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Abstract

In this paper, we investigate differences in and determinants of technical efficiency across three groups of OECD, Asian and Latin American countries. As technical efficiency determines the capacity with which countries absorb technology produced abroad, these differences are important to understand differences in growth and productivity across countries, especially for developing countries which depend to a large extend on foreign technology. Using a stochastic frontier framework and data for 22 manufacturing sectors for 1996-2005, we find notable differences in technical efficiency between the three country groups we examine. We then investigate the effect of human capital and domestic R&D, proxied by the stock of patents, on technical efficiency. We find that while human capital has always a strongly positive effect on efficiency, an increase in the stock of patents has positive effects on efficiency in high-tech sectors, but negative effects in low-tech sectors.

1 Introduction

Despite the emergence of newly industrialized economies and an increasing fragmentation of global production, most innovations are still carried out in a small number of R&D-intensive countries (Eaton and Kortum 2001, Caselli and Wilson 2004). The large majority of developing and newly industrialized countries import technology from these countries (Mastromarco 2008). Gerschenkron (1962) and Abramovitz (1986) have argued that developing countries have a higher growth potential than advanced countries, as they can realize larger productivity gains in adopting advanced technologies. In a theoretical paper, Acemoglu et al. (2006) formalized the idea that developing countries should focus on adopting foreign technology before starting to innovate themselves. According to the case study literature, this is indeed what happened in newly industrialized countries such as South Korea, Taiwan or more recently China (Amsden 1989, 2001, Wade 1990, Breznitz and Murphree 2011). In all these economies, the capacity to successfully absorb foreign technology has played a crucial role in sustaining high growth rates.

Understanding differences in absorptive capacity is thus key to understand the large differences in productivity and income across countries (Prescott 1998). While the technological distance from R&D-intensive countries determines the scale of potential benefits from importing technology, and trade liberalization opens up channels of technology transfer, the ability of a country to absorb imported technology is crucial to realize the potential gains from catching-up and trade.

The aim of this paper is to examine levels of technical efficiency and determinants of absorptive capacity for two groups of industrialized and emerging economies in Asia and Latin America, and a group of European OECD countries that also includes the US. While this last

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group is composed of countries that have been leading industrialized nations for a long time, the Asian and Latin American countries in our sample, with the exception of Japan, are mostly developing and newly industrialized economies. Comparing these three country groups permits us to investigate if efficiency levels and determinants of absorptive capacity systematically differ across regions that are at different levels of economic development, and share different political and historical contexts.

We use stochastic frontier analysis (SFA) and sectoral data, which permits us to treat technical efficiency and technical change as two distinct components of total factor productivity (TFP) in each industry. SFA allows us to simultaneously estimate levels and determinants of technical efficiency, with technical efficiency being a close approximation of the concept of absorptive capacity we have in mind.

Instead of using SFA, most previous studies in the absorptive capacity literature have employed a two-stage modelling strategy (Senhadji 2000, Miller and Upadhyay 2000, Madden et al. 2001, Okabe 2002, Wang 2007, Madsen et al. 2010), which however suffers from a number of flaws (that we discuss in section 2). The few studies using SFA have either focused on OECD countries (Griffith et al. 2003, 2004, Kneller and Stevens 2006), or have used aggregate data (Mastromarco 2008, Henry et al. 2009), and do not have data for recent years.

Using sectoral instead of aggregate data permits us to get more precise results, and to distinguish between effects on low-tech and high-tech sectors. As sectoral data has become available only recently for many developing countries, this paper is the first one, to our knowledge, that combines SFA with the use of sectoral data for both developed and developing countries.

We investigate the effect of two potential determinants of absorptive capacity, namely human capital measured by years of schooling, and the effectiveness of domestic R&D, proxied by the stock of patents filed by a country. While most previous studies have either examined the effects of human capital (Nelson and Phelps 1966, Cohen and Levinthal 1989, Benhabib and Spiegel 1994, 2005) or R&D expenditure (Verspagen 1991, Fagerberg 1994, Aghion and Howitt 2005) on absorptive capacity, we follow more recent studies that look on both determinants (Kneller and Stevens 2006). However, instead of R&D expenditure we use stock of patents as a proxy for R&D, which to our knowledge has not been done before in this context.

The contributions of this paper to the literature are thus twofold. To our knowledge, this paper is the first using SFA and sectoral data to comparatively analyse efficiency levels and determinants of absorptive capacity across three groups of developed and developing countries. Secondly, instead of R&D expenditure, we introduce the use of stock of patents as a proxy for R&D to the absorptive capacity literature.

We find that levels of technical efficiency slightly increase over the time span covered in our study, with the exception of Latin America, where efficiency in high-tech sectors experiences a sharp drop after 1999. A temporary drop in high-tech efficiency, albeit less pronounced, is also noticeable for Asia and OECD countries after 1999. While in Europe low-tech sectors are on average more efficienct than high-tech sectors, the opposite is the case for Asia and the US, with Latin America showing mixed results. Looking on the *determinants* of technical efficiency, we find that human capital has always a strongly positive effect on efficiency, especially in low-tech sectors. An increase in the stock of patents has positive effects on efficiency in high-tech sectors, but negative effects in low-tech sectors, especially for Asia and Latin America.

In the following, section 2 will discuss our empirical strategy, and section 3 presents the data. Section 4 shows the results for our frontier estimation, the efficiency levels and for determinants of technical efficiency, and section 5 concludes.

2 Empirical strategy

We use stochastic frontier analysis (SFA), as it provides an ideal framework to estimate technical inefficiency. SFA is prefered to the more popular two-stage modelling approach used in most of the previous literature, since it is statistically more accurate and matches more closely the idea of absorptive capacity we want to capture. The two-stage approach consists in estimating TFP as residual of a parameterized production function, and then regressing it against a number of factors which are considered to be linked to changes in productivity (Senhadji 2000, Miller and Upadhyay 2000, Madden et al. 2001, Okabe 2002, Wang 2007, Madsen et al. 2010). However, Koop et al. (1999, 2000) point out that while in the first stage of this approach the efficiency terms are assumed to be identically and independently distributed, in the second stage they are a function of a number of variables which might directly enter the production function specification (or be correlated with explanatory variables), thereby contradicting the assumption of identically distributed inefficiency terms (Battese and Coelli 1995, pp. 326). SFA overcomes this problem by assuming that technical inefficiency effects of production are *independently* but *not identically* distributed, and then by simultaneously estimating the stochastic frontier and the inefficiency model.

Another important feature of SFA is that it allows us to distinguish between technical progress, technical efficiency, and a stochastic component of TFP. This distinction is omitted in the two-stage approach, where TFP is used as a measure of technical inefficiency. A third criticism concerns the use of the country with the highest TFP as the numeraire in a measure of relative productivity, to account for the distance to the technical frontier (Griffth et al. 2004, Kneller 2005). This approach is based on two unrealistic assumptions. First, it assumes that the country with the highest TFP is at the frontier, which might not be true. Secondly, it assumes that a unique technology frontier exists for all countries. In the SFA approach, the concept of absorptive capacity is instead related to that of production frontier, which represents the maximum output that can be produced starting from any given input vector (i.e. the upper boundary of the production possibilities set).

Our emprical strategy is based on that of Battese and Coelli (1995). Following their formulation, the stochastic production frontier can be expressed as

$$Y_{ijt} = exp(x_{ijt}\beta + V_{ijt} - U_{ijt}) \tag{1}$$

where Y_{ijt} is output, x_{ijt} is a vector of inputs of production, β is a vector of parameters to be estimated, V_{ijt} are random errors which capture the stochastic nature of the frontier, and U_{ijt} are non-negative random variables which denote technical inefficiency of production and are obtained by a truncation at zero of the normal distribution with mean $z_{it}\delta$ and variance σ^2(see Battese and Coelli 1995).

The technical inefficiency effect is specified by the following equation

$$U_{ijt} = z_{it}\delta + W_{ijt} \tag{2}$$

where z_{it} is a vector of explanatory variables associated with technical inefficiency of production, δ is a vector of unknown coefficients, and W_{ijt} is a random variable defined by the truncation of a normal distribution with zero mean and variance σ^2. The requirement that $U_{ijt} \geq 0$ is ensured by truncating W_{ijt} such that $W_{ijt} \geq -z_{ijt}\delta$.

The parameters of equations (1) and (2) are estimated simultaneously by the method of maximum likelihood.[1]The likelihood function is expressed in terms of the variance parameters $\sigma_S^2 \equiv \sigma_V^2 + \sigma^2$ and $\gamma \equiv \frac{\sigma^2}{\sigma_S^2}$.[2] The technical efficiency of production of sector j in country i at time t is

$$TE_{ijt} = exp(-U_{ijt}) = exp(-z_{it}\delta - W_{ijt}) \tag{3}$$

[1]The parameters of the model defined by (1) and (2) are estimated simultaneously using Frontier 4.1 which is a package for SFA developed by Battese and Coelli. Frontier 4.1 provides maximum-likelihood estimates of the parameters and predicts technical efficiencies.

[2]For the derivation of the likelihood function and its partial derivatives with respect to the parameters of the model see Battese and Coelli (1993).

The prediction of the technical efficiency terms is based on their conditional distribution $U_{ijt} \mid E_{ijt}$ where $E_{ijt} = V_{ijt} - U_{ijt}$, given the model assumptions (See Battese and Coelli 1993).

To estimate equation (2), we assume a semi-translog specification (i.e. translog in k and l, as proposed by Kneller and Stevens 2003), which provides a less restrictive functional form for a production function

$$y_{ijt} = \beta_{0j} + \beta_1 k_{ijt} + \beta_2 l_{ijt} + \beta_3 k_{ijt}^2 + \beta_4 l_{ijt}^2 + \beta_5 k_{ijt} l_{ijt}$$

$$+\beta_6 p_{it} + \beta_7 r_{it} + \beta_8 year^2 + \beta_9 c_i + \beta_{10} s_j - u_{ijt} + v_{ijt} \tag{4}$$

where all lower case letters represent logarithms.

y_{ijt} is value added, $k_{ijt}$is physical capital, $l_{ijt}$is labour supply, p_{it} is domestic knowledge measured by local R&D and r_{it} represents foreign knowledge spillovers, which are assumed to be a function of the stock of R&D in the five countries that contribute most to the global stock of R&D.

We make the simplifying assumption that technology is factor-neutral, implying that output is separable in the production function and technology, so that we can separate technological change p_{it} from efficiency u_{ijt} in TFP. A quadratic time trend, $year^2$, is also included to measure technical progress not captured by local and foreign R&D.[3] Finally, a set of country fixed effects c_i and a set of sector fixed effects s_j are included to control for country and sector specific characteristics.

Following Griliches and Lichtenberg (1984), knowledge is assumed to be an input in the production function. As Kneller and Stevens (2006), we assume that knowledge evolves with the local stock of R&D and with foreign knowledge spillovers, capturing technical change. To measure foreign R&D spillovers to the domestic economy, we follow Coe and Helpman (1995) and Henry et al. (2009). They use a bilateral-imports-share weighted sum of R&D capital stocks of trade partners. Using the same logic, we weight the stock of R&D of the five countries that contribute most to the total stock of R&D by the share of imported machinery and equipment from these countries. This is motivated by the evidence that most of the world's R&D is produced in a small number of R&D-intensive countries and imported through R&D-intensive inputs (Eaton and Kortum 2001, Caselli and Wilson 2004).

Finally, we assume that knowledge transfer is partial, depending on the degree of economic integration across countries. Barriers to knowledge transfer are captured by weighting the stock of R&D by the distance to the source.

$$R_{it} = \sum_{n=5} \left(\frac{P_{nt} * m_{int}}{D_{in}}\right)$$

where n is an index for the five top countries, $P_{nt}$is the stock of R&D in country n, m_{in} is the share of machinery and equipment imported by country i from country n, and D_{in} is the distance between country i to country n.

Technical inefficiency is defined by

$$v_{ijt} = \delta_{oj} + \delta_1 z_{it} + \delta_2 lowtech * z_{it} + \delta_3 h_{it} + \delta_4 lowtech * h_{it} + \delta_5 s_i + w_{ijt} \tag{5}$$

where, as before, all lower case letters represent logarithms.

z_{it} is stock of patents, $h_{it}$is human capital, $lowtech$ is a dummy variable taking value 1 when the sector is low-tech and 0 otherwise, s_i are sector fixed effects, and w_{ijt} has been defined after equation (2).

The impact of knowledge on inefficiency is captured by the stock of patents. To our knowledge, the use of stock of patents is new in the empirical literature on absorptive capacity. Kneller

[3]A similar assumption is made by Henry et al. (2009).

and Stevens (2006) use spending on R&D in the industry to measure the effect of knowledge on inefficiency. In our analysis, we prefer to use stock of patents as a measure of knowledge for two reasons: first we believe that stock of patents is a more reliable indicator of effective knowledge production in a country, and second we find stock of patents to be more robust to multicollinearity problems, given the high correlation between spending in R&D and years of schooling that we found ($\rho = 0.77$).

We use average years of schooling in country i as proxy for human capital. The effect of both stock of patents and years of schooling is allowed to vary between high-tech and low-tech sectors. Finally, a set of sector fixed effects are added to control for sector specific characteristics. If the stock of knowledge and human capital positively affect absorptive capacity in the high-tech sectors, we should expect δ_1 and δ_3 to have a negative sign. In the low-tech sectors, we should expect the sum of the coefficients for both the stock of patents and years of schooling to be negative (e.i. $\delta_1 + \delta_2 < 0$ and $\delta_3 + \delta_4 < 0$).

3 Data

The model is estimated for a sample of 10 European and North-American OECD countries (United Kingdom, United States, France, Germany, Italy, Belgium, Norway, Sweden, Netherlands, Denmark), 7 Asian countries (China, India, Indonesia, Japan, Philippines, Singapore, South Korea), 5 Latin American countries (Bolivia, Chile, Colombia, Mexico, Uruguay) and for twenty-two manufacturing industries over the period 1996-2005.[4] We divide the 22 manufacturing sectors into high-tech and low-tech sectors, following the standard OECD sector classification.[5]

While the first group of 10 OECD countries is included as a benchmark, we have chosen the other two country groups from regions that are characterized by different historical and political pre-conditions, i.e. Asia and Latin America. Whereas the countries in the first group have been among the world's leading industrialized nations for a long time, most countries in the two other groups are developing and newly industrialized economies that are still at a much lower level of economic development. Many of them share a recent history of successful economic catch-up, which makes them especially interesting for an analysis of absorptive capacity.

Our choice of countries was limited by the availability of sectoral data. Sectoral data is not yet available for many developing countries, and has only recently been made available for most of the non-OECD countries in our sample. As of now, our sample is thus the largest possible considering issues of data availability. Furthermore, we have exluded developing countries from Africa, as data availability was very limited and technology absorption has arguably played only a marginal role in these countries until recently (Lall and Pietrobelli, 2002).

Data for valued added, gross fixed capital formation and number of employees are taken from the UNIDO ISDB database (3-4 digit level). Data are comparable across years, having been deflated to 2000 prices and converted using measures of purchaising power parity (PPP) to US$. Both the GDP deflator and the PPP conversion factor are taken from World Bank.

The perpetual inventory method (PIM) is used to construct the capital stock.

$$K_{ijt+1} = K_{ijt} + I_{ijt+1} - \delta K_{ijt} \tag{6}$$

$$K_{ij0} = \frac{I_{ij0}}{g_i^K + \delta^K} \tag{7}$$

where K_{ij} is capital stock of sector j in country i , I_{ij} is capital formation/investment, δ^K is the depreciation rate set at 4% (Liao et al. 2009), and g_i^K is the average growth in the first five years of investment series.

[4]Stock of R&D, years of schooling and number of patents are available only at the country level.

[5]See Table 6 in the Appendix.

Human capital is measured by average years of schooling in the population in country i, and is taken from Barro and Lee (2010). The PIM is also used to compute stock of R&D using total R&D expenditure in country i deflated to 2000 prices, and converted using measures of PPP to US$.

$$P_{it+1} = P_{it} + R_{it+1} - \delta P_{it} \tag{8}$$

$$P_{i0} = \frac{R_{i0}}{g_i^R + \delta^p} \tag{9}$$

where P_i is the stock of R&D in country i, R_i is the expenditure in R&D, $g_i^R$is the average annual growth rate of R&D and $\delta^R$is the rate of depreciation of R&D stock that we set at 15% (Griliches 1984).

Data on patents are obtained from OECD. We use the triadic patent families which are a set of patents filed at the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO), and the Japan Patent Office (JPO), for the same invention, by the same applicant. The PIM is used to compute the stock of patents:

$$Z_{it+1} = Z_{it} + TPF_{it+1} - \delta Z_{it} \tag{10}$$

$$Z_{i0} = \frac{TPF_{i0}}{g_i^Z + \delta^Z} \tag{11}$$

where Z_{it} is the stock of patents in country i, TPF_i is the number of triadic patent families, g_i^Z is the average annual growth rate of patents, and $\delta^Z$is the depretiation rate set at 15% (Hall and MacGarvie 2010).

Foreign R&D spillovers are computed using the stock of R&D of the United States, Japan, Germany, France and the United Kingdom, which are the countries which contributed most to the stock of total R&D over the period 1996-2005. The share of imported machinery and equipment is calculated by using data on total imports and imported machinery and equipment from UN Comtrade, deflated to 2000 prices and converted using measures of PPP to US$.

Distance between capital cities in kilometers is taken from Gleditsch (2003).

For about 50% of our observations we have a balanced panel, while for more than 63% we have 9 out of 10 years, and for almost 70% 8 out of 10 years. [6]

Table 1 shows the basic descriptive statistics for all the variables of our analysis.

4 Results

4.1 Frontier Estimates

We report the results of our frontier estimation in Tables 2 and 3, with Table 2 showing frontier estimates, and Table 3 output elasticities. Estimated elasticities are within the range of what is found elsewhere in the literature, although we find slightly higher values for the elasticity of value added with respect to labour than studies using data for earlier periods (Kneller, Stevens 2006, Liao et al. 2009). For the full sample, the elasticity of value added with respect to physical capital is 0.201, and that with respect to labour 0.802. While we find evidence for mildly increasing returns to scale for physical capital and labour concerning OECD countries and Latin America (1.025 and 1.081), returns to scale are slightly decreasing for Asia (0.938).

The estimated effect of the stock of local R&D on output is strongly positive and significant at the 1% level for OECD countries (0.233), but only weakly positive and not significant for Asia

[6]Table 7 in the Appendix summarizes the number of available sectors by country and by year.

Table 1: Descriptive statistics

	Total						OECD				
	Q1	Median	Q2	Mean	St. Dev.		Q1	Median	Q2	Mean	St. Dev.
y	6.57	7.98	9.20	7.80	2.06	y	7.01	8.23	9.32	8.17	1.86
k	7.18	8.852	10.28	8.68	2.19	k	8.00	9.24	10.31	9.08	1.85
l	9.43	10.78	12.15	10.69	1.98	l	9.79	11.08	12.17	10.89	1.80
p	27.65	29.17	30.34	28.84	2.08	p	28.81	29.64	30.60	29.79	1.37
r	26.55	27.30	27.81	27.16	0.70	r	27.50	27.80	27.92	27.61	0.59
z	3.40	7.22	8.83	6.38	3.42	z	7.34	8.45	9.38	8.56	1.46
h	2.07	2.23	2.38	2.17	0.31	h	2.23	2.35	2.44	2.35	0.13
	Asia						Latin America				
	Q1	Median	Q2	Mean	St. Dev.		Q1	Median	Q2	Mean	St. Dev.
y	7.36	8.53	9.65	8.36	1.83	y	4.63	6.36	7.43	6.07	1.96
k	8.11	9.89	10.88	9.51	1.93	k	5.28	6.50	7.66	6.46	1.87
l	10.35	11.71	12.66	11.45	1.82	l	7.82	9.23	10.29	9.08	1.73
p	27.49	29.45	30.20	29.01	1.94	p	24.50	26.58	26.90	26.21	1.39
r	26.25	26.63	27.26	26.67	0.54	r	26.46	26.65	26.99	26.73	0.32
z	3.59	5.43	8.19	5.86	3.39	z	0.32	1.73	2.41	1.69	1.20
h	1.63	2.08	2.36	1.97	0.43	h	1.96	2.02	2.08	2.03	0.11

(0.038). For Latin America, stock of R&D has a negative effect on output (-0.426), significant at the 10% level.

Our results for OECD countries are similar to those found by earlier studies. Kneller and Stevens (2006) obtain slightly lower coefficients for a group of twelve OECD countries during the period 1973-1990 (0.03-0.09, pp.10). Coe and Helpman (1995) find that for the seven most adavanced OECD countries between 1971 and 1990, the estimated elasticity of TFP with respect to domestic R&D varies between 0.22 and 0.23, while for the remaining group of fifteen less advanced OECD countries, the elasticity lies between 0.6 and 1 (pp. 869). Kneller (2005) finds much lower coefficients for a group of twelve OECD countries over the same period (0.02-0.04, pp. 10), while Griffith et al. (2004) obtain larger coefficients for the same panel of OECD countries (0.4-0.6, pp.889). However, they use TFP growth instead of TFP as dependent variable, and assess the rate of return to R&D.

We thus find that local stock of R&D directly affects production in our sample of OECD countries. For Asia, the weaker and not significant effect suggests that local R&D plays mainly a role in facilitating the absorption of foreign technology, instead of affecting output directly.

For Latin America, although a negative effect of the stock of local R&D on output seems to be counterintuitive at first sight, our results confirm findings by earlier studies. In a study of 16 Latin American countries between 1996 and 2006, Castillo et al. (2012) find a negative contribution of R&D expenditure to productivity, which they attribute to recent changes in the pattern of specialization in the region in favour of industries with low-value added content that rely less and less on domestic R&D. Cimoli and Katz (2003) make the same argument, outlining that “dramatic changes in the sources of technical change” have occured in Latin America in the 1990s, with “a rapidly increasing share of external sources emerging at the expense of domestic ones” (Cimoli and Katz (2003), pp. 390). While import substitution policies until the 1980s had focused on the building of domestic knowledge creation, they maintain

Table 2: Results - frontier

	Total	OECD	Asia	Latin America
k	0.354*** (0.024)	0.375*** (0.023)	0.360*** (0.079)	-0.142* (0.085)
l	0.705*** (0.035)	0.503*** (0.029)	0.962*** (0.112)	1.525*** (0.129)
k^2	0.003 (0.003)	0.048*** (0.005)	0.003 (0.006)	0.045*** (0.009)
l^2	0.013*** (0.003)	0.063*** (0.003)	0.0002 (0.009)	-0.030*** (0.012)
lk	-0.020*** (0.005)	-0.105*** (0.007)	-0.021* (0.012)	-0.022 (0.018)
p	-0.068 (0.045)	0.233*** (0.064)	0.038 (0.076)	-0.426* (0.070)
r	0.026 (0.051)	0.045 (0.058)	0.030 (0.093)	0.012 (0.073)
$year^2$	0.0006*** (0.0002)	0.0001 (0.0002)	0.0009* (0.0005)	-0.0002 (0.0005)
const	-1.150 (0.990)	-9.568*** (1.122)	-6.300*** (1.010)	4.965*** (1.034)
Log-likelihood	-858.355	694.804	-260.021	-106.590
N	3904	1968	1148	788

The level of significance is shown with the following notation: *** 1%, ** 5%, and * 10%

that today those industries still relying on domestic R&D are inefficient and lagging behind. Efficient industries are clustered within the natural resource sectors or are performing assembly operations of imported parts ('maquiladoras'), relying almost exclusively on foreign R&D and cheap labour. It thus seems that our results for Latin America reflect recent structural changes on the continent, and capture the decreasing importance of local R&D.

The estimated effect of foreign R&D spillovers on output is slightly lower than what is found elsewhere in the literature (for example, Coe and Helpman (1995) find an elasticity of TFP with respect to foreign R&D spillovers of 0.06-0.092, and Kneller and Stevens (2006) an elasticity of output with respect to foreign R&D of 0.084-0.091). However, for our sample effects are not significant. This could mean that foreign R&D spillovers through machinery and equipment imports have only a weak or indirect effect on domestic production. As we are only capturing foreign knowledge embodied in R&D-intensive inputs, we leave out other potential channels through which foreign R&D might affect domestic output directly, such as FDI, licensing, etc.

Table 3: Elasticity of value added w.r.t. (at the sample mean)

	Labour	Physical capital
Total	0.802	0.201
OECD	0.924	0.101
Asia	0.763	0.175
Latin America	0.845	0.236

4.2 Efficiency Levels

Table 4 presents efficiency scores for low-tech and high-tech sectors in each country group. In general, efficiency scores slightly increase over the time span covered in our study, with the exception of Latin America, where efficiency in high-tech sectors experiences a sharp drop after 1999. A temporary drop in high-tech efficiency, albeit less pronounced, is also noticeable for Asia and OECD countries after 1999. Possibly, the Asian and Russian financial crises and the burst of the dot-com bubble are responsible for this drop in high-tech efficiency around the turn of the millenium, with the effect in Latin America being amplyfied by the aftermath of recent structural adjustment programs that made the region more vulnerable to economic shocks.

For the full sample, mean efficiency in low-tech sectors is slightly lower than mean efficiency in high-tech sectors (Figure 2). However, regional differences are quite pronounced. While from 1996 to 2000 mean efficiency for low-tech and high-tech sectors is almost the same in OECD countries, in 2001 efficiency drops notably in high-tech sectors, which then remain consistently less efficient than low-tech sectors. In Latin America, high-tech sectors are more efficienct than low-tech sectors until 2000, and then experience a similar, albeit much stronger drop. Finally, in Asia high-tech sectors are consistently more efficient than low-tech sectors.

Figure 1: Mean efficiency by country group

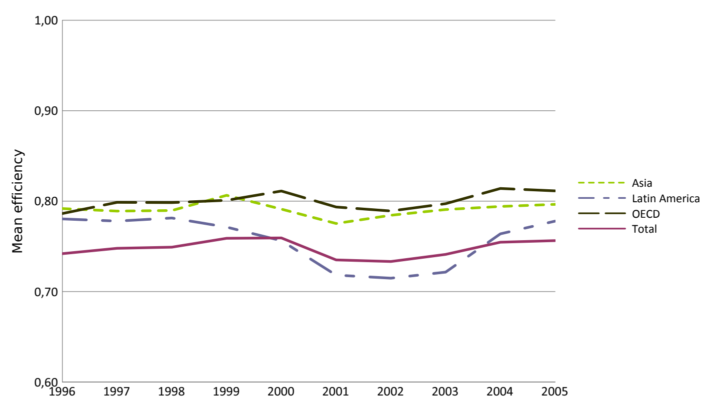
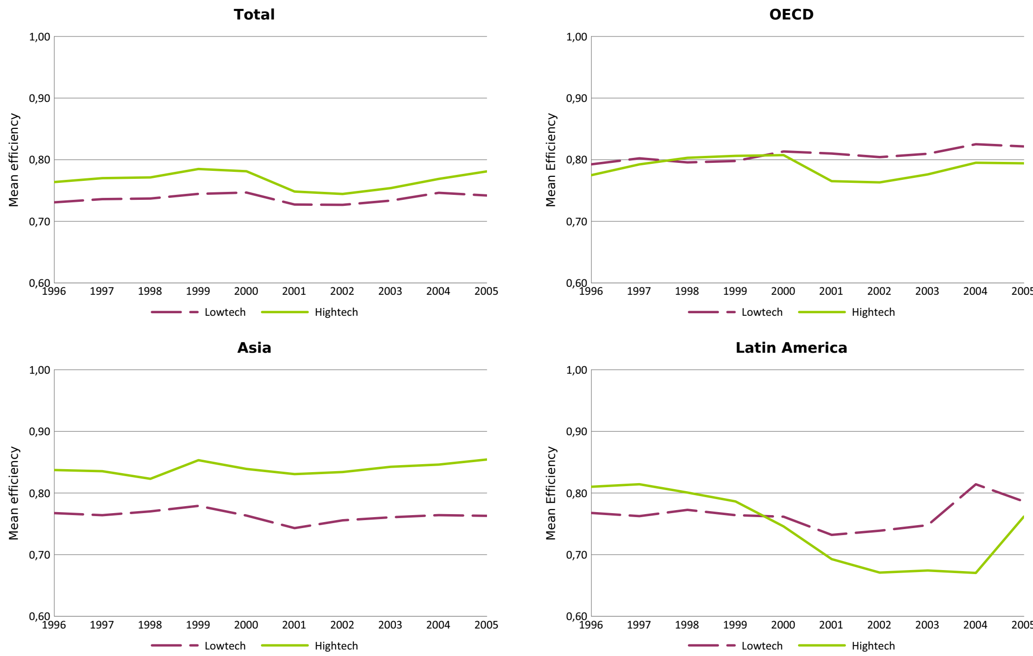


Figure 2: Mean efficiency by country group, low-tech and high-tech sectors



Figures 3, 4 and 5 look on the performance of individual countries within our three regional groups. For OECD countries, a marked drop in high-tech efficiency for France, the Netherlands, Sweden and Italy is notable from 2000 onwards, with Italy remaining stuck at a level of high-tech efficiency that is the lowest of all 22 countries in our sample. On the other hand, the United States, Denmark and Norway significantly improve their efficiency during the second half of the period observed, while efficiency levels for the UK, Germany and Belgium remain roughly the same from 1996 to 2005.

What we capture here is probably the divergence in productivity between the US and some Scandinavian countries on the one hand, and most European OECD countries on the other hand, which became notable since the late 1990s and is most often attributed to the better exploitation of ICT-induced productivity gains by the US (Van Ark et al. 2003). Less flexible and more regulated labour markets in Europe might also play a role in this respect (Bassanini et al. 2009).

In Asia, a group of high performers includes South Korea, Japan, Singapore and the Philippines, while Indonesia remains at a lower level of technical efficiency. India and China lie in between, and seem to be fast catching up to the group of high-performers. India significantly increased its efficiency between 1997 and 2005, especially in high-tech sectors, where it has become the most efficient of all 22 countries in our sample by 2005. However, despite a 0.1 increase between 1997 and 2005, low-tech sectors are still very inefficient in the country, so that - with the exception of Mexico - they remain the most inefficient of all countries in our sample in 2005. With respect to the debate about the relative importance of technical efficiency improvements to growth in India (Bhaumik, Kumbhakar 2010, Kim, Saravanakumar 2012), our paper thus finds evidence for an increase in technical efficiency, especially in high-tech sectors. The marked divide that we find between efficiency in low- and high-tech sectors also confirms conclusions by earlier studies (D'Costa 2003), which suggest that the Indian economy is driven forward by some efficient high-tech industries, especially in the ICT sector, while low-tech industries are still lagging behind. With respect to China, even though we only have data for 2003-2005, it

Table 4: Mean efficiency by country, low-tech and high-tech sectors

	Total		OECD		Asia		Latin America	
Year	l.tech	h.tech	l.tech	h.tech	l.tech	h.tech	l.tech	h.tech
1996	0.731	0.764	0.793	0.775	0.767	0.837	0.768	0.810
1997	0.736	0.770	0.802	0.792	0.764	0.835	0.763	0.814
1998	0.737	0.771	0.796	0.803	0.770	0.823	0.773	0.801
1999	0.745	0.785	0.798	0.806	0.779	0.853	0.764	0.786
2000	0.747	0.781	0.813	0.807	0.763	0.839	0.762	0.746
2001	0.727	0.748	0.810	0.765	0.743	0.831	0.732	0.693
2002	0.727	0.744	0.804	0.763	0.756	0.834	0.739	0.671
2003	0.734	0.754	0.810	0.776	0.761	0.843	0.748	0.674
2004	0.746	0.769	0.825	0.795	0.764	0.846	0.814	0.670
2005	0.742	0.781	0.822	0.794	0.763	0.854	0.786	0.762

looks as if China has successfully managed, within a short time-span, to leave the group of low performers and join the group of high-efficiency countries.

For Latin America, a sharp drop in efficiency for high-tech sectors in Chile, Mexico, Colombia and Uruguay is notable between 1999 and 2001, followed by a slight recovery afterwards. After 2000, high-tech sectors are consistently much less efficient in Latin America than in OECD countries and Asia. This drop in efficiency might be a consequence of the series of financial crises that hit the continent around the year 2000. Colombia was hit by a crisis in 1998, Brazil in 1999, and Argentina, Ecuador and Uruguay in 2001, and most countries suffered from a recession for some of the years between 1999 and 2003 (Rojas-Suarez 2010). For Colombia and Uruguay, the year of their respective financial crisis coincides with the drop in efficiency we notice (Figure 9, Appendix). Although Chile and Mexico were not directly affected, their drop in efficiency might be related to close links with the crisis countries. For all four countries, the drop in efficiency is closely related to negative rates of GDP growth. Chile experienced negative GDP growth in 1999, preceeding the 0.23 drop in high-tech efficiency we notice for 2000-2001 (Figure 9). Mexico had a short recession in 2001 and low GDP growth rates for 2002 and 2003, corresponding with a 0.15 drop in high-tech efficiency for 2000-2002 (Figure 9). In Uruguay, GDP per capita decreased in four consecutive years between 1999 and 2002, and high-tech efficiency by 0.13 points between 2001 and 2004. Finally, Colombia's GDP decreased by -4.2% in 1999, and high-tech efficiency by 0.22 points from 1999 to 2000. The fact that efficiency in high-tech sectors decreased notably during this period of economic turbulence, while low-tech sectors remained remarkably stable, could indicate that high-tech sectors in Latin America are more internationally integrated but also more vulnerable to economic perturbations than low-tech sectors.

Figure 3: Mean efficiency - OECD

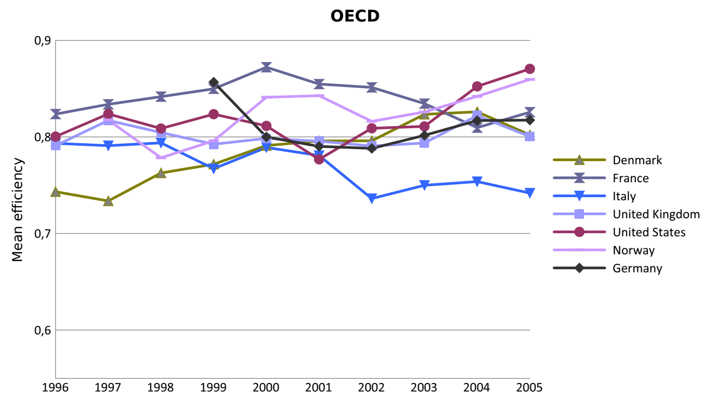


Figure 4: Mean efficiency - Asia

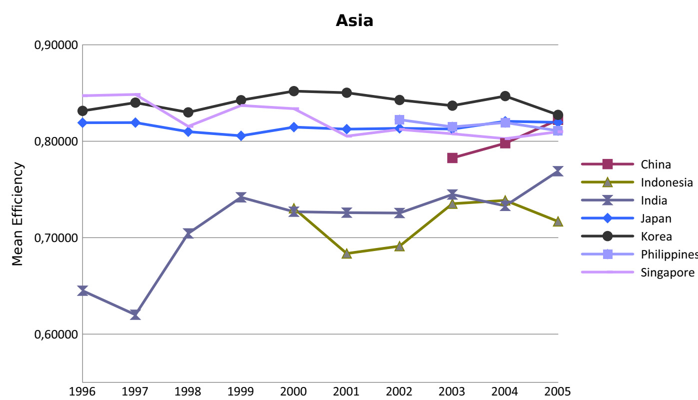
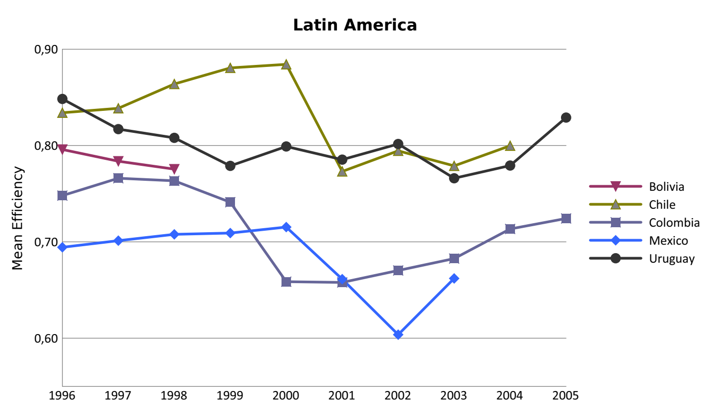


Figure 5: Mean efficiency - Latin America



4.3 Determinants of Technical Efficiency

Stock of Patents

Table 5 reports the results of our efficiency estimation. We find that an increase in the stock of patents has a negative and significant effect on technical inefficiency in high-tech sectors across all country groups. A 1% increase in the stock of patents decreases inefficiency in high-tech sectors in OECD countries by 0.219%, by 0.14% in Asia and by 0.119% in Latin America. Interestingly, this effect changes once we look on low-tech industries. Here, we consistently find that an increase in the stock of patents *increases* technical inefficiency. While the effect is very low for OECD countries, with a 1% increase in the stock of patents leading to a 0.013% increase in inefficiency, in Asia inefficiency increases by 0.177%, and in Latin America by 0.351% in low-tech sectors for a 1% increase in the stock of patents.

Our findings differ from those of Kneller and Stevens (2006), who find that R&D "has only an insignificant effect on inefficiency" (Kneller and Stevens 2006, pp. 19). Using stock of patents instead of R&D expenditure as a proxy for the effectiveness of domestic R&D in a stochastic frontier framework reveals a significant effect of domestic R&D on efficiency, which however fundamentally differs between high-tech and low-tech sectors.

Large parts of the more general literature on the effects of R&D on productivity also find such a difference between high-tech and low-tech sectors (see Kumbhakar et al. (2011) for a literature review). While domestic R&D has generally a strong and positive impact on productivity in high-tech sectors, the impact is low or not significant for low-tech sectors. For instance, using a dataset of top European R&D investors over the period 2000–2005, Kumbhakar et al. (2011) find that R&D in low-tech sectors "has a minor effect in explaining productivity", whereas in high-tech sectors the effect of R&D on productivity is found to be strong and positive. By analyzing a sample of 156 large Taiwanese firms for the period 1994-2000, Tsai and Wang (2004) find a positive but very low effect of R&D on productivity for low-tech sectors, whereas the effect was positive and strong for high-tech sectors.

Our findings are coherent with previous studies in that we also find a substantial difference between high-tech and low-tech sectors. However, the difference we find is even larger, since for our sample an increase in the stock of domestic knowledge has a positive effect on inefficiency for low-tech sectors. This effect is much stronger in developing countries than in our group of OECD countries. A possible explanation might be that we use patents as a proxy for effectiveness of R&D. As patenting activity is higher in high-tech sectors (Brouwer and Kleinknecht 1999, Lotti and Schivardi 2006), and resources for R&D are scarce, a crowding-out effect might occur that diverts resources from R&D in low-tech to R&D in high-tech sectors, due to expected greater returns to R&D in high-tech sectors. As we have only aggregate data for patents, it is possible that we capture this effect in our regression. An increase in patenting activity in an environment where resources for R&D are relatively scarce could thus lead to the negative effect on efficiency in low-tech sectors that we find. If this interpretation comes close to what is actually happening, it would suggest that the crowding-out effect is stronger for Latin America than for Asia.

Human Capital

The second determinant of technical efficiency we examine is human capital, measured by years of schooling (Barro and Lee 2010). We find that an increase in years of schooling has almost always a strong and significant negative effect on technical inefficiency, with the effect being stronger for low-tech sectors. For high-tech sectors, increasing years of schooling by 1% decreases inefficiency by 0.843% in OECD countries, by 1.876% in Asia and by 0.363% in Latin America, although results for Latin America are not significant. In low-tech sectors, a 1% increase in years of schooling decreases inefficiency by 1.39% in OECD countries, by 2.56% in Asia and by 4.07% in Latin America.

Our results are in line with those of previous studies. For a group of twelve OECD countries,

Table 5: Results - efficiency determinants

	Total	OECD	Asia	Latin America
z	-0.187*** (0.013)	-0.219*** (0.021)	-0.140*** (0.019)	-0.119* (0.071)
Low-tech*z	0.361*** (0.020)	0.232*** (0.021)	0.317*** (0.020)	0.470*** (0.074)
h	0.660*** (0.136)	-0.843*** (0.168)	-1.876*** (0.198)	-0.363 (0.437)
Low-tech*h	-2.992*** (0.157)	-0.548*** (0.174)	-0.685*** (0.208)	-3.705*** (0.3402)
const	0.838*** (0.211)	1.722*** (0.354)	1.654*** (0.413)	4.066 (0.935)
sigma squared	0.658*** (0.022)	0.291*** (0.007)	0.558*** (0.029)	0.377*** (0.022)
gamma	0.943*** (0.004)	0.974*** (0.003)	0.912*** (0.009)	0.911*** (0.012)
N	3904	1968	1148	788

The level of significance is shown with the following notation: *** 1%, ** 5%, and * 10%

Kneller and Stevens (2006) find that a 1% increase in human capital decreases inefficiency by 1.86%. Their coefficient is slightly higher than ours. As they look on an earlier period (1973-1990), this could be a sign for marginal decreasing returns of human capital over time in OECD countries. To our knowledge, there are no previous studies that use a stochastic frontier framework and specifically look at the effect of human capital on inefficiency in Asia and Latin America. However, looking at a group of 57 developing countries for the period 1960-2000, Mastromarco (2008) finds that increasing human capital by 1% decreases inefficiency by 2.33%.

We find that an increase in human capital reduces technical inefficiency more in low-tech than in high tech-sectors. This could mean that the type of human capital captured by the years of schooling data provided by Barro and Lee (2010) is more relevant in low-tech than in high-tech sectors. While an additional year of schooling has a strong impact on efficiency in low-tech activities, efficiency improvements in high-tech sectors are mainly induced by increases in "highly qualified" human capital (e.g. education at a post-graduate and doctoral level, specialist qualifications, etc.), which are not captured by Barro and Lee's data on years of schooling.

Comparing OECD countries and Asia to Latin America reveals further interesting results. Whereas in the former the effect of schooling on low-tech sectors is only slightly higher than the effect on high-tech sectors, for Latin America the effect of schooling on efficiency in low-tech sectors is exceptionally strong, whereas the effect on high-tech sectors is relatively small and insignificant. This suggests that the quality of human capital in low-tech sectors is still very low in Latin America.

5 Conclusion

Using a stochastic frontier framework and data for 22 manufacturing sectors, we found notable differences in technical efficiency between a group of 10 OECD countries, 7 Asian countries and 5 Latin American countries. As the efficiency with which countries use frontier technology determines their capacity to absorb technology produced abroad, these differences are important to understand differences in growth and productivity, especially for developing countries which depend to a large extend on foreign technology.

We examine the effect of two potential determinants of a country's absorptive capacity: human capital measured by years of schooling, and the effectiveness of domestic R&D, proxied by the stock of patents. We find that years of schooling always has a strongly positive effect on efficiency, especially in low-tech sectors and for developing countries. The stock of patents positively affects efficiency in high-tech sectors, but has a consistently negative effect on efficiency in low-tech sectors, especially for Asia and Latin America.

To our knowledge, this is the first study using a stochastic frontier approach and sectoral data not only for OECD countries, but also for two groups of emerging economies. Using sectoral data permits us to disaggregate the efficiency effect of schooling and stock of patents between low-tech and high-tech sectors. However, as in many developing countries sectoral data has only been made available recently, and is not yet available to a sufficient extend for human capital, stock of R&D and patents, there is a lot of scope for future work once better data becomes available.

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6 Appendix

Table 6: Sector classification (ISIC Rev. 3)

15 Food and beverages	Low-tech
16 Tobacco products	Low-tech
17 Textiles	Low-tech
18 Wearing apparel	Low-tech
19 Leather, leather products and footwear	Low-tech
20 Wood products (excl. furniture)	Low-tech
21 Paper and paper products	Low-tech
22 Printing and publishing	Low-tech
23 Coke,refined petroleum products, nuclear fuel	Low-tech
24 Chemicals and chemical products	High-tech
25 Rubber and plastics products	Low-tech
26 Non-metallic mineral products	Low-tech
27 Basic metals	Low-tech
28 Fabricated metal products	Low-tech
29 Machinery and equipment n.e.c.	High-tech
30 Office, accounting and computing machinery	High-tech
31 Electrical machinery and apparatus	High-tech
32 Radio,television and communication equipment	High-tech
33 Medical, precision and optical instruments	High-tech
34 Motor vehicles, trailers, semi-trailers	High-tech
35 Other transport equipment	High-tech
36 Furniture; manufacturing n.e.c.	Low-tech

Table 7: Number of available sectors by country and year

Year	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	Total
Belgium				22	22	22	22	22	22	22	154
Bolivia	18	18	18								54
Chile	18	18	18	16	16	19	19	19	19		162
China								22	22	22	66
Colombia	18	18	18	18	21	20	20	20	20	20	193
Germany				18	22	22	22	22	22	22	150
Denmark	22	22	22	22	20	20	20	19	19	19	205
France	21	21	21	21	21	21	21	21	21	21	210
Indonesia					22	22	22	22	22	22	132
India	18	18	22	22	22	22	22	22	22	22	212
Italy	22	22	22	22	22	22	22	21	21	21	217
Japan	22	22	22	22	22	22	22	22	22	22	220
Korea	22	22	22	22	22	22	22	22	22	22	220
Mexico	22	22	22	22	22	22	22	21			175
Netherlands	22	22	22	22	22	21	21	21	21	21	215
Norway		21	22	22	21	21	21	21	22	21	192
Philippines							22	22	22	22	88
Sweden		21	21	21	21	21	21	21	21	21	189
Singapore	21	21	21	21	21	21	21	21	21	21	210
United Kingdom	22	22	22	22	22	22	22	22	22	22	220
United States	18	22	22	22	22	22	22	22	22	22	216
Urugay	18	18	21	21	21	21	21	21	21	21	204
Total	304	350	358	378	404	405	427	446	426	406	3,904

Figure 6: Efficiency

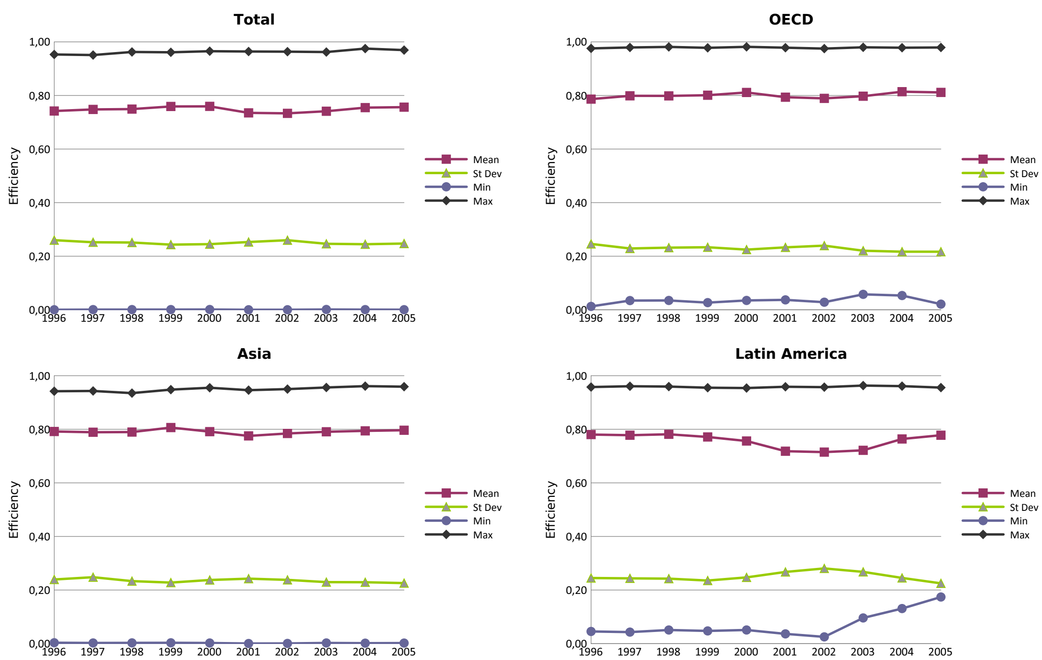


Figure 7: Mean efficiency by country - OECD

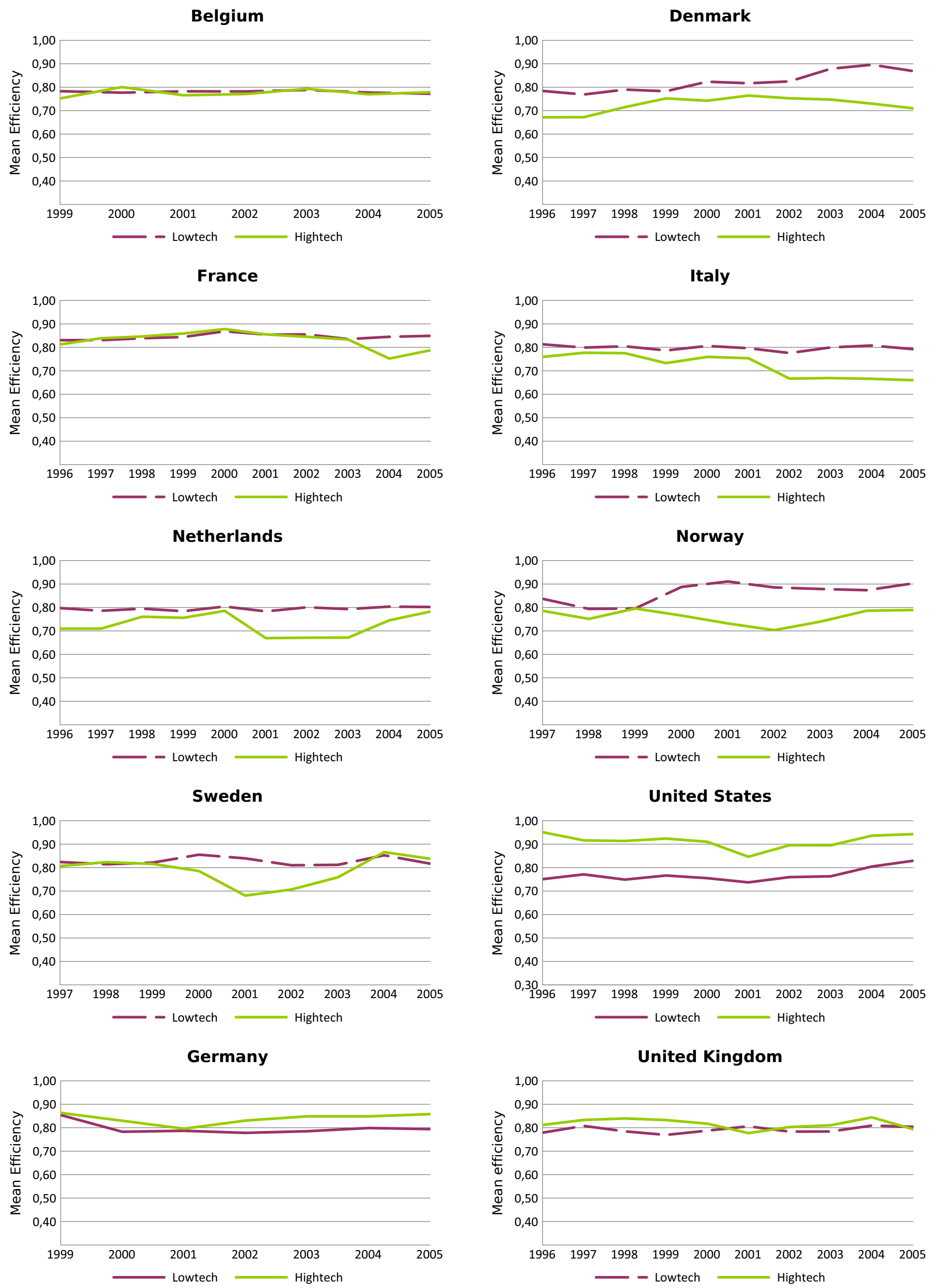


Figure 8: Mean efficiency by country - Asia

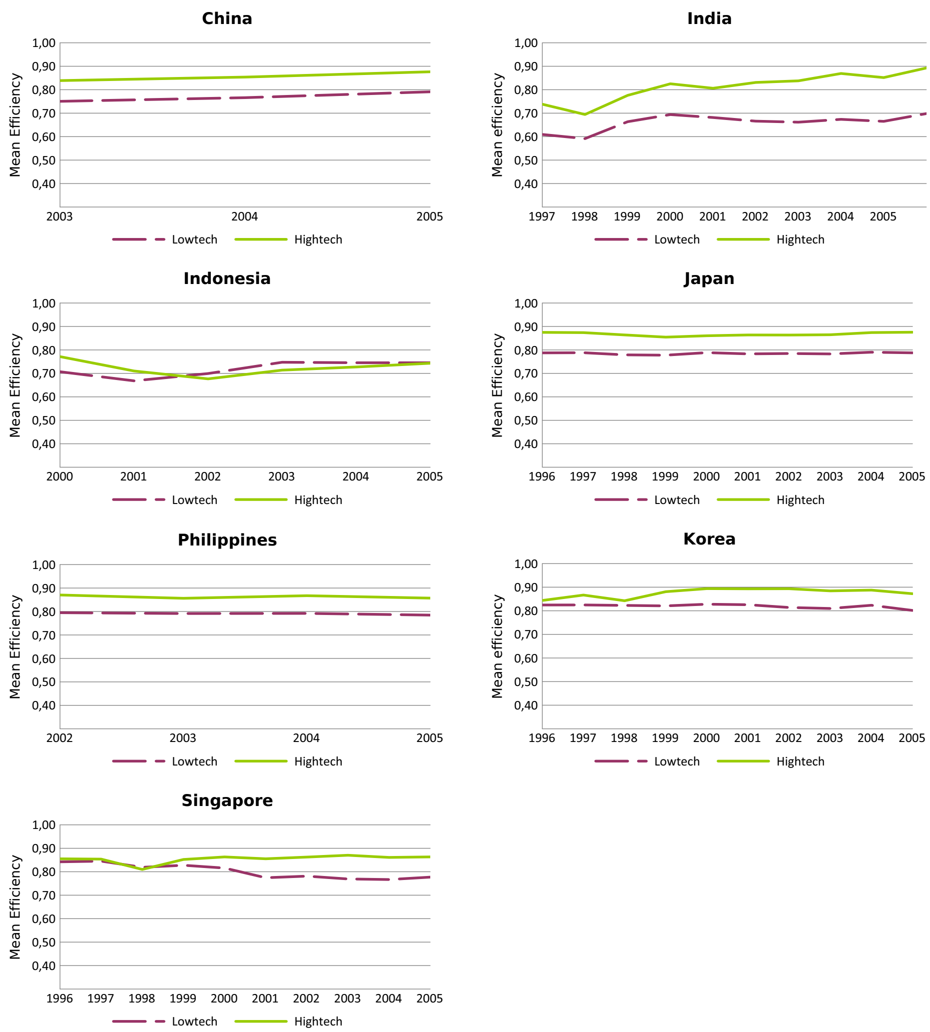
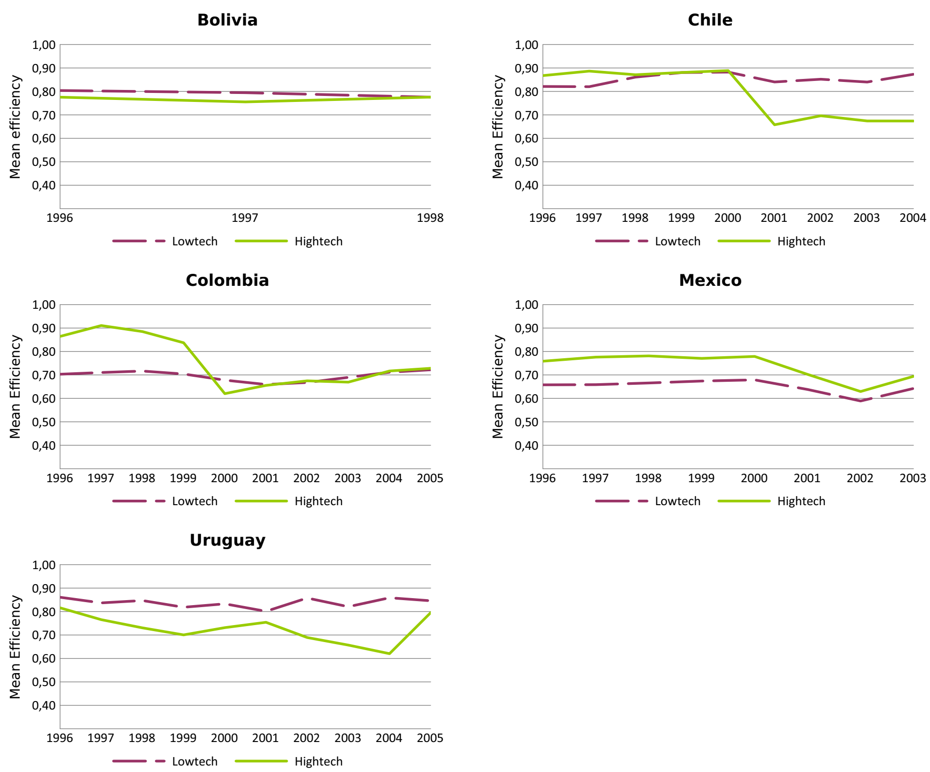


Figure 9: Mean efficiency by country - Latin America



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