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Article

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Is the convergence of the manufacturing sector unconditional?

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Abstract

In *Unconditional Convergence*, Rodrik (2011b) documented that manufacturing industries exhibit unconditional convergence in labor productivity. We provide a novel semi-parametric specification for convergence equations and show that the speed of convergence varies systematically with country-specific characteristics. We consider the flexible smooth transition model with multiple transition variables, which allows each group to have distinct dynamics controlled by a linear combination of known variables. We found evidence that the laws of motion for industry productivity growth are different across countries, varying with political institutions. The speed of convergence also has a non-monotonic relationship with trade openness and education.

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Resumo

Em *Unconditional Convergence*, Rodrik (2011b), documentou que indústrias do setor de manufaturas possuem convergência incondicional da produtividade do trabalho. Neste artigo nós propomos um modelo semi-paramétrico para equações de convergência e mostramos que a velocidade de convergência muda sistematicamente com características específicas dos países estudados. Nós consideramos um modelo flexível de transição suave e com múltiplas variáveis de transição. Nós encontramos evidências que as leis do movimento para o crescimento na produtividade da indústria é diferente nos países.

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Palavras-chave: Convergência incondicional; Modelos semi-paramétricos; Crescimento

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1. Introduction

The rapid economic growth that emerging and developing economies experienced in the last decades, specially in the run-up to the global financial crisis of 2008–2009, gave a new life to the debate about economic convergence – i.e., whether poorer countries tend to grow faster than the richer ones, then converging in living standards. Discussions about the risk of decay of the supremacy of the U.S. and other advanced economies (Eichengreen, 2011; Subramanian, 2011), and the prospects of the developing world growth (O’Neill, 2011; Rodrik, 2011a) abound.

Rodrik (2011a,b) documented that manufacturing industries exhibit unconditional convergence in labor productivity. Differences between the results with country-level data and those obtained for industrial sectors can be associated to the process of technology dissemination and capital mobility. In particular, the results obtained by Rodrik (2011a,b) suggest that technology and capital spread easier across industrial sectors than across countries. Therefore, sectors are more likely to face similar steady-states than countries.

In this paper we bring evidence that speed of labor productivity convergence changes across countries, identifying key drivers of the convergence process. Our basic questions are: Can we identify a multiple regime dynamics in industry productivity growth across countries? Are country-specific features related to the industry productivity growth? In what magnitude? Using the same data set as Rodrik (2011a,b) – UNIDO’s INDSTAT 4, available for a wide range of countries –, we provide a novel semi-parametric specification for convergence equations and show that the speed of convergence varies systematically with country-specific characteristics.

We investigate whether unobserved heterogeneity in the convergence coefficient at the country level is associated with geographic conditions, trade openness, political institutions and education. In principle, these variables might affect the steady-state and the process of capital accumulation. Hence, the goal is to test if these variables change the convergence process, at the country level, on top of the mechanisms identified in Rodrik (2011a,b).

We consider the flexible smooth transition model with multiple groups and multiple transition variables proposed by Medeiros and Veiga (2005). This model allows that each group has distinct dynamics controlled by a linear combination of known variables. This specification is very flexible and nests several linear and nonlinear models and can be as well interpreted as a semi-parametric model.

We found evidence that the laws of motion for growth are different across countries and those with political institutions that are more permissive converge faster. Less democratic states grow at higher paces according to our estimates, a result that is compatible with those documented in Barro (1996, 1999). The speed of convergence also has a non-monotonic relationship with trade openness and education, suggesting faster convergence at the extremes. Differences across countries in the convergence coefficient is not only of statistical significance, but also economically meaningful. The lower and upper values of the estimated convergence coefficient are, respectively, -3.7% and -2.8% per year, which means that the half life to productivity convergence varies in a range of about 7 years (between 18 and 25 years). The mechanisms through which these elements affect convergence are beyond the scope of the paper but, in contrast to the results found in Rodrik (2011a,b), we found salient features at the country level that affect income and growth.

1.1. Literature

Whether income levels of poorer economies are growing more rapidly than richer economies is not only an important question in the literature of Development Economics, but it is also related with the issue of validating competing growth theories. In the neoclassical growth literature, unconditional convergence implies that there is only one steady state level of per capita income to which all economies approach, and conditional convergence implies that equilibrium differs by economy, and each particular economy approaches its own but unique per capita income equilibrium (Islam, 2003). There are numbers of works with different approaches showing evidences of conditional convergence (Mankiw et al., 1992; Islam, 1995). It is widely known, however, that empirical works have found to be hard to prove unconditional economic convergence when a broad and diversified sample of countries is considered (Islam, 2003; Durlauf et al., 2005).

Baumol (1986) shows that (unconditional) convergence of output per capita is observed among developed countries, but it is not shared by less developed economies, suggesting that there would exist “convergence clubs”. Indeed, a non-linear specification for the growth equation hold for a class of growth models, starting with Azariadis and Drazen (1990). Their model produces multiple locally stable steady states in per capita output. Cross-country growth behavior

in these models exhibits multiple regimes as countries associated with the same steady state obey a common linear regression. [Durlauf and Johnson \(1995\)](#) and [Sachs and Warner \(1995\)](#) divide a sample of develop and developing countries in groups based on country characteristics. They show that the laws of motion for growth within each subgroup are different: in growth regressions, the estimated coefficient on the initial level of GDP per capita (the convergence coefficient), although always negative, changes substantially, and is not statistically significant in all cases. More recently, [Canova \(2004\)](#) proposed a Bayesian procedure to examine the likelihood of convergence clubs in the distribution of income per capita. The break points are identified through the ordering of observations according to country characteristics, and this method allows him to identify clubs and estimate the convergence coefficient of each club. However, we still cannot assess *how* each of these variables are related to the converge coefficient.

In recent works, [Rodrik \(2011a,b\)](#) gave a new breath to the debate about convergence. His works suggest that we can find unconditional convergence if we look at industries instead of the whole economy. He documents evidence of unconditional convergence in 4-digit manufacturing industries for a large group of develop and developing countries over a period since 1990. Since unconditional convergence implies the existence of only one income per capita equilibrium level to be shared among all economies, is quite intuitive that it is true in sectors that face more external influence. [Rodrik \(2011a,b\)](#) presented evidence that the productivity growth of low-productivity industries is larger. He also suggests that the industry-level unconditional convergence is not uniform across manufacturing industries, i.e., the speed of convergence changes across industries. There would exist a hierarchy within manufacturing – the convergence would be most rapid in machinery and equipment and least rapid in textiles and clothing.

Many empirical attempts to identify different dynamics of growth across countries have been made ([Baumol, 1986](#); [Durlauf and Johnson, 1995](#); [Sachs and Warner, 1995](#); [Canova, 2004](#)). None of them allow us to assess how variables used to group countries with common growth dynamics are related to the growth dynamics itself. It is important, for example, to assess to what extent countries that adopt sound policies have been awarded with higher growth.

1.2. Our approach

Instead of splitting samples (as in [Baumol, 1986](#); [Durlauf and Johnson, 1995](#); [Sachs and Warner, 1995](#)), we will allow the convergence coefficient in equations describing labor productivity growth to vary across countries, and this variation will depend on geographic, political and educational indicators. We propose a semi-parametric approach to identify unobserved heterogeneity in the convergence coefficient through these indicators. We will consider the flexible smooth transition model with multiple groups (or time regimes) and multiple transition variables proposed by [Medeiros and Veiga \(2005\)](#). This model allows that each group has distinct dynamics controlled by a linear combination of known variables such as geographic, political and educational indicators.

There are at least two advantages of this approach in comparison with splitting samples approach: first, we do not need to choose *ad hoc* thresholds (as in [Sachs and Warner, 1995](#)), and second, by modeling the coefficient itself, we can assess how policy variables affect industry productivity growth and convergence.

The remainder of the paper is organized as follows. In Section 2, we present the data. In Section 3, we discuss the underlying specification, motivated by a model *a la* Solow, and make some first exercises with the data. Section 4 presents the estimation method, Section 5 discuss the results, and Section 6 concludes.

2. Data

Our industrial database is the same as in [Rodrik \(2011a,b\)](#). We use data from UNIDO's INDSTAT 4 database, which provides industrial statistics for a wide range of countries at the ISIC 4-digit level ([UNIDO, 2011](#)). These statistics cover a series of variables, including value added and employment, for up to 127 manufacturing industries per country. As in [Rodrik \(2011a,b\)](#), because of data availability we take 1990 as the starting point for the empirical work. To maximize the number of observations, we estimate pooled regressions using rolling 10-year distances (with 1990 as the starting date) for each industry data available. Our sample includes 127 industries, 49 countries and 8 periods (total of 13,296 observations).

Our educational indicator is years of schooling of the population over the age of 25 (the same as in [Glaeser et al., 2004](#)). Data is from [Barro and Lee's \(2013\)](#) Education Attainment Dataset. These variables are provided in 5-year intervals and the gaps are replaced by a linear interpolation. We also use the indicator of executive constraint (from Polity IV Data Series version 2010) and the economic openness indicator from the Penn World Table 7.0. These variables

are both provided in 1-year intervals. The indicator of executive constraint ranges from 1 (unlimited authority) to 7 (executive parity or subordination). The openness indicator is trade (exports plus imports) as a ratio of GDP.

We also use the vector of latitude and longitude of country's capital as a geographical indicator. Latitude and longitude are proxies for initial endowments, climate and exposition to natural disasters. Data is from the website <http://www.newstrackindia.com>.

The use of variables not from UNIDO's INDSTAT 4 database reduces the number of countries in our data set because these variables are missing for some countries. Trade openness reduces the number of countries to 48, and the number of observations to 13,265; the executive constraints indicator reduces the number of countries to 38, and the number of observations to 11,363; the years of schooling indicator reduces the number of countries to 43, and the number of observations to 12,499. Finally, the use of all the three indicators reduces the number of countries to 37, and the number of observations to 11,098. A list of countries in each group is presented in [Appendix A](#).

3. The underlying specification and a first look at data

Call v_{ijt} the log of nominal labor productivity (nominal value added per employee) in industry i , country j and year t . The growth of labor productivity in real terms, Δy_{ijt} , is given by $\Delta y_{ijt} = \Delta v_{ijt} - \pi_{ijt}$, where π_{ijt} is the increase in the industry-level deflator and the Δ before a variable denotes percent changes. Neoclassical growth equations are designed for country aggregates (GDP per capita, country's savings, population growth, among others). To undertake the task of estimating industrial productivity growth, we need to adapt them for such a task. [Rodrik \(2011b\)](#) assumed that the growth in labor productivity in industry is a function of the gap between industry's productivity and its potential (the frontier technology), so

$$\Delta y_{ij,t+1} = \beta(y_{ijt} - y_{it}^*) + D_j, \quad (1)$$

where Δy_{ijt} is labor productivity growth (measured in US dollars) over some period and D_j is a dummy variable that stands for all time- and industry-invariant country-specific factors. The convergence (or growth) coefficient we are interested in is β .

Assuming a common global U.S. dollar inflation for each individual industry, $\pi_{ijt} = \pi_{it} + \varepsilon_{ijt}$, and that dollar inflation rates are not systematically correlated with an industry's distance from the technological frontier allow us to express the growth of nominal labor productivity as follows:

$$\Delta v_{ij,t+1} = \beta y_{ijt} + (\pi_{it} - \beta y_{it}^*) + D_j + \varepsilon_{ijt}.$$

Re-arranging terms, we have the following estimating equation

$$\Delta v_{ij,t+1} = \beta y_{ijt} + D_{it} + D_j + \varepsilon_{ij,t+1}, \quad (2)$$

where D_{it} is a set of industry and period dummies.¹ The more negative is β within a subgroup of countries, the stronger the estimated convergence among them. Or, the larger β , the larger the estimated productivity growth given its initial level. [Rodrik \(2011b\)](#) estimated different versions of Eq. (2). [Rodrik \(2011b, p. 8\)](#) argues that a test for unconditional convergence consists of estimating this equation with no country dummies and check whether the estimated convergence coefficient is negative and statistically significant. [Tables 1 and 2](#) show the results. In [Table 2](#), we weight each observation ijt by the inverse of the sampling probability of country j , so each country is equally represented. Note in both tables that the convergence coefficient is negative and statistically significant in all specifications with no country dummies (columns (1)–(4)) and the result hardly changes with the inclusion of period and industry dummies. The estimated convergence coefficient seems to be even stronger in the weighted regressions (in the case with period and industry dummies, it is -0.023 in the non-weighted specification and -0.030 in the weighted specification).

We are interested in testing the existence of multiple regime dynamics in industrial productivity growth across countries. Therefore, the whole point in this paper is to allow the convergence β to vary. We estimate the following equation:

$$\Delta v_{ij,t+1} = \beta_j y_{ij,t} + D_i + D_t + \varepsilon_{ijt}. \quad (3)$$

¹ As noted in [Bernard and Durlauf \(1996\)](#), convergence coefficient estimated in equations like (5) may be biased, because it does not include the steady-state level of output (y^*). Is a caveat in our paper as well as in [Rodrik \(2011a,b\)](#).

Table 1
Pooled regressions – 10 year growth rates – 1990–2000 to 1997–2007.

	(1)	(2)	(3)	(4)	(5)
$\ln(\text{valempl})_{t-10}$	–0.020 (45.61)***	–0.019 (45.14)***	–0.023 (52.11)***	–0.022 (50.22)***	–0.066 (80.18)***
Constant	0.239 (52.74)***	0.210 (42.86)***	0.290 (18.10)***	0.199 (3.47)***	0.589 (11.81)***
Period Dummies	No	Yes	Yes	Yes	Yes
Industry Dummies	No	No	Yes	Yes	Yes
Period × Industry Dummies	No	No	No	Yes	Yes
Country Dummies	No	No	No	No	Yes
Observations	13,296	13,296	13,296	13,296	13,296
R-squared	0.14	0.19	0.25	0.29	0.59

Absolute value of *t* statistics in parentheses.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Table 2
Pooled regressions – 10 year growth rates – 1990 to 2007 – weighted (all countries with the same weight).

	(1)	(2)	(3)	(4)	(5)
$\ln(\text{valempl})_{t-10}$	(9) –0.024*** (0.00)	(10) –0.023*** (0.00)	(11) –0.030*** (0.00)	(13) –0.028*** (0.00)	(14) –0.073*** (0.00)
Constant	0.266*** (0.02)	0.243*** (0.02)	0.392*** (0.04)	0.318*** (0.02)	0.560*** (0.03)
Period Dummies	No	Yes	Yes	Yes	Yes
Industry Dummies	No	No	Yes	Yes	Yes
Period × Industry Dummies	No	No	No	Yes	Yes
Country Dummies	No	No	No	No	Yes
Observations	13,296	13,296	13,296	13,296	13,296
R-squared	0.12	0.17	0.28	0.39	0.68

Absolute value of *t* statistics in parentheses.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Note that we did not include country dummies. This way, our results are directly comparable to the findings in [Rodrik \(2011b\)](#). To reduce the computational cost especially in the semi-parametric specifications, from now on we give up using the interaction of industry and period dummies.²

[Fig. 1](#) shows the histogram of the estimated $\hat{\beta}_j$'s. In Panel A, we see the results of regression (3) with no dummies; in Panel B, period dummies are included; finally, in Panel C the equation has industry and period dummies. The $\hat{\beta}_j$'s histograms suggest that the dispersion of the convergence coefficient distribution should not be neglected. For the specification with no dummies, the standard deviation/mean ratio of the $\hat{\beta}_j$'s is 16.2%; in the case with only period dummies, this ratio is 15.3% and, with period and industries dummies, it is 12.3%. We performed Wald tests, in which the null hypothesis is that all countries have the same coefficient. In all three cases (models with no dummies, with only period dummies and with period and industry dummies) the null is rejected (*F*-statistics around 5000 for the first two cases, and of over 9000 for the last specification)³. Note also that in all the three cases, the estimated convergence

² We do not believe that it should be a source of concern. [Tables 1 and 2](#) suggest that, if we are already controlling for industry and period dummies, controlling for the interaction of these dummies causes a very small change in the point estimation and the standard errors of the convergence coefficient.

³ We should expect that the distribution of $\hat{\beta}_j$'s is more concentrated in specifications with period and industries dummies if part of the difference in the convergence coefficients across countries is due to the country-specific production structure.

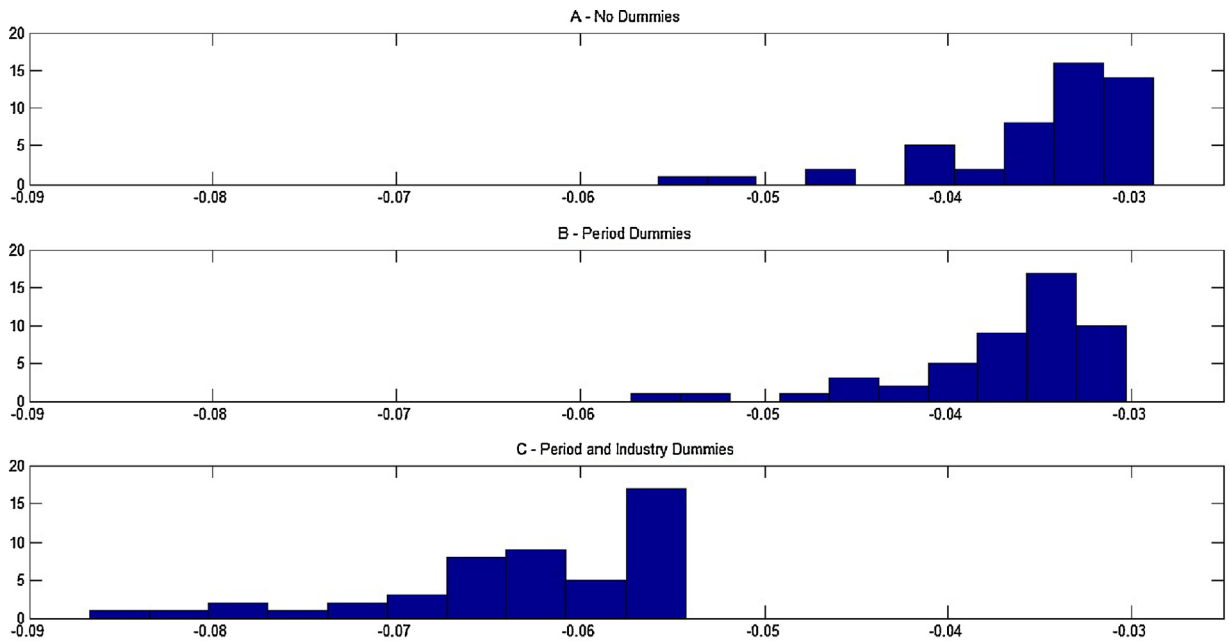


Fig. 1. $\hat{\beta}_j$'s histograms.

coefficients are larger (in absolute value) than the analog estimated coefficients in Eq. (2), shown in Table 1. Actually, they are much closer to the ones estimated in Eq. (2) where country dummies are included.

In a cross-country regression, the fact that the estimated $\hat{\beta}_j$ is typically negative derives from the empirically suggested fact that industry productivity countries with low industry productivity levels grow faster than the analog for countries with high industry productivity levels. This could be a sign unconditional convergence, i.e., that there is only one steady state level of industry i productivity across countries. But note that if β_j is different across countries, their steady-state levels of productivity are also different. To see that, consider a model with only one industry.⁴ Hence,

$$\Delta v_{j,t+1} = \alpha_{0t} + \beta_j y_{jt} + \varepsilon_{jt},$$

where $\alpha_{0t} = D_t + \pi_t$. In the steady-state, period effects vanish (i.e., $D_t = D$ and $\pi_t = \pi$), $\Delta v_{j,t+1} = \pi$ and y_{jt} equals the steady-state level y_j^* . We can then write

$$y_j^* = \frac{\pi - \alpha_0}{\beta_j}. \tag{4}$$

Therefore, if we can find variables that help us to group countries with the same β_j , we will also be identifying convergence clubs. To capture more accurately the relationship between the relative productivity growth β and country-specific indicators, we allow the convergence coefficient to also vary across decades. This way, we gain one more source of variation. We now estimate the following equation:

$$\Delta v_{ij,t+1} = \beta_{jt} y_{ij,t} + D_i + D_t + \varepsilon_{ijt}. \tag{5}$$

The exact way this equation is estimated is shown in Appendix A. Table 3 shows the results of the linear regression of $\hat{\beta}_{jt}$'s (estimated in the equation with industry and period dummies) on various indicators, measured as its decadal initial level. We estimate:

$$\hat{\beta}_{jt} = \gamma_0 + \mathbf{F}' \mathbf{INDIC}_t + \zeta_t, \tag{6}$$

⁴ Multi-industry analysis is similar, we should just condition on industry dummies.

Table 3
 $\hat{\beta}_{jt}$'s and selected variables in the first year of the decade (t_0). Estimated coefficients are multiplied by 100.

	(1)	(2)	(3)	(4)
Latitude	0.569 (7.50)***	0.241 (3.14)***	0.109 (1.25)	0.103 (1.18)
Longitude	0.010 (0.15)	0.095 (1.75)*	0.048 (0.86)	0.073 (1.43)
Openness, t_0	0.084 (2.02)**			0.061 (1.42)
Executive Constraint, t_0		0.201 (2.60)**		0.168 (1.49)
Years of Schooling, t_0			0.237 (2.81)***	0.328 (3.76)***
Constant	-6.221 (85.59)***	-5.889 (94.68)***	-5.924 (83.83)***	-5.991 (70.63)***
Observations	152	121	135	116
R-squared	0.28	0.24	0.14	0.34

Absolute value of t statistics in parentheses.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

where *INDIC* is a combination the following country indicators: latitude, longitude, trade openness, executive constraints and years of schooling. Eight overlapping different decades are covered (1990–2000 through 1997–2007) so that each country enters the data (a maximum of) eight times.⁵

Linear regressions indicate that a more educated population in the beginning of the period is associated with a large industry productivity growth. One standard deviation of years of schooling is related to an increase in the convergence coefficient of 0.002–0.003, depending on the covariates considered. Once the standard deviation of $\hat{\beta}_{jt}$ is 0.0069 for the model with industry and period dummies, the magnitude of the estimated relation between years of schooling and the convergence coefficient is relevant. Note also that the R^2 of regressions that involve years of education are larger than the ones that do not involve this education indicator.

The relationship between β and trade openness and executive constraints seems to be of less importance. The positive (even though not always statistically significant) coefficient on trade openness indicates that countries with large participation of international trade as a ratio of GDP also faced a large relative productivity growth. This result is quite intuitive, and is in line with studies that relate trade liberalization with productivity gains in industry (for instance, [Pavcnic, 2002](#) for the Chilean case and [Tybout \(2000\)](#) for the Mexican case).

The estimated relationship between the executive constraint and the relative productivity growth, although positive when we take only this variable as regressor (column (2) in [Table 3](#)), is not always statistically significant when trade openness and years of education are also taken into consideration. This result is in line with the findings in [Glaeser et al. \(2004\)](#). The main goal of their work is to assess whether political institutions cause economic growth and the results indicate that poor countries get out of poverty through good policies, often pursued by dictators.

4. Estimation method

We have presented evidence that the convergence coefficient changes across countries. We have also presented evidence that the time and country-variant convergence coefficient is correlated with some variables. Therefore, the convergence equation we are interested in is (5)

$$\Delta v_{ij,t+1} = \beta_{jt} y_{ij,t} + D_i + D_t + \varepsilon_{ijt},$$

where

$$\beta_{jt} = \lambda_0 + f(z_{jt}; \eta). \tag{7}$$

⁵ Note that standard errors reported in [Table 3](#) do not take into account the variance of the estimated β_{jt} 's from the first step equation (5).

In the above equation, z_{jt} is a q -dimensional vector of institutional and policy country-specific variables, η is a vector of parameters of limited dimension and $f(\cdot; \cdot)$ is an unknown function. Hence, the model can be rewritten as

$$\Delta v_{ij,t+1} = (\lambda_0 + f(z_{jt}; \eta))y_{ij,t} + D_i + D_t + \varepsilon_{ijt}. \tag{8}$$

Because there is no economic theory linking these variables to the country and time-specific speed of convergence β_{jt} , the functional form $f(\cdot; \cdot)$ is not known. We advocate here the use of a semi-parametric approach based on series (sieves) expansion to approximate the unknown function in Eq. (8) by

$$t(z_j; \psi_N) = \left\{ \sum_{m=1}^{M_N} \lambda_m G(z_j; \omega_m, c_m) \right\}, \tag{9}$$

where $\psi_N = (\lambda'_N, \eta'_N)' \in \mathbb{R}^{1+M_N*(2+q)}$, $\lambda_N = \{\lambda_m\}_{m=0}^{M_N} \in \mathbb{R}^{M_N+1}$, $\eta_N = \{\omega_m, c_m\}_{m=1}^{M_N} \in \mathbb{R}^{M_N*(1+q)}$, $\omega_m = (\omega_{1m}, \dots, \omega_{qm})' \in \mathbb{R}^q$ and $c_m \in \mathbb{R}$, $m = 1, \dots, M_N$ are parameters to be estimated,

$$G(z_j; \omega_m, c_m) = \frac{1}{1 + e^{-(\omega'_m z_j - c_m)}}, \tag{10}$$

and $|\alpha_o| < \infty$, $|\alpha_m| < \infty$, $|c_m| < \infty$, and $\|\omega_m\| < \infty$, $m = 1, \dots, M_N$. The function $G(\cdot; \cdot)$ is called the sieve function. Note that $f(\cdot; \cdot)$ is approximated by a series of logistic sieve functions. This is known in the literature as Neural Network (NN) approximation; see, for example, [Chen and Shen \(1998\)](#), [Chen \(2007\)](#), and [Grenander \(1981\)](#).

As noted in [McAleer et al. \(2008\)](#) and [Medeiros et al. \(2008\)](#), most of the recent applied papers concerning NN models have advocated the “black-box” nature of such kind of specifications, claiming that, due to their “universal approximation” capability, NN models are very flexible and are able to approximate very accurately a vast number of nonlinear mappings. In fact, NNs may be viewed as a kind of smooth transition regression ([van Dijk et al., 2002](#)), where the transition variable is an unknown linear combination of the explanatory variables. In this case there is an optimal number of logistic terms in (9), M , that can be translated as the number of limiting regimes (M is fixed); see, for example, [Trapletti et al. \(2000\)](#), [Medeiros and Veiga \(2000, 2005\)](#), [Medeiros et al. \(2006\)](#), and [Medeiros et al. \(2008\)](#) for similar interpretations.

On the other hand, when M is large enough, the NN model is an “universal approximator” to any Borel-measurable function over a compact set, and a nonparametric interpretation should be advocated. The number of logistic terms (sieves) increases with the sample size and NN models can be seen as the sieve-approximator of [Grenander \(1981\)](#). [Hornik et al. \(1994\)](#), [Chen and Shen \(1998\)](#), and [Chen and White \(1998\)](#) provide the technical details.

$\psi_N = (\lambda_N, \eta_N) \in \mathbb{R}^r$, $r = 1 + M_N * (q + 2)$, is the vector of all parameters of the model in Eq. (8). We advocate the parametric estimation of NN models by making use of the following assumption about the data generating mechanism:

Assumption 1. There exists a finite constant $M_o \in \mathbb{N}$ and a unique set of parameters $\psi_o = (\lambda_0, \dots, \lambda_{M_o}, \eta_o)$ such that

$$\Delta v_{ij,t+1} = \beta_{jt}y_{ij,t} + D_i + D_t + \varepsilon_{ijt} = (\lambda_0 + f(z_{jt}; \eta_o))y_{ij,t} + D_i + D_t + \varepsilon_{ijt},$$

where

$$f(z_j; \psi_o) = \left\{ \sum_{m=1}^{M_o} \lambda_m G(z_j; \omega_m, c_m) \right\}. \tag{11}$$

Under [Assumption 1](#), if $\mathbb{E}[\varepsilon_{ijt} | z_{jt}, y_{ij,t}, D_i, D_t] = 0$, there exist a NN model that can actually correctly approximate the true model when the number of observations goes to infinity. In this case, quasi-maximum likelihood estimators (QMLE) delivery consistent estimators for ψ . The “true” vector of parameters ψ depends on the number of logistic terms M . When NN models are interpreted as semi-parametric devices, M must grow with the sample size. Here, we suppose that there exists one finite number M_o such that the “true” data generating mechanism can be approximated arbitrarily well (see [McAleer et al., 2008](#)).

Assumption 2. The $(r \times 1)$ parameter vector ψ_o is an interior point of the compact parameter space Ψ which is a subspace of $\mathbb{R}^r \times \mathbb{R}^1$, the r -dimensional Euclidean space.

Assumption 3. The parameters satisfy the conditions $c_1 \leq \dots \leq c_{M_N}$, and $\omega_{qm} > 0 \forall q$ and m .

Assumption 4. The model given by Eqs. (8)–(10) has no irrelevant nonlinear terms.

Assumptions 3 and 4 guarantees the global identifiability of the model.

Call N the number of countries and industry units (i.e., there are N combinations of i and j , so that we can refer to the pair (i, j) as the unit $n, n = 1, \dots, N$). Call T the number of fixed time periods. Each unit n is observed a maximum of eight times, from 2000 to 2007. Let the quasi-likelihood function evaluated at an arbitrary parameter ψ be given as

$$\mathcal{L}_N(\psi) = \frac{1}{N} \sum_{n=1}^N \ell_n(\psi) = \frac{1}{N} \sum_{n=1}^N \left\{ -\frac{1}{2} \ln(2\pi) - \frac{1}{2} \ln(\sigma_n) - \frac{1}{2} \frac{\varepsilon_n^2}{\sigma_n} \right\}.$$

Define the QMLE as

$$\hat{\psi}_N = \arg \max_{\psi \in \Psi} \mathcal{L}_N(\psi) = \arg \max_{\psi \in \Psi} \frac{1}{N} \sum_{n=1}^N \ell_n(\psi).$$

In order to establish the asymptotic normality result, we introduce the following matrices:

$$A(\psi_o) = \mathbb{E} \left[-\frac{\partial^2 \ell_n(\psi)}{\partial \psi \partial \psi'} \Big|_{\psi_o} \right], \quad B(\psi_o) = \mathbb{E} \left[\frac{\partial \ell_n(\psi)}{\partial \psi} \frac{\partial \ell_n(\psi)}{\partial \psi'} \Big|_{\psi_o} \right].$$

Proposition 1. Under Assumptions 1–4, the QMLE $\hat{\psi}$ is almost surely consistent for ψ_o and

$$N^{1/2}(\hat{\psi}_N - \psi_o) \xrightarrow{d} N(0, \Omega_o), \tag{12}$$

where $\Omega_o = A(\psi_o)^{-1} B(\psi_o) A(\psi_o)^{-1}$.

Proof. The strategy of the proof is similar to the ones in McAleer et al. (2008) and Medeiros et al. (2008), making appropriate adaptations to our model. To prove consistency we use White (1994), Theorem 3.5, showing that the assumptions stated therein are fulfilled. Assumptions 2.1 and 2.3 in White (1994), related to the probability space and to the density functions, are trivially fulfilled under our Assumption 2. Assumption 3.1 in White (1994), related to the existence and continuity of $\mathbb{E}[\ell_n(\psi)]$ and is satisfied by our Assumption 1. Assumption 3.2 in White (1994) is satisfied by our Assumptions 3 and 4, and can also be shown to be related to the negative definiteness of $B_N(\psi)$.

To prove asymptotically normality of the QMLE we follow McAleer et al. (2008, Theorem 2). We need the following conditions in addition to those to proof consistency (see also White (1994, p. 92)): (1) The true parameter vector ψ_o is interior to Ψ ; (2) the matrix $A_N(\psi)$ exists and is continuous in Ψ ; (3) $A_N(\psi) \xrightarrow{p} A(\psi)$ for all ψ in Ψ ; (4) the score vector satisfies

$$\frac{1}{N} \sum_{i=1}^N \left[\frac{\partial \ell_i(\psi)}{\partial \psi} \Big|_{\psi_o} \right] \xrightarrow{d} N[\mathbf{0}, B(\psi_o)], \tag{13}$$

where $B(\psi_o)$ is positive definite.

Condition (1) is satisfied by our Assumption 2. Condition (2) follows from the fact that ℓ_n is differentiable of order two on $\psi \in \Psi$ under Assumption 1. Condition (3) is also trivial to verify. Finally, standard application of the Central Limit Theorem guarantees that Condition (8) holds.

In applications, the number of sieves is unknown and should be determined from the data. One popular solution is to estimate R models, with $M_N = 0, \dots, R$, for R sufficiently large, and choose the optimal M_N^* based on the use of model selection criteria (MSC) or cross-validation. In this paper we fix $R = 5$ and advocate the use of the Schwarz Bayesian Information Criterion (SBIC) to determine the number of sieves.

Table 4

Country-and-year mean partial effects. Industry productivity growth regressions: 10-year growth rates. Dependent variable: growth rate of labor productivity over relevant period. Estimated coefficients and standard values are multiplied by 100.

	(1)	(2)	(3)	(4)
Latitude	0.247 (0.04)***	0.172 (0.35)	−0.033 (0.06)	0.070 (0.05)
Longitude	−0.026 (0.02)	0.095 (0.22)	−0.080 (0.10)	−0.035 (0.05)
Openness	−0.020 (0.07)			0.072 (0.02)***
Executive Constraint		0.319 (0.22)		0.147 (0.07)**
Years of Schooling			0.263 (0.04)***	0.182 (0.08)**
Number of Sieves	5	5	5	5
Number of Observations	13,265	11,363	12,499	11,098
R-squared (underlying regression)	0.34	0.38	0.42	0.41

Standard deviations in parenthesis based on Monte Carlo simulations (1000 repetitions).

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

5. Results

Our main target is to explain the differences in β_{jt} defined in Eq. (3) by institutional and policy variables. Because there is no economic theory linking these variables to the relative productivity growth β_{jt} , we use NN models, taking advantage of their “universal approximation” capability.

Table 4 presents the country-and-year mean partial effects of latitude, longitude, trade openness, years of schooling and executive constraints on the relative productivity growth. These values are the partial effects of one standard deviation increase in these variables on the estimated convergence coefficient. Under Assumption 1, the partial effect of variable z_q on convergence coefficient is

$$\frac{\partial \beta_{jt}}{\partial z_{jq}}(z_j; \psi) = \sum_{m=1}^{M_N} \lambda_m \omega_{qm} [G(z_j; \omega_m, c_m) (1 - G(z_j; \omega_m, c_m))].$$

We can estimate the parameters that govern the distribution of parameters ψ (Eq. (12)). It allows us undertake Monte Carlo experiments and compute means and standard deviations of the mean partial effects, which are reported in Table 4. Table 4 is the semi-parametric analog of Table 3. Indeed, note that the point estimates are similar. In the more complete specifications in column (4), Table 3, the estimated mean partial effects of trade openness, executive constraint and years of schooling are, respectively, 0.061, 0.168 and 0.328; in Table 4, the corresponding mean partial effects are 0.072, 0.147, 0.182. In our more complete specification in Eq. (4), trade openness, executive constraints and years of schooling are statistical significant. However, as opposed to years of schooling, the statistical significance of the partial effect of latitude, longitude, trade openness and executive constraints does not seem to be robust. Depending on which variables are considered in the model, and which dummies are included, the standard deviation of the point estimates of the mean partial effects of these variables can be high.⁶

Figs. 2 and 3 help us understand this. Let us first focus on Fig. 2. Each panel in Fig. 2 plots the mean (across Monte Carlo simulations) of the mean (across observed countries and years) values of β'_{jt} s as a function of observed values of normalized (zero mean, variance one) values of trade openness (Panel A), executive constraints (Panel B) and years of schooling (Panel C) measured by the model with latitude, longitude, openness, executive constraints, years of

⁶ See in Appendix C the versions of Tables 4 and 3 in exercises where the convergence coefficient is estimated in an equation with no dummies and with only period dummies.

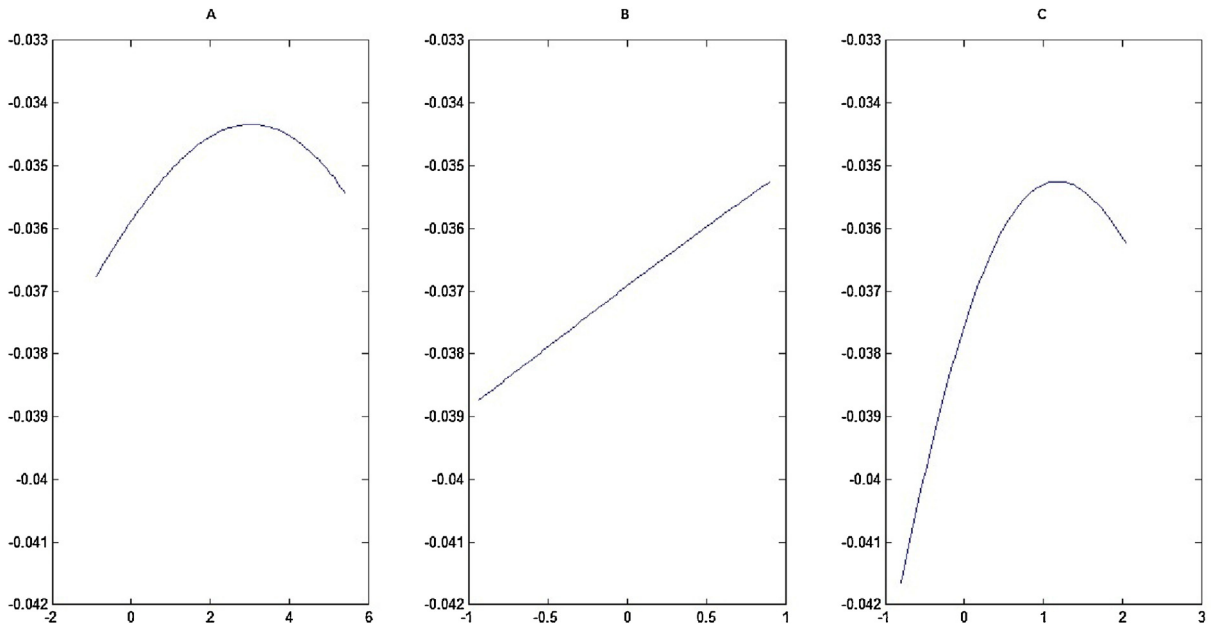


Fig. 2. β_{jt} and normalized (zero mean, variance one) values of openness (Panel A), executive constraints (Panel B) and years of schooling (Panel C) measured by the model with latitude, longitude, openness, executive constraints, years of schooling and period and industry dummies.

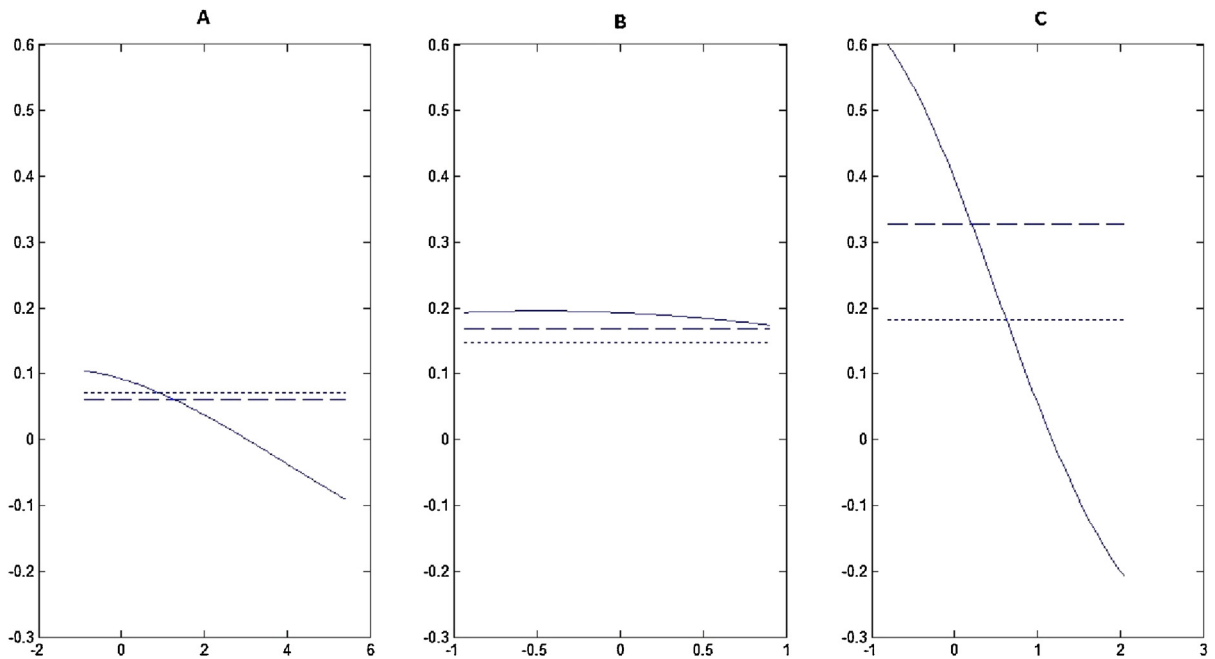


Fig. 3. Partial effects and normalized (zero mean, variance one) values of openness (Panel A), executive constraints (Panel B) and years of schooling (Panel C) measured by the model with latitude, longitude, openness, executive constraints, years of schooling and period and industry dummies. The dashed line is the partial effect of variables in the semi-parametric model and the dotted line is the partial effect as measured in the linear model.

schooling and period and industry dummies. In Panel A, for example, we change the values trade openness along the observed range and check how β_{jt} changes, keeping all other variables fixed in their sample mean.

Panel A indicates that, up to a certain point, opening the economy to foreign trade makes the relative productivity growth increase. But results suggest that, when trade openness is high, everything else constant, additional opening reduces growth. The statistical non-significance of trade openness in Table 4 may be explained by this non-linear

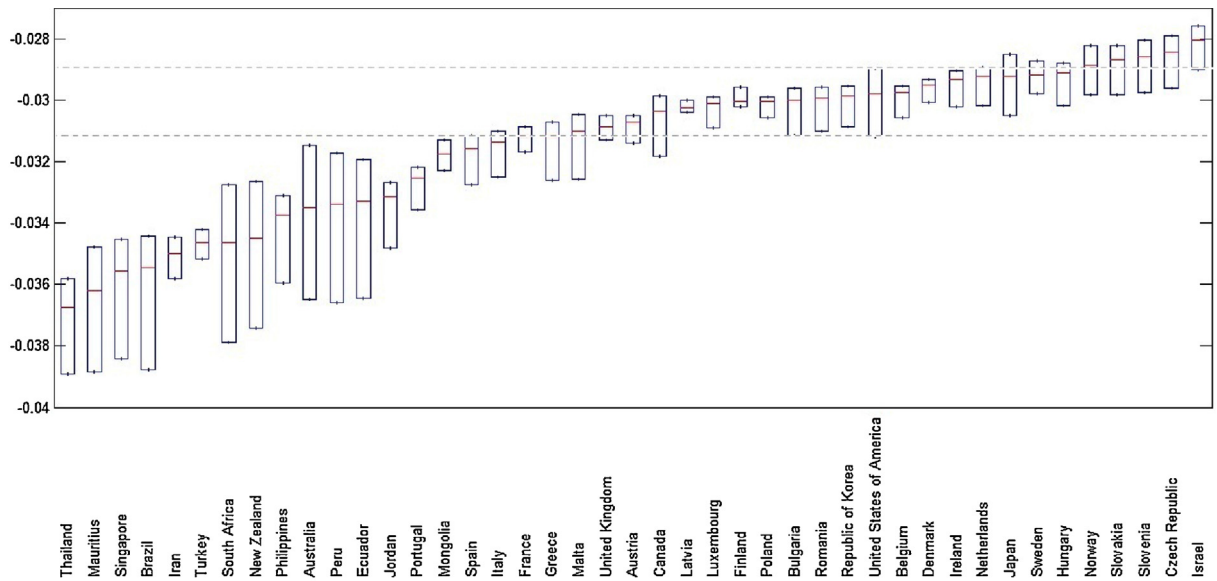


Fig. 4. Estimated convergence coefficient median (central mark) and 90% confidence interval (box) by country (period mean) as measured by the model with latitude, longitude and years of schooling. Models with period and industry dummies.

behavior. The effect of executive constraint is always positive and almost linear, indicating that, for this variable, our semi-parametric tool does not add much information to the analysis. Panel C in Fig. 2 suggests that the effect of years of schooling has an interesting concave shape. For countries with low levels of education, increases in years of schooling brings large gains in growth, but gains diminish as education improves, reaching negative values for countries with high levels of education. Panel C brings evidence that convergence is weaker within groups with higher levels of education. This finding parallels the results of Durlauf and Johnson (1995) who failed to find evidence of convergence among the high-output economies, and De Long (1988) who rejected convergence over a much longer time span (from 1870 to 1979) when studying economies with similar high initial outputs.

Fig. 3 plots the partial effect itself, i.e., the slope of curves presented in Fig. 2. The continuous line is the estimated partial effect of variables in the semi-parametric model. The dashed line is the mean (across Monte Carlo simulations) of the mean (across observed countries and years) partial effect of variables in the semi-parametric model (the same value as in Table 4). The dotted line is the partial effect as measured in the linear model (the same value as in Table 3). Observing Fig. 3 helps us understand what we lose estimating the productivity growth equation linearly. Note that, specially for openness and years of schooling, the partial effect of variables changes importantly as the level the variable that originates the effect changes.

Finally, Fig. 4 shows the estimated convergence coefficient median (central mark) and 90% confidence interval (box) by country (period mean) as measured by the model with latitude, longitude, years of schooling, and period and industry dummies. This figure can be seen as an exercise to group countries with the same convergence coefficient. We discussed in Section 3, Eq. (4), that if we can find variables that help us to group countries with the same β_j , we will also be identifying convergence clubs. Let us use the United States as an example. The edges of the confidence interval box for this country are marked with light dashed lines. With 90% of confidence, we cannot reject that the United States is in the same group as Italy, France, until Israel, following the order of countries in Fig. 4. But, we reject that the United States is in the group of Thailand, Mauritius, until Spain, following the order of countries.

The differences in the convergence coefficient across countries is not only of statistical significance, but it is also economically meaningful. The extreme values of the estimated convergence coefficient shown in Fig. 4 are -3.7% per year for Thailand, and -2.8% per year for Israel. It means that the half life to productivity convergence for Thailand is of 18 years and, for Israel, it is of 25 years.

Here, we present is a different way of grouping countries in convergence clubs. In this way, country-specific variables tell us how countries must be grouped, in some confidence interval, and we can also estimate how these variables are related to the convergence coefficient.

6. Concluding remarks

Our goal in this paper is not to assess how institutions affect industry convergence. We are less ambitious. In the first place, the word “affect” implies causality and we are not denying the well established fact that a country’s growth (and specifically, its industrial growth) over time affects its institutional variables (see [Acemoglu et al. \(2001\)](#) and [Glaeser et al. \(2004\)](#)). Secondly, as noted in [Glaeser et al. \(2004\)](#), the word “institution” is related to constraints on individual behavior and need to be reasonably permanent or durable. The fact that we use variables such as educational and trade openness indicators makes clear that we are not pursuing *permanent constraints*. After the work of [Rodrik \(2011a,b\)](#), that helped us to understand that we should search for unconditional convergence in the industry sector, our goal is to establish two related facts: (i) the speed of convergence is different across countries; and (ii) the speed of convergence is related to some important variables.

Appendix A. Countries in the sample

Countries, years and the number of industries observed for each country-year pair are shown in [Tables 5–8](#)). To be present in the sample, it is necessary that data on productivity is available in t and in $t - 10$. But recall that the use of variables not from UNIDO’s INDSTAT 4 database reduces the number of countries in our data set because these variables are missing for some countries.

Trade openness reduces the number of countries to 48, and the number of observations to 13,265 ([Table 5](#)); the executive constraints indicator reduces the number of countries to 38, and the number of observations to 11,363 ([Table 6](#)); the years of schooling indicator reduces the number of countries to 43, and the number of observations to 12,499 ([Table 7](#)). Finally, the use of all the three indicators reduces the number of countries to 37, and the number of observations to 11,098 ([Table 8](#)).

Table 5

Observed countries, years and number of industries. Trade openness and INDSTST4 available data in common.

Australia	Years	–	–	–	2003	–	–	–	–	All
	No. of industries	–	–	–	9	–	–	–	–	9
Austria	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	59	64	62	62	62	98	10	92	509
Belgium	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	99	97	103	299
Brazil	Years	–	–	–	–	–	–	2006	2007	All
	No. of industries	–	–	–	–	–	–	35	35	70
Bulgaria	Years	–	–	–	–	–	–	2006	2007	All
	No. of industries	–	–	–	–	–	–	27	28	55
Canada	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	106	106	106	106	102	100	102	101	829
Czech Republic	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	58	65	55	178
Denmark	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	73	72	73	218
Ecuador	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	95	95	91	281
Ethiopia	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	10	40	39	40	41	40	44	43	297
Eritrea	Years	–	–	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	–	34	34	34	30	29	34	195
Finland	Years	–	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	11	11	11	10	107	106	109	365
France	Years	2000	2001	2002	2003	2004	–	2006	2007	All
	No. of industries	104	104	100	98	104	–	120	122	752
Greece	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	31	32	29	28	30	150
Hungary	Years	–	–	–	–	2004	2005	2006	2007	All
	No. of industries	–	–	–	–	76	78	78	78	310
Iran	Years	–	–	–	–	2004	2005	–	–	All
	No. of industries	–	–	–	–	121	119	–	–	240

Table 5 (Continued)

United Kingdom	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	109	113	113	117	116	568
United States of America	Years	–	–	–	–	–	–	–	2007	All
	No. of industries	–	–	–	–	–	–	–	113	113
All countries	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	504	778	914	1507	1912	2487	2701	2462	13,265

Table 6

Observed countries, years and number of industries. Executive constraint and INDSTST4 available data in common.

Australia	Years	–	–	–	2003	–	–	–	–	All
	No. of industries	–	–	–	9	–	–	–	–	9
Austria	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	59	64	62	62	62	98	10	92	509
Belgium	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	99	97	103	299
Brazil	Years	–	–	–	–	–	–	2006	2007	All
	No. of industries	–	–	–	–	–	–	35	35	70
Bulgaria	Years	–	–	–	–	–	–	2006	2007	All
	No. of industries	–	–	–	–	–	–	27	28	55
Canada	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	106	106	106	106	102	100	102	101	829
Denmark	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	73	72	73	218
Ecuador	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	95	95	91	281
Finland	Years	–	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	11	11	11	10	107	106	109	365
France	Years	2000	2001	2002	2003	2004	–	2006	2007	All
	No. of industries	104	104	100	98	104	–	120	122	752
Greece	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	31	32	29	28	30	150
Hungary	Years	–	–	–	–	2004	2005	2006	2007	All
	No. of industries	–	–	–	–	76	78	78	78	310
Iran	Years	–	–	–	–	2004	2005	–	–	All
	No. of industries	–	–	–	–	121	119	–	–	240
Ireland	Years	–	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	60	47	62	57	54	47	37	364
Israel	Years	–	–	–	–	–	2005	2006	–	All
	No. of industries	–	–	–	–	–	24	24	–	48
Italy	Years	–	–	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	–	123	121	121	121	119	120	725
Japan	Years	–	–	–	–	2004	2005	2006	2007	All
	No. of industries	–	–	–	–	119	120	119	119	477
Jordan	Years	–	–	–	–	2004	2005	2006	2007	All
	No. of industries	–	–	–	–	74	74	76	74	298
Republic of Korea	Years	2000	2001	2002	2003	2004	2005	2006	–	All
	No. of industries	117	127	126	126	126	126	126	–	874
Mauritius	Years	–	–	–	–	–	–	–	2007	All
	No. of industries	–	–	–	–	–	–	–	7	7
Mongolia	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	3	4	7	6	7	27
Oman	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	50	53	55	53	54	265
Netherlands	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	75	84	81	240
New Zealand	Years	–	–	–	–	–	–	2006	2007	All
	No. of industries	–	–	–	–	–	–	4	4	8
Norway	Years	–	2001	2002	2003	2004	2005	2006	–	All
	No. of industries	–	81	70	69	105	102	96	–	523

Table 6 (Continued)

Peru	Years	–	–	–	–	–	2005	2006	–	All
	No. of industries	–	–	–	–	–	9	9	–	18
Philippines	Years	–	–	–	–	–	–	2006	–	All
	No. of industries	–	–	–	–	–	–	21	–	21
Poland	Years	–	–	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	–	11	12	12	12	110	112	269
Portugal	Years	–	–	–	–	–	–	2006	2007	All
	No. of industries	–	–	–	–	–	–	66	62	128
Romania	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	9	9	9	8	8	7	6	7	63
Singapore	Years	–	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	71	71	70	53	59	58	61	443
South Africa	Years	–	2001	–	–	–	–	2006	–	All
	No. of industries	–	9	–	–	–	–	11	–	20
Spain	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	123	123	123	123	123	615
Sweden	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	95	92	90	93	96	85	83	89	723
Thailand	Years	–	–	–	–	–	–	2006	–	All
	No. of industries	–	–	–	–	–	–	121	–	121
Turkey	Years	–	–	2002	2003	2004	2005	2006	–	All
	No. of industries	–	–	11	99	99	98	11	–	318
United Kingdom	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	109	113	113	117	116	568
United States of America	Years	–	–	–	–	–	–	–	2007	All
	No. of industries	–	–	–	–	–	–	–	113	113
All countries	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	490	734	837	1262	1670	2062	2260	2048	11,363

Table 7

Observed countries, years and number of industries. Years of schooling and INDSTST4 available data in common.

Australia	Years	–	–	–	2003	–	–	–	–	All
	No. of industries	–	–	–	9	–	–	–	–	9
Austria	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	59	64	62	62	62	98	10	92	509
Belgium	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	99	97	103	299
Brazil	Years	–	–	–	–	–	–	2006	2007	All
	No. of industries	–	–	–	–	–	–	35	35	70
Bulgaria	Years	–	–	–	–	–	–	2006	2007	All
	No. of industries	–	–	–	–	–	–	27	28	55
Canada	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	106	106	106	106	102	100	102	101	829
Czech Republic	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	58	65	55	178
Denmark	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	73	72	73	218
Ecuador	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	95	95	91	281
Finland	Years	–	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	11	11	11	10	107	106	109	365
France	Years	2000	2001	2002	2003	2004	–	2006	2007	All
	No. of industries	104	104	100	98	104	–	120	122	752
Greece	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	31	32	29	28	30	150
Hungary	Years	–	–	–	–	2004	2005	2006	2007	All
	No. of industries	–	–	–	–	76	78	78	78	310
Iran	Years	–	–	–	–	2004	2005	–	–	All
	No. of industries	–	–	–	–	121	119	–	–	240

Table 7 (Continued)

Ireland	Years	–	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	60	47	62	57	54	47	37	364
Israel	Years	–	–	–	–	–	2005	2006	–	All
	No. of industries	–	–	–	–	–	24	24	–	48
Italy	Years	–	–	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	–	123	121	121	121	119	120	725
Japan	Years	–	–	–	–	2004	2005	2006	2007	All
	No. of industries	–	–	–	–	119	120	119	119	477
Jordan	Years	–	–	–	–	2004	2005	2006	2007	All
	No. of industries	–	–	–	–	74	74	76	74	298
Republic of Korea	Years	2000	2001	2002	2003	2004	2005	2006	–	All
	No. of industries	117	127	126	126	126	126	126	–	874
Latvia	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	83	80	80	83	45	371
Luxembourg	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	4	4	4	5	5	18	16	17	73
Malta	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	56	58	59	173
Mauritius	Years	–	–	–	–	–	–	–	2007	All
	No. of industries	–	–	–	–	–	–	–	7	7
Mongolia	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	3	4	7	6	7	27
Netherlands	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	75	84	81	240
New Zealand	Years	–	–	–	–	–	–	2006	2007	All
	No. of industries	–	–	–	–	–	–	4	4	8
Norway	Years	–	2001	2002	2003	2004	2005	2006	–	All
	No. of industries	–	81	70	69	105	102	96	–	523
Peru	Years	–	–	–	–	–	2005	2006	–	All
	No. of industries	–	–	–	–	–	9	9	–	18
Philippines	Years	–	–	–	–	–	–	2006	–	All
	No. of industries	–	–	–	–	–	–	21	–	21
Poland	Years	–	–	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	–	11	12	12	12	110	112	269
Portugal	Years	–	–	–	–	–	–	2006	2007	All
	No. of industries	–	–	–	–	–	–	66	62	128
Romania	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	9	9	9	8	8	7	6	7	63
Singapore	Years	–	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	71	71	70	53	59	58	61	443
Slovakia	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	74	82	61	68	73	358
Slovenia	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	82	78	79	239
South Africa	Years	–	2001	–	2003	–	–	2006	–	All
	No. of industries	–	9	–	9	–	–	11	–	29
Spain	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	123	123	123	123	123	615
Sweden	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	95	92	90	93	96	85	83	89	723
Thailand	Years	–	–	–	–	–	–	2006	–	All
	No. of industries	–	–	–	–	–	–	121	–	121
Turkey	Years	–	–	2002	2003	2004	2005	2006	–	All
	No. of industries	–	–	11	99	99	98	11	–	318
United Kingdom	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	109	113	113	117	116	568
United States of America	Years	–	–	–	–	–	–	–	2007	All
	No. of industries	–	–	–	–	–	–	–	113	113
All Countries	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	494	738	841	1383	1784	2362	2575	2322	12,499

Table 8

Observed countries, years and number of industries. Trade openness, executive constraint, years of schooling and INDSTST4 available data in common.

Australia	Years	–	–	–	2003	–	–	–	–	All
	No. of industries	–	–	–	9	–	–	–	–	9
Austria	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	59	64	62	62	62	98	10	92	509
Belgium	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	99	97	103	299
Brazil	Years	–	–	–	–	–	–	2006	2007	All
	No. of industries	–	–	–	–	–	–	35	35	70
Bulgaria	Years	–	–	–	–	–	–	2006	2007	All
	No. of industries	–	–	–	–	–	–	27	28	55
Canada	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	106	106	106	106	102	100	102	101	829
Denmark	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	73	72	73	218
Ecuador	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	95	95	91	281
Finland	Years	–	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	11	11	11	10	107	106	109	365
France	Years	2000	2001	2002	2003	2004	–	2006	2007	All
	No. of industries	104	104	100	98	104	–	120	122	752
Greece	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	31	32	29	28	30	150
Hungary	Years	–	–	–	–	2004	2005	2006	2007	All
	No. of industries	–	–	–	–	76	78	78	78	310
Iran	Years	–	–	–	–	2004	2005	–	–	All
	No. of industries	–	–	–	–	121	119	–	–	240
Ireland	Years	–	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	60	47	62	57	54	47	37	364
Israel	Years	–	–	–	–	–	2005	2006	–	All
	No. of industries	–	–	–	–	–	24	24	–	48
Italy	Years	–	–	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	–	123	121	121	121	119	120	725
Japan	Years	–	–	–	–	2004	2005	2006	2007	All
	No. of industries	–	–	–	–	119	120	119	119	477
Jordan	Years	–	–	–	–	2004	2005	2006	2007	All
	No. of industries	–	–	–	–	74	74	76	74	298
Republic of Korea	Years	2000	2001	2002	2003	2004	2005	2006	–	All
	No. of industries	117	127	126	126	126	126	126	–	874
Mauritius	Years	–	–	–	–	–	–	–	2007	All
	No. of industries	–	–	–	–	–	–	–	7	7
Mongolia	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	3	4	7	6	7	27
Netherlands	Years	–	–	–	–	–	2005	2006	2007	All
	No. of industries	–	–	–	–	–	75	84	81	240
New Zealand	Years	–	–	–	–	–	–	2006	2007	All
	No. of industries	–	–	–	–	–	–	4	4	8
Norway	Years	–	2001	2002	2003	2004	2005	2006	–	All
	No. of industries	–	81	70	69	105	102	96	–	523
Peru	Years	–	–	–	–	–	2005	2006	–	All
	No. of industries	–	–	–	–	–	9	9	–	18
Philippines	Years	–	–	–	–	–	–	2006	–	All
	No. of industries	–	–	–	–	–	–	21	–	21
Poland	Years	–	–	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	–	11	12	12	12	110	112	269
Portugal	Years	–	–	–	–	–	–	2006	2007	All
	No. of industries	–	–	–	–	–	–	66	62	128
Romania	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	9	9	9	8	8	7	6	7	63

Table 8 (Continued)

Singapore	Years	–	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	–	71	71	70	53	59	58	61	443
South Africa	Years	–	2001	–	–	–	–	2006	–	All
	No. of industries	–	9	–	–	–	–	11	–	20
Spain	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	123	123	123	123	123	615
Sweden	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of industries	95	92	90	93	96	85	83	89	723
Thailand	Years	–	–	–	–	–	–	2006	–	All
	No. of industries	–	–	–	–	–	–	121	–	121
Turkey	Years	–	–	2002	2003	2004	2005	2006	–	All
	No. of industries	–	–	11	99	99	98	11	–	318
United Kingdom	Years	–	–	–	2003	2004	2005	2006	2007	All
	No. of industries	–	–	–	109	113	113	117	116	568
United States of America	Years	–	–	–	–	–	–	–	2007	All
	No. of industries	–	–	–	–	–	–	–	113	113
All countries	Years	2000	2001	2002	2003	2004	2005	2006	2007	All
	No. of Industries	490	734	837	1212	1617	2007	2207	1994	11,098

Appendix B. Estimation of Eq. (5)

To estimate Eq. (5), we create the following matrix of regressors $y'_{ij,t}$

$$y'_{ij,t} = \begin{bmatrix} y_{11,1990} & 0 & 0 & 0 & 0 & 0 & 0 \\ \vdots & 0 & 0 & 0 & 0 & 0 & 0 \\ y_{I_1,1990,1,1990} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \ddots & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & y_{11,1997} & 0 & 0 & 0 & 0 \\ 0 & 0 & \vdots & 0 & 0 & 0 & 0 \\ 0 & 0 & y_{I_1,1997,1,1997} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \ddots & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & y_{1J,1990} & 0 & 0 \\ 0 & 0 & 0 & 0 & \vdots & 0 & 0 \\ 0 & 0 & 0 & 0 & y_{I_J,1990,J,1990} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & y_{1J,1997} \\ 0 & 0 & 0 & 0 & 0 & 0 & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & y_{I_J,1997,J,1997} \end{bmatrix}$$

In each column are listed the observations of all industries of industry $i = 1, \dots, I_{j,t}$, country $j = 1, \dots, J$, year $t = 1990, \dots, 1997$, where $I_{j,t}$ is the number of observed industries in country j , year t . We then regress the equation

$$\Delta y_{ijt} = \beta y'_{ij,t} + D_i + D_t + \varepsilon_{ijt},$$

and obtain one different β_{jt} for each country j , year t .

Appendix C. Versions of Tables 4 and 3 in exercises where the convergence coefficient is estimated in an equation with no dummies and with only period dummies

Table 9 shows the results of the linear regression of $\hat{\beta}_{jt}$'s on various indicators, measured in decadal initial level. The coefficients $\hat{\beta}_{jt}$'s are estimated according to Eq. (6). It is the analog of Table 3 for equations with no dummies (Panel A) and with only period dummies (Panel B).

Table 10 presents the country-and-year mean partial effects of latitude, longitude, trade openness, years of schooling and executive constraints on the relative productivity growth. These values are the partial effects of one standard deviation increase in these variables on the estimated convergence coefficient. It is the analog of Table 4 for equations with no dummies (Panel A) and with only period dummies (Panel B).

Table 9

$\hat{\beta}_{jt}$'s from the linear model and selected variables in the first year of the decade (t_0). Estimated coefficients are multiplied by 100.

	(1)	(2)	(3)	(4)
Panel A – dependent variable: $\hat{\beta}_{jt}$'s from the equation with no dummies.				
Latitude	0.393 (8.99) ^{***}	0.113 (2.77) ^{***}	0.028 (0.71)	−0.032 (0.76)
Longitude	−0.036 (0.92)	0.017 (0.60)	−0.012 (0.48)	0.008 (0.35)
Openness, t_0	0.054 (2.27) ^{**}			−0.006 (0.27)
Executive Constraint, t_0		0.144 (3.52) ^{***}		0.086 (1.60)
Years of Schooling, t_0			0.241 (6.30) ^{***}	0.277 (6.65) ^{***}
Constant	−3.515 (83.98) ^{***}	−3.302 (100.17) ^{***}	−3.332 (103.37) ^{***}	−3.337 (82.53) ^{***}
Observations	152	121	135	116
R-squared	0.37	0.29	0.36	0.50
	(5)	(6)	(7)	(8)
Panel B – dependent variable: $\hat{\beta}_{jt}$'s from the equation with period dummies.				
Latitude	0.415 (4.65) ^{***}	0.206 (1.82) [*]	0.071 (0.62)	0.049 (0.36)
Longitude	−0.013 (0.17)	0.037 (0.46)	0.013 (0.17)	0.011 (0.14)
Openness, t_0	0.039 (0.80)			−0.012 (0.18)
Executive Constraint, t_0		0.138 (1.20)		−0.043 (0.24)
Years of Schooling, t_0			0.240 (2.17) ^{**}	0.352 (2.58) ^{**}
Constant	−3.459 (40.52) ^{***}	−3.263 (35.51) ^{***}	−3.292 (35.45) ^{***}	−3.246 (24.51) ^{***}
Observations	152	121	135	116
R-squared	0.14	0.08	0.08	0.12

Absolute value of t statistics in parentheses.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Table 10
Country-and-year mean partial effects.

	(1)	(2)	(3)	(4)
Panel A – equation with no dummies				
Latitude	0.237 (0.06)***	0.066 (0.19)	−0.018 (0.09)	0.035 (0.13)
Longitude	−0.113 (0.05)**	0.003 (0.28)	0.008 (0.09)	−0.023 (0.07)
Openness	0.086 (0.04)**			0.046 (0.26)
Executive Constraint		0.072 (0.24)		0.056 (0.37)
Years of Schooling			0.255 (0.10)**	0.240 (0.11)**
Number of Sieves	5	4	3	5
Number of Observations	13,265	11,363	12,499	11,098
R-squared (underlying regression)	0.24	0.16	0.30	0.26
	(5)	(6)	(7)	(8)
Panel B – equation with period dummies				
Latitude	0.262 (0.15)	0.085 (0.04)**	−0.015 (0.16)	−0.035 (0.10)
Longitude	−0.071 (0.25)	0.011 (0.03)	0.013 (0.03)	0.027 (0.06)
Openness	0.057 (0.18)			−0.003 (0.10)
Executive Constraint		0.052 (0.02)***		0.163 (0.15)
Years of Schooling			0.263 (0.05)***	0.225 (0.11)**
Number of Sieves	5	4	3	5
Number of Observations	13,265	11,363	12,499	11,098
R-squared (underlying regression)	0.29	0.22	0.34	0.30

Standard deviations in parenthesis based on Monte Carlo simulations (1000 repetitions).

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

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