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Abstract. How much of the convergence in labor productivity that we observe in manufacturing is due to convergence in technology versus convergence in capital-labor ratios? To shed light on this question, we introduce a nonparametric counterfactual decomposition of labor productivity growth into growth of the capital-labor ratio (K/L), technological productivity (TEP) and total factor productivity (TFP). Our nonparametric specification enables us to model technology allowing for heterogeneity across all relevant dimensions (i.e. countries, sectors and time). Using data spanning from the 1960s to the 2000s, covering 42 OECD and non OECD countries across 11 manufacturing sectors, we find TEP and TFP to account for roughly 46% and -6% of labor productivity growth respectively, on average. While technological growth at the world level is driven primarily by the US and a handful of other OECD countries, we find strong evidence of convergence in both technology and capital-labor ratios. Interestingly, very few of the usual growth determinants are found to enhance the process of technological catching-up.

JEL Classification: C14, D24, O41, O47

1. Introduction

Income and growth disparities among countries are commonly traced back to either capital accumulation (K/L hereafter) or total factor productivity (henceforth TFP). When measured as the Solow residual of a cross-country production function, TFP is often found to be at least as important as capital accumulation (Easterly and Levine, 2001; Caselli, 2005). Thus, to the extent that the capital stock is correctly measured, approximately 50% of income differentials across countries is commonly found to depend on capital accumulation, with the remaining half being attributed to the broad notion of TFP. As it stands, TFP encompasses a number of hard-to-measure components;

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Michele Battisti, University of Palermo, CeLEG LUISS Guido Carli and RCEA; email: michele.battisti@unipa.it. Massimo Del Gatto, G.d'Annunzio University and CRENoS; e-mail: m.delgatto@unich.it. Christopher F. Parmeter, Corresponding Author, University of Miami; e-mail: cparmeter@bus.miami.edu. This paper has benefited greatly from comments made by the associate editor, three anonymous referees, and participants at Dynamics, Economic Growth and International Trade (DEGIT), Lima; Structural Change, Dynamics, Economic Growth (SCDEG), Livorno; RCEA Advances in Business Cycles and Economic Growth Analysis, Rimini; and the Cyprus Economics Department Seminar Series. The usual caveat applies.

among these components, a growing body of literature concentrates on technology, both in terms of creation of new technologies and adoption/diffusion of already available technologies.

However, despite the potential implications of understanding how, and by how much, technology has changed over time, few empirical studies have directed their attention towards identifying and quantifying different forms of technological progress. As Easterly and Levine (2001, p.1) note, "...empirical work does not yet decisively distinguish among the different theoretical conceptions of TFP growth. Economists should devote more effort toward modeling and quantifying TFP."

In this paper we investigate the role played by technological change, as compared to capital accumulation, in fostering labour productivity growth in manufacturing, and examine how much technological convergence has taken place. To accomplish these tasks, we introduce a novel decomposition of the change in output over time which allows for technological heterogeneity across all relevant dimensions - i.e. countries, sectors, and time. This decomposition does not require parametric specification of the production function, which allows us to avoid assumptions on the shape of the production technology. This enables us to incorporate both Hicks-neutral and biased technical change at the country-sector level, and obtain a measure of TFP which isolates the contribution of the former to labour productivity.

Standard TFP measures assume the shape of the production function - the slope - is the same in all countries (in the same sector) and only the Solow residual is allowed to differ across countries. A downside of these measures is that they offer no insight into technological progress stemming from a change in the slope. To highlight the importance of disentangling changes in technology due to the shape of the production function from standard TFP, Bernard and Jones (1996a,b) use the expression "total technological productivity". One reason why this endeavor is challenging is that it implies estimating production functions that are both sector and country specific, which entails both detailed cross-country data as well as a large loss of degrees of freedom in a standard parametric setup.

To overcome this limitation, we exploit the flexibility of nonparametric generalized kernel regression methods to derive a counterfactual decomposition of aggregate labor productivity growth that isolates the contribution of technical change affecting the production function at the country-sector level, referred to as technological productivity (TEP), from the growth of both the capital-labor ratio (i.e. capital accumulation) and Hicks-neutral technical change. The key intuition for the advantage associated to moving from a standard parametric setup to our nonparametric framework is that the changes in the production function, inclusive of any biased form of technological progress (i.e. the TEP term), can be estimated as country-sector-time specific and, as a consequence, the usual TFP term can be viewed as a measure of technical change (i.e. shifts in the production function common to all countries and sectors).[1] This is equivalent to saying that technology is modeled as country-sector-time specific.

We implement the decomposition using data spanning from 1963 to 2007 and covering 42 developed and developing countries across 11 manufacturing sectors. The analysis develops along two lines.

First, we estimate country-sector specific production functions and construct the *counterfactual decomposition* of the cross-country sectoral change in labour productivity into separate components quantifying capital accumulation, TEP and TFP, for which we provide average relative contributions of 60%, 46% and -6%, respectively. Although these average figures hide large differences across countries and across sectors, even within the same country, these results point towards balanced contributions of TEP and capital accumulation and, notably, posits that the shift in the production function due to the overall contribution of Hicks-neutral technical change to labour productivity growth is quite small.

Second, we focus on *technological gaps* and *convergence*. In doing so, we apply our country-sector estimates to a question posed by Bernard and Jones (1996a): "How much of the convergence that we observe is due to convergence in technology versus convergence in capital-labor ratios?" Apart from Bernard and Jones (1996a), who find no evidence of convergence in manufacturing, either in labor productivity or in a measure of multi-factor productivity (in a sample of OECD countries, over the period 1970-1987), this issue has received little attentionin the convergence literature. Our nonparametric approach enables us to study the country-sector evolution of the difference between TEP growth in a given country and TEP growth in a benchmark country in the same sector (TEP gaps). The growth of TEP can then be compared to changes in capital-labor ratios across countries and sectors.

With the US as the benchmark country, we find that TEP gaps have slightly increased on average. The average decrease in labor productivity gaps (amounting to an overall -1% per year) is significantly higher within OECD countries, essentially being driven by relative changes in the capital-labor ratio.[2] We then find strong evidence of convergence in both technology and capital accumulation (consistent with Madsen and Timol (2011) and Rodrik (2013), in labor productivity). Interestingly, none of the usual growth determinants are found to possess a statistically significant contribution to the process of technological catching-up, with the exception of geographical proximity to the US (the "technological" leader), years of schooling, and the size of the population aged between 15 and 64 years.

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[1] The expression 'biased technical change' is used here to refer to forms of technical change directly affecting factor elasticities - i.e. the percent change in output associated to a one percent change in a given factor.

[2] Schelkle (2014) finds similar evidence of experiences of successful catch-up to the United States that are mainly driven by relatively faster factor accumulation. His approach differs from that here in two main dimensions. First his analysis is at the country level rather than the sector level, and second, he explicitly takes into account human capital as a factor of production.

2. Related literature

From a methodological point of view, our work complements and expands on existing approaches for constructing cross-country income decompositions.[3] Among others, Beaudry et al. (2005) and Fiaschi et al. (2013) use counterfactual decompositions in the spirit of Oaxaca (1973) and Blinder (1974). While the former uses least squares, imposing the same coefficients across all countries, Fiaschi et al. (2013) propose a semi-parametric framework in which the coefficients vary across EU regions, but not across sectors. Beaudry et al. (2005) show that changes in the distribution of GDP between 1960 and 1990 are better explained by physical, rather than human, capital accumulation.

In an alternative decomposition of cross-country output, data envelopment analysis is used. An incomplete list includes Färe et al. (1994), Kumar and Russell (2002), Henderson and Russell (2005), Los and Timmer (2005), Jerzmanowski (2007) and Filippetti and Peyrache (2015). In particular, Kumar and Russell (2002) construct the world frontier from country data spanning from 1965 to 1990 and quantify the relative contribution of efficiency, technology and capital accumulation to the change in output per worker. Los and Timmer (2005) compute a country (but not sector) specific technological frontier and then suggest a decomposition into assimilation, spillover potential and localized innovation. They use the decomposition to test the Basu and Weil (1998) model of appropriate technology, according to which, if technological progress is localized, as Atkinson and Stiglitz (1969) suggest, technological upgrading is less likely at low levels of capital intensity, whereas the global technology frontier is steadily pushed upward at high capital intensities (see also Jones, 2005 and Caselli and Coleman, 2006). Interestingly, Los and Timmer (2005) find evidence of technological catching up through assimilation, though they describe this process as occurring slowly, characterized by substantial cross-country heterogeneity.

While there is ample evidence that technology differs across countries, most approaches that allow for technological differences do so in a limited fashion. For example, Bos et al. (2010 a,b) deploy parametric mixture models to allow technology to differ across a finite number of endogenously determined groups of countries. More recently, Filippetti and Peyrache (2015), following the decomposition of Kumar and Russell (2002), allows for technological heterogeneity at the regional level.

Aside from decomposing changes in output across countries and sectors, learning how these changes have differed, if at all, across countries ties our study in with the literature focusing on technological convergence. The idea of technological convergence is intimately related to that of technology adoption and diffusion, a literature dating back to Gerschenkron (1962), Nelson and

[3]The appeal of these decompositions is that they impose few parametric assumptions on the underlying structure. Further, this style of semi- and nonparametric estimation has recently witnessed an increased interest in the cross-country growth literature (Maassoumi et al. 2007, Henderson et al. 2012, 2013). These methods are invaluable when little *a priori* information exists regarding the unknown relationship between economic output and the factors of production.

Phelps (1966), Parente and Prescott (1994), and Barro and Sala-i-Martin (1997). In particular, Nelson and Phelps (1966) postulate that the further a country is behind the technological frontier, the higher is its growth potential, provided that it has a sufficiently high level of human capital, or absorptive capacity, to take advantage of its backwardness. Beginning with Cameron et al. (2005), and also Ciccone and Papaioannou (2009) and Madsen (2014), the effectiveness of such a mechanism has been documented.

The importance of testing for convergence in technology dates at least to Bernard and Jones (1996a, p. 1037), who notice that "technology is featured prominently in almost every other analysis of economic growth except for the convergence literature." Bernard and Jones (1996b) find no evidence of convergence in manufacturing, either in labor productivity or in a measure of multi-factor productivity over the period 1970-1987 for a sample of OECD countries. A similar finding emerges in the convergence analysis in Kumar and Russell (2002), suggesting that relatively wealthy countries benefit more from technological progress than less developed countries.

In a seminal contribution, Parente and Prescott (1994) argue that differences in barriers to technology adoption, which vary across countries and time, account for the great disparities in income across countries. Recent contributions investigate empirically the role played by technology adoption and diffusion in growth and convergence taking the sectoral dimension into account. Rodrik (2011) stresses how productivity differences between developed and developing countries (the so-called "convergence gap") are affected by the ability to adopt/imitate more advanced technologies, and how this capacity is influenced by the distance from the technological frontier. Madsen and Timol (2011) find R&D to be a major driver of convergence in manufacturing for nineteen OECD countries over the period from 1870 to 2006. Rodrik (2013) points to the fact that while manufacturing industries exhibit strong unconditional convergence in labor productivity, this is not the case for a majority of economies as a whole, due in part to the small share of manufacturing employment in low-income countries and the slow pace of industrialization. Moreover, convergence in manufacturing is shown to be related to factors such as global competition and technology diffusion. Thus, even if the share of manufacturing decreases with the degree of economic development, the manufacturing sector is a natural setting to analyze the extent of technology diffusion and capital accumulation.

3. Empirical Strategy

3.1. **Decomposition of Technology.** Let us start with the production function (in logarithmic form) of country c, in sector s, at time t

$$y_t^{cs} = m_t^{cs}(k_t^{cs}) + a_t^{cs}. \tag{1}$$

Here country c's output per worker in sector s at time t, y_t^{cs}, depends on contemporaneous values of capital per worker, k_t^{cs}, through the production technology $m_t^{cs}(\cdot)$, as well as a_t^{cs}, which captures both TFP and idiosyncratic shocks.

According to (1), for a given stock of capital, country c can be relatively more productive in sector s, with respect to country f at time t, or with respect to itself at $t-1$, due to using improved technology m_t^{cs}, compared to m_t^{fs}, or m_{t-1}^{cs}. This framework describes a world in which alternative productive technologies are available worldwide and two countries may or may not use the same technology in the same industry at time t. Once cross-country differences in the production function are controlled for by m_t^{cs}, referred to as "technological productivity" (henceforth TEP), neutral technical change is then captured, together with a country-sector residual component, a_t^{cs}, which thus accounts for cross-country differences in labor productivity not explained by different input choices (captured by k_t^{cs}) or country-sector specific differences in the production technology (captured by m_t^{cs}). Our nonparametric approach allows us to estimate m_t^{cs} as country-sector-time specific avoiding explicit assumptions concerning the functional form of technology (e.g. Cobb-Douglas) or the type of technical change (i.e. neutral vs. biased technical change). We only require that log-TFP enters additively, ending up in a_t^{cs}.

In (1), labor productivity of country c, in sector s, at time t can differ from that of any other country along three dimensions: i) capital intensity, k_t^{cs}, ii) TEP, m_t^{cs}, and iii) TFP, a_t^{cs}. We propose a decomposition over time to isolate these effects. To condense slightly on notation we omit the industry index and start by writing labor productivity growth as:

$$\Delta y_{t,T}^c = y_T^c - y_t^c = [\widehat{m}_T^c(k_T^c) + \widehat{a}_T^c] - [\widehat{m}_t^c(k_t^c) + \widehat{a}_t^c]. \tag{2}$$

where $\widehat{m}_T^c(k_T^c) = \widehat{y}_T^c$ and $\widehat{m}_t^c(k_t^c) = \widehat{y}_t^c$ are the predicted labor productivities, at time T and t respectively, obtained by applying each period's estimated TEP, $\widehat{m}(\cdot)$, to the corresponding actual value of k; $\widehat{a}_T^c$ and $\widehat{a}_t^c$ are estimated TFP in period T and t, respectively.

As explained in Section 3.2, one of the advantages of our nonparametric approach lies in the ability to estimate a country-sector-time specific production function. With this we have the ability to construct the counterfactual output per worker $m_T^c(k_t^c)$ that, given a_t^c and k_t^c, country c would have produced at time t using time T's technology. Using this counterfactual, (2) can be written as

$$\Delta y_{t,T}^c = y_T^c - y_t^c = \underbrace{[\widetilde{m}_T^c(k_t^c) - \widehat{m}_t^c(k_t^c)]}_{\Delta\widetilde{(TEP)}_{t,T}^c} + \underbrace{[\widehat{m}_T^c(k_T^c) - \widetilde{m}_T^c(k_t^c)]}_{\Delta\widetilde{(K/L)}_{t,T}^c} + \underbrace{[\widehat{a}_T^c - \widehat{a}_t^c]}_{\Delta\widehat{(TFP)}_{t,T}^c}. \tag{3}$$

The three terms in brackets refer to the contribution to the overall change in labor productivity due to TEP, capital accumulation per worker and TFP, respectively. A tilde is used to highlight terms obtained through estimated counterfactuals.

For the analysis in Section 6, it will be useful to compare a given country's decomposition to that of a benchmark (or leader) country. For this we use the labor productivity growth of a benchmark country (referred to with an asterisk), to restate (2) as[4]

$$\underbrace{\Delta y^c_{t,T} - \Delta y^*_{t,T}}_{\Delta(Y/L)gap^c_{t,T}} = \underbrace{[\widehat{m}^c_T(k^c_T) + \widehat{a}^c_T] - [\widehat{m}^*_T(k^*_T) + \widehat{a}^*_T]}_{(Y/L)gap^c_T} - \underbrace{\{[\widehat{m}^c_t(k^c_t) + \widehat{a}^c_t] - [\widehat{m}^*_t(k^*_t) + \widehat{a}^*_t]\}}_{(Y/L)gap^c_t}. \tag{4}$$

Now consider the counterfactual output per worker $m^*_t(k^c_t)$ that, given a^c_t and k^c_t, country c would have produced at time t with the benchmark country's technology. Adding and subtracting the growth rate from t to T of this counterfactual, $m^*_T(k^c_T) - m^*_t(k^c_t)$, the observed difference in the growth rate of labor productivity between country c and the benchmark country can be decomposed into:

$$\Delta(Y/L)gap^c_{t,T} = \Delta\widetilde{(TEP)gap}^c_{t,T} + \Delta\widetilde{(K/L)gap}^c_{t,T} + \Delta\widehat{(TFP)gap}^c_{t,T} \tag{5}$$

where

$$\begin{aligned}
\Delta(Y/L)gap^c_{t,T} &= \underbrace{[y^c_T - y^*_T]}_{(Y/L)gap^c_T} - \underbrace{[y^c_t - y^*_t]}_{(Y/L)gap^c_t}; \\
\Delta\widetilde{(TEP)gap}^c_{t,T} &= \underbrace{[\widehat{m}^c_T(k^c_T) - \widetilde{m}^*_T(k^c_T)]}_{\widetilde{(TEP)}gap^c_T} - \underbrace{[\widehat{m}^c_t(k^c_t) - \widetilde{m}^*_t(k^c_t)]}_{\widetilde{(TEP)}gap^c_t}; \\
\Delta\widetilde{(K/L)gap}^c_{t,T} &= \underbrace{[\widetilde{m}^*_T(k^c_T) - \widehat{m}^*_T(k^*_T)]}_{\widetilde{(K/L)}gap^c_T} - \underbrace{[\widetilde{m}^*_t(k^c_t) - \widehat{m}^*_t(k^*_t)]}_{\widetilde{(K/L)}gap^c_t}; \\
\Delta\widehat{(TFP)gap}^c_{t,T} &= \underbrace{[\widehat{a}^c_T - \widehat{a}^*_T]}_{\widehat{(TFP)}gap^c_T} - \underbrace{[\widehat{a}^c_t - \widehat{a}^*_t]}_{\widehat{(TFP)}gap^c_t}.
\end{aligned} \tag{6}$$

Using the counterfactual output per worker $m^*_T(k^*_t)$ that, for given TFP, the benchmark country would have produced at time T with time t's capital per worker, the sectoral specific shifts from t to T in terms of TEP, K/L and TFP of a benchmark country (the technological leader) are given by

$$\begin{aligned}
\Delta\widetilde{(TEP)}^*_{t,T} &= \widetilde{m}^*_T(k^*_t) - \widehat{m}^*_t(k^*_t); \\
\Delta\widetilde{(K/L)}^*_{t,T} &= \widehat{m}^*_T(k^*_T) - \widetilde{m}^*_T(k^*_t); \\
\Delta\widehat{(TFP)}^*_{t,T} &= \widehat{a}^*_T - \widehat{a}^*_t.
\end{aligned} \tag{7}$$

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[4]It is worth noting that no a priori assumption in terms of the world frontier (see, for example, Caselli and Coleman, 2006) is needed in our approach. Since a different production function is estimated for each country-sector-period, any country-sector-period might be used as benchmark.

Thus, the growth rate of country c's labour productivity from t to T can be written as

$$\begin{aligned}\Delta y^c_{t,T} =&\Delta(\widetilde{TEP)gap}^c_{t,T} + \Delta(\widetilde{K/L)gap}^c_{t,T} + \Delta(\widehat{TFP)gap}^c_{t,T} + \\ &+ \underbrace{\Delta(\widetilde{TEP})^*_{t,T} + \Delta(\widetilde{K/L})^*_{t,T} + \Delta(\widehat{TFP})^*_{t,T}}_{\Delta y^*_{t,T}}\end{aligned} \tag{8}$$

This framework enables us to compare the relative contribution of K/L, TEP and TFP to labor productivity across countries, net of the technological leader's shifts in (8). This allows us to account for catching-up within our decomposition exercise. This also represents a novelty with respect to the decompositions used by Beaudry et al. (2005) and Fiaschi et al. (2013), among others.

3.2. **Nonparametric Estimation.** To estimate the production function in (1), we treat $m^{cs}_t(\cdot)$ as an unknown smooth function varying across countries, sectors and time. In a parametric context this would seem a daunting task as we have more parameters than observations. However, following the intuition of Li and Racine (2004) and Racine and Li (2004), we can deploy nonparametric generalized kernel estimation by leveraging nearby observations. Generalized kernel estimation (see Online Appendix A for a more detailed discussion) allows smoothing over continuous (the capital-labor ratio), ordered (time) and unordered (a country-sector indicator) covariates simultaneously. The ability to smooth over discrete cells affords us the ability to estimate time and country-sector specific technology.

To be more concrete, we write the model in (1) as

$$y^{cs}_t = m^{cs}_t(k^{cs}_t) + a^{cs}_t = m(k^{cs}_t, d^{cs}, d_t) + a^{cs}_t, \tag{9}$$

where, aside from the continuous variable k^{cs}_t, two discrete variables are used: a country-sector effect d^{cs} (which is constant over time) and a time effect d_t. While the latter is ordered by nature, the former has no natural ordering. We treat a^{cs} as a random error term which also includes Hicks-neutral technical change. Whereas in a parametric setting to allow for country-sector-year effects would introduce a large (and infeasible) number of unobserved effects, by smoothing across both time and sector, we can lessen the impact that common parametric strategies have, such as time and country intercept shifts, by leveraging 'nearby' cells for local information. This comes at the expense of introducing bias into the estimators (Li and Racine, 2007) but has the potential to lower variance, and has been shown to lead to substantial finite sample gains (Racine and Li, 2004). The work of Racine and Li (2004) focuses on the iid setting, whereas our setting here is more aptly characterized by data dependence over time. Robinson (1983), for strongly dependent data, Li and Racine (2007, chapter 18), where the error term is a martingale difference process, and Li, Ouyang and Racine (2009), with weakly dependent mixed discrete and continuous data, demonstrate that the main large sample properties of the regression estimator in the iid setting carry over to the dependent data case. Further, in our empirical investigation, we deploy a number of alternative data checks to determine if various forms of time series dependence may have an undue influence on our results. These robustness checks are designed to determine if underlying data collection and measurement issues may be influencing our results.

To estimate the production function in (9), we use the local-linear estimator with bandwidths selected with the AIC_c criterion of Hurvich et al. (1998), which Li and Racine (2004) suggest works well in practice (albeit in *iid* settings); see Henderson and Parmeter (2015) for more intuition as well as Online Appendix A for specific details. Alternatively, we could have used least-squares cross-validation, which Xia and Li (2002) have shown to work quite well in the time series setting.

What makes the generalized kernel regression approach particularly appealing for our purposes is the ability to estimate the function m_t^{cs} including country-sector and year effects. As discussed earlier, this would be difficult in a standard parametric setup, as the number of parameters to be estimated could easily surpass the number of observations (country c at time t in sector s). By smoothing over continuous (the capital-labor ratio), ordered (time) and unordered (the country-sector indicator) covariates simultaneously, the nonparametric estimator affords us the ability to identify a country-sector-year specific relationship between labor productivity and capital per worker (i.e. the function m_t^{cs}), thereby differing from conventional estimates, in which the estimated relationship is restricted to have a common form across countries (input coefficients are sector but not country specific).

As shown by Racine and Li (2004) and Li et al. (2009), the addition of discrete regressors does not affect the convergence rate of the conditional mean, as it is *only* dependent on the number of continuous regressors. This is extremely important, as the curse of dimensionality is one of the main criticisms levied against the use of nonparametric methods in empirical work. In our context, the number of observations is in the hundreds. If we had three continuous variables, this would be difficult to handle given the finite sample bias that would likely arise. Instead, with two of the three variables being discrete, the insights of Racine and Li (2004) and Li et al. (2009) suggest that our sample size should be adequate to learn about the underlying technologies.

It is worth noting that embedded in (9) is biased technical change b_t^{cs} - i.e. $y_t^{cs} = m(b_t^{cs} k_t^{cs}, d^{cs}, d_t) + a_t^{cs}$. The effect of b_t^{cs} on y_t^{cs} cannot be identified directly in our setup and is estimated through $m_t^{cs}(\cdot)$. Hence, among the country-sector-time specific factors captured by our TEP growth rate is any biased form of technical change. In Section 5.1 we discuss this as it pertains to the presence of human capital.

3.3. **Understanding TEP**[5]**.** To understand how the estimation in Equation (9) maps into the decompositions in (5) and (8), consider that d_t characterizes the contribution of time on technology and d^{cs} captures technology differences arising from country and sector specific factors (which

[5]We thank an anonymous Associate Editor for helping us think about these issues.

could be related to barriers to adoption, technology diffusion across a given sector, etc.). While all country-sector specific factors are embedded into the TEP component (the effect that all of these factors have on y_t^{cs} is estimated through $m_t^{cs}(\cdot)$), Hicks-neutral technical change is encapsulated in TFP.

Positive growth in TEP can stem from either a shift in the country-sector specific production function or an increase in the productivity of inputs at the country-sector level. To see how these different effects influence TEP change, begin with the TEP component from Equation (3): $\widetilde{m}_T^{cs}(k_t^{cs}) - \widehat{m}_t^{cs}(k_t^{cs})$. Technology in each period can be approximated in a linear fashion as $\widetilde{m}_T^{cs}(k_t^{cs}) \approx \hat{\gamma}_T^{cs} + \hat{\beta}_T^{cs} k_t^{cs}$ and $\widehat{m}_t^{cs}(k_t^{cs}) \approx \hat{\gamma}_t^{cs} + \hat{\beta}_t^{cs} k_t^{cs}$, respectively. This entails the following decomposition:

$$(10)\quad \Delta TEP = \widetilde{m}_T^{cs}(k_t^{cs}) - \widehat{m}_t^{cs}(k_t^{cs}) \approx (\hat{\gamma}_T^{cs} + \hat{\beta}_T^{cs} k_t^{cs}) - (\hat{\gamma}_t^{cs} - \hat{\beta}_t^{cs} k_t^{cs}) = (\hat{\gamma}_T^{cs} - \hat{\gamma}_t^{cs}) + (\hat{\beta}_T^{cs} - \hat{\beta}_t^{cs}) k_t^{cs}$$

where $(\hat{\gamma}_T^{cs} - \hat{\gamma}_t^{cs})$ and $(\hat{\beta}_T^{cs} - \hat{\beta}_t^{cs})$ are approximations of a 'shift' and a 'slope' effect, respectively. Thus, in light of our decomposition in (3), we have four different components which lead to changes in output: intercept and slope changes to technology (i.e. TEP), changes in inputs, and changes in the term a_t^{cs} (i.e. TFP). Positive growth in TEP can stem from either a specific change in the intercept - i.e. γ in Equation (10), which indicates that the output of a given country in a given sector can be increased for the same level if inputs in that country and sector, or a change in the slope - i.e. β in Equation (10), which indicates that an input is, in a given country and sector, more productive at the same level than it previously was. If the intercept remains roughly constant over time, then the majority of an increase in technological productivity is due to changes in the shape of the production function, with inputs being more productive at a given level than they previously were. One might be interested in understanding which effect is contributing the larger share to the overall change in the TEP component (after isolating Hicks-neutral technical change). This is an aspect that we reserve for future research, as the linear approximation in Equation (10), although promising, poses a number of issues that need to be attended to and are currently beyond the scope of the paper.

4. Data

We take advantage of the country-sector information provided by UNIDO in the INDSTAT2 - Industrial Statistics Database - 2013 (Ciccone and Papaioannou, 2009; Madsen and Timol, 2011; and Rodrik, 2011, 2013 also use this data).[6] From INDSTAT2 we draw data on value added (for Y), number of employees (for L), and gross fixed capital formation (for K). The capital stock K is constructed through a perpetual inventory method in which the initial stock is computed

[6]A more detailed description of the database can be found in Rodrik (2013).

following Harberger (1978).[7] To prevent our capital variable from being unduly influenced by missing observations and/or outliers, we smooth capital stocks at the country-sector level using a weighted moving average of the one year lagged observation, the one year forward observation, and the current observation. Finally, only combinations with coverage of at least five consecutive years are considered.

In principle, the database covers 166 countries over the period 1963-2010, at the 2-digit (or, for some countries and sectors, combination of 2-digits) ISIC Rev3 sectoral breakdown. However, available information after cleaning the data is much lower, mainly due to missing information for either Y, K and/or L. The final number of non-missing country-sector combinations are reported, together with the average values of y and k, in Tables 1 (by country) and 2 (by sector). The analysis considers 11 distinct manufacturing sectors, comprising the entire manufacturing industry. We see that we have complete coverage for the Chemical sector and almost full coverage of the Paper/Publishing sector whereas the Coke/Petroleum and Furniture sectors have the least coverage across countries. As expected, Coke and Petroleum is the largest sector in terms of both value added and capital stock per worker, while Textiles is the smallest sector.

Different from other available datasets, INDSTAT allows for long-run country-sector analysis with good country coverage beyond OECD nations. To the best of our knowledge, only Rodrik (2013) uses INDSTAT to take advantage of this feature. It is common in analyses of this type that the sectoral dimension is usually not taken into account. This is the case, for example, in Beaudry et al. (2005), Los and Timmer (2005), and Fiaschi et al. (2013), who rely on different versions of the Penn World Table (versions 6.0, 5.6, and 7.1, respectively). In other country-sector databases, such as EUKLEMS, the number of countries available is too small for our purposes; for example, the capital stock is available for 17 OECD countries, and for only 12 countries does the information date back to the 1970s.

While production function estimation requires output and inputs to be expressed in quantities, UNIDO only provides us with data at current prices. Given that country-sector specific deflators dating back to the 1960s are not available at the level of granularity of our data, we are, in principle, exposed to the risk of interpreting differentials in prices (or inflation rates) as differences in technology. A possible remedy might consist of using country-specific deflators. However, as Rodrik (2013) discusses, this would likely introduce a bias on an inter-sectoral basis. For our purposes, this is more risky than working with current prices. More specifically, three types of price differences matter: cross-country, cross-sector and between Y and K (L is reported as a stock, not a value). Our nonparametric approach enables us to include a country-sector control in the estimation of the production function, so that the first two sources of bias are weakened, but not eliminated. Price levels can change over time, including relative prices, so country-sector effects

[7] The Harberger approach assumes that the initial capital stock is estimated as if the economy was in steady-state in the first period, and thus, output grows at the same rate as the capital stock.

will not be sufficient to eliminate all of the existing inter-sectoral bias, nor would country-time and sector-time effects be sufficient here. To attempt to control for these price biases, Rodrik (2013) uses a sector control to take into account differences in industry prices; accounting for these price variations are an important issue in the broader cross-country production literature and we follow suit with our inclusion of controls. Lastly, even with our country-sector regressors, we remain with the third source of bias: if the price of output is higher, or grows more rapidly, than the price of capital, our estimates are likely to interpret such differences in terms of improved technology - i.e. a larger TEP.

To gain intuition on this aspect, we consider country-level differences in the ratio of the inflation rate of K to the inflation rate of Y between the 1960s (period 1) and the 2000s (period 2). These are reported in Figure 1, with (country-level) data drawn from Penn World Table 8.0 (Feenstra et al., 2015). Interpretation problems may arise when the ratio changes considerably across the two periods. Ideally, if all the observations are aligned along the 45° line then no issues would arise. We can see that there are two countries which deviate heavily from the 45° line, namely Kuwait and Malta. To check for the importance of the price effect above, we conducted our analysis excluding these two countries and compared the decomposition results with those reported in the following sections. The impact was negligible and the results are available upon request.

For the convergence analysis in Section 6, we use the additional variables:

- *Geo Distance to US*: bilateral geodesic distance between the biggest cities of country c and the US, with inter-city distances calculated using the great circle formula and weighted by the share of the city in the overall country's population (source: CEPII - GeoDist database);
- *POP density*, Δ *POP 15-64*: ratio of total population to country size and growth of population aged 15-64, respectively (source: World Development Indicators);
- *Rule of law*: rule of law index from Knack and Keefer (1995);
- *Financial development*: ratio of deposit money bank claims on domestic nonfinancial real sector to the sum of deposit money bank and Central Bank claims on domestic nonfinancial real sector (source: World Bank. Financial Development and Structure Database - see Beck et al., 2000);
- *Inward FDI*: total inward FDI flows to country c, from all other countries, divided by GDP (source: UNCTAD);
- *Trade with US*: total trade (aggregate imports and exports) of country c with the US, divided by current GDP (source: CHELEM-IT and CHELEM-GDP databases);
- *Patents*: total (residents plus non-residents) patent applications per capita (source: WIPO Statistics Database);
- *Avg yrs school*: average years of education of population aged > 25 (source: Cohen and Soto, 2007, Cohen and Leker, 2014).

In order to avoid potential endogeneity issues (Durlauf, 2009), for all these variables we consider the average value in the first period, except for the population growth rate, for which we use the growth rate of the average population from the period 1963-1974 to the period 2000-2010 (see Mankiw et al., 1992). Notably, the first year available in the case of *Rule of law* was 1984 (one decade after the 1963-1974 period). However, this might not be an issue, as institutions for a majority of the countries in our sample are likely to have been relatively stable over time.[8]

5. Decomposition results

5.1. **Benchmark estimation.** We estimate the production function in (1) using the generalized kernel method described in Section 3.2. Estimation is performed on a sample of 782 observations obtained by collapsing the time dimension of an unbalanced (1963-2007) panel of 21,760 country-sector-year observations into a sample that is balanced across two aggregate time periods which, after removal of outliers in (Y/L) and (K/L) consists of 391 observations in period 1 (covering the period from 1963-1972) and period 2 (covering the period 1998-2007).[9] This choice allows us to exploit the time dimension of the data as much as possible, while, at the same time, it mitigates the impact of oil shocks, in period 1, and the recent financial crisis, in period 2. Moreover, since non-missing long time series are available only for a few countries, this strategy seeks to maximize the number of countries that can be included, allowing for adequate coverage of less developed economies.[10] In Section 5.2, we discuss the consequences of considering different time periods and frequencies.

The country-sector specific decomposition estimates, based on Equation (3), are presented by country in Table 3 and by sector in Table 4.[11] In averaging across countries (sectors), we weight by the the average relative workforce of each sector (country) in the whole period, so that two equal but opposite changes in two sectors result in a positive net contribution to the overall change, if the sector that grows is larger in size than the sector that shrinks.

To account for noise in our decompositions we deploy the exchangeable bootstrap of Chernozhukov et al. (2012) to construct resampled standard errors. This bootstrap approach resamples from all of the residuals from the model (both period 1 and 2) and allows them to be exchanged across time. We use 1,000 resamples to construct the standard errors. The main terms of our

[8]We also used the variable Polity2 (defined as the difference between democracy and autocracy scores) from Polity IV (Marshall et al., 2015) as an alternative to *Rule of law* given that the time coverage is much longer. Using Polity2 does not yield statistically different results than *Rule of law.* The results are not reported here, but are available upon request.

[9]A total of 12 observations, marked as outliers by the Billor et al. (2000) algorithm, were dropped at this stage.

[10]In general, the longer the time span, the smaller is the number of countries that can be included, with poorer economies particularly affected.

[11]The three terms in the decomposition, $\Delta\widetilde{(TEP)}^{cs}_{t,T}$, $\Delta\widetilde{(K/L)}^{cs}_{t,T}$, and $\Delta\widehat{(TFP)}^{cs}_{t,T}$, are obtained using the estimated $\widehat{m}^{cs}_T(\cdot)$ to compute the counterfactual $m^{cs}_T(k^{cs}_t)$ as the predicted labor productivity based on country c's time T *estimated* TEP and time t *observed* capital per worker.

decomposition, namely TEP and capital accumulation, appear to be statistically significant across countries and sectors.

An overall increase in labor productivity is in line with traditional expectations. This increase is mainly driven by capital accumulation (60%) and all countries except Kenya accumulate capital, relative to labor, across time. Estimated TEP grows by about 46% on average, while average TFP slightly decreases, by about 6%.

High variability amongst our estimates emerges across countries and sectors. For instance, average labor productivity growth for the Asian Tigers (South Korea and Singapore) is much larger than the average, and this increase is mainly driven by capital accumulation. This result is in line with Los and Timmer (2005), who do not account for the sectoral dimension, and Young (1995), who uses a lower number of manufacturing sectors, which should be expected given that their construction of TFP contains our measure of TEP. Growth rates well above the average are also documented for countries like Ireland and Japan, but in these cases the relative contribution of K/L and TEP is much more even. OECD countries and the Asian Tigers report increases in labor productivity slightly larger than in the US, with growth rates in sub-Saharan Africa and Latin America amounting to just 30% and 80% of the US growth rate, respectively. Interestingly, even though many countries are characterized by higher degrees of capital accumulation than the US, the estimated TEP growth rate of the US is among the highest in the sample. This provides support to the role of technological leader played by US manufacturing in the period under consideration. Moreover, both in the OECD (without the US) and in the Rest of World (RoW), as a whole, the TEP growth rate is lower than that of the US (bottom of Table 3).

More balanced growth patterns in terms of labor productivity emerge from the sectoral aggregation (Table 4). The leading sectors are energy (where capital accumulation does not seem to play an important role, and TEP seems to account for most of the labor productivity growth), manufacturing of machinery and transport equipment, as well as non-metallic mineral products. Considering the sources of labor productivity change, low skill sectors, such as Textiles, grow in K/L relatively more than in TEP, compared to other sectors, such as the Chemical industry in particular. Coke and petroleum refinement has the largest TEP, as well as the largest relative effect of technology with respect to K/L across all sectors. These results are consistent with conventional intuition.

A notable result of the decomposition is that the contribution of TFP is small on average, although it is quite large in some countries, such as Sweden and Australia, and industries, such as 'Machinery and equipment' and 'Motor vehicles, trailers, semi-trailers'. This implies that the contribution of the Hicks-neutral component of technical change is relatively small compared to the effect of technology change on labour productivity. Since isolating the relative contribution of Hicks-neutral technical change is not possible with standard, parametric techniques, this finding has no direct comparison in the literature and highlights the opportunity to devote more effort to understanding the extent to which conventional assumptions about the nature of technological progress are supported by the data.

It is worth stressing how a proper comparison of the decomposition results with the extant literature is hampered by the fact that we also allow for a sectoral dimension, which is mainly ignored elsewhere. For example, a table similar to our Table 3 is reported by Kumar and Russell (2002), who use country level data spanning from 1965 to 1990. The absence of the sectoral dimension probably helps to explain the larger role for capital accumulation which they find: 78% of the overall change in labor productivity, against our 60%. While we find technological growth to explain about 46% of labor productivity, they find the remaining 22% (of the growth in output per worker) to be distributed almost equally between efficiency and technology. Thus, their result concerning the role of technology is in stark contrast with ours. As well as the presence of a sectoral dimension in our analysis, the difference in estimation techniques and countries are also likely to influence the difference in findings. Similarly, Beaudry et al. (2005), using aggregate data, find the economic performance of countries to be explained by returns to capital accumulation. Since their approach does not allow the production function coefficients to differ across countries and sectors, compared to ours, those results could overestimate the role of capital accumulation with respect to that of technology.

It is also useful to compare our results with those obtained in a standard growth accounting exercise with a constant output-capital elasticity equal to 0.3 across all countries and industries. For our data, this implies a contribution of capital accumulation to labor productivity growth of 36%. Alternatively, one might use an Oaxaca-Blinder decomposition to compare the contribution of capital per worker to labor productivity growth across the two periods (the two groups consist of the same country-sector combinations observed in the two periods), on the one hand, and capital coefficient, on the other hand. This provides us with a quite different result, with a percentage weight of the capital-labor ratio amounting to 70%. Compared to these estimates, our estimated contribution of capital per worker lies in the middle. This provides cursory evidence that the assumption of time and sector-country homogeneity is not supported by the data.

Given that our decomposition relies only on the capital-labor ratio, one may question to what extent our estimated TEP term captures technological productivity effects that are distinct from human capital effects. As highlighted in Section 3.2, a feature of our nonparametric approach is the ability to estimate a country-sector and time specific production function. To the extent that country-sector and time specific heterogeneity in labor productivity is captured in our framework by the terms d^{cs} and d_t, the estimated TEP term encapsulates the action of any effect not occurring through the capital-labor ratio. One prominent effect is human capital. Indeed, while Ciccone and Papaionnaou (2009) find countries with higher initial education levels **to** experience faster value-added and employment growth in schooling-intensive industries in the 1980s and 1990s, at least part of these effects seem to occur through the interaction of educational attainment with the distance to the world technology frontier (i.e. distance to the country with the highest TFP). This effect, first found by Cameron et al. (2005), and also documented in Madsen (2014), is roughly in line with the world described by Nelson and Phelps (1966), in which "educated people make good innovators, so that education speeds the process of technological diffusion." In the absence of country by sector by time data on education attainment, however, we cannot definitively eliminate a potential impact of human capital on our estimated TEP, arising through a direct effect of human capital on labor productivity.

Lack of country-sector specific education data prevent us from directly recovering this effect and so an alternative approach is required.[12] Following Ciccone and Papaioannou (2009), we construct a country-sector human capital endowment variable by interacting the Cohen and Soto (2007) measure of education of each country in 1970 and 2005 with the industry schooling intensity of the US in 1980, drawn from IPUMS (2015).[13] Beyond assuming sectoral schooling intensity to be the same in all countries, we also have to assume, as in Ciccone and Papaioannou (2009), that industry intensity is constant over the years covered by the analysis. The result of this experiment, carried out on a sample of 38 countries (we lose 4 countries due to missing education data), is summarized in column (7) of Table 5. As expected, including human capital results in a lower relative weight of technology, compared to capital accumulation; this is a common occurrence in growth accounting exercises. However, even including human capital at the sectoral level, we still find a large and statistically significant TEP in overall labor productivity growth (25.8%). This suggests that, even with all the limits involved in our construction of human capital, most of the TEP component in our benchmark analysis is not due to the omission of human capital. Further, we view this smaller estimate of TEP's contribution as a lower bound on the overall effect of TEP on labor productivity growth.

5.2. **Robustness checks.** We assess the robustness of our primary decomposition estimates to a number of alternative strategies concerning the time frame, the data source, and the sectors used.[14] The These robustness checks appear in Table 5. To allow ease of comparison of our decomposition estimates across alternative setups, rather than present estimates by country or sector, we focus on the relative contributions of K/L and TEP.

We first address robustness with respect to alternative specifications of the time periods by splitting our sample into subperiods of 5 years, in column (1), and 10 years, in column (2). In this way, the global change investigated in the benchmark analysis is broken down into seven and

[12]We thank an anonymous referee for suggesting this exercise.

[13]In principle, IPUMS data on schooling intensity is also available for 2005. However, the two samples are not fully comparable.

[14]Since the decomposition with leader reported in Section 6 is formally equivalent to Equation (3), after re-scaling on US TEP and capital per worker, the robustness checks in this section also apply to the decomposition results of Section 6.

four subperiods, respectively. Since there is a trade-off between the number of subperiods and the number of country-sector combinations available, the number of observations fall to 230 in the first exercise and to 326 in the second. The relative weight of TEP growth shrinks to 32% in the 5-year case and to 26.23% in the 10-year case. The fact that these estimates are smaller than our initial results is intuitive, given the fact that changes in technology over smaller time windows have less time for both innovations to take place and technology to diffuse across countries.

In columns (3) and (4), we balance the data in such a way to have the same number and type of industries included for all countries.[15] In column (3) we limit the analysis to countries featuring non-missing observations in all 11 sectors. Since this induces a substantial drop in the number of observations, in column (4) we exclude the food sector in order to keep the number of countries as high as possible (20). Compared to our benchmark results, the contribution of technology is slightly higher in one case and slightly lower in the other. Arguably, this can be the consequence of dropping Sub-Saharan African countries, characterized by relatively low TEP growth in our original decomposition.

As noted above, our labor productivity and capital per worker variables are expressed at current prices, implying that changes over time are nominal, and as such, potentially overstated. While this is much less of an issue for the decomposition in gaps (where the only condition which has to hold is the absence of systematic deviations across time of input-output prices with respect to the US), the relative contribution of TEP to the overall variation in labor productivity estimated in Section 5.1 is likely to be understated, given that TEP is estimated in real terms.[16] In the absence of suitable country-sector deflators for a sufficiently large number of countries, we check the importance of this issue experimenting with the country-sectoral information at constant prices provided by the STAN - OECD database (see column 5). The amount of information suitable for our purposes consists of an unbalanced panel of 20 countries and 8 sectors over the period 1991-2009, corresponding to 130 observations in total. Even with this much smaller sample we still see that the percentage change of technology is only one percentage point lower than the benchmark case.

Finally, we address the fact that in the main estimation we avoid imposing theoretical restrictions on the production function.[17] Specifically, even though our nonparametric estimator is consistent without making functional form assumptions, it could be the case that the estimated production function is non-monotonic, violating basic axioms of production theory.[18] In column (6) we estimate

[15]We thank an anonymous referee for suggesting this robustness check.

[16]This consideration finds support in aggregate data. For instance, changes at constant prices in Penn World Table 8.0 sum to 147% for output and to 174% for capital. The corresponding numbers in our data are, respectively, 174% and 170%.

[17]We thank an anonymous referee for raising this issue.

[18]Concavity is also a standard assumption for a production function. However, other aspects, such as biased technical change, shift the $m(\cdot)$ function, which makes concavity in K/L (at fixed technology and human capital levels) difficult to impose/test.

the productivity growth decomposition using the benchmark data and time periods, imposing monotonicity of the production function, following the procedure of Du et al. (2013). We find very minor changes, with a 3% drop in the relative weight of technology.

Apart from the human capital augmented version, which follows a different theoretical specification, the relative weights of TEP and K/L provided by the various checks in Table 5 fall in a ±5% band around the benchmark results and, in particular, point to a contribution of technology to labor productivity growth amounting to roughly 37% on average, which is not qualitatively different from the 46% we initially found. Thus, taking into account the huge differences in time, country, and sector coverage, our benchmark estimates of the contributions of technology and capital accumulation to overall labor productivity growth prove to be quite robust.

6. Technology gaps and convergence

6.1. **Technology gaps.** We now turn our focus towards the evolution of the productivity gaps with respect to a benchmark country and estimate the decomposition illustrated in Equation (8). To this aim, we have to choose a benchmark estimated technology to compute the counterfactual $m_t^{*s}(k_t^{cs})$ and $m_T^{*s}(k_T^{cs})$, needed to obtain the gaps in K/L, TEP and TFP. We take the US as our comparison and the corresponding productivity gaps are reported in Table 6 by country.[19]

The 35.4% overall decrease in labor productivity gaps, which maps into slightly more than a 1% average annual reduction (considering a gap of 27 years from the end of our first period and the start of our second period), is consistent with the composition of our dataset, in which the majority of countries are either OECD nations or Asian tigers. As shown at the bottom of Table 6, the decrease in the labor productivity gap is in fact much more marked in the OECD. However, most of the variation is explained by capital accumulation, while the TEP gap increases slightly during the period under consideration. Strongly decreasing TEP gaps exist for Latin American countries (Colombia in particular). This is consistent with the findings of Crespi and Zuniga (2012), who show how innovation rates are higher in Latin America than in OECD countries, though confined to imitation, with Colombia being the leader of this group. The catching-up strategy of Asian countries is, as expected, strongly driven by K/L accumulation, particularly in South Korea and Singapore.

Coupled with the results obtained from our baseline decomposition, a key message that we can draw from Table 6 is that, even though large differences across countries exist, technological growth at the world level is pretty much driven by the leader. This is consistent with the theoretical literature cited in Section 2 and with the mechanisms of technology adoption and diffusion suggested by, among others, Desmet and Parente (2010), Comin et al. (2012), and Desmet and Rossi-Hansberg (2013).

[19]Productivity gaps by sector are available in Online Appendix B.

6.2. **Convergence of technology.** Graphical inspection of Figure 2, in which the growth rate of the TEP gap is plotted against the initial gap (i.e. period 1), seems to highlight a general process of technological catching-up. To more formally explore this potential relationship, we estimate standard and conditional cross-sectional convergence regressions in TEP, K/L and labor productivity. In our notation, the usual cross-section convergence framework is:

$$\ln(Z_T^{cs}/Z_{t0}^{cs}) = \alpha + \beta \ln Z_{t0}^{cs} + \gamma \ln \mathbf{X}_{t0}^{cs} + \varepsilon_T^{cs}, \tag{11}$$

where Z is the variable of interest (the TEP, K/L, or Y/L gaps), $\ln(Z_T^{cs}/Z_{t0}^{cs})$ is its growth rate between the initial period $t0$ (the average 1963-1972) and the final period T (the average 1998-2007), $\mathbf{X}$ is a vector of control variables, and ε_T^{cs} is an error term.

We are interested in understanding: i) whether technological convergence took place between the 1960s and the 2000s; ii) whether the usual growth determinants also play a role in the evolution of the cross-country technological gaps; iii) between K/L and TEP, which is the main driver of labor productivity convergence.

In Table 7 we use (11) to test for the presence of technological convergence by regressing the estimated growth rate of the TEP gap, $\ln(Z_T^{cs}/Z_{t0}^{cs}) = \Delta\widetilde{(TEP)gap}_{t0,T}^{cs}$, on its initial level, $Z_t^c = \widetilde{(TEP)gap}_{t0}^{cs}$, as well as on a number of control variables usually found to explain economic convergence (columns 3, 6, and 9).[20] In the same table, we contrast the results with those obtained from the analogous regressions for the labor productivity (columns 1, 4, and 7) and K/L gaps (columns 2, 5, and 8). Since the regressors are generated, we use bootstrapped standard errors to take into account this additional source of variability.[21]

We start with a simple convergence regression in which we include only sector-specific controls and the average levels of the respective gaps in the initial period (as proxies for initial conditions). In particular, we use the gap in Y/L, observed at time $t0$ (i.e. $\widetilde{(Y/L)gap}_{t0}^{cs}$) when investigating convergence in labor productivity, and the estimated gaps in K/L (i.e. $\widetilde{(K/L)gap}_{t0}^{cs}$) and TEP (i.e. $\widetilde{(TEP)gap}_{t0}^{cs}$) at time $t0$ when investigating convergence in K/L and TEP, respectively. These estimates, reported in columns (1) through (3), confirm the presence of convergence. Column (1), in particular, compares to Rodrik (2013) and Madsen and Timol (2011), notwithstanding the differences in terms of specification (we use gaps), time, and country coverage.

In columns (4) to (6), we add several fundamental determinants of economic growth: geographical distance to the US (*Geo Distance to US*), institutions (*Rule of Law*), and population density (*POP density*), together with a control for the growth rate of population amongst working age (15-64) individuals (Δ *POP 15-64*). Estimates for the labor productivity regression, in column (4), are mostly as expected, with the geographical distance to the technological frontier (the US)

[20]Different from usual growth regressions, we use gaps, instead of levels. Alternatively, one might use absolute terms and include the leader shift as an additional regressor.

[21]See Pagan (1984). We obtain qualitatively similar results using jackknife standard errors.

fostering labor productivity convergence through technology. This is consistent with theoretical work stressing the spatial dimension of the process of technology adoption/diffusion. For example, Desmet and Rossi-Hansberg (2013) suggest a model in which technology diffusion affects economic development because technology diffuses spatially and firms in each location produce using the best technology they have access to. Comin et al. (2012) propose a theory in which technology diffuses slower to locations that are farther away from adoption leaders and, moreover, the effect of distance vanishes over time.[22]

As for the other fundamental determinants of growth, column (5) is fully in line with column (4) concerning the role of population density and institutional quality. While these two variables have negative and significant effects in columns (5) and (6), they seem to be unimportant for TEP convergence. While the effect of population density on labor productivity seems to occur through capital accumulation, the effect of overall population on labor productivity seems to run mainly through convergence in technology.

Lastly, we add a number of policy variables which appear in columns (7) to (9): degree of financial development (*Financial Development*), number of patent applications per capita (*Patents*), average years of secondary schooling (*Avg yrs sec-school*), total FDI inflows (*Inward FDI*) and degree of trade openness with the leader (*Trade with US*). Different from the previous collection of variables, these new covariates possess country-sector variability. As expected, inclusion of these policy variables raises the explanatory power in the new regressions.[23]

The labor productivity estimates which appear in column (7) display the expected sign for financial development and for schooling, while FDI is found to increase the labor productivity gap through the TEP channel (see column 9). Moreover, once the control variables are added, proximity to the technological frontier is found to work against convergence in terms of capital accumulation. Different from other studies, in which patents are found to significantly affect labor productivity (see e.g. Madsen and Timol, 2011), we find no statistically significant effect for patents; this is also true for trade openness with the US.

The inclusion of both FDI and trade openness is designed to capture the idea that countries which have greater access to global markets should be able to acquire better technology. This is discussed, for instance, in Desmet and Parente (2010), who model the relationship between market size and technological upgrading, and in Alvarez et al. (2013), who provide a model in which the

[22]We tried to replace geographic distance with the measure of linguistic distance recently provided by CEPII, but it was never found to be statistically significant or to have a meaningful economic effect on growth. These estimates are available upon request.

[23]A number of other potential variables might be used for this exercise. However, as well as being beyond the scope of our current analysis, this would open the door to the classical growth regression issue of exchangeability (Durlauf, 2009). It is however worth noting that we obtain qualitatively similar results using private credit by deposit banks and other financial institutions and the deposit money bank assets ratio as measures of financial development, and using secondary and tertiary enrollment schooling data from Barro and Lee (2013).

flow of new ideas is the engine of growth and trade generates a selection effect by putting domestic producers in contact with the most efficient producers. These regressors are measured at their average value in the initial period; while this might result in lower explanatory power with respect to their construction using a time average, it helps to mitigate some concerns over endogeneity, even if it does not entirely rule out the possibility of omitted variables (Durlauf, 2009).

Trade with the technological leader is not found to be influential in any of the regressions and the amount of inward FDI, relative to GDP, is associated with increasing TEP gaps.[24] As expected, the degree of financial development is associated with decreasing labor productivity gaps. However, this effect is due to capital accumulation and not to technology, which is unaffected by this dimension.

Interestingly, among the variables considered, only education is found to help convergence through both capital accumulation and technology. This result is robust to switching from the proxy of average years of education of population aged > 25 to measures of secondary and tertiary enrollment drawn from Barro and Lee (2013). This finding also tallies with empirical studies at the country level, for instance Sala-i-Martin et al. (2004).

As a robustness check, we estimate a semiparametric version of the technological convergence regression in column (9), in order to account for the potential presence of nonlinearities in the relationship. With our sample size and the number of continuous covariates, a fully nonparametric analysis is likely to suffer from small sample biases, but a recent semiparametric approach proposed by Li et al. (2015), known as model average marginal regression (MAMAR), represents a useful compromise. This method, and the results of the estimation, are described in more detail in Online Appendix C. The MAMAR estimates confirm the presence of technological convergence across sectors.

To sum up, keeping all the limits of simple growth regressions in mind (see e.g. Durlauf, 2009 and Battisti et al. 2013), we find strong evidence of convergence in labor productivity, technology and capital accumulation in manufacturing industries between the 1960s and the 2000s. While Madsen and Timol (2011) and Rodrik (2013), in a country-sectoral analysis, document convergence in labor productivity, consistent with our findings, the result on technological convergence is in stark contrast with Bernard and Jones (1996b) and Kumar and Russell (2002). Among the usual growth determinants, only the proximity to the technological frontier and the size of the working age population are found to have a statistically significant effect on the process of technological catching-up. The former effect is in line with the recent literature building on Nelson and Phelps (1966); the latter might be associated with Jones' (2003) suggestion of "more people more ideas."

[24] In unreported analysis, we verified that even when total trade (not only with the US) is included it is never found to have a statistically or economically significant effect. We also tried to use outward FDI instead of inward flows and found a positive estimated coefficient in the K/L regression and no statistically significant effect in the TEP regression. Outward FDI, while not influencing TEP, acts against capital accumulation and consequently against convergence in labor productivity. These results are available upon request.

7. Conclusions

"How much of the convergence that we observe is due to convergence in technology versus convergence in capital-labor ratios?" This question, posed by Bernard and Jones (1996a), has so far received little attention, mostly because of the intrinsic difficulty of dealing with technology within the standard growth accounting framework.

In this paper we address the role played by technology, as compared to capital accumulation, as a potential factor of labour productivity growth in manufacturing and ask whether a process of technological convergence has been in force over the past several decades. To do so we introduce a counterfactual decomposition of aggregate labor productivity growth into growth of the capital-labor ratio (K/L), growth of technological productivity (TEP) and growth of total factor productivity (TFP). The key intuition for the advantage associated to moving from a standard parametric setup to our nonparametric framework is the ability to estimate technology as country, sector, and time specific. While this is a daunting task with standard productivity measures based on parametric approximations, recently developed nonparametric methods allow us to empirically implement the decomposition in such a way that the enitre contribution of technical change affecting the production function at the country-sector level is encapsulated by the TEP component, with the Hicks-neutral component (i.e. a shift in the production function common to all countries and sectors) isolated in the TFP term.

Applying the decomposition to data on 11 manufacturing industries, covering the period from the 1960s to the early 2000s, points to a balanced contribution of TEP and capital accumulation to labor productivity growth (as compared to Kumar and Russell, 2002 for example): 46% of labor productivity growth comes from TEP, on average, while average TFP slightly decreases, by about 6%. This result seems to contradict the conventional representation of technological change as a "shift" in the production function and highlights that putting more effort on the understanding of the extent to which the standard assumptions about the nature of technological progress are supported by the data would be worthwhile.

As expected, large differences across countries and across sectors, even within the same country. In particular, while the relative contribution of capital accumulation is substantially higher in the Asian Tigers (Singapore and South Korea), we find technological growth at the world level to be pretty much driven by the US.

In the second step we use our decomposition to focus on convergence of TEP gaps by considering the difference between the TEP growth in a given country-sector and the TEP growth in the US (i.e. technology leader), in the same sector.

The analysis of the gaps reveals an average reduction in the labour productivity gaps of -1% per year. While capital accumulation is responsible for most of this reduction in OECD countries as a whole, the general trend of catching up in K/L across Asian countries is particularly strong in South Korea. Strongly decreasing TEP gaps exist for Latin American countries.

We finally provide strong evidence of convergence in both capital accumulation and technology, as well as in labor productivity. Interestingly, among the usual growth determinants, only the proximity to the technological frontier and the increase in working age population are found to influence the process of technological catching-up significantly. Conventional results on the quality of the financial system and the quality of institutions reducing labor productivity gaps are exclusively driven by the process of capital accumulation. Geographical distance to the technological frontier (the US) exerts opposite effects on capital accumulation and technology growth, being associated with increasing K/L gaps and decreasing TEP gaps.

In conclusion, we mention several fruitful avenues to explore for future developments. First, it would be interesting to develop a theoretical explanation for the empirical phenomena that we have quantified. Second, our exercise is carried out starting from a production function in intensive form. An alternative growth accounting exercise, not in intensive form, in order to better address the role of labor (although this requires limiting the number of countries), would provide even more insight on the nature of technological change over time. Obtaining sector specific measures of human capital, and more formally extending our decomposition to more than a single continuous variable, would be useful additions as well. Lastly, and perhaps most importantly, a novel contribution would be to further disentangle skill-biased technical change from technology effects.

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Table 1. Descriptive statistics: average labor productivity, average capital per worker, and number of nonmissing observations by country.

COUNTRY	y	k	# nonmissing sectors
Australia	33858	140204	8
Austria	39503	60162	10
Belgium	57875	87771	6
Bolivia	7483	8636	7
Chile	23436	33517	9
Colombia	21798	20619	11
Cyprus	22469	36415	11
Denmark	38857	85146	11
Ecuador	26432	36979	11
Egypt	6157	25060	9
Fiji	8123	9442	7
Finland	42902	74635	11
France	55497	119992	8
Greece	28988	157349	8
Hungary	12858	34141	10
Indonesia	6123	35857	10
Iran	14236	22556	6
Ireland	56485	55126	8
Israel	24228	31993	10
Italy	40583	78876	11
Japan	65756	125258	11
Kenya	6031	6422	9
Kuwait	39000	169090	11
Malawi	3334	9178	6
Malaysia	31038	56180	11
Malta	14300	25375	10
Netherlands	44140	97962	10
New Zealand	16160	146646	6
Norway	36845	52631	10
Panama	10784	15642	7
Philippines	34900	36112	11
Poland	14721	22042	11
Portugal	20082	73445	11
South Korea	57502	102932	11
Singapore	43234	87279	10
Spain	27017	28454	7
Sweden	43812	112941	10
Tunisia	33676	452417	9
Turkey	45684	72383	11
United Kingdom	45163	60067	11
United Republic of Tanzania	5322	17300	5
United States of America	79694	86724	11
Total	-	-	391

TABLE 2. Descriptive statistics: average labor productivity, average capital per worker, and number of nonmissing observations by sector.

SECTOR	Abbreviation	y	k	# nonmissing countries
Food, beverages and tobacco	FD	25131	62952	35
Textiles, wearing apparel, leather products, footwear	TX	13910	21267	39
Wood products	WO	16543	23632	36
Paper and paper products, Printing and publishing	PP	24387	38296	40
Coke, refined petroleum products, nuclear fuel	PT	144337	479141	28
Chemicals and chemical products, Rubber and plastics products	CH	35748	59120	41
Non-metallic mineral products	NM	25221	46677	37
Basic metals, Fabricated metal products	MT	22672	44890	38
Machinery and equipment n.e.c.	MA	25193	40583	35
Motor vehicles, trailers, semi-trailers, other tr. eq.	TR	24699	45043	35
Furniture; manufacturing n.e.c.	OT	17559	28192	27
Total	-	-	-	391

TABLE 3. Decomposition results without leader country; 1963-1972 to 1998-2007 growth rates by country. $\Delta(Y/L)^c_{t,T}$, $\Delta\widetilde{(K/L)}^c_{t,T}$, $\Delta\widetilde{TEP}^c_{t,T}$, $\Delta\widehat{TFP}^c_{t,T}$ represent the country averages of the country-sector values of, respectively, the observed variation in labor productivity and the counterfactual changes in the capital-labor ratio, TEP, and TFP. In averaging across countries, we weight by the size of the average relative (to the country) workforce of each sector in the whole period.

COUNTRY	$\Delta(Y/L)^c_{t,T}$	Std.Err.	$\Delta\widetilde{(K/L)}^c_{t,T}$	Std.Err.	$\Delta\widetilde{TEP}^c_{t,T}$	Std.Err.	$\Delta\widehat{TFP}^c_{t,T}$	Std.Err.
Australia	2.119	0.232	1.586	0.157	1.307	0.165	-0.774	0.200
Austria	2.460	0.145	1.400	0.125	1.097	0.124	-0.037	0.138
Belgium	2.740	0.136	1.440	0.145	1.265	0.147	0.036	0.127
Bolivia	1.582	0.235	0.885	0.048	0.524	0.067	0.173	0.218
Chile	1.530	0.205	0.197	0.041	0.848	0.085	0.485	0.180
Colombia	1.928	0.338	0.135	0.023	1.163	0.101	0.631	0.255
Cyprus	2.210	0.192	0.860	0.055	0.707	0.082	0.642	0.170
Denmark	2.093	0.247	1.307	0.117	1.029	0.115	-0.243	0.231
Ecuador	1.681	0.202	1.328	0.084	0.700	0.085	-0.346	0.189
Egypt	1.537	0.609	0.813	0.054	0.564	0.094	0.160	0.543
Fiji	1.732	0.166	0.839	0.036	0.710	0.062	0.183	0.153
Finland	2.641	0.224	1.218	0.114	1.117	0.121	0.305	0.208
France	2.392	0.220	1.455	0.124	1.121	0.126	-0.183	0.206
Greece	2.684	0.222	1.279	0.101	0.877	0.102	0.529	0.206
Hungary	1.788	0.142	1.058	0.054	0.575	0.068	0.155	0.131
Indonesia	2.479	0.728	2.304	0.131	0.673	0.101	-0.498	0.643
Iran	1.881	0.209	1.219	0.062	0.575	0.069	0.087	0.195
Ireland	3.229	0.387	1.697	0.129	1.184	0.133	0.348	0.349
Israel	2.032	0.184	1.464	0.114	0.949	0.113	-0.381	0.173
Italy	2.222	0.131	1.274	0.119	1.063	0.121	-0.115	0.127
Japan	3.048	0.226	1.753	0.161	1.395	0.167	-0.099	0.196
Kenya	0.835	0.313	-0.293	0.021	0.945	0.103	0.183	0.276
Kuwait	1.466	0.175	0.585	0.092	1.171	0.074	-0.290	0.141
Malawi	1.535	0.709	1.567	0.097	0.427	0.148	-0.460	0.573
Malaysia	2.079	0.251	1.617	0.092	0.688	0.091	-0.226	0.235
Malta	2.723	0.217	1.954	0.099	0.799	0.095	-0.030	0.203
Netherlands	2.615	0.154	1.512	0.127	1.166	0.126	-0.064	0.149
New Zealand	2.036	0.320	0.238	0.265	1.545	0.313	0.253	0.188
Norway	2.489	0.220	1.287	0.116	1.054	0.116	0.148	0.206
Panama	0.937	0.232	0.923	0.073	0.551	0.081	-0.537	0.217
Philippines	1.506	0.254	0.970	0.051	0.586	0.075	-0.050	0.217
Poland	1.857	0.162	1.353	0.073	0.565	0.078	-0.060	0.149
Portugal	2.143	0.342	1.626	0.113	0.932	0.112	-0.415	0.320
Singapore	3.094	0.108	2.026	0.115	1.091	0.113	-0.024	0.105
South Korea	3.932	0.150	2.399	0.138	1.226	0.133	0.307	0.138
Spain	2.770	0.242	1.487	0.106	0.825	0.104	0.458	0.223
Sweden	2.145	0.168	1.280	0.143	1.240	0.143	-0.374	0.156
Tanzania	0.407	1.234	0.961	0.054	0.315	0.195	-0.869	1.060
Tunisia	1.603	0.352	0.972	0.055	0.529	0.067	0.103	0.325
Turkey	1.935	0.162	1.397	0.084	0.668	0.083	-0.130	0.152
United Kingdom	2.437	0.224	1.519	0.119	1.017	0.118	-0.099	0.210
United States	2.121	0.424	1.196	0.127	1.238	0.124	-0.313	0.390
OECD (w/o US)	2.582	-	1.528	-	1.157	-	-0.103	-
RoW	2.241	-	1.524	-	0.737	-	-0.020	-
wAVG	2.383	-	1.434	-	1.093	-	-0.144	-
% of $\Delta(Y/L)_{t,T}$	-	-	60%	-	46%	-	-6%	-

- OECD (w/o US) is computed using the average relative (to the whole sample) workforce of each OECD country in the whole period as weight, excluding the US.
- RoW is computed using the average relative (to the whole sample) workforce of each non-OECD country in the whole period as weight.
- wAVG (weighted average) is computed using the average relative (to the whole sample) workforce of each country in the whole period as weight.
- Std.Err.: Resampled standard errors with 1,000 replications (Chernozhukov, Fernández-Val and Melly, 2012).

TABLE 4. Decomposition results without leader country; 1963-1972 to 1998-2007 growth rates by sector. $\Delta(Y/L)^s_{t,T}$, $\Delta\widetilde{(K/L)}^s_{t,T}$, $\Delta\widetilde{TEP}^s_{t,T}$, $\Delta\widehat{TFP}^s_{t,T}$ represent the sectoral averages of the country-sector values of, respectively, the observed variation in labor productivity and the counterfactual changes in the capital-labor ratio, TEP, and TFP. In averaging across sectors, we weight by the size of the average relative (to the sector) workforce of each country in the whole period.

SECTOR	$\Delta(Y/L)^s_{t,T}$	Std.Err.	$\Delta\widetilde{(K/L)}^s_{t,T}$	Std.Err.	$\Delta\widetilde{TEP}^s_{t,T}$	Std.Err.	$\Delta\widehat{TFP}^s_{t,T}$	Std.Err.
FD	2.292	0.378	1.296	0.101	0.967	0.103	0.029	0.347
TX	2.228	0.187	1.546	0.081	0.761	0.081	-0.079	0.172
WO	2.305	0.220	1.444	0.082	0.750	0.087	0.112	0.194
PP	2.289	0.230	1.276	0.094	1.095	0.095	-0.083	0.214
PT	2.502	0.395	0.393	0.796	2.195	0.789	-0.086	0.358
CH	2.400	0.255	1.135	0.128	1.230	0.131	0.035	0.219
NM	2.528	0.150	1.298	0.108	1.066	0.109	0.165	0.139
MT	2.310	0.367	1.179	0.093	1.022	0.116	0.110	0.298
MA	2.533	0.147	1.763	0.093	1.354	0.088	-0.584	0.139
TR	2.558	0.212	1.605	0.066	1.361	0.074	-0.407	0.189
OT	2.282	0.325	1.507	0.096	0.704	0.091	0.071	0.300
wAVG	2.383	-	1.434	-	1.093	-	-0.144	-
% of $\Delta(Y/L)_{t,T}$	-	-	60%	-	46%	-	-6%	-

- wAVG (weighted average) is computed using the average relative (to the whole sample) workforce of each sector in the whole period as weight.
- Std.Err.: Resampled standard errors with 1,000 replications (Chernozhukov, Fernández-Val and Melly, 2012).

TABLE 5. Robustness Checks for the Decomposition. $\Delta\widetilde{(K/L)}^{cs}_{t,T}$ and $\Delta\widetilde{TEP}^{cs}_{t,T}$ are expressed in terms of share of the overall change in labor productivity.

	(1) 5 years avgs	(2) 10 years avgs	(3) Balanced sectors 1	(4) Balanced sectors 2
$\Delta\widetilde{(K/L)}^{cs}_{t,T}$	69.50%	72.46%	56.50%	59.17%
$\Delta\widetilde{TEP}^{cs}_{t,T}$	32.00%	26.23%	47.39%	44.07%
# Observations	230	326	176	200
# Periods	7	4	2	2
Countries	26	35	16	20
Sectors	11	11	11	10
Time span	1965 to 2010	1970 to 2010	(1963-72) vs (1998-2007)	(1963-72) vs (1998-2007)

	(5) STAN	(6) Monotonicity	(7) HC augmented
$\Delta\widetilde{(K/L)}^{cs}_{t,T}$	62.13%	67.52%	75.34%
$\Delta\widetilde{TEP}^{cs}_{t,T}$	38.16%	32.70%	25.84%
# Observations	130	391	349
# Periods	2	2	2
Countries	20	42	38
Sectors	8	11	11
Time span	1991 vs 2009	(1963-72) vs (1998-2007)	(1963-72) vs (1998-2007)

TABLE 6. Estimated gaps: 1963-1972 to 1998-2007 growth rates by country. $\Delta(Y/L)gap^{c}_{t,T}$, $\Delta\widetilde{(K/L)gap}^{c}_{t,T}$, $\Delta\widetilde{TEPgap}^{c}_{t,T}$ and $\Delta\widehat{TFPgap}^{c}_{t,T}$ represent the country averages of the country-sector values of, respectively, the observed variation in labor productivity gap and the counterfactual changes in the capital-labor ratio, TEP, and TFP gaps. Gaps are expressed with respect to the US (leader country). In averaging across countries, we weight by the size of the average relative (to the country) workforce of each sector in the whole period.

COUNTRY	$\Delta(Y/L)gap^{c}_{t,T}$	$\Delta\widetilde{(K/L)gap}^{c}_{t,T}$	$\Delta\widetilde{TEPgap}^{c}_{t,T}$	$\Delta\widehat{TFPgap}^{c}_{t,T}$
Australia	0.000	-0.592	0.071	0.521
Austria	-0.350	-0.159	-0.011	-0.180
Belgium	-0.617	-0.669	-0.038	0.090
Bolivia	0.560	0.622	0.000	-0.062
Chile	0.615	1.255	-0.151	-0.489
Colombia	0.217	1.156	-0.274	-0.664
Cyprus	-0.080	0.655	-0.138	-0.598
Denmark	0.042	0.049	0.001	-0.008
Ecuador	0.496	0.066	0.027	0.403
Egypt	0.630	0.786	-0.003	-0.153
Fiji	0.266	0.551	-0.049	-0.236
Finland	-0.546	0.082	-0.064	-0.563
France	-0.276	-0.088	0.006	-0.195
Greece	-0.492	0.228	-0.042	-0.677
Hungary	0.342	0.872	-0.036	-0.494
Indonesia	-0.333	-0.812	-0.027	0.505
Iran	0.220	0.577	-0.020	-0.337
Ireland	-1.052	-0.448	-0.026	-0.578
Israel	0.091	-0.095	0.019	0.168
Italy	-0.094	0.063	-0.021	-0.135
Japan	-0.914	-0.762	0.065	-0.217
Kenya	1.313	1.270	0.201	-0.159
Kuwait	0.717	0.337	0.122	0.258
Malawi	0.681	-0.112	0.154	0.639
Malaysia	0.070	0.120	0.018	-0.068
Malta	-0.580	-0.455	0.031	-0.156
Netherlands	-0.516	-0.239	-0.005	-0.273
New Zealand	0.130	0.447	0.125	-0.442
Norway	-0.396	-0.005	-0.020	-0.371
Panama	1.220	0.550	0.006	0.663
Philippines	0.653	0.721	0.025	-0.094
Poland	0.292	0.422	0.017	-0.147
Portugal	-0.027	-0.409	0.044	0.338
Singapore	-0.936	-0.406	0.014	-0.544
South Korea	-1.786	-1.167	-0.007	-0.612
Spain	-0.685	-0.345	0.017	-0.356
Sweden	-0.062	-0.027	-0.013	-0.022
Tanzania	1.818	0.580	0.188	1.050
Tunisia	0.540	0.699	0.021	-0.180
Turkey	0.205	0.163	0.008	0.034
United Kingdom	-0.308	-0.101	0.003	-0.211
United States	0.000	0.000	0.000	0.000
OECD	-0.458	-0.314	0.021	-0.165
RoW	-0.094	0.066	-0.011	-0.149
wAVG	-0.354	-0.206	0.012	-0.160

- OECD is computed using the average relative (to the whole sample) workforce of each OECD country in the whole period as weight.
- RoW is computed using the average relative (to the whole sample) workforce of each non-OECD country in the whole period as weight.
- wAVG (weighted average) is computed using the average relative (to the whole sample) workforce of each country in the whole period as weight.

TABLE 7. Convergence regressions following Equation (11).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	$\Delta(Y/L)gap$	$\Delta(\widetilde{K/L})gap$	$\Delta(\widetilde{TEP})gap$	$\Delta(Y/L)gap$	$\Delta(\widetilde{K/L})gap$	$\Delta(\widetilde{TEP})gap$	$\Delta(Y/L)gap$	$\Delta(\widetilde{K/L})gap$	$\Delta(\widetilde{TEP})gap$
$(Y/L)gap$ (t)	-0.088 (0.06)			-0.247*** (0.08)			-0.482*** (0.15)		
$(\widetilde{K/L})gap$ (t)		-0.605*** (0.08)			-0.811*** (0.10)			-0.882*** (0.12)	
$(\widetilde{TEP})gap$ (t)			-0.837*** (0.13)			-0.851*** (0.12)			-0.932*** (0.21)
ln *Geo Distance to US* (t)				0.239* (0.13)	-0.116 (0.10)	0.120*** (0.03)	0.180** (0.09)	-0.207* (0.12)	0.115*** (0.04)
ln *POP density* (t)				-0.173*** (0.02)	-0.111*** (0.03)	-0.000 (0.01)	-0.064*** (0.02)	0.012 (0.02)	-0.001 (0.01)
ln *Rule of law* (t)				-0.539*** (0.08)	-0.708*** (0.07)	0.014 (0.02)	-0.398*** (0.11)	-0.508*** (0.12)	0.027 (0.03)
Δ *POP 15-64*				-0.026*** (0.01)	-0.003 (0.01)	-0.006*** (0.00)	-0.051*** (0.01)	-0.013 (0.01)	-0.015*** (0.00)
ln *Financial development* (t)							-0.214*** (0.07)	-0.403*** (0.12)	0.023 (0.04)
ln *Inward FDI* (t)							0.116*** (0.04)	0.004 (0.04)	0.026*** (0.01)
ln *Trade with US* (t)							0.026 (0.03)	-0.000 (0.03)	0.010 (0.01)
ln *Patents* (t)							0.035 (0.03)	-0.033 (0.03)	-0.002 (0.01)
ln *Avg yrs school* (t)							-0.783*** (0.13)	-0.335*** (0.11)	-0.072*** (0.03)
N	380	380	380	357	357	357	234	234	234
R^2	0.132	0.388	0.379	0.386	0.596	0.444	0.612	0.716	0.473

Sectoral dummies included in all specifications. Bootstrapped standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

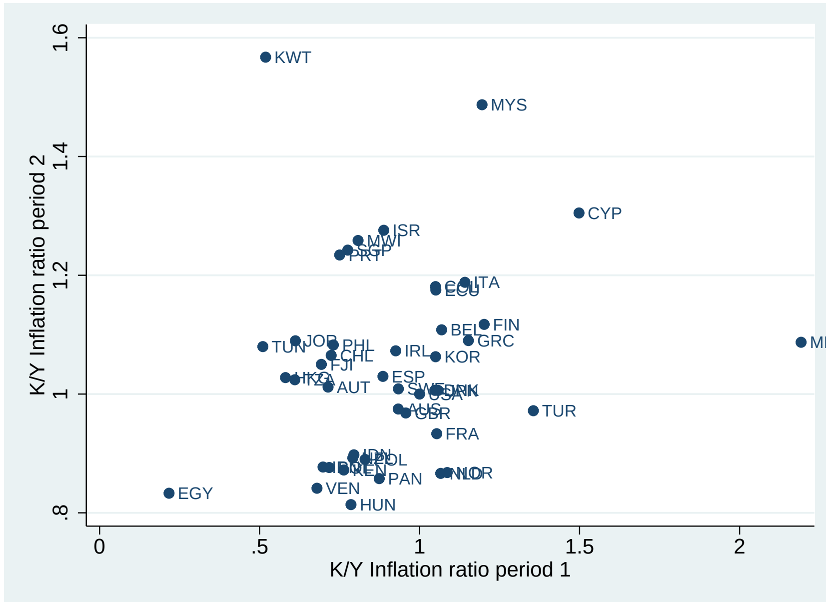

FIGURE 1. K/Y inflation ratios across periods (US in 2005 = 1).

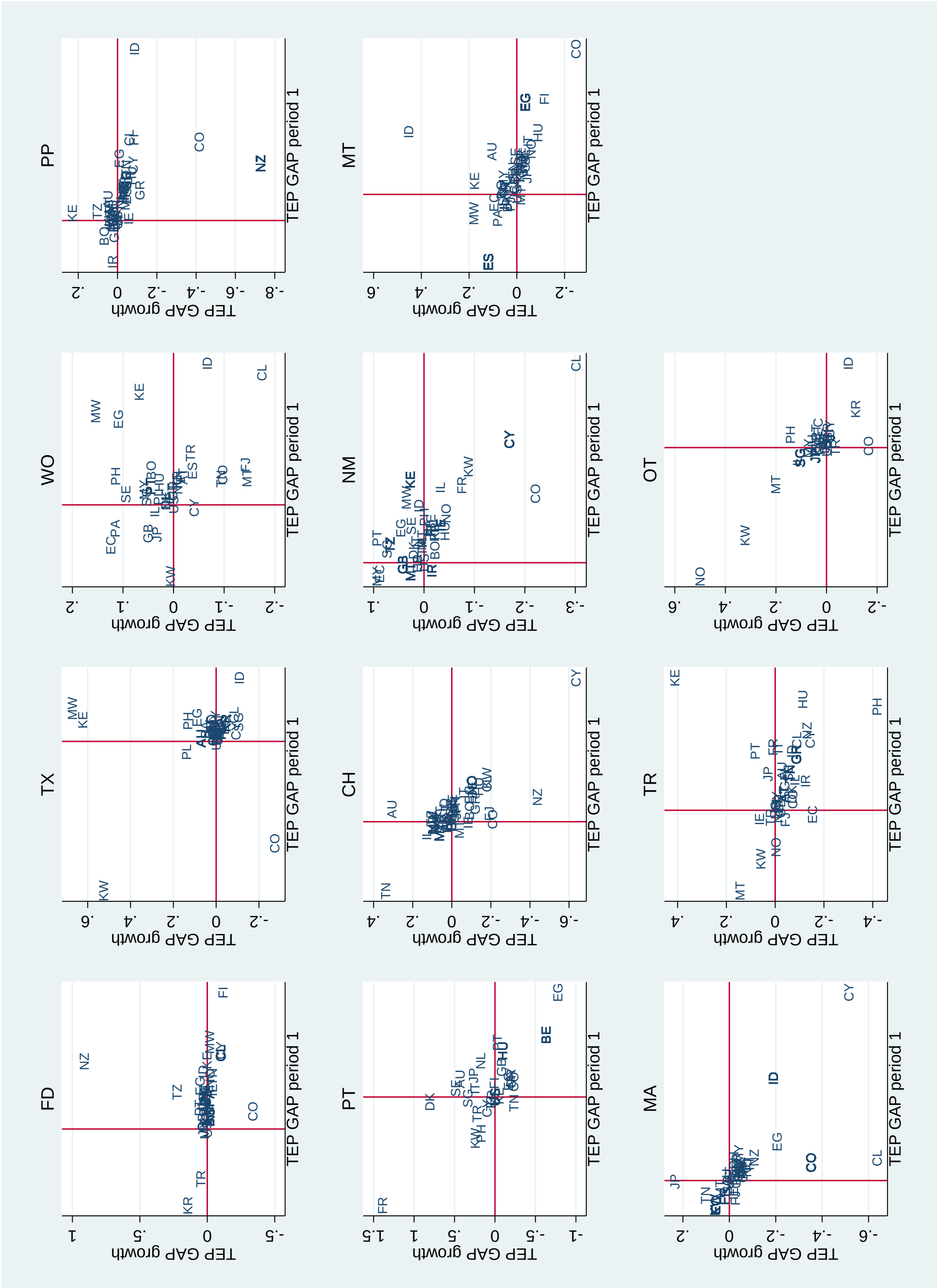

FIGURE 2. Estimated technological convergence.

Online Appendix A. Details on Generalized Kernel Estimation

To describe the estimation procedure in details, let us start with a standard nonparametric regression model

$$y_i = m(x_i) + \varepsilon_i, \qquad i = 1, \ldots, N. \tag{1}$$

in which $x_i = [x_i^C, x_i^D]$ makes the distinction between continuous variables and discrete variables. We can further decompose x_i^D as $[x_i^o, x_i^u]$ where x^o captures variables that are ordered by nature, and x^u captures variables that have no natural ordering. ε_i is a random error term and N is the total number of observations.

Estimation of (1) requires the construction of the product kernel, which is the product of univariate kernel functions (smoothing functions) for each variable. A different type of kernel function is used for each type of data (continuous, discrete ordered and discrete unordered). The product kernel is written succinctly as:

$$G_{i,x} = \prod_{s=1}^{q_C} K\left(x_{is}, x_s, h_s^C\right) \prod_{s=1}^{q_u} g^u\left(x_{is}^u, x_s^u, \lambda_s^u\right) \prod_{s=1}^{q_o} g^o\left(x_{is}^o, x_s^o, \lambda_s^o\right), \tag{2}$$

where q_C is the number of continuous covariates (in our example $q_C = 1$) and $K\left(x_{is}, x_s, h_s^C\right)$ is the kernel function used for continuous variables with bandwidth h_s^C, q_u is the number of unordered discrete regressors (in our example $q_u = 1$) with $g^u\left(x_{is}^u, x_s^u, \lambda_s^u\right)$ is the kernel function for a particular unordered discrete regressor with bandwidth λ_s^u and q_o is the total number of ordered discrete regressors with $g^o\left(x_{its}^o, x_s^o, \lambda_s^o\right)$ the kernel function for a particular ordered discrete regressors with bandwidth λ_s^o.

The product kernel is then used to construct point-specific weights which are then used to calculate a local average estimator. While many different local estimators can be deployed, they all generally have the form

$$\widehat{m}(x) = \sum_{i=1}^{N} y_i A_{ix}. \tag{3}$$

where A_{ix} is a function of the product kernel; different types of local estimators will produce different forms of A_{ix}. The estimator in Equation (3) is nothing more that a weighted average of output for observations that are close, where closeness is dictated exclusively through the bandwidths used in the construction of the estimator (see Li and Racine, 2007 and Henderson and Parmeter, 2015 for more intuition).

For the continuous regressor we choose the Gaussian kernel function

$$K\left(x_{is}^C, x_s^C, h_s^C\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x_{ix}^C - x_s^C}{h_s^C}\right)^2}; \tag{4}$$

where the bandwidth ranges from zero to infinity.

A variation of the Aitchison and Aitken (1976) kernel function for unordered categorical regressors is given as

$$g^u\left(x_{is}^u, x_s^u, \lambda_s^u\right) = \begin{cases} 1-\lambda_s^u & \text{if } x_{is}^u = x_s^u \\ \frac{\lambda_s^u}{d-1} & \text{otherwise} \end{cases}; \tag{5}$$

where the bandwidth is constrained to lie in the range $[0, (d-1)/d]$ and d is the number of unique values the unordered variable will take. For example, for the case where the unordered variable is a traditional 'dummy variable', the upper bound will be 0.50.

Finally, the Wang and Van Ryzin (1981) kernel function for ordered categorical regressors is given by

$$g^o\left(x_{is}^o, x_s^o, \lambda_s^o\right) = \begin{cases} 1-\lambda_s^o & \text{if } x_{is}^o = x_s^o \\ \frac{1-\lambda_s^o}{2}\left(\lambda_s^o\right)^{|x_{is}^o - x_s^o|} & \text{otherwise} \end{cases}, \tag{6}$$

where the bandwidth ranges from zero to unity.

To estimate the production function in the paper, we use a local-linear approximation which can be viewed as the equivalent of a local Taylor expansion at any point x^c. That is, for the relationship $y = m(x) + u$, we have data for $(y_1, x_1), (y_2, x_2), \ldots, (y_n, x_n)$ and as such, for each point x_i, we can take a linear Taylor approximation for the point x. From the discussion in the paper, x_i is meant as an observation which is indexed over country, sector and time.

To begin, we consider a Taylor expansion about x for observation i as (note the expansion is only for continuous covariates, x^C)

$$\begin{aligned} y_i &= m(x_i) + u_i \\ &\approx m(x) + (x_i - x)\beta(x) + u_i, \end{aligned}$$

where $(x_i - x)$ is a $1 \times q_C$ vector and $\beta(x)$ is the gradient (column) vector of dimension q_C. By ignoring the higher-order terms and treating $m(x)$ and $\beta(x)$ as parameters, we have

$$y_i = a + (x_i - x)b + u_i.$$

Minimizing a quadratic objective function with respect to a and b gives us

$$\begin{aligned} \widehat{\delta}(x) = \begin{pmatrix} \widehat{m}(x) \\ \widehat{\beta}(x) \end{pmatrix} &= \left[\sum_{i=1}^n G_{i,x} \begin{pmatrix} 1 \\ x_i - x \end{pmatrix} \begin{pmatrix} 1, & (x_i - x) \end{pmatrix}\right]^{-1} \sum_{i=1}^n G_{i,x} \begin{pmatrix} 1 \\ x_i - x \end{pmatrix} y_i \\ &= \left(\mathbf{X}' G(x) \mathbf{X}\right)^{-1} \mathbf{X}' G(x) y. \end{aligned}$$

where $\widehat{\delta} = (\widehat{a}, \widehat{b})$. $\mathbf{X}$ is a $n \times (1 + q_C)$ matrix with first column of all ones and the remaining columns equal to $x_i - x$. Lastly, $G(x)$ is the diagonal matrix with $G_{i,x}$ as its (i, i) element.

Nearly all theoretical work on nonparametric estimation points to the fact that use of a specific kernel weighting function has little impact on the overall performance of the estimator. However, the vector of bandwidths is viewed as the most crucial element. It is recommended that to avoid *ad hoc* selection of the bandwidths a data-driven or plug-in approach be used. A popular data-driven approach is least-squares cross-validation (LSCV). Specifically, LSCV selects bandwidths which minimize

$$CV\left(h, \lambda^o, \lambda^u\right) = \sum_{i=1}^{n} \left[y_i - \widehat{m}_{-i}(x_i)\right]^2, \tag{7}$$

where $\widehat{m}_{-i}(x_i)$ is the leave-one-out estimator of $m(\cdot)$. The idea of the leave-one-out estimator is that the conditional mean of y_i is estimated without using the observation with the most information, x_i. In this way the bandwidths are selected so that the surrounding observations are providing as much information as possible to assist with smoothing. LSCV is well known to produce bandwidths which are quite small relative to the theoretical optimum and as such, will produce estimates which are highly noisy.

An alternative selection mechanism is AIC_c bandwidth selection (Hurvich et al., 1998). The AIC_c criterion is

$$AIC_c(h) = \ln(\widehat{\sigma}^2) + \frac{1 + tr(\mathbf{H})/n}{1 - (tr(\mathbf{H}) + 2)/n}, \tag{8}$$

where

$$\widehat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^{n} \left[y_i - \widehat{m}(x_i)\right]^2 \quad \text{and} \quad \mathbf{H} = \left(\mathbf{X}' G(x) \mathbf{X}\right)^{-1} \mathbf{X}' G(x).$$

Notice that a leave-one-out estimator for $m(\cdot)$ is not used. This is because the AIC_c criterion penalizes overfitting based on the number of effective parameters used, which is captured by the trace of $\mathbf{H}$. As the bandwidths decrease (fit improves) this trace increases and leads to larger penalties. The empirical results in the paper are derived from bandwidths selected using the criterion in (8).

Online Appendix B. Estimated Gaps by Sector

Table 1. Estimated gaps: 1963-1972 to 1998-2007 growth rates by sector. $\Delta(Y/L)gap^s_{t,T}$, $\widetilde{\Delta(K/L)gap}^s_{t,T}$, $\Delta \widetilde{TEPgap}^s_{t,T}$ and $\Delta \widehat{TFPgap}^s_{t,T}$ represent the sectoral averages of the country-sector values of, respectively, the observed variation in labor productivity gap and the counterfactual changes in the capital-labor ratio, TEP, and TFP gaps. Gaps are expressed with respect to the US (leader country). In averaging across sectors, we weight by the size of the average relative (to the sector) workforce of each sector in the whole period.

SECTOR	$\Delta(Y/L)gap^s_{t,T}$	$\Delta(\widetilde{K/L)gap}^s_{t,T}$	$\Delta T\widetilde{EPgap}^s_{t,T}$	$\Delta T\widehat{FPgap}^s_{t,T}$
FD	-0.002	-0.333	0.030	0.302
TX	-0.131	-0.190	0.004	0.055
WO	-0.466	-0.620	0.014	0.141
PP	-0.773	-0.394	-0.022	-0.356
PT	0.751	0.423	0.143	0.185
CH	-0.268	-0.347	-0.005	0.084
NM	-0.508	-0.587	0.000	0.079
MT	-0.574	-0.653	-0.001	0.080
MA	-0.389	0.317	0.043	-0.749
TR	-0.575	0.190	-0.009	-0.756
OT	-0.340	-0.537	0.023	0.174
wAVG	-0.354	-0.206	0.012	-0.160

LEADER SHIFT	$\Delta(Y/L)^{*s}_{t,T}$	$\Delta\widetilde{(K/L)}^{*s}_{t,T}$	$\Delta\widetilde{TEP}^{*s}_{t,T}$	$\Delta\widehat{TFP}^{*s}_{t,T}$
FD	2.291	1.125	0.905	0.261
TX	2.124	0.780	1.379	-0.035
WO	1.967	0.829	0.924	0.214
PP	1.796	1.139	0.968	-0.310
PT	3.010	2.870	0.101	0.039
CH	2.204	1.391	0.717	0.096
NM	2.121	1.147	0.747	0.228
MT	1.900	0.991	0.742	0.167
MA	2.266	1.590	1.774	-1.099
TR	2.168	1.576	1.511	-0.919
OT	2.063	0.692	1.189	0.182
wAVG	2.121	1.238	1.196	-0.313

wAVG (weighted average) is computed using the average relative (to the whole sample) workforce of each sector in the whole period as weight.

Online Appendix C. Model Averaging Marginal Regression (MAMAR)

Li, Linton and Liu (2015) propose a weighted average additive nonparametric regression model which they term model averaging marginal regression (MAMAR). This technique is useful when there exist (potentially) many covariates. Rather than estimate a high dimensional nonparametric regression model, instead they estimate a series of univariate nonparametric regression models and then average across these individual estimates to construct a final estimate of the conditional mean.

Consider S different potential covariates, the MAMAR estimator estimates the individual one dimensional regressions, to obtain estimates, $\widehat{m}_s(x_{(s)})$ $(s = 1, 2, \ldots, S)$, where $x_{(s)}$ is the s^{th} covariate. The MAMAR estimator is then constructed as

$$\widehat{m}(x) = \sum_{s=1}^{S} \widehat{w}_s \widehat{m}_s(x_{(s)}), \tag{1}$$

where w_s is the weight assigned to the sth model. Define

$$\widehat{M} \equiv \begin{pmatrix} \widehat{m}_1(x_{(1),1}) & \cdots & \widehat{m}_S(x_{(S),1}) \\ \vdots & \vdots & \vdots \\ \widehat{m}_1(x_{(1),n}) & \cdots & \widehat{m}_S(x_{(S),n}) \end{pmatrix}, \tag{2}$$

$y \equiv (y_1, \cdots, y_n)'$, $w \equiv (w_1, \cdots, w_S)'$ and $x_{(s),j}$ is the j^{th} observation of the s^{th} covariate. The least-squares estimator for the weights is given by $\widehat{w} = (\widehat{M}'\widehat{M})^{-1}\widehat{M}'y$.

Given the linearity of $\widehat{m}(x_i)$ with regards to $\widehat{w}$, construction of model averaged gradients is also straightforward. We have

$$\widehat{\beta}(x_i) = \sum_{s=1}^{S} \widehat{w}_s \widehat{\beta}_s(x_{(s),i}), \tag{3}$$

where $\beta_s(x_{(s),i})$ is the gradient of the (kernel estimated) conditional mean function evaluated at the point $x_{(s),i}$.

Bandwidths can be selected for each individual regression using a data-driven approach, such as least-squares cross-validation or improved AIC selection. See Li et al. (2015) for more details on the MAMAR estimator.

In the exercise we estimate a series of one-dimensional nonparametric regression models and then average across these one-dimensional estimators to produce a final estimate. For each continuous covariate, we estimate the regression model also including dummy variables for both sector and OECD membership. Bandwidths are selected using least-squares cross-validation and the local-constant estimator is deployed. The approach of Li et al. (2015) produces weights for each of the models designed for optimal prediction and the weights are not required to sum to one, or be nonnegative.

Applying this estimator reveals that only the lagged TEP gap has a statistically significant and economically meaningful impact on technological convergence. More specifically, we find that out of the 234 observations, 211 of those observations have weighted gradient estimates for lagged TEP which are negative. The estimates range from -0.27 to 0.08, with an interquartile range of -0.055 to -0.014. Additionally, inward FDI and trade with the US received weights of 0, essentially removing them entirely from the model. The weights appear in Table 1. The remaining variables (Distance to the US, population density, rule of law, financial development, patents and years of education) have economically inconsequential effects. Thus, these semiparametric estimate point to the presence of convergence in technology. This process appears to be highly nonlinear and independent of many of the standard cross-country growth determinants which appear in this literature.

TABLE 1. Weights for MAMAR procedure.

Dependent Variable	Weight	Median Unweighted Effect	Median Weighted Effect
$\widetilde{(TEP)}gap$ (t)	0.393	-0.064	-0.025
ln *Geo Distance to US* (t)	0.912	0.000	0.000
ln *POP density* (t)	-0.261	0.001	-0.0004
ln *Rule of law* (t)	-0.012	-0.030	0.0004
Δ *POP 15-64*	0.104	-0.0003	-0.00003
ln *Financial development* (t)	0.265	-0.017	-0.004
ln *Inward FDI* (t)	0.000	0.000	0.000
ln *Trade with US* (t)	0.000	0.000	0.000
ln *Patents* (t)	-0.074	0.002	-0.0002
ln *Avg yrs school* (t)	-0.151	-0.005	-0.001