove individual means.

[15] The second-level bootstrap quasi-estimator $\tilde{\beta}^{**}_{bd}$ is computed as follows:

$$\tilde{\beta}^{**}_{bd} = \hat{\beta}^*_b + (\dot{\boldsymbol{X}}^{*\prime}_b\dot{\boldsymbol{X}}^*_b)^{-1}\dot{\boldsymbol{X}}^{**\prime}_{bd}(\dot{\boldsymbol{y}}^{**}_{bd} - \dot{\boldsymbol{X}}^{**}_{bd}\hat{\beta}^*_b)$$

where $\boldsymbol{X}^{**}_{bd}$ and $\boldsymbol{y}^{**}_{bd}$ are the series as they result in each second-level MBB replication made on each first-level bootstrap sample and the dot denotes the within transformation.

[16] This procedure is different from the one discussed by Gonçalves (2011), who uses the sandwich form of the covariance matrix and a kernel variance estimator to studentize the test statistic, and a multivariate analogue of the estimator of the MBB variance proposed by Götze and Künsch (1996) to studentize the bootstrap test statistics. It is also different from the naive bootstrap discussed by Gonçalves and Vogelsang (2011), which uses the same sandwich covariance matrix estimator to studentize both the original statistic and the bootstrap ones.

[17] An alternative procedure could have been to compute bootstrap t statistics also in this case. In fact, Gonçalves and White (2004) have proved the first-order asymptotic validity of the bootstrap distribution of MBB analogs of Wald and LM statistics for hypotheses testing in quasi-Maximum Likelihood estimates. This notwithstanding, it is not yet entirely clear if and when this leads to asymptotic refinements.

[18] Actually, testing the null $\beta_j = 0$ or $\gamma_j = 0$ is equivalent to a linearity test. The general problem of inference with weak identification has been very recently addressed by Andrews and Cheng (2011).

[19] All the computations were made using gretl 1.9.5. Code available at request.

4. Data and results

To maintain the comparability with the work of Coe and Helpman (1995), we focus on the sample of 24 OECD countries over the period 1971-2004 analyzed by Coe et al. (2009).[20] Accordingly, domestic and (trade-weighted) foreign R&D stocks, human capital (average years of schooling), and TFP indexes come from Coe et al. (2009). In accordance with the discussion in Section 2, we take absorptive capacity and relative backwardness as possible factors affecting in a nonlinear fashion the impact of foreign knowledge on countries' TFP and therefore they are our candidate transition variables. We use the country's lagged human capital ($H_{i,t-1}$) as a measure of its absorptive capacity, and the lagged percentage difference of each country's and the highest GDP per capita in constant Purchasing Power Parity (PPP) in each period ($\text{gap}_{i,t-1}$) to measure its relative backwardness.[21]

Following the procedure outlined in Section 3.2, we start by testing the null of linearity against the PSTR model of equation (3) with two regimes ($r = 1$) and each of the two candidate transition variables H_{t-1} and gap_{t-1}. The test statistics, along with the associated p-values, are reported in Table 1. In particular, we report the asymptotic p-value of the heteroskedasticity-robust Taylor expansion-based LM_F test statistic (LST-LM_F) and the bootstrap p-values of the heteroskedasticity-robust ExpLM and wLM (with critical values calculated via fixed-design wild bootstrap).[22]

All the test statistics strongly reject the null, thus corroborating the working hypothesis of a nonlinear impact of human capital and gap on the TFP elasticity to foreign knowledge.

As for the choice of the transition variable to include in the PSTR estimation,

[20] The panel is balanced. The countries are Australia, Austria, Belgium-Luxembourg, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK, US.

[21] Data on countries' GDP per capita in constant PPP come from the OECD.

[22] To calculate ExpLM and wLM, we first compute a heteroskedasticity-robust LM test statistic for each of 1000 pairs (γ_1, c_1): $LM(\gamma_1^{(j)}, c_1^{(j)})$. Each pair is built as follows: γ_1 is drawn from a uniform distribution 0-100; c_1 is drawn uniformly at random from the set of observed values of the transition variables within the 5-95 percentile in the sample. Then we apply the following formulas:

$$\text{ExpLM} = \ln\left(\sum_{j=1}^{1000} \frac{\exp\left(0.5LM(\gamma_1^{(j)}, c_1^{(j)})\right)}{1000}\right)$$

$$\text{wLM} = \frac{1}{1000}\sum_{j=1}^{1000} \omega_j LM(\gamma_1^{(j)}, c_1^{(j)})$$

where $\omega_j = LM(\gamma_1^{(j)}, c_1^{(j)}) / \sum_{j=1}^{1000} LM(\gamma_1^{(j)}, c_1^{(j)})$. We decided not to use AveLM since its power could be negatively affected by the presence of possible redundant values of γ_1 and c_1.

To calculate bootstrap p-values via fixed-design wild bootstrap, we compute ExpLM and wLM for 999 bootstrap replications, where, in each replication, we randomize the sign of the residuals of the estimated linear model. The bootstrap p-value is equal to the fraction of bootstrap test statistics greater than the original one.

Table 1: Tests of linearity

Transition variable			p-value
H_{t-1}	LST-LM$_F$	3.77022	0.0105
	ExpLM	22.7020	0.0000
	wLM	0.03310	0.0000
gap$_{t-1}$	LST-LM$_F$	25.6022	0.0000
	ExpLM	16.0325	0.0000
	wLM	0.02139	0.0000

the various test statistics lead to different conclusions: the strongest rejection is obtained for H_{t-1} (gap$_{t-1}$) using wLM and ExpLM (LST-LM$_F$). As wLM and ExpLM are usually more reliable, we estimate equation (3) setting $r = 1$ and $q_{it}^{(1)} = H_{i,t-1}$.

For the estimation of the nonlinear parameters, we set the starting values as suggested by the SA, which is less likely to find local minima than the usually adopted grid search.[23] The results of the NLS are reported in Table 3.[24] This is not the conclusion of the procedure which, as illustrated in the previous section, ends when the null of no remaining nonlinearity cannot be rejected. Accordingly, we conclude the whole estimation procedure and identify our preferred specification before discussing point estimates and inference.

On the basis of the tests of no remaining nonlinearity (reported in Table 2), we end up estimating a PSTR model with four regimes ($r = 3$): the linear one, one regime associated with human capital and two regimes associated with the technological gap. In all the estimates, thus irrespectively of including or not the regimes for gap$_{t-1}$, the location parameter associated with human capital ($c_1 = 8.33$) is rather close to the sample mean (8.54)—H ranges from 2.51 (Portugal in 1971) to 12.29 (USA in 2003) and the 5-95 percentiles are, respectively, 4.98 and 11.53—and the related smoothness parameter is roughly equal to 4, that is, the transition is moderately smooth.[25] On the contrary, the location parameters of the regimes associated with the gap are much closer to the extremes. In particular, the location parameter of the third regime ($c_2 = -58.8$) is near the lower bound, but still within the 5-95 percentiles, respectively, -59.2 and -2.0.

[23] We set the initial temperature at 100, far above the average difference in SSR. The temperature reduction factor is 0.85. The algorithm adjusts the step-size vector every 20 parameter changes and this loop is repeated 50 times before each temperature reduction. In all the cases, the procedure converges after on average 6 million function evaluations.

[24] As a robustness check, the third column of the Table also reports the results of the alternative estimate of a two-regime PSTR model with gap$_{t-1}$ as transition variable.

[25] Although it might look quite high, the associated standard error is actually not so when compared with the results usually obtained in STR models. As well known, it is very difficult to obtain a precise estimate of γ in this kind of models (see, for instance, the discussion in Franses and van Dijk, 2003, Section 3.2.2). Moreover, one should not judge the significance of the coefficient by looking at the associated t-statistic, because of the identification problem discussed in Section 3.3.

Table 2: Tests of no remaining nonlinearity

Hypothesis	Transition variables				p-value
	Estimated regimes	Additional			
H_0: $r=1$; H_1: $r=2$	H_{t-1}	H_{t-1}	LST-LM$_F$	4.3843	0.0045
			ExpLM	7.4068	0.0000
			wLM	0.0112	0.0000
		gap_{t-1}	LST-LM$_F$	24.739	0.0000
			ExpLM	21.315	0.0000
			wLM	0.0190	0.0000
H_0: $r=2$; H_1: $r=3$	H_{t-1}, gap_{t-1}	H_{t-1}	LST-LM$_F$	0.2815	0.8388
			ExpLM	1.7287	0.0601
			wLM	0.0048	0.0350
		gap_{t-1}	LST-LM$_F$	4.1860	0.0059
			ExpLM	4.5622	0.0030
			wLM	0.0061	0.0170
H_0: $r=3$; H_1: $r=4$	H_{t-1}, gap_{t-1}, gap_{t-1}	H_{t-1}	LST-LM$_F$	0.6573	0.5785
			ExpLM	1.1691	0.2092
			wLM	0.0034	0.1732
		gap_{t-1}	LST-LM$_F$	0.7128	0.5445
			ExpLM	2.1588	0.0301
			wLM	0.0037	0.1201

The location parameter of the last regime ($c_3 = -1.5$) is instead above the 95 percentile.[26] This last regime has got an associated smoothness parameter which is quite high ($\gamma_3 = 27.9$), i.e., the transition is rather sharp. This entails that only few observations—namely, three countries (Norway, Switzerland and US) in few years— end up in this additional regime. On these grounds we would conclude that the estimates of the fourth regime should not be considered as fully reliable and be neglected. To lay on the cautionary side, however, we consider further evidence on the impact of including (or excluding) this additional nonlinear component.

First, given that the fourth regime encompasses only very few observations, its omission does not affect much the value of β^f_{it} for the other countries. Similarly, its exclusion from the specification does not affect the estimates on the other nonlinear parameters: as can be seen in Table 3, the estimated values of c_1, γ_1, c_2, and γ_2 are almost unchanged. Nor are seriously affected the estimates of the implied linear coefficients β's, reported in Table 4. This table shows the conditional fixed effects estimates in the PSTR model of equation (3) with, respectively, three and four regimes—second and third column—, along with those associated with the linear model of equation (2)—first column—, to be used as a benchmark to gauge the other results. Once robust inference is done, moreover, the coefficient β^f_3 is not statistically significant. Indeed, Table 4 reports in square brackets the bootstrap p-value of the t statistics computed via the double bootstrap discussed in Section 3.3 (with 1000 second-level bootstrap replications

[26]The variable gap ranges from -89.9 (Korea in 1971) to 0 with a mean about -32.6 and a standard deviation equal to 16.0.

for each of 999 first-level bootstrap replications using PMBB resampling with block size equal to 3). Although this result might not be taken as conclusive, and one should stick to the result of the tests of no remaining nonlinearity, for the identification problem discussed in Section 3 in testing the null $\beta_3^f = 0$, the bootstrap procedure used here to compute the p-values of the test is also robust to serial and simultaneous correlation in the data, something which the nonlinearity tests are not.

Hence, although evidence of some residual nonlinearity associated with gap_{t-1} cannot be rejected for the three-regime specification with H_{t-1} and gap_{t-1} as transition variables, our preferred specification is that with three regimes.[27] Accordingly, in the following discussion of the main results, we focus on the differences between the benchmark linear model and the three-regime PSTR model.

The estimates of the PSTR model support the idea that the human capital of a country—determining its absorptive capacity—positively affects the exploitation of foreign knowledge, as the TFP elasticity to the trade-weighted foreign R&D stock is positively related with it: β_1^f is positive and significant. Such impact is not huge (the maximum relative difference in β^f accounted by H is approximately 7.5%), but statistically significant. Crespo-Cuaresma et al. (2004) find a positive impact of human capital on the effect of foreign knowledge on growth, but fail to reject the hypothesis that the effect for the countries with less human capital is insignificant. We do not encounter such a problem here. Our result is qualitatively in line with that in Kneller (2005), which however measures foreign knowledge in a different way and adopts a liner interacting term. The effects of the regime switching due to H_{t-1} are depicted in Figure 1 which plots the values of $\hat{\beta}_0^f + \hat{\beta}_1^f g(\bar{H}_i; \hat{\gamma}_1, \hat{c}_1) + \hat{\beta}_2^f g(\bar{\text{gap}}; \hat{\gamma}_2, \hat{c}_2)$ for each country, where $\bar{\text{gap}}$ is the sample mean of gap and $\bar{H}_i$ is the average human capital by country in each of two sub-periods: 1971-1987 and 1988-2003.

A much greater and negative difference in the elasticity of TFP to foreign knowledge across countries and periods is related with the countries' relative backwardness. Indeed, according to our estimates, the TFP elasticity to foreign knowledge in laggard countries (e.g. Korea, Portugal and Greece) is significantly lower than the same elasticity in leading countries (e.g. USA, Norway and Switzerland). For instance, the TFP elasticity to foreign knowledge for Korea in the 1970s would have been on average 70% higher if Korea had filled before the technological gap.[28] The effects of the switching in the regime associated with the gap for the different countries are summarized in Figure 2, which plots the values of $\hat{\beta}_0^f + \hat{\beta}_1^f g(\bar{H}; \hat{\gamma}_1, \hat{c}_1) + \hat{\beta}_2^f g(\bar{\text{gap}}_i; \hat{\gamma}_2, \hat{c}_2)$ for each country, with $\bar{H}$ being

[27] It is worth stressing that our choice is in line with the literature. It would be inappropriate to use the PSTR model to single out very few observations. As shown in (Franses and van Dijk, 2003), outliers may affect the tests of no remaining nonlinearity without leading to actual regimes. This suggests that the tests are to be interpreted with a grain of salt and also with reference to the overall fit of the specifications they would lead to estimate.

[28] These results hold when South Korea, which exhibits a low human capital and the largest gap, is excluded from the sample.

Table 3: Estimates of nonlinear parameters (Pooled data 24 countries 1972-2004: 792 obs.)

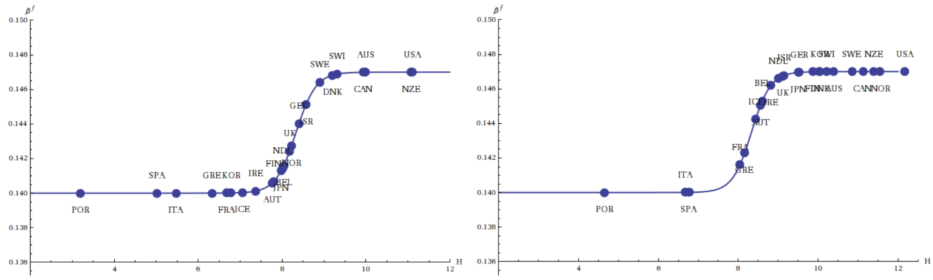
Regimes $(r+1)$	1	2	2	3	4
Transition variables		H_{t-1}	gap_{t-1}	H_{t-1}, gap_{t-1}	H_{t-1}, gap_{t-1}, gap_{t-1}
γ_1		3.3552		4.4459	4.1366
		(0.7493)		(3.8759)	(4.8629)
c_1		8.3815		8.3307	8.3270
		(0.0976)		(0.1512)	(0.1755)
γ_2			0.1028	0.1164	0.1218
			(0.0100)	(0.0140)	(0.0122)
c_2			-59.440	-58.809	-58.777
			(1.1701)	(1.2736)	(1.2327)
γ_3					27.941
					(3.7788)
c_3					-1.5029
					(0.0188)
SSR	5.43068	4.94314	3.14351	2.97204	2.78815
log-L	849.269	886.518	1065.77	1088.14	1113.28

Robust standard errors in brackets (QML estimator).

Table 4: Estimates of linear parameters (Pooled data 1972-2004 24 countries: 792 obs.)

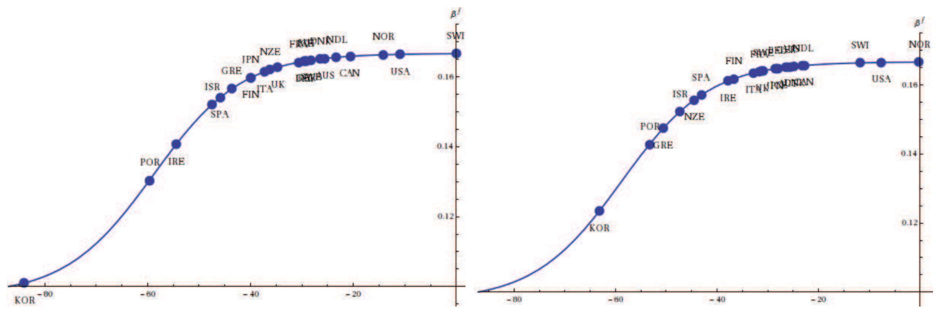
Regimes $(r+1)$	1	3	4
Transition variables		H_{t-1}, gap_{t-1}	H_{t-1}, gap_{t-1}, gap_{t-1}
β^d	0.0450	0.0278	0.0294
	(0.0259)	(0.0140)	(0.0129)
	[0.0051]	[0.0040]	[0.0010]
β^h	0.6555	0.3408	0.2922
	(0.1249)	(0.1034)	(0.0992)
	[0.0000]	[0.0560]	[0.0901]
β_0^f	0.1491	0.0939	0.1052
	(0.0558)	(0.0391)	(0.0391)
	[0.0000]	[0.0000]	[0.0000]
β_1^f		0.0070	0.0063
		(0.0038)	(0.0032)
		[0.0000]	[0.0010]
β_2^f		0.0692	0.0705
		(0.0109)	(0.0103)
		[0.0000]	[0.0000]
β_3^f			0.0090
			(0.0011)
			[0.1041]

Unreported country dummies. Asymptotic HACC standard errors in round brackets. Bootstrap p-values of t statistics calculated via PMBB double-bootstrap in square brackets: 999 first-level replications; 1000 second-level replications; block size 3.



(a) Average human capital 1971-1987 (b) Average human capital 1988-2003

Figure 1: Effect of the regime switching associated with human capital on TFP elasticity to import-weighted foreign R&D stock



(a) Average gap 1971-1987 (b) Average gap 1988-2003

Figure 2: Effect of the regime switching associated with relative backwardness on TFP elasticity to import-weighted foreign R&D stock

the sample mean of human capital and $\bar{\text{gap}}_i$ the mean gap by country during 1971-1987 and 1988-2003.

These findings indicate that the elasticity of TFP to foreign knowledge is non marginally affected by the internal conditions of the recipient country and that, even in a sample of developed economies, leading countries have an advantage over the others. This is supportive of the intuition of Matthews's (1969) and, despite non-negligible differences in the estimated relationships, our results are at odds with Crespo-Cuaresma et al. (2004) and in line with those in Falvey et al. (2007). Although we do find that the marginal increase in the elasticity of TFP to foreign knowledge deriving from further reductions in the gap is decreasing, we do not find evidence of a hump-shaped relationship as suggested in the three-regime specification discussed by Falvey et al. (2007). It is worth noticing, though only in passing, that our specification builds on those adopted to study international R&D spillovers and differs from medium-term growth convergence models. By the same token, one should be careful not to interpret these results as implying lack of convergence.

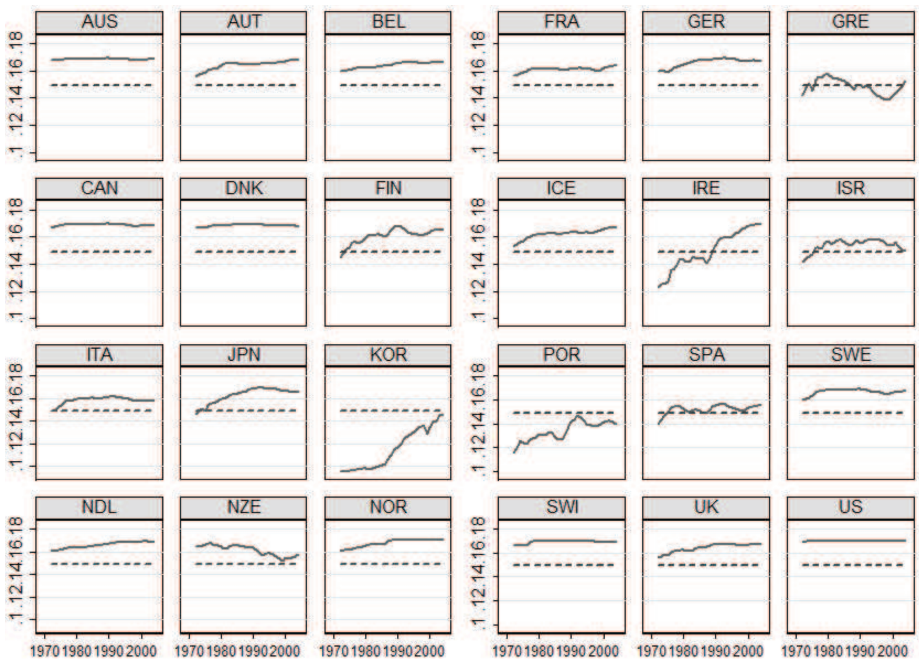


Figure 3: TFP elasticity to import-weighted foreign R&D stock by country

The total effect on β^f of the smooth transitions across the nonlinear regimes for the different countries over time is summarized in Figure 3. It allows to grasp the extent of variation of the elasticity of TFP to foreign knowledge over time and across countries. As to the latter, it is worth noticing that the elasticity of Portugal, Korea, and, in part, Ireland is lower than the value of β^f estimated with a linear panel. The linear estimates seem to fit Greece, Israel, Italy, Spain and in the last periods New Zealand. In all the other cases, the linear estimates fall short of the value obtained taking nonlinear effects into account.

To gauge the overall fit of the models we focus on the sums of square residuals and the log-likelihood values, which we report in Table 3. The former passes from 5.43 in the linear estimation to 2.97 in our preferred specification and the log-likelihood from 848.27 to 1065.77. In line with the more moderate impact of relative backwardness, the fit of the model improves more because of the inclusion of gap_{t-1} than of H_{t-1}. These findings, together with the strong statistical significance of the individual coefficients even after a proper robustification of the tests, support the adoption of a PSTR model where absorptive capacity and relative backwardness drive two regime changes.

Finally, we should briefly comment on how the parameters of domestic R&D stock and human capital change passing from the linear to the nonlinear specification. As for the former, the decline in β^d is common to Kneller (2005) and, in any case, compatible with the standard errors of the estimated coefficients.

As for the latter, as it enters in the specification both as regressor and (lagged) as transition variable, its overall impact on TFP is not directly comparable in the baseline and nonlinear estimation. In fact, in the linear specification the estimate of the (constant) TFP elasticity to human capital is $\hat{\beta}^h = 0.6555$. In the nonlinear specification, $\hat{\beta}^h = 0.3408$ is instead just the lower bound. This is the elasticity for the countries having H greater than 10 or less than 7, i.e., those that are far away from the location parameter $c_1 = 8.33$. For the other countries, this elasticity can be significantly higher. So, for instance, when evaluated at the sample means, the point estimate of the long-run TFP elasticity to human capital implied by our specification happens to be very high (higher than 1).[29]

5. Conclusions

In this paper, we have looked at whether domestic factors affect the impact that foreign knowledge has on the TFP of the recipient countries. Although economic intuition and theoretical modeling suggest that both absorptive capacity and relative backwardness of countries exposed to foreign knowledge can affect TFP and growth, no conclusive empirical results have been reached yet.

Applying the PSTR model to the workhorse empirical specification in this strand of the literature (Coe and Helpman, 1995; Coe et al., 2009), we test on a sample of OECD countries over the period 1971-2004 whether absorptive capacity and relative backwardness have nonlinear effects on the elasticity of foreign R&D on domestic TFP. This nonlinear approach relaxes the assumptions of parameter homogeneity across countries and parameter constancy over time, and it allows to relate the nonlinear effects to observable proxies of absorptive capacity and relative backwardness (respectively, the level of human capital and the gap with respect to the leading country in terms of GDP per capita in PPP).

Despite its flexibility, PSTR modeling requires the adoption of non trivial econometric techniques to test properly the hypothesis of linearity in the presence of nuisance parameters. Accordingly, we run a battery of tests used in the literature (González and Teräsvirta, 2006) and take heteroskedasticity into account by means of a fixed-design wild bootstrap procedure (Hurn and Becker, 2009).

The results of our nonlinear estimations suggest that absorptive capacity is significantly associated with higher R&D spillovers. The indirect impact of human capital on TFP via the increase in the absorption of foreign knowledge can be quite significant. In addition, and in contrast with previous results, we found that relative backwardness has a negative impact on the transmission of

[29]The long-run TFP elasticity to human capital of country i is given by:

$$\frac{\partial \ln F_i}{\partial \ln H_i} = \beta^h + \beta_1^f \gamma_1 \frac{\mathrm{e}^{-\gamma_1 (H_i - c_1)}}{\left(1 + \mathrm{e}^{-\gamma_1 (H_i - c_1)}\right)^2} H_i \ln S_i^f$$

This formula has been evaluated using our point estimates of the parameters and at the sample mean of H and $\ln S^f$.

foreign knowledge. Laggard countries seem to derive lower benefits from foreign R&D stocks than more advanced countries.

All these results are strongly statistically significant even though we adopt a series of up-to-date econometric measures to make inference robust to unspecified forms of heteroskedasticity, and serial and simultaneous correlation in the data. In particular, we join the Bravo and Godfrey's (2011) double bootstrap method with the panel moving block bootstrap of Gonçalves (2011) This is, to our knowledge, the first time such method is applied.

The adoption of a technique encompassing nonlinear effects has allowed us to differentiate the elasticity of foreign knowledge on domestic TFP across countries and over time: a good number of countries in the sample exhibit an elasticity higher than that estimated by means of a linear, homogeneous parameter panel model, whereas Korea, Portugal and (in part) Ireland score worse than all the others. Interestingly but not surprisingly, Greece, Italy and Spain appear in an intermediate position.

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