Measuring China's innovative capacity. A stochastic frontier exercise

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Abstract

We adopt a Stochastic Frontier Analysis (SFA) of innovative activity to disentangle countries patenting capacity from patenting efficiency. We analyse the determinants of innovative capacity of a set of 26 OECD countries plus China, over the period 1992-2007, to show how China's technological system is growing faster than commonly held, in comparison to most innovative countries of the world. Our results highlight that both internal and external elements are necessary to enhance countries innovative capacity and efficiency. In particular, while government funded R&D is more important for innovative capacity, private funded R&D affects technical efficiency. The same holds for high–tech export and FDI. Moreover, as for the whole set of countries FDI seems to exert a resource seeking role (as they affect negatively technical efficiency), this does not happen for China, where FDI exerts positive effects thus contradicting the results found so far. General measures of human capital do not seem to have any impact on both patenting capacity and efficiency.

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1 Introduction

As recognised by many studies, over the last years China has reached the goal of growing at an increasing rate. This high and rapid GDP growth has stimulated some comparisons with other Asian experiences. Indeed, as Young (1995) and Renuka and Kalirajan (1999) have convincingly shown, the four Asian Tigers (i.e. Singapore, Hong Kong, Taiwan, and South Korea) have been performing their remarkable rate of growth mainly because they were "travelling along" the production function (i.e. by increased capital accumulation and efficiency in resource allocation), rather than "shifting upward" the production function (i.e. by means of technological progress).

On the whole, total factor productivity has been used to assess the relative contribution of the different factors to growth. These results are derived from growth accounting exercises, based on Solow (1957), in which the contribution of the various factors to economic growth is measured, and also it is indirectly calculated (as a residual) the rate of growth of technical change (e.g. Jorgenson and Griliches, 1967; Denison, 1962) (for a recent survey see Barro (1999)). Starting from these early contributions, several papers analysed the input contribution to total factor productivity of several cross country databases (a thorough review of which is in Caselli (2005)). Results of this kind, for instance, prompted Krugman (1994) to play down the Chinese progress in GDP growth, more or less, for the same reasons.

However, China's growth can not be considered to be due only to an increase in the use of labour and capital, but, a higher technological knowledge is responsible of such effect as well. Indeed, China is expected to become the second largest spender in R&D, overcoming Japan (*Battelle R&D Magazine*, http://www.rdmag.org). What is noteworthy, however, it is not the fact that China is now second only to USA as far as R&D is concerned (indeed, it overcame Japan by a narrow margin), but that China managed to keep high rates of growth in R&D spending during a period of deep economic crisis, thus increasing its share of global R&D spending.

Several studies are starting to investigate more deeply the determinants of emerging countries innovation capacities, in particular many paper are concentrated on the Chinese case (e.g. Altenburg et al. (2008)). This innovative capacity, in turn, led to a structural change in the fundamentals behind the sustained GDP growth, which has prompted analyses highlighting how China is now becoming a technological leader (Zhou and Leydesdorff, 2006; Kostoff, 2008). Some papers also addressed, although in a very qualitative way, the emergence of a National System of Innovation in China (Gu and Lundvall, 2006; Liu and White, 2001; Gabriele and Khan, 2008), pointing to the emergence of private sector–funded S&T activities, which are progressively taking over the burden of R&D investments from publicly funded institutions.

Therefore, the aim of this paper is to quantitatively assess how China performed with regard to the world technological leaders, in order to assess if and how China was able to change the "usual" patterns of development followed by lagging countries so far. By using USPTO patenting activity as a proxy for new–to–the–world innovation, we will assess how China fares with respect to the most advanced innovative economies in order to quantitatively evaluate the capacity of the Chinese S&T system to catch–up with the technological leaders. In so doing, our aim is to understand whether China was able to develop effective innovative capabilities, or whether Chinese economic performance is less technology intensive and thus destined to hit the ceiling of decreasing marginal productivity of factors of production. To do this, we apply Stochastic Frontier Analysis (SFA) in order to empirically estimate both the absolute position with respect to the world technological frontier and the efficiency with which the gap is managed and eventually overcome. We will perform our analysis with regard to the whole set of the most innovative countries (i.e. the OECD countries) plus China for the period 1990–2007.

The paper is organised as follows. Section 2 will present the theoretical background to the paper. Section 3 will describe the empirical approach adopted while Section 4 describes the dataset. Finally, Section 5 will offer a discussion of the main empirical results and Section 6 will offer some concluding remarks.

2 Determinants of innovative performance

The capacity of a nation to perform innovative activities has been the focus of a huge series of contribution, focusing in particular on which framework is more conducive to innovation, and on the relationships among innovative inputs and outputs. A set of particularly relevant contributions focused on the determinants of the capacity of a nation to perform new–to–the–world innovation, which indicates the capacity of staying on (or close) to the technology frontier, thus gaining a competitive edge with respect to other countries. Focusing on such a topic implies an effort to understand what are the main idea–driven elements that allow a country to be the leader in certain sectors.

The main implication of this perspective is that it stresses the role of the sources of disembodied innovation (disregarding other forms of innovative activity, such as, for instance, technological transfer embodied in machinery or licenses), which rests on a set of more abstract principles and ideas that are supposedly codified, not appropriable, and based on "freely available" scientific activity. If this is so, countries could easily benefit from a common pool of intangible resources upon which they all can build their innovative capacity.

However, the historical record strongly suggests that this picture is not close to reality. On the contrary, even when tacitness, idiosyncratic elements and causal ambiguities are excluded, we observe marked differences in the innovative capacity of countries despite the possibility that they can benefit from the same pool of common knowledge. This is true especially when emerging countries are observed: indeed, observing catching–up, and even forging–ahead, is confronted with the fact that the closer to the frontier a country happens to be, the more likely that it will experiment decreasing marginal productivity of its innovative efforts.

In this paper we support the view that the capacity of a country to perform efficiently some innovative activity close to the frontier can be explained by referring to two different concepts of new–to–the–world innovative activity, that are respectively, innovative capacity and innovative efficiency. Indeed, if we separate the analysis of the capacity of a country to set its position with respect to the technological frontier, and the efficiency with which innovative inputs are converted into innovative output, we are in the position to understand variations in the nation's capacity to perform innovative activities, within a common framework.

The model we employ to investigate the relationship between innovation input and output draws from studies in which a knowledge production function is estimated. Our dependent variable that represents the innovation output is proxied by the number of patents granted at the USPTO.[1] Following previous literature, we use logs only for quantities in levels and not for percentages or ratios, to obtain estimates less sensitive to outliers as might be for this kind of data, and to have readable elasticities that can be easily

[1]As we usually observe some lag between a patent application and a grant we lag the variable 3 years forward. In this way we are also able to control for some endogeneity occurring because of the simultaneity between dependent and independent variables.

Table 1: Determinants of innovation capacities

Dependent Variable: $lnPATENTS(t+3)_{USPTO}$

	1	2	3	4	5	6	7	8
	FGLS	FGLS	FGLS	FGLS	NEWEY	NEWEY	NEWEY	NEWEY
GOVERD	2.252***	2.903***	2.765***	2.036***	4.205***	3.241***	3.041***	2.414***
	(0.48)	(0.41)	(0.43)	(0.42)	(0.71)	(0.54)	(0.59)	(0.65)
HTEXP	0.038***	0.040***	0.041***	0.030***	0.061***	0.050***	0.056***	0.050***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
JOURNALART	1.327***	1.200***	1.192***	1.162***	1.297***	1.181***	1.158***	1.112***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)	(0.06)
GDPPC	0.843***	0.493***	0.505***	1.141***	0.628***	0.367***	0.386***	0.724***
	(0.09)	(0.08)	(0.09)	(0.13)	(0.14)	(0.14)	(0.14)	(0.21)
BERD		0.786***	0.768***	0.610***		0.830***	0.783***	0.716***
		(0.09)	(0.09)	(0.10)		(0.16)	(0.16)	(0.18)
FDI			-0.001	-0.001			-0.005	-0.006
			(0.00)	(0.00)			(0.01)	(0.01)
CHINA				2.891***				1.708***
				(0.42)				(0.64)
$Wald\chi^2$	2711.681***	3948.903***	3785.054***	23652.677***				
N	339	339	339	339	339	339	339	339
F					56.66***	81.96***	81.93***	92.89***

***,**,* denote significance at the 1%, 5%, 10% level, respectively.

standardised.

The benchmark model is the following:

$$PAT_{j,t+3} = \beta_0 + \beta_1 GOVERD_{jt} + \beta_2 HTEXP_{jt} + \\ + \beta_3 JART_{jt} + \beta_4 GDPPC_{jt} + \gamma_t + \epsilon_{jt}$$

where γ_t represents a set of time dummies to control for possible business cycle effects. To this benchmark model we added progressively other variables that should account for the innovation capacity of the country such as BERD, the stock of FDI and the Chinese dummy. Due to the low number of zero values we consider patent as a continuous variable, estimating the model through Feasible Generalized Least Square (FLGS) to take into consideration the presence of heteroschedasticity and serial autocorrelation of order 1. To test the robustness of our results we also present estimates obtained by OLS regression with Newey–West standard errors that are both heteroschedastic and autocorrelation consistent. A detailed description of each variable used in the regressions is given in Section 4.

As we can see from Table 2, coefficients are robust to both estimations. As expected, we find that all coefficients are positive and highly significant. However, we do not find any evidence of the fact that FDI may results of some usefulness for a country to innovate, pointing out a double issue: in the first place, as we are using an aggregate measure, we are not able to disentangle the various motivations that characterize FDI, that is asset seeking vs. asset exploiting FDI. Moreover, we are not able to consider what is the effect of spillovers that receiving countries are able to absorb and transform it into innovation activities. For these reasons, a non significant result is found for this variable. The Chinese dummy is found to be positive and significant meaning that China is progressively improving its innovative capacity. The highest coefficient is the one represented by government R&D that outperforms business R&D investment which nevertheless remains a powerful predictor of innovative capacity.

3 Measuring technical efficiency with SFA

While multivariate empirical analysis finds a positive relationships (as shown in the previous section) between the innovative output (usually, and also in this paper, patents) and the innovative input covariates, they are not able to discriminate the contributions of each covariate to the innovative capacity versus the efficiency enhancing contributions. Therefore, a further step can be made in order to better qualify these contributions, by means of Stochastic Frontier Analysis.[2] Such a framework has been developed in order to build a production frontier with respect to which it is possible to measure separately the movements along the frontier (i.e. increases in the use of inputs) from those of the frontier (i.e. technological change). The idea of disentangling two elements making up for the innovative carrying capacity of a nation is appealing as it allows to rely on few theoretical and methodological elements in order to depict the intertwining of discrete and incremental elements of the innovative activity.

Therefore, starting from the contribution of Kumar and Russell (2002), several papers examined factors contribution to growth within a stochastic frontier approach (e.g. Hiebert, 2002). Nevertheless, the same approach can also be applied to the framework of the knowledge production function. In this way, the output of innovation, such as patents, can be different across countries because of differences in the efficient use of innovation inputs, such

[2]It is not the purpose of this paper to discuss the different empirical specifications of the methodology for the construction of the frontier. See Kumbhakar and Lovell (2000) for a survey.

as, for instance, R&D.

In the original framework, the SFA approach builds a model in which the error structure of a production function is decomposed into two terms: the first is the usual error term capturing the noise, the second, one–sided and strictly positive error component, that captures the technical inefficiency (Kumbhakar and Lovell, 2000; Kumbhakar and Wang, 2005). With this approach we estimate a patenting world frontier to first evaluate the basic patenting capacity of transforming innovative inputs into innovative output; secondly, we use the distance from the frontier to measure how some factors affect the efficiency with which those inputs are used. Our starting model is the following:

$$Y_{it} = X'_{it}\alpha + \epsilon_{it}$$

in which ϵ_{it} is decomposed in the two terms referred above:

$$\epsilon_{it} = \nu_{it} + \mu_{it}$$

where ν_{it} represents an independent normally distributed measurement error and μ_{it} is the inefficiency error term which follows a one-sided normal distribution truncated at 0. Y_{it} measure the innovative capacity in country i at time t while X_{it} represents the vector of input factors that determines the world patenting frontier. The residuals of this first step of the analysis represent the the dependent variable of the second step in which the following model is estimated:

$$u_{it} = z'_{it}\beta$$

in which u_{it} is the mean of inefficiency error explained by a vector of efficiency factors z_{it}. In this way we are able to estimate what determines inefficiency, or, in other words, what increases or decreases the distance from the frontier. More precisely, u_{it} is estimated from the residuals of the first step as $-log(E(\mu_{it}/\epsilon_{it})$.

4 The variables and the dataset

In line with the previous theoretical account, it is crucial to correctly identify the variables for the first and the second step of the empirical analysis. Several papers have addressed this issue, with different outcomes of the variables selection, and thus with very different results.

It is necessary to keep in mind that the variables needed for the first step of the regression are to be related with the establishment of the "absolute" position of the frontier and thus with the "absolute" distance of the various countries from it. This implies that the search must be focused on variables able to explain how countries' absolute patenting activities differ from each other. For this reason, we follow the benchmark specification of the model we estimated when investigating for the factors underlying the patenting capacity of countries (with the exclusion of GDP per capita):

$$PAT_{j,t+3} = \beta_0 + \beta_1 GOVERD_{jt} + \beta_2 HTEXP_{jt} + \beta_3 JART_{jt} + \epsilon_{it}$$

All variables are in log. The measure of the innovation output is the variable represented by patents (PAT) granted by the USPTO for country j in year t 3 years later (although the specification is robust to changes in the lag in patenting activity). The literature is not unanimous in considering this variable as a good proxy for innovative activity (e.g. Archibugi (1992)), as not all inventive activity is patentable and not all patent data represent technological innovations. Even though other possible innovation output variables can be used, such as the number of patent citations or the new product sales, they are affected by the same flaws as patents. The choice of using the number of patents granted at the USPTO allows us to avoid comparability problems across countries as national granted patents may be different in standards, costs or protection offered.

The dependent variables we identified as relevant are:

- Government financed R&D (GOVERD): it is measured as a percentage of GDP and it is the main element that contributes to determine the patenting capacity of a country as it is the main input in the knowledge production function. However, it is crucial for our purpose, to address the composition of R&D by funds. According to the literature on the topic, it is commonly assumed that public funded R&D usually addresses more basic research and aims, while privately funded R&D usually addresses more applied kind of problems trying to give more practical answers. If this distinction is assumed, then the former type of R&D can easily be assumed as contributing to the S&T infrastructure of a nation, thus enhancing its potential.

- High–Tech Export (HTEXP): it is measured as a percentage of manufactured exports and we decided to include this variable as we need to understand how much of the technological potential of a country is directly linked to its high–tech opportunities and thus its ability to capture world market shares directly from its high potential production capacity.

- Scientific and technical journal articles (JART): by means of this variable we capture the idea that generating new ideas is one way to push forward the frontier of production of new and advanced goods, determining the absolute position in the technological space of the frontier of production capacity. This goal can be achieved by adding to the model the number of relevant scientific articles published by the researchers of a certain country. We make the hypothesis that the higher the number of articles the higher the possibility of translating the ideas into first class technological objects.

For all the reasons explained above, the four regressors are supposed to influence positively the position of the patenting frontier, as they should all contribute positively to enhance the patenting capacity of the countries.

A different goal is pursued in the second stage, which is aimed at highlighting the efficiency with which every country manage to fill the gap of its inefficiency with respect to the world frontier, thus giving an idea of the distance of each country from the frontier The benchmark model is the following:

$$Ln\mu_i = \beta_0 + \beta_1 BERD_{jt} + \beta_2 GDP_{jt} + \beta_3 FDI_{it} + \gamma$$

where the dependent variable is the log of the non–negative part of the residuals from step one regression. We estimate the model through OLS with robust standard errors.

As already pointed out, the second step must utilize regressors able to explain the efficiency in patenting activity, rather than its absolute performance. The variables we use are represented by:

- Business Enterprise R&D (BERD): measured as a percentage of GDP, it is used at this stage as private R&D spending, being a direct measure of input to the knowledge production function, is thus considered a direct generator of the knowledge output. Indeed, privately funded R&D is considered to be closer to the production stage to which it contributes by targeted problem solving activity and for this reason it is turned towards more applied domains that can be generally retained as contributing to increase the efficiency of the innovative activity.

- GDP per capita (in constant 2000 US$): it can be considered as a rough measure of the development level of a country and it reflects the socio–economic ability of a country to transform its scientific and technological knowledge stock into economic value. As a more developed economy implies a more articulated technological and industrial structure, it is more likely that, within a well diversified economy, new–to–the–world ideas find a proper environment to be further developed into proper innovative output.

- Foreign Direct Investments (FDI): they are measured as a stock (% GDP) and, even though from a certain point of view they perform a similar function to Openness in influencing the capacity of a country to perform innovative activities, they have been added to the model for a different reason. Rather than contributing to the general innovation capacity of domestic firms, FDIs are more correctly supposed to capture the efficiency part of a country innovative potential, because they usually represent additions to the existing stock of knowledge, and therefore contribute to increase the efficiency of processes that are already performed within the host country. Nevertheless, FDI can be characterized by different motivations and not in all of them the additive component is straightforward to isolate: in the case of strategic asset seeking motivation, FDI are oriented towards the access to new technologies already present in the host country, or in the case of efficiency seeking, FDI are oriented towards exploiting comparative advantages of localisation within the host country (e.g. by delocalising particular phases of the production process). In both cases, FDI constitutes an additive component to the indigenous one, thus increasing its efficiency. In the case of market and/or resource seeking FDI, there can be additive elements, which consists in searching for eventual complementarities between the indigenous and the foreign component of the investment, thereby causing an increase in efficiency, but there can be also a negative impact on innovative capacity if 'pure' resource and market seeking FDI are considered.

The expected signs of the impact of the GDP variable is obviously positive, while the impact of the other two covariates on patenting efficiency is

Table 2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
PATUSPTO	4948.717	16650.586	0	111152.273	432
GOVERD (%GDP)	0.256	0.125	0.021	0.746	425
HTEXP (%man)	16.327	10.495	1.2	57.125	428
JART	19300.637	37926.797	10	209694.703	431
BERD (%GDP)	0.969	0.718	0.01	3.23	425
FDISTOCK (%GDP)	25.603	23.035	0.39	149.273	431
GDPPC (US$, 2000 constant)	17495.338	10824.798	475.931	41900.793	432
TERTIARY (%gross enrollment)	50.42	21.005	2.898	97.976	407
RDPERS (FTE)	172903.594	270856.201	1244	1736155	367

Table 3: Cross-correlation table

PATUSPTO	1.00								
GOVERD	0.33	1.00							
HTEXP	0.61	0.32	1.00						
JART	0.78	0.08	0.41	1.00					
BERD	0.68	0.41	0.57	0.45	1.00				
FDI	-0.18	-0.19	0.32	-0.12	-0.05	1.00			
GDPPC	0.51	0.26	0.48	0.26	0.61	0.14	1.00		
TERTIARY	0.31	0.25	0.35	0.26	0.50	0.24	0.67	1.00	
RDPERS	0.71	0.13	0.32	0.94	0.38	-0.25	-0.00	0.01	1.00

difficult to assess a priori.

In this second step, as done in regressions of section 2, we use variables either in log form or as ratio as this allow us to interpret results as elasticities and at the same time to mitigate the problem of outliers.[3]

The sample used for our empirical analysis is constituted by 26 OECD countries (we excluded Luxembourg and Chile because of the relevant number of missing data) to which we added China. The time span covered by the analysis is the period 1992-2007. The data are gathered from three different databases: the first is the Main Science and Technology Indicators (MSTI) released by OECD providing several technological indicators from which we obtained patents grants at the USPTO, considering the applicant as reference country and priority date as reference date. We also obtained from that database data measuring Government Intramural Expenditure on R&D

[3] In the first step of the stochastic frontier approach a log-log specification is required by Stata routine.

(GOVERD) expressed as a percentage of GDP, the expenditure on R&D in the Business Enterprise Sector (BERD) expressed as a percentage of GDP as well. Instead, the number of scientific and technical journal articles, GDP per capita (in constant 2000 US$), the amount of exports and imports of goods and services (in constant 2000 US$) are all taken from World Development Indicators (WDI) of the World Bank. In the end, data relative to the stock of FDI on GDP are drawn from UNCTAD database. Summary statistics are displayed in Table 2, while Table 3 reports the cross–correlation between covariates, and shows that the only high correlations are among variables used in either one of the two stages of the empirical analysis.

5 Empirical results

The empirical results for the SFA analysis are shown in Table 4, where the first and the second step of the empirical analysis are presented.

The results of the empirical analysis overall confirm the role of the co–variates chosen in our ex–ante theoretical discussion. Indeed, as far as the first step of the analysis is concerned (results are reported in column 5 of Table 4) we note that Government spending in R&D, the share of hi–tech export and the number of scientific journal articles all determine positively the position of the innovative stochastic frontier. In particular, other things being equal, a one percent increase in Government spending in R&D increases the patenting capacity by 0.24%, thus confirming that the overall capacity of a country to increase its innovative position depends on the public contribution to basic research. However, our results seem to confirm that, although the role of the Government is certainly positive and important, its impact is the smallest among the selected co–variates. Indeed, innovative activity is enhanced more by the number of journal articles published in a country. This co–variate has a quite high elasticity, thus confirming that in order to perform sustained innovative activity, a country must develop also an internal capacity (that can be conceived as a sort of absorptive capacity). Finally, an important role in determining the innovative capacity of a country is also associated to the share of hi–tech exports confirming that a country, being part of a global network through which the relevant knowledge is channelled, is increasingly less able to rely only on its internal capacities.

With respect to the second step, which indicates the efficiency with which a country is able to innovate thus decreasing its distance from the frontier, results for patenting efficiency at USPTO are shown in column 6 of Table 4. In this case, GDP and BERD have negative signs, thus indicating their role in decreasing inefficiency (or in increasing efficiency), although with different elasticities: in the case of USPTO, for instance, one standard deviation increase in private R&D increases efficiency in innovation by 25%, while GDP has a smaller increasing patenting by 14%. Interestingly, the impact of FDI (about which we had also an ex–ante uncertain sign), seems to confirm that FDI have usually a nature that is not oriented towards the exploitation of other country's knowledge, although its effect is very small.

As a robustness check, we have also added co–variates relative to human capital, in order to check if it has a direct role in enhancing the technical efficiency, but it seems not to be a determinant of it. Indeed, while tertiary education (column 7 of Table 4) shows a positive impact on technical efficiency, its coefficient is not significantly different from zero while R&D personnel (column 8 of Table 4) has a negative impact on technical efficiency. The reasons for this result seems to be, as for tertiary education, the generic nature and its "distance" from patenting activity, and, as for R&D personnel, the fact that not all the R&D personnel is involved in activities directly related to patenting (or in perspective), but with more incremental and "maintenance" activities.

Once time dummies are added (columns 1 to 4 of Table 4) the overall results are confirmed, with the exception of two covariates of the first step.

As a further robustness check, we re–estimate the models using a simultaneous estimator of the parameters of the stochastic frontier and covariates explaining determinants.[4] The results are displayed in Table 5, and they overall confirm and give more substance to our previous results. In fact, we find confirming evidence of the types of relationships already discussed, of the relative magnitude of the elasticity values, of the decreasing technological frontier, and the negative impact of general human capital indicators. Moreover, the model is more robust as the various specifications, and the addition of time dummies, do not alter the signs and significance of the estimated coefficients.

When a dummy variable for China is added to the second step regression,

[4]As a matter of fact, Battese and Coelli (1995) acknowledge that the two step model may be affected by some flaws related to assumptions about the independence of the of inefficiencies in the first stage. For this reason, they propose to adopt an extended version of the model by Kumbhakar et al. (1991) who suggest a single stage Maximum Likelihood procedure.

it turns out to be statistically significant and negative (column 2 and 4 of Table 6) that is, it implies an increase in efficiency. As this is the only significant country dummy (together only with Ireland), this justifies our decision to focus on China the empirical analysis of the rest of the paper.

In order to investigate the patterns with which the Chinese economy is structurally changing its innovative activity (Gu and Lundvall (2006); Zhou and Leydesdorff (2006); Kostoff (2008)), we have recalculated the second step of our SFA analysis by interacting our co–variates with the Chinese country dummy (results are shown in Table 7). From Table 7 some interesting results emerge, in particular as far as the sign of FDI is concerned, which is negative. This means that FDI in China are indeed able to contribute to increase the efficiency of the inventive activity, implying a very effective capacity of China to benefit from its position within the global knowledge network. It is thus an important result, as it hints to a quite different role of inward FDI in China from what is generally reputed: FDI in this case have a role, although the elasticity does not appear to be large: an increase of one standard deviation increases patenting efficiency by 2%. This indicates that the patterns followed by China in the last decade is usually not properly recognized when Chinese technological system is analysed. Moreover, BERD is not significant, while R&D personnel has a positive impact on technical efficiency. This seems to hint to what we referred above about the fact that, although R&D by itself does not deliver potential for world quality patenting activity, R&D personnel seems to deliver more incremental (and thus less visible) kind of patenting activities. This is also reinforced by the positive and biggest impact of GDP.

6 Conclusion

In recent years, Chinese economy has been witnessing such a sustained process of economic growth inducing fears of a Chinese economic threat (e.g. Elwell et al., 2007; Morrison and Martin, 2008). This rapid growth in GDP has been mainly fuelled by increasing the use of inputs, and this has prompted many authors to point out that the Chinese parable could resemble previous experiences (such as Russia and the Asian Tigers), whereas the growth in input led inevitably to decreasing marginal productivity and thus to a slow–down of income growth. TFP exercises show that Chinese growth has been due, on the one side, to the huge reallocation of labour from a low-productivity sector (agriculture) to higher-productivity ones, and, on the other side, to total factor productivity growth in the private sector (Dekle and Vandenbroucke, 2010). However, the approach of growth accounting does not allow to disentangle between the lack of inputs and the efficiency with which those inputs are used.

This is possible by means of the use of the SFA analysis that is adopted in the present paper. Indeed, it seems that in the last few years Chinese growth is reaching a new peak thanks to a very strong innovative path due to sustained technological change. To account for this surge in China's technological capacity, we try to dig deeper into the matter to disentangle innovation capacity from innovation efficiency and to understand what economic factors affect each dimension.

For this reason, the paper is divided in two main parts: in the first we investigate what determines the innovation capacity of a country. The main results can be summarized by pointing out that both domestic R&D inputs and external sources of knowledge such as high–tech trade positively contribute to enhance the number of patents granted at the USPTO. Chinese is moving on an innovation path which is converging with the technological leaders. However, this approach, even though it could lead us to draw some policy implications, such as the need to strengthen investment in R&D, would tell us only half of the story. Indeed, the second empirical approach used, namely SFA, help us to better evaluate which is the position of each country with respect to the world patenting frontier, focusing our attention on the Chinese case. Indeed, SFA splits patenting activity into two elements: the potential for innovative activity with respect to the best practice, and the differences in efficiency with respect to the frontier.

Some interesting results can be singled out: the first is that, while in the first step of the SFA approach we found that FDI were not relevant in affecting patenting efficiency, we find that in the case of China this variable turns put to be of extreme importance in contributing to innovation efficiency. This sheds some light on the type of FDI entering China: they are changing their nature, as they are now mainly of an asset seeking nature. The same positive contribution to Chinese innovation efficiency is given by BERD pointing to the fact that internal R&D capacities are not less relevant than external knowledge sources in influencing the Chinese ability of introducing new and improved products.

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Table 4: SFA analysis: two step

Dependent Variable: $ln\ PATENTS(t+3)_{USPTO}$

	1	2	3	4	5	6	7	8
GOVERD	-0.188				0.244*			
	(0.16)				(0.14)			
HTEXP	-0.142				1.067***			
	(0.10)				(0.10)			
JOURNALART	1.321***				1.161***			
	(0.12)				(0.06)			
Dependent Variable: lnu_i								
BERD		-0.546***	-0.533***	-0.697***		-0.256***	-0.245***	-0.335***
		(0.07)	(0.06)	(0.09)		(0.03)	(0.03)	(0.04)
FDI		0.003**	0.003**	0.003**		0.005***	0.005***	0.006***
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
GDPPC		-0.125***	-0.083	-0.060		-0.140***	-0.118***	-0.103***
		(0.04)	(0.07)	(0.04)		(0.02)	(0.03)	(0.02)
TERTIARY			-0.003				-0.001	
			(0.00)				(0.00)	
RDPERS				0.067***				0.057***
				(0.02)				(0.02)
Cons	-5.405***	2.676***	2.419***	1.433***	-4.904***	2.816***	2.674***	1.883***
	(1.15)	(0.33)	(0.48)	(0.47)	(0.58)	(0.18)	(0.24)	(0.27)
$\ln\sigma^2$	1.252***				1.067***			
	(0.36)				(0.27)			
γ	2.977***				1.788***			
	(0.39)				(0.33)			
μ	3.154***				4.176***			
	(0.55)				(0.42)			
η	-0.010**				-0.118***			
	(0.00)				(0.02)			
Time Dummies	YES	YES	YES	YES	NO	NO	NO	NO
χ^2	803.226***				888.353***			
N	316	424	400	367	316	424	400	367
F		170.995***	106.385***	105.688***		189.420***	119.499***	92.448***

***,**,* denote significance at the 1%, 5%, 10% level, respectively.

Table 5: SFA analysis: one step

Dependent Variable: $ln\ PATENTS(t+3)_{USPTO}$

	1	2	3	4	5	6
GOVERD	0.666***	0.674***	0.589***	0.698***	0.733***	0.653***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.11)
HTEXP	0.962***	0.968***	0.993***	0.986***	0.937***	1.045***
	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.11)
JOURNALART	1.140***	1.132***	1.092***	1.131***	1.129***	1.138***
	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.06)
Cons	-7.867***	-7.850***	-7.871***	-4.448***	-4.464***	-4.855***
	(0.45)	(0.45)	(0.55)	(0.37)	(0.38)	(0.48)
$ln\sigma_v^2$	-0.639***	-0.517***	-0.497***	-1.086***	-0.825***	-0.777***
	(0.18)	(0.13)	(0.12)	(0.30)	(0.26)	(0.30)
BERD	-1.739***	-1.998***	-1.877***	-0.478***	-0.746***	-0.563***
	(0.65)	(0.70)	(0.62)	(0.18)	(0.22)	(0.22)
GDPPC	-0.587***	-0.978***	-0.791**	-0.308**	-0.967***	-0.260*
	(0.22)	(0.32)	(0.31)	(0.12)	(0.20)	(0.15)
FDI	0.017**	0.016**	0.018**	0.035***	0.030***	0.039***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
TERTIARY		0.020			0.042***	
		(0.01)			(0.01)	
RDPERS			-0.170			0.199**
			(0.23)			(0.10)
Cons	6.047***	8.566***	9.349**	3.788***	8.001***	0.950
	(1.78)	(2.33)	(4.66)	(1.08)	(1.48)	(1.83)
Time Dummies	YES	YES	YES	NO	NO	NO
χ^2	2185.178***	1951.661***	1170.871***	1794.178***	1607.564***	939.806***
N	316	298	287	316	298	287

***,**,* denote significance at the 1%, 5%, 10% level, respectively.

Table 6: SFA analysis: China interaction

Dependent Variable: $lnPATENTS(t+3)_{USPTO}$

	1	2	3	4	5	6
GOVERD	-0.188		0.244*		0.667***	0.698***
	(0.16)		(0.14)		(0.10)	(0.10)
HTEXP	-0.142		1.067***		0.918***	0.986***
	(0.10)		(0.10)		(0.09)	(0.11)
JOURNALART	1.321***		1.161***		1.142***	1.131***
	(0.12)		(0.06)		(0.03)	(0.04)
BERD		-0.511***		-0.232***	-1.604***	-0.477**
		(0.09)		(0.04)	(0.58)	(0.19)
FDI		0.003**		0.005***	0.017**	0.035***
		(0.00)		(0.00)	(0.01)	(0.01)
GDPPC		-0.184***		-0.181***	-1.192***	-0.309*
		(0.07)		(0.03)	(0.35)	(0.17)
CHINA		-0.319*		-0.222***	-2.185**	-0.003
		(0.18)		(0.08)	(0.92)	(0.60)
Time Dummies	YES	YES	NO	NO	YES	NO
χ^2	803.226***		888.35***		2150.476***	1751.985***
N	316	424	316	424	316	316
F		164.927***		158.573***		

***,**,* denote significance at the 1%, 5%, 10% level, respectively.

Table 7: Second step-China

Dependent Variable: $lnPATENTS(t+3)_{USPTO}$

	1	2	3	4	5	6	7	8	9	10
BERD	-0.609***	-0.513***	-0.514***	-0.527***	-0.664***	-0.274***	-0.234***	-0.234***	-0.241***	-0.307***
	(0.09)	(0.08)	(0.09)	(0.07)	(0.10)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
FDI	0.002**	0.003**	0.003**	0.003**	0.004***	0.005***	0.005***	0.005***	0.005***	0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GDPPC	-0.103*	-0.182***	-0.179***	-0.091	-0.150**	-0.142***	-0.179***	-0.178***	-0.125***	-0.181***
	(0.06)	(0.07)	(0.07)	(0.08)	(0.07)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
BERD*CHINA	-0.030					-0.081				
	(0.23)					(0.11)				
FDI*CHINA		-0.023**					-0.016***			
		(0.01)					(0.01)			
GDPPC*CHINA			-0.043*					-0.030**		
			(0.03)					(0.01)		
TERTIARY				-0.003					-0.001	
				(0.00)					(0.00)	
TERTIARY*CHINA				-0.005					-0.004	
				(0.01)					(0.00)	
RDPERS					0.091***					0.077***
					(0.02)					(0.02)
RDPERS*CHINA					-0.037**					-0.032***
					(0.02)					(0.01)
Cons	2.522***	3.194***	3.165***	2.491***	2.000***	2.844***	3.175***	3.158***	2.730***	2.374***
	(0.52)	(0.57)	(0.59)	(0.60)	(0.62)	(0.26)	(0.28)	(0.29)	(0.29)	(0.30)
Time Dummies	YES	YES	YES	YES	YES	NO	NO	NO	NO	NO
N	399	424	424	400	367	399	424	424	400	367
F	138.368***	160.597***	162.584***	89.006***	115.219***	151.134***	156.086***	157.104***	95.961***	86.726***

***,**,* denote significance at the 1%, 5%, 10% level, respectively.

Table 8: Technical efficiency scores

Country	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Canada	0,523	0,483	0,441	0,398	0,355	0,312	0,270	0,230	0,191	0,156	0,124	0,096	0,072
China	0,277	0,236	0,197	0,161	0,128	0,099	0,074	0,054	0,037	0,025	0,016	0,009	0,005
Czech Republic				0,132	0,102	0,077	0,056	0,039	0,026	0,016	0,010	0,006	0,003
Denmark	0,342	0,299	0,257	0,217	0,179	0,145	0,114	0,087	0,064	0,045	0,031	0,020	0,012
Finland	0,488	0,446	0,403	0,360	0,317	0,275	0,234	0,196	0,160	0,127	0,099	0,074	0,054
France	0,335	0,292	0,251	0,211	0,174	0,140	0,109	0,083	0,061	0,043	0,029	0,019	0,011
Germany	0,518	0,478	0,436	0,393	0,350	0,307	0,265	0,225	0,187	0,152	0,120	0,093	0,069
Greece		0,161		0,099		0,054		0,025		0,009		0,003	0,001
Hungary	0,180	0,145	0,114	0,087	0,064	0,045	0,031	0,020	0,012	0,007	0,004	0,002	0,001
Iceland	0,698	0,667	0,635	0,600	0,563	0,524	0,484	0,443	0,401	0,358	0,316	0,275	0,235
Ireland	0,357	0,314	0,272	0,231	0,192	0,157	0,124	0,096	0,072	0,052	0,036	0,024	0,015
Italy	0,442	0,400	0,356	0,313	0,271	0,231	0,192	0,157	0,124	0,096	0,072	0,052	0,036
Japan	0,657	0,623	0,588	0,550	0,511	0,470	0,428	0,386	0,343	0,301	0,260	0,220	0,183
Korea				0,594	0,557	0,518	0,477	0,436	0,394	0,351	0,309	0,268	0,228
Mexico	0,250	0,210	0,173	0,139	0,109	0,082	0,060	0,043	0,029	0,018	0,011	0,006	0,003
Netherlands	0,396	0,353	0,310	0,268	0,228	0,189	0,154	0,122	0,094	0,070	0,050	0,035	0,023
New Zealand	0,352	0,310		0,227		0,154		0,094		0,051		0,023	
Norway		0,321		0,238		0,162		0,101		0,055	0,038	0,026	0,016
Poland	0,244	0,205	0,168	0,135	0,105	0,079	0,058	0,040	0,027	0,017	0,010	0,006	0,003
Portugal	0,284	0,243	0,204	0,167	0,133	0,104	0,078	0,057	0,040	0,027	0,017	0,010	0,006
Slovak Republic			0,205	0,168	0,134	0,105	0,079	0,058	0,040	0,027	0,017		0,006
Slovenia		0,383		0,297	0,256	0,216	0,178	0,144	0,113	0,086	0,064	0,046	
Spain	0,302	0,260	0,220	0,182	0,147	0,116	0,088	0,065	0,047	0,032	0,021	0,013	0,007
Sweden		0,414		0,328		0,245		0,169		0,106		0,059	0,042
Turkey	0,306	0,264	0,223	0,185	0,150	0,118	0,091	0,067	0,048	0,033	0,022	0,013	0,008
United Kingdom	0,228	0,189	0,154	0,122	0,094	0,070	0,050	0,034	0,023	0,014	0,008	0,005	0,002
United States	0,537	0,497	0,456	0,413	0,370	0,327	0,285	0,244	0,205	0,168	0,135	0,105	0,080