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Productivity Growth, Human Capital, and Technology Spillovers

Nonparametric Evidence for EU Regions

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Abstract

This paper assesses the strength of productivity spillovers nonparametrically in a data-set of 12 industries and 231 NUTS2 regions in 17 European Union member countries between 1992 and 2006. It devotes particular attention to measuring catching up through spillovers depending on the technology gap of a unit to the industry leader and the local human capital endowment. We find evidence of a non-(log-)linear relationship between the technology gap to the leader as well as human capital and growth. Spillovers are strongest for units with a small technology gap to the leader and with abundant human capital.

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1 Introduction

A large body of empirical work in macroeconomics emphasizes the role of total factor productivity (TFP) spillovers through knowledge diffusion for catching up and convergence. Nelson and Phelps (1966) suggested that the extent of knowledge spillovers depends on two factors, the distance to the technological frontier (the technology gap) and an economic units' knowledge stock or human capital endowment. There is now broad evidence on the importance of either one of the two for catching up and convergence. Virtually all of this evidence assumes a parametric if not a (log-)linear relationship between spillovers and TFP growth. Little is known about the appropriateness of this assumption and the actual form of the relationship.

For instance, Benhabib and Spiegel (1994) identified two roles of human capital levels for economic growth in a large cross section of countries in 1965-1985: for steady-state growth of TFP and for catching up, i.e., the absorption of spillovers from the technology leader. Griffith, Redding, and van Reenen (2004) assessed the determinants of TFP growth in a panel of OECD countries and manufacturing industries in 1974-1990. Their findings suggest that human capital as well as R&D levels affect TFP growth and convergence. Kneller and Stevens (2006) found further support along those lines in a panel of industries and OECD countries in 1973-1991, though suggesting that human capital was more robust a driver of spillovers than R&D in their data.[1] In all of the just-mentioned work, a parametric relationship between human capital and catching up was assumed.

The goal of this paper is to apply nonparametric rather than parametric estimation techniques in assessing the functional form of the relationship between the technology gap and human capital for TFP growth and catching up. This is accomplished in a (panel) data-set on 231 NUTS2 subnational regions (of 17 European Union member countries) and 12 industries over the period 1992-2006.[2] The findings are aligned with ones in earlier work to the

[1] At the level of the firm, Griffith, Harrison, and van Reenen (2006) found evidence in support of R&D as a key determinant of catching up in TFP growth. Along different lines, the studies by Coe and Helpman (1995) and Coe, Helpman, and Hoffmaister (1997) emphasized the role of international trade and foreign direct investment as transmission channels of international R&D spillovers (see Keller, 2004, for a survey of this and related work).

[2] *NUTS2* is a classification adopted by the statistical office of the European Union, Eurostat. It refers to regions of a size of mn 0.8-3 inhabitants all over the European Union.

extent that the speed of convergence is positively related to the size of the TFP gap *on average*, and that the speed of convergence towards the TFP leader is positively related to a unit's level of human capital *on average*. Yet, the semi- and nonparametric evidence reveals large areas in technology-gap and human-capital-endowment space where monotone convergence is absent and leapfrogging or low-growth traps exist. Standard, monotone convergence in TFP growth to the industry leader as suggested by earlier, parametric work applies only to part of the region-industry units in the data.

The nonparametric estimator explains more than twice as much of the variation in the data on TFP growth than the parametric estimator in the data at hand. The deviation of the predictions from the data are on average much smaller for the nonparametric estimator and particularly so where the where the gap to the industry leader is large (i.e., for industry-region dyads that are in the poverty trap). Moreover, the nonparametric estimator reveals a much greater variance in the marginal effect of human capital across regions and industries. Hence, allowing for flexible functional forms when assessing convergence processes and spillovers appears desirable and turns out to be qualitatively and quantitatively important.

The remainder of the paper is organized as follows. Section 2 derives a flexible empirical model for inference about the closure of technology gaps within and across industrial boundaries. Section 3 discusses estimation issues and outlines semi-parametric and nonparametric estimation strategies. Section 4 summarizes the data and Section 5 the corresponding results. The last section concludes with a summary of the key findings.

2 Data

The empirical analysis in this paper involves two types of variables, one relating to TFP (a region's gap to the industry leader in an initial period as well as its average annual growth) and one relating to human capital endowments. Since TFP is not observed directly, we follow Griffith, Redding, and van Reenen (2004) for measurement.

2.1 Construction of TFP indices

Define $\Delta \ln Y_{it} \equiv \ln Y_{it} - \ln Y_{it-1}$ as the log change in region-industry dyad i's value added in real terms between periods $t-1$ and t, $\Delta \ln L_{it} \equiv \ln L_{it} - \ln L_{it-1}$ as the log change in labor, $\Delta \ln K_{it} \equiv \ln K_{it} - \ln K_{it-1}$ as the log change in capital stock, and $\widetilde{\alpha}_{it} \equiv 0.5(\alpha_{it} + \alpha_{it-1})$ as the average cost share of labor in value added in periods t and $t-1$. Then, the log change in i's TFP can be defined as

$$\text{TFP growth}_{it} \equiv \Delta \ln A_{it} = \Delta \ln Y_{it} - \widetilde{\alpha}_{it} \Delta \ln L_{it} - (1 - \widetilde{\alpha}_{it}) \Delta \ln K_{it}. \quad (1)$$

Use $\ln \bar{V}_{it}$ to denote the geometric mean of a generic variable $\ln V_{it}$ within an industry and a year across all regions,[3] $D \ln V_{it} \equiv \ln V_{it} - \ln \bar{V}_{it}$ to denote the i's deviation from $\ln \bar{V}_{it}$ in the same industry and year t, $\mathfrak{D} \ln V_{it} \equiv D \ln V_{Lit} - D \ln V_{it}$ to denote the difference between the sector-year specific technology leader (L) and unit i in $D \ln V_{it}$, and $\sigma_{it} \equiv 0.5(\alpha_{it} + \bar{\alpha}_{it})$. Then, we may define

$$\text{TFP gap}_{it} \equiv \mathfrak{D} \ln A_{it} = \mathfrak{D} \ln Y_{it} - \sigma_{it} \mathfrak{D} \ln L_{it} - (1 - \sigma_{it}) \mathfrak{D} \ln K_{it}. \quad (2)$$

Hence, information on the cost share of labor in value added, α_{it}, on value added in real terms, Y_{it}, on employment, L_{it}, and on the capital stock, K_{it} is required to measure TFP growth$_{it}$ and TFP gap$_{it}$.

2.2 Data sources

Information about α_{it}, Y_{it}, L_{it}, and K_{it} is based on data from Cambridge Econometrics. L_{it} and Y_{it} are measured directly with 2006 being the base year for the deflator. K_{it} is calculated by using the perpetual inventory method, using data on gross fixed capital formation, I_{it}, assuming a depreciation rate of 15%, $\delta = 0.15$ (see Harrigan, 1999), and an initial capital stock of $K_{i,1991} = \sum_{t=1980}^{1985} I_{it}$, so that $K_{it} = (1-\delta)K_{i,t-1} + I_{it}$ for all $t = 1992, ..., 2006$. As in Harrigan (1997) and Griffith, Redding, and van Reenen (2004), we exploit the properties of the translog production function to smooth region-industry specific labor shares α_{it}, which are obtained as predicted values of a regression of the observed labor shares on a country-industry-specific fixed effect and the log of the capital-labor ratio, whose parameter is industry-specific. Data on regional human capital stocks H_{it} as one measure of absorptive capacity are based on the European Union's Labour Force Survey and the European Values Study. We employ information on the share of workers with at least secondary education which varies across NUTS2 regions but not across industries. Overall we have data for 10

[3] Note that $\ln \bar{V}_{it}$ carries an index i since i refers to region-industry dyads and the geometric mean is industry(-year)-specific.

industries across 231 regions and 15 years such that our estimates correspond to $n = 34,650$ observations.[4]

3 Empirical framework

3.1 An empirical model of total factor productivity growth and convergence

A general, semi- or nonparametric catching up process for TFP growth of region-industry dyad i at time t in the spirit of Benhabib and Spiegel (1994) and Griffith, Redding, and van Reenen (2004) may be formulated as

$$\Delta \ln A_{it} = f(X_{it-1}) + u_{it}, \text{ where } X_{it-1} = (H_{it-1}, \mathfrak{D} \ln A_{it-1}) \,. \tag{3}$$

Of course, the process in (3) is not consistent with convergence (e.g., non-leapfrogging) in general terms. However, there will be convergence to the same steady-state – an absence of leapfrogging and of no-growth regions at a high TFP gap – as long as $\Delta \ln A_{it}$ increases monotonically with $\mathfrak{D} \ln A_{it-1}$. The latter should not be expected to generally emerge empirically.[5] This paper's main interest is to reveal the functional form of $f(X_{it-1})$, to contrast the findings with a parametric form as assumed in earlier work on the matter, and to outline conclusions for economic policy and future research.

3.2 Semi- and nonparametric estimation of technology spillovers

In this subsection, we are concerned with the specification of $f(X_{it-1})$. By considering convergence forces in TFP as a potentially nonlinear function of two arguments, the technology gap to the industry leader, $\mathfrak{D} \ln A_{it-1}$, and

[4]Our data-set covers the following industries following the NACE classification: Food, beverages and tobacco; Textiles and leather etc.; Coke, refined petroleum, nuclear fuel and chemicals etc.; Electrical and optical equipment; Transport equipment; Other manufacturing; Hotels and restaurants; Transport, storage and communications; Financial intermediation; Real estate, renting and business activities.

[5]For instance, it is well known that some countries are locked at least locally (in time) in what macro-economists call a poverty trap so that there is divergence between richer and poorer economies (see, e.g., Sachs, McArthur, Schmidt-Traub, Kruk, Bahadur, Faye, and McCord, 2004).

human capital endowment, H_{it-1}, we are interested in estimating semiparametric and fully nonparametric models about $f(X_{it-1})$.

Semiparametric estimation of technology spillovers:

In semiparametric models, we allow $f(X_{it-1})$ to be fully nonparametric about $\mathfrak{D} \ln A_{it-1}$ but parametric about H_{it-1}. A partially linear model with no interaction of H_{it-1} and $\mathfrak{D} \ln A_{it-1}$ is

$$\Delta \ln A_{it} = \beta_H H_{it-1} + g(\mathfrak{D} \ln A_{it-1}) + u_{it}. \tag{4}$$

We estimate (4) by applying a differencing approach as proposed by DiNardo and Tobias (2001) and Yatchew (2003). For this, we sort the data by ascending values of $\mathfrak{D} \ln A_{it}$ and calculate first differences of all the sorted data. Hence, we replace every generic variable V_{it} in (4) by its differenced counterpart, $\widetilde{V}_{it} \equiv V_{it} - V_{i-1,t}$. By this strategy, $\widetilde{g(\mathfrak{D} \ln A_{it-1})}$ is differenced out, and we can estimate β_H by regressing $\widetilde{\Delta \ln A_{it}}$ on $\widetilde{H}_{it-1}$. Then, we use $\Delta \ln A_{it} - \widehat{\beta}_H H_{it-1}$ as a new dependent variable and estimate the nonparametric component $g(\mathfrak{D} \ln A_{it-1})$ by way of local linear regression based on a radially symmetric Epanechnikov kernel $K_b(\cdot)$ with bandwidth b. The optimal bandwidth b^* is chosen from a leave-one-out cross-validation procedure as proposed in Fan and Gijbels (1996) and Härdle, Müller, Sperlich, and Werwatz (2004). Confidence intervals of the local point estimates are computed via the bootstrap procedure suggested by Yatchew (2003).[6] To increase the efficiency of the estimator we perform a third-order differencing which follows the procedure described above but employs optimal differencing weights.[7] One important feature of the semiparametric approach in (4)

[6] One adds the residuals from an under-smoothed estimation of $g(\mathfrak{D} \ln A_{it-1})$ to the predictions of the nonparametric component from an over-smoothed local linear regression to construct a bootstrap sample from which one resamples. As suggested by Yatchew (2003, p.161), we use the 0.9 and 1.1-fold of the optimal bandwidth for under- and over-smoothed local linear regressions, respectively. For each draw from the bootstrap sample, we estimate local linear regressions using b^* which obtains a distribution of $g(\mathfrak{D} \ln A_{it-1})$. This distribution is merged with a distribution of $\widehat{\beta}_H$ to obtain a distribution of $\Delta \ln A_{it}$. The 0.025 and 0.975 quantiles of that distribution determine the 95% confidence interval.

[7] With Pth-order differencing, any generic variable V_{it} is differenced as $\widetilde{V}_{it} \equiv \sum_{p=0}^{P} w_p V_{i-p,t}$, where the weights w_p sum up to unity, $\sum_{p=0}^{P} w_p = 1$, and optimal weights are tabulated in Yatchew (2003, p.61). With the data at hand, first- and second-order differencing turn out very similar to third-order differencing, but the latter yields the lowest root mean squared error.

is that the derivative of predicted outcome with respect to the technology gap, $\partial\widehat{\Delta \ln A_{it}} \Big/ \partial\mathfrak{D} \ln A_{it-1}$, is independent of H_{it-1} and vice versa unlike as in earlier work.[8]

Nonparametric estimation of technology spillovers:

For fully nonparametric estimation of the model in (3), we employ a multivariate local linear estimator based on an Epanechnikov product kernel $K_{b_H}(H_{it-1} - H_{st-1})K_{b_A}(\mathfrak{D} \ln A_{it-1} - \mathfrak{D} \ln A_{st-1})$ with bandwidths b_H and b_A (see Fan and Gijbels, 1996).[9] The local linear regression model for all units i in the neighborhood of unit s (3) employs

$$\sum_{i=1}^{n} \{\Delta \ln A_{it} - (X_{it-1} - X_{st-1})\,\beta\}^2 \, K_{b_H}(H_{it-1}-H_{st-1})K_{b_A}(\mathfrak{D} \ln A_{it-1}-\mathfrak{D} \ln A_{st-1}). \tag{5}$$

The predictions for $f(X_{it-1})$ is based on this smoother, and its confidence bounds are estimated by the same bootstrap procedure, using over- and under-smoothing, as outlined above.[10] Again, the optimal bandwidths b_H and b_A are chosen from a leave-one-out cross-validation procedure. An important difference to the semiparametric approach is that in the fully nonparametric framework $\partial\widehat{\Delta \ln A_{it}} \Big/ \partial\mathfrak{D} \ln A_{it-1}$ depends on H_{it-1}. Accordingly, we utilize three-dimensional plots of $\partial\widehat{\Delta \ln A_{it}} \Big/ \partial\mathfrak{D} \ln A_{it-1}$ against $\mathfrak{D} \ln A_{it-1}$ and H_{it-1} for illustration.

[8] It is advisable to estimate derivatives of nonparametric functions by utilizing higher-order polynomial regressions for the derivative than for the level of the function. In general an odd difference between the polynomial order of the level function and the derivative function is preferable in terms of bias reduction (see Härdle, Müller, Sperlich, and Werwatz, 2004, p.99). We estimate $\partial\widehat{\Delta \ln A_{it}} \Big/ \partial\mathfrak{D} \ln A_{it-1}$ by employing a local quadratic regressions for $g(\mathfrak{D} \ln A_{it-1})$ based on a radially symmetric Epanechnikov kernel and optimal bandwidth.

[9] Using a bivariate radially symmetric Epanechnikov kernel instead yields almost identical results.

[10] For estimation of $\partial\widehat{\Delta \ln A_{it}} \Big/ \partial\mathfrak{D} \ln A_{it-1}$, we employ a local quadratic regression in H-$\mathfrak{D} \ln A$-space.

3.3 Results

In this section, we summarize the results of the semiparametric and nonparametric empirical analysis by way of plots. For each estimator, there are two plots, one for the level function $\widehat{\Delta \ln A_{it}}$ (panel A) and one for the gradient function $\partial\widehat{\Delta \ln A_{it}} \Big/ \partial \mathfrak{D} \ln A_{it-1}$ (panel B). With two estimators – a 3rd-order differencing semiparametric model and a fully nonparametric model – this results in two figures and, altogether, four panels. In all three-dimensional plots we use the following coloring to illustrate significance at the 5% level: dark-red for negative values of outcome (level or derivative) that are significantly different from zero; light-red for negative values of outcome (level or derivative) that are not significantly different from zero; dark-blue for positive values of outcome (level or derivative) that are significantly different from zero at; light-blue for positive values of outcome (level or derivative) that are not significantly different from zero;

– Figures 1 and 2 –

Semiparametric estimates:

The semiparametric results are qualitatively very similar between 1**st**, 2**nd**, and 3**rd** order differencing (we only present 3**rd** order differencing results in the interest of brevity) with regard to both the levels function $\widehat{\Delta \ln A_{it}} = f(X_{it-1})$ and the derivative function $\partial\widehat{\Delta \ln A_{it}} \Big/ \partial \mathfrak{D} \ln A_{it-1}$. We focus on third-differenced estimation results for robustness and efficiency reasons. Moreover, $\hat{\beta}_H$ based on (4) amounts to about 0.115 (at a robust standard error of 0.004). Hence, the semiparametric estimates suggest that human capital abundance allows region-industry dyads to entertain positive TFP growth, even if the gap to the industry leader is small. Under human capital scarcity, regions may face negative TFP growth in spite of a big gap to the industry's technology leader. Both features work against mean reversion (convergence). The highest level of TFP growth is predicted for the maximum level of human capital and an intermediate gap to the industry leader ($\mathfrak{D} \ln A_{it-1} \simeq 3$).

The (two-dimensional) estimate of $\partial\widehat{\Delta \ln A_{it}} \Big/ \partial \mathfrak{D} \ln A_{it-1}$ in Figure 1B suggests the following conclusions. First, when starting with the smallest gap to the technology leader and then raising the gap, the derivative function is positive and significantly different from zero at 5% up to a value of

$\mathfrak{D}\ln A_{it-1} \simeq 2.4$ or for about 64% of (region-industry) units with the smallest gaps. These units significantly benefit from spillovers due to innovations by the respective industry's technology leader. Second, $\partial\widehat{\Delta\ln A_{it}}\Big/\partial\mathfrak{D}\ln A_{it-1}$ is indistinguishably different from zero for about 33% of the units in the center of the distribution of TFP gaps or in the interval $\mathfrak{D}\ln A_{it-1} \in (2.4, 6.5)$. Third, $\partial\widehat{\Delta\ln A_{it}}\Big/\partial\mathfrak{D}\ln A_{it-1}$ is positive and significantly different from zero again for TFP gaps in the interval $\mathfrak{D}\ln A_{it-1} \in (6.5, 7)$ or for about 1.3% of the units. The difference between the second and third segment points to leapfrogging in that part of the distribution. Finally, the derivative is not significantly different from zero (positive or negative) for values of $\mathfrak{D}\ln A_{it-1} > 7$. The latter points to a low-growth trap for about 1.7% of the units. The non-monotonicity of the spillovers with respect to the TFP gap is also evident when focusing on the fractions of units where a positive significant point estimate for the gradient is found. The plot in Figure 2 suggests that a positive, statistically significant TFP-growth gradient is more likely at either a quite small or at a sufficiently large gap to the leader. Overall, the semiparametric estimates suggest that the relationship between the gap to the leader and TFP growth is not monotonic, a salient feature that is concealed in previous parametric work on TFP growth. Moreover, about 34% of the industry-region-dyads do not display convergence to the technology leader in a large region in $\mathfrak{D}\ln A$-space with a medium-to-large TFP gap, according to Figure 1B, when applying 95% confidence bounds. Finally, along the whole range of productivity gaps sufficient levels of human capital can ensure significantly positive TFP growth rates.

Nonparametric estimates:

Let us now relax the assumption that $\partial\widehat{\Delta\ln A_{it}}\Big/\partial\mathfrak{D}\ln A_{it}$ is independent of H_{it-1} through fully nonparametric estimation. The corresponding results are illustrated in Figure 3 and can be summarized as follows. First, the estimated levels function $\widehat{\Delta\ln A_{it}} = \widehat{f(X_{it-1})}$ is unsurprisingly similar to its semiparametric counterpart. The nonparametric estimates are somewhat less smooth and somewhat less efficient (see the larger size of light-colored regions in Figure 3A relative to Figure 1A). While having not too big of a technology gap to the leader is best for convergence in general and independent of human capital endowments, convergence to the leader is more likely possible with a medium-high level of human capital as the technology gap rises. The gradient plot in Figure 3B suggests that significant convergence to the leader (indicated by dark-blue dots) surfaces more frequently at medium-high levels of H_{it-1}.

The relative importance of a technology gap to the industry leader and of human capital for convergence can be visualized by plotting the fractions of units at certain levels of a technology gap or human capital where the point estimate for the gradient is positive and significant. The corresponding fractions for $\partial\widehat{\Delta \ln A_{it}} \Big/ \partial\mathfrak{D} \ln A_{it-1}$ across different levels of $\mathfrak{D} \ln A_{it-1}$ and H_{it-1} are displayed in Figures 4A and 4B. Again, a positive, statistically significant TFP-growth gradient is more likely at either a quite small or a very large gap to the leader. Moreover, the fraction of positive significant values of $\partial\widehat{\Delta \ln A_{it}} \Big/ \partial\mathfrak{D} \ln A_{it-1}$ rises with human capital endowments according to Figure 4B. The latter indicates a positive cross derivative which reinforces the importance of human capital in addition to its direct effect on TFP growth. There is evidence of a lack of catching up at intermediate levels of technology gaps and at scarce human capital endowments.

An analysis of variance of an indicator variable which is unity for positive significant catching up and zero else reveals the following. First, only about one-tenth of the variation in this variable is explained by industry-specific and region-specific indicators, with the two being about equally important. Hence, there is relatively little concentration of TFP spillovers across specific industries or specific regions on average. The fraction of significantly positive spillovers varies across industries with values between 0.161 (Transport equipment) and 0.470 (Other manufacturing) being centered around an average of 0.319. The fraction of significantly positive spillovers varies across regions with values between 0.075 (Észak-Alföld in Hungary) and 0.674 (Lancashire in the United Kingdom).

– Figures 3-4B –

The nonparametric estimates reveal a larger variation in the role of H_{it} compared to a parametric counterpart in the spirit of Griffith, Redding, and van Reenen (2004), where $\Delta \ln A_{it}$ is (log-)additive in a constant, H_{it-1}, $\mathfrak{D} \ln A_{it-1}$, and an interaction $H_{it-1}\mathfrak{D} \ln A_{it-1}$. While such a parametric approach yields for our sample an average marginal effect of about 0.088 for H_{it-1} the fully nonparametric approach predicts only about 0.043. The standard deviation of the marginal effect of H_{it-1} is 0.007 and 0.723 in the parametric and the nonparametric model, respectively. Either approach is relatively parsimonious, since TFP growth is explained by just two factors of influence. Yet, the parametric approach explains about 2.7% of the variation in $\Delta \ln A_{it}$, while the fully nonparametric framework explains 6.6%, which is more than twice as much. On average, the nonparametric estimator exhibits smaller residuals than the parametric estimator in the data at hand, indicating that the parametric assumption is violated. In particular, the nonparametric estimator outperforms the parametric approach where the technology gap to the leader is large, hence, for units in the non-convergence trap according to Figures 4A-4B.[11]

4 Conclusions

This paper studies the role of the technology gap and absorptive capacity of regions and industries for catching up. The functional relationship between TFP growth and the technology gap and human capital endowments features considerable nonlinearities and even non-monotonicities that can typically not be captured by parametric specifications. The estimates suggest that spillover effects from the technological leader are strongest to regions within an industry where the technology gap is either quite small or sufficiently large, at least in Europe. For a medium-sized technology gap, we do not identify positive spillovers. This provides evidence for leapfrogging at large to medium-sized technology gaps to the industry leader. Moreover, we find evidence of a low-growth trap at very large technology gaps to the leader. Regarding the effects of human capital in facilitating spillovers from the technology leader the nonparametric estimation reveals a much bigger variation at a much smaller average than the conventional approach. This appears particularly important when thinking of returns to human capital across regions and industries and the funding of education in federal unions that operate under financial constraints.

[11] This statement is based on the following procedure. Define a binary variable which is unity whenever the residuals of the parametric estimator are at least as large in absolute value as the ones of the nonparametric estimator. Regressing this binary indicator on the technology gap to the leader, $\mathfrak{D} \ln A_{it-1}$, in a linear model yields a positive constant of 0.372 (at a robust standard error of 0.004) and a positive coefficient of 0.028 (at a robust standard error of 0.001). Regressing the binary indicator on human capital endowments, H_{it-1}, in a linear model yields a positive constant of 0.424 (at a robust standard error of 0.010) and a coefficient of 0.027 (at a robust standard error of 0.017).

References

Benhabib, Jess and Mark M. Spiegel (1994), The Role of Human Capital in Economic Development - Evidence from Aggregate Cross-Country Data. *Journal of Monetary Economics*, 34, 143-173.

Coe, David T. and Elhanan Helpman (1995), International R&D Spillovers, *European Economic Review*, 39, 859-887.

Coe, David T., Elhanan Helpman, and Alexander W. Hoffmaister (1997), North-South R&D Spillovers, *Economic Journal*, 107, 134-49.

DiNardo, John and Justin L. Tobias (2001), Nonparametric Density and Regression Estimation, *Journal of Economic Perspectives*, 15, 11-28.

Fan, Jianqing and Irene Gijbels (1996), *Local Polynomial Modelling and its Applications*, Chapman and Hall, London.

Griffith, Rachel, Stephen Redding, and John van Reenen (2004), Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries, *Review of Economics and Statistics*, 86, 883-895.

Griffith, Rachel, Rupert Harrison, and John van Reenen (2004), How Special is the Special Relationship? Using the Impact of U.S. R&D Spillovers on U.K. Firms as a Test of Technology Sourcing, *American Economic Review*, 96, 1859-1875.

Harrigan, James (1997), Technology, Factor Supplies, and International Specialisation, *American Economic Review*, 87, 475-494.

Harrigan, James (1999), Estimation of Cross-Country Differences in Production Functions, *Journal of International Economics*, 47, 267-293.

Härdle, Wolfgang K., Marlene Mller, Stefan Sperlich, and Axel Werwatz (2004), *Nonparametric and Semiparametric Models*, Springer Verlag, Heidelberg.

Keller, Wolfgang (2004), International Technology Diffusion, *Journal of Economic Literature*, 42, 752-782.

Kneller, Richard and Philip A. Stevens (2006), Frontier Technology and Absorptive Capacity: Evidence from OECD Manufacturing Industries, *Oxford Bulletin of Economics and Statistics*, 68, 1-21.

Nelson, Richard and Edmond Phelps (1966), Investment in Humans, Technological Diffusion, and Economic Growth, *American Economic Review: Papers and Proceedings*, 61, 69-75.

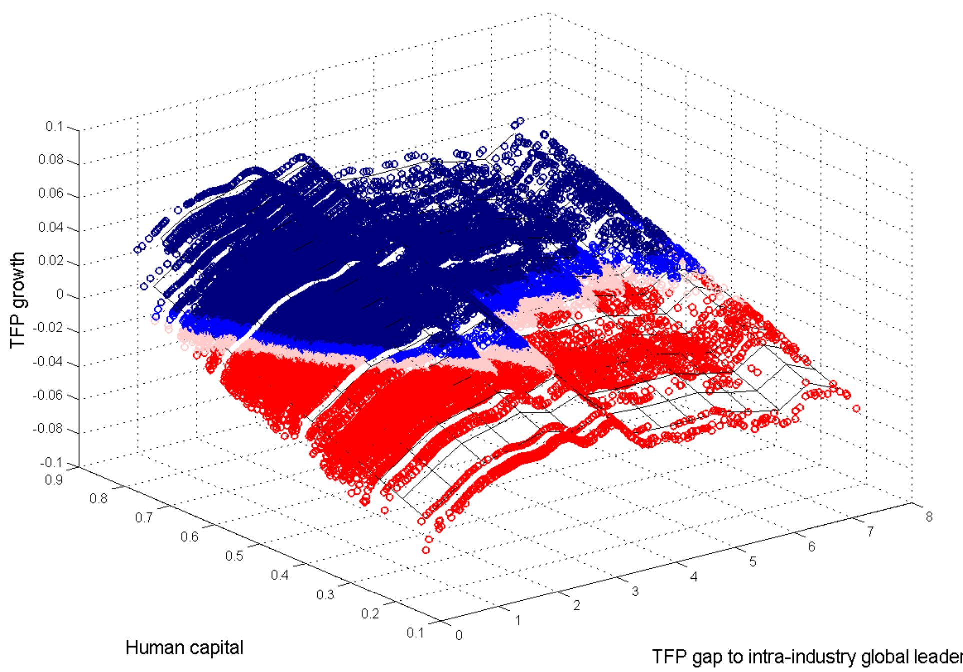
Sachs, Jeffrey D., John W. McArthur, Guido Schmidt-Traub, Margaret Kruk, Chandrika Bahadur, Michael Faye, and Gordon McCord (2004), Ending Africa's poverty trap, *Brookings Papers on Economic Activity*, 35, 117-216.

Yatchew, Adonis (2003). *Semiparametric Regression for the Applied Econometrician*, Cambridge University Press, Cambridge.

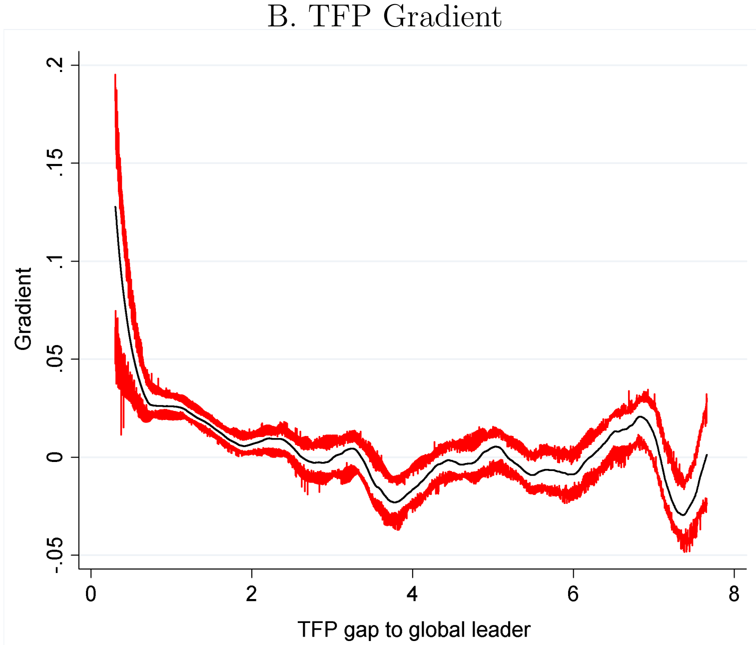
Tables and Figures

Figure 1: Semiparametric Spillovers - Third Order Differencing

A. TFP Growth

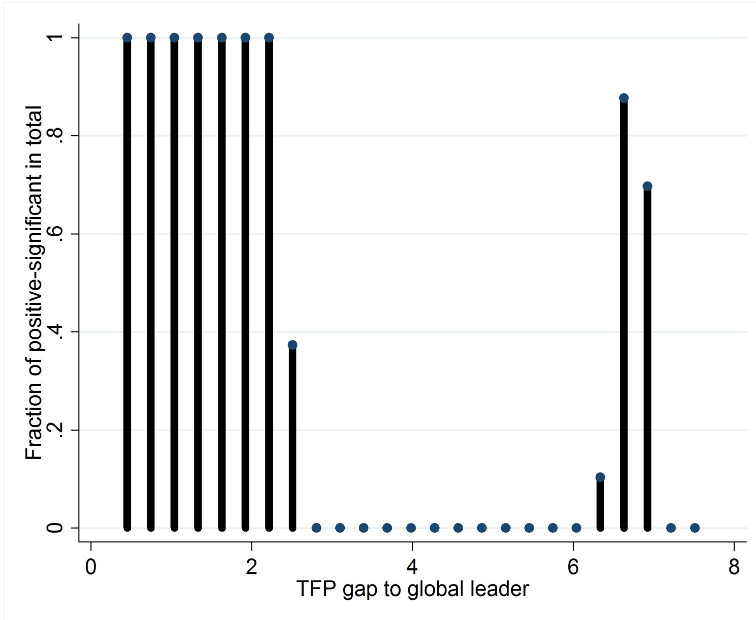


B. TFP Gradient



Note: The estimates base on a sample of 41,580 observations. Panel A illustrates the estimates for the level $\Delta \ln A_{it}$ where we use the following coloring: dark-red for for negative values of outcome that are significantly different from zero at 5%; light-red for negative values of outcome that are not significantly different from zero at 5%; dark-blue for positive values of outcome that are significantly different from zero at 5%; light-blue for positive values of outcome that are not significantly different from zero at 5%. Panel B refers to the estimates for the gradient $\partial\widehat{\Delta \ln A_{it}}\Big/\partial\mathfrak{D}\ln A_{it-1}$ where the red lines mark the 95% confidence interval.

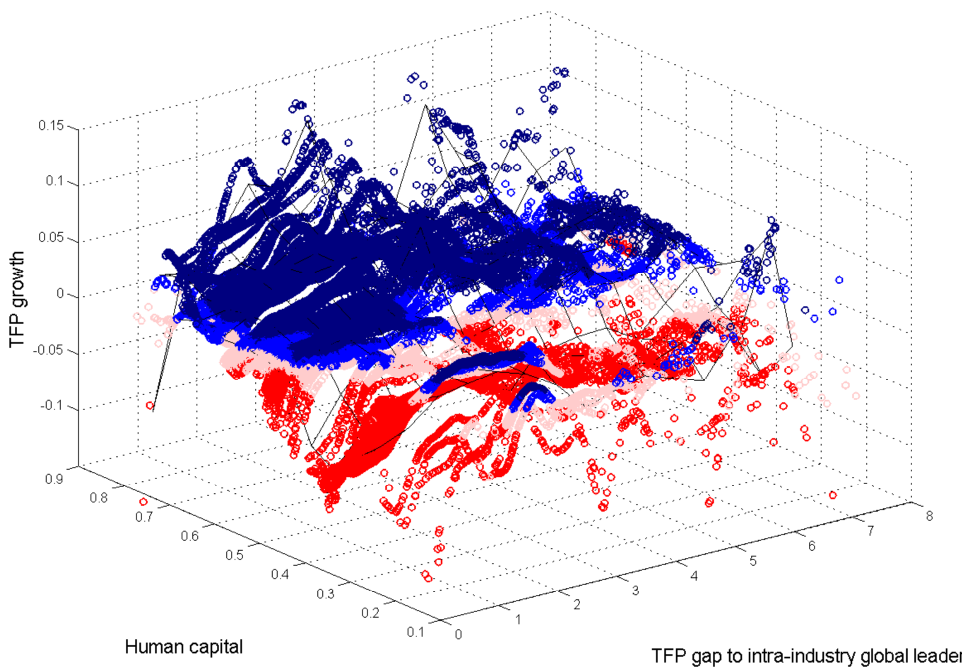
Figure 2: Positive and Significant Spillovers - Semiparametric



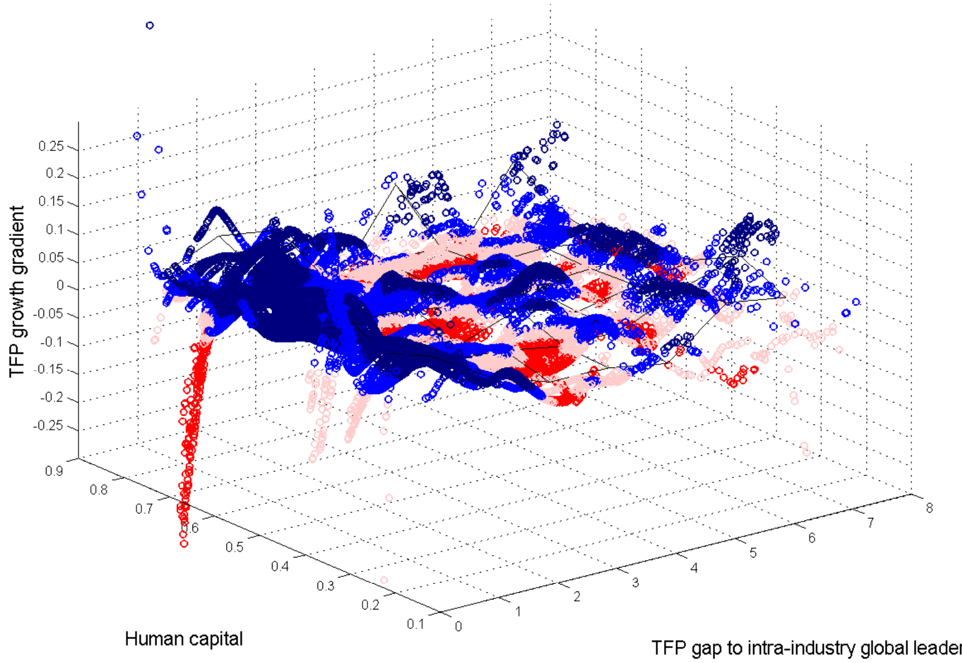
Note: The above figure plots the fractions of observations within 25 equally sized bins of $\mathfrak{D}\ln A_{it-1}$ for which the semiparametric estimator predicts a significantly positive gradient $\partial\widehat{\Delta \ln A_{it}} \Big/ \partial\mathfrak{D}\ln A_{it-1}$.

Figure 3: Nonparametric Spillovers

A. TFP Growth



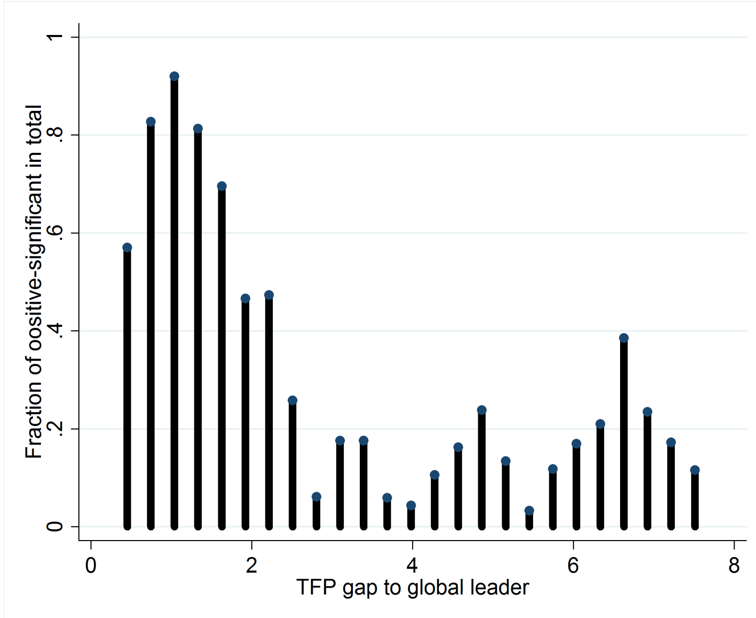
B. TFP Gradient



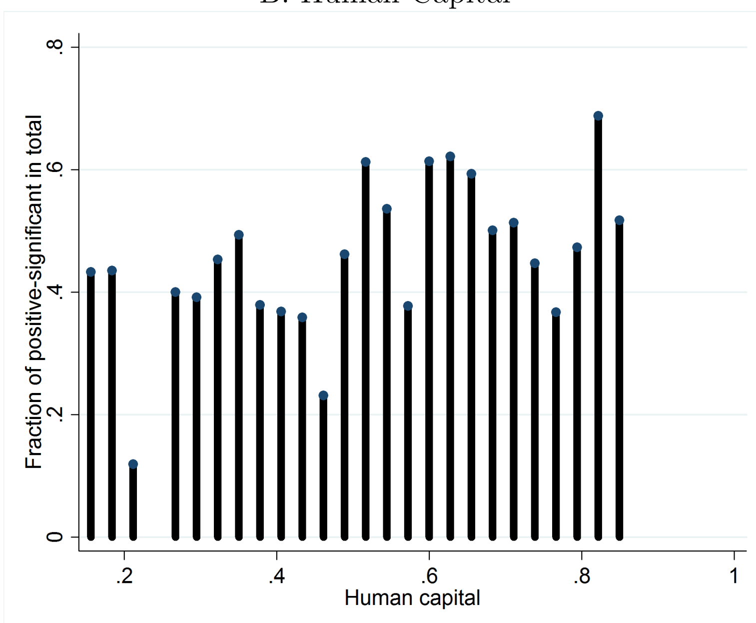
Note: The estimates base on a sample of 41,580 observations. Panel A illustrates the estimates for the level $\Delta \ln A_{it}$ where we use the following coloring: dark-red for for negative values of outcome that are significantly different from zero at 5%; light-red for negative values of outcome that are not significantly different from zero at 5%; dark-blue for positive values of outcome that are significantly different from zero at 5%; light-blue for positive values of outcome that are not significantly different from zero at 5%. Panel B refers to the estimates for the gradient $\partial \widehat{\Delta \ln A_{it}} \Big/ \partial \mathfrak{D} \ln A_{it-1}$ using the same coloring as in Panel A.

Figure 4: Positive and Significant Spillovers - Nonparametric

A. Technology Gap



B. Human Capital



Note: Panel A plots the fractions of observations within 25 equally sized bins of $\mathfrak{D}\ln A_{it-1}$ for which the semiparametric estimator predicts a significantly positive gradient $\partial\widehat{\Delta \ln A_{it}} \Big/ \partial\mathfrak{D}\ln A_{it-1}$. Panel B plots these fractions against 25 equally sized bins of H_{it-1}.

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