Paper to be presented at the DRUID 2011

on

INNOVATION, STRATEGY, and STRUCTURE -
Organizations, Institutions, Systems and Regions
at
Copenhagen Business School, Denmark, June 15-17, 2011

# Measuring China's innovative capacity.A stochastic frontier exercise


**Chiara Franco**

Economics
chiara.franco2@unibo.it

**Riccardo Leoncini**
University of Bologna
Depratment of Economics
riccardo.leoncini@unibo.it



## Abstract

It is since Krugman (1994) article that the high growth rates of emerging countries have been under close scrutiny. Based on the results of growth accounting exercises, total factor productivity has been used to determine the relative contribution of the different factors to growth. However, as they are not explicitly focused on technological change and do not distinguish between the lack of inputs and the efficiency with which those inputs are used, we revert to a Stochastic Frontier Analysis (SFA) of innovative activity which allows us to disentangle patenting capacity from patenting efficiency. We therefore can show that the innovative capacity of China's technological system is growing faster than commonly held, in comparison to the OECD countries, representing the most innovative countries for the period 1990?2007. Our results highlight China's capacity to enhance both its innovative capacity and efficiency with a stronger effect in the last years. In particular and differently from other countries, we find a clear positive effect of the openness of the economy, contradicting the usual market exploitation thesis: both imports and exports and FDI exerts positive effects, but while the former impacts patenting capacity, the latter impacts its efficiency.

Jelcodes:O31,O33

# Measuring China's innovative capacity. A stochastic frontier exercise

February 28, 2011


**Abstract**

It is since Krugman (1994) article that the high growth rates of emerging countries have been under close scrutiny. Based on the results of growth accounting exercises, total factor productivity has been used to determine the relative contribution of the different factors to growth. However, as they are not explicitly focused on technological change and do not distinguish between the lack of inputs and the efficiency with which those inputs are used, we revert to a Stochastic Frontier Analysis (SFA) of innovative activity which allows us to disentangle patenting capacity from patenting efficiency. We therefore can show that the innovative capacity of China's technological system is growing faster than commonly held, in comparison to the OECD countries, representing the most innovative countries for the period 1990-2007. Our results highlight China's capacity to enhance both its innovative capacity and efficiency with a stronger effect in the last years. In particular and differently from other countries, we find a clear positive effect of the openness of the economy, contradicting the usual market exploitation thesis: both imports and exports and FDI exerts positive effects, but while the former impacts patenting capacity, the latter impacts its efficiency.



**Keywords**: China; Innovation, Stochastic Frontier Analysis.
**JEL code**: O31;O33

# 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 "traveling 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 labor 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 draw 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 into innovative output, we are in the position to understand variations in the nation's capacity to perform innovative activities, within a common framework.

In this regard, the most important contributions are those related to the concept of National Innovation System broadly defined as the institutional infrastructure that supports, influences, shapes and determines the rate and direction of technological learning(Lundvall, 1992; Nelson and Rosenberg, 1993). Drawing on the previous seminal contributions, some papers have tried to put a more robust empirical (Furman et al., 2002; Furman and Hayes, 2004) specification than the more qualitative empirical analysis usually done. As such these contributions were heavily based on the idea of a solid public support to innovation in order to build national competitiveness, based on institutional learning, university firms collaboration, interactive learning (Dosi et al., 1988).

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. As a robustness check we also estimate the equation using the application of patents to EPO.[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 standardised.

The benchmark model is the following:

$$PAT_{j,t+4} = \beta_0 + \beta_1 GOVERD_{jt} + \beta_2 HTEXP_{jt} + \beta_3 OPEN_{jt} + \beta_4 JART_{jt} + \beta_5 GDP_{jt} + \gamma_t + \epsilon_{jt} \tag{1}$$

where $\gamma_t$ represent 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, 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 1 and Table 2 coefficients are robust to both estimations. As expected, we find that all coefficients are positive and highly significant even when we estimate the model using the patent applications to EPO. 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

[1] As we usually observe some lag between a patent application and a grant we lag the variable 4 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: $ln\ PATENTS(t+4)_{USPTO}$

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| | FGLS | FGLS | FGLS | FGLS | NEWEY | NEWEY | NEWEY | NEWEY |
| GOVERD | 2.113*** | 2.380*** | 2.616*** | 1.026* | 3.978*** | 3.779*** | 3.554*** | 2.722*** |
| | (0.46) | (0.42) | (0.40) | (0.58) | (0.86) | (0.63) | (0.64) | (0.65) |
| HTEXP | 0.027*** | 0.025*** | 0.030*** | -0.002 | 0.046*** | 0.029*** | 0.036*** | 0.032*** |
| | (0.00) | (0.00) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| OPEN | 0.426*** | 0.527*** | 0.588*** | -0.213 | 0.540** | 0.827*** | 0.808*** | 0.703*** |
| | (0.12) | (0.11) | (0.10) | (0.31) | (0.22) | (0.17) | (0.17) | (0.18) |
| JART | 0.974*** | 0.778*** | 0.714*** | 0.853*** | 0.848*** | 0.505*** | 0.501*** | 0.531*** |
| | (0.10) | (0.10) | (0.09) | (0.22) | (0.17) | (0.14) | (0.15) | (0.16) |
| GDP | 0.929*** | 0.616*** | 0.584*** | 1.593*** | 0.720*** | 0.371*** | 0.392*** | 0.775*** |
| | (0.10) | (0.09) | (0.08) | (0.57) | (0.17) | (0.14) | (0.14) | (0.18) |
| BERD | | 0.712*** | 0.758*** | -0.013 | | 0.986*** | 0.932*** | 0.837*** |
| | | (0.08) | (0.08) | (0.10) | | (0.13) | (0.13) | (0.14) |
| FDI | | | -0.002 | -0.001 | | | -0.005 | -0.006 |
| | | | (0.00) | (0.00) | | | (0.00) | (0.00) |
| CHINA | | | | 4.175 | | | | 1.967*** |
| | | | | (4.07) | | | | (0.59) |
| Wald $\chi^2$ | 3188.153*** | 23513.527*** | 4617.887*** | 2226.366*** | | | | |
| F | | | | | 65.22*** | 102.86*** | 106.31*** | 136.72*** |
| N | 355 | 349 | 346 | 346 | 355 | 349 | 346 | 346 |

***,**,* denote significance at the 1%, 5%, 10% level, respectively. Regressions with Newey-West standard errors use autocorrelation up to the 5 lag to compute standard error. The calculation of the correlation structure is obtained following the usual rule of thumb (0.75*(N$\hat{1}$/3)).

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. Globalisation is confirmed to be one of the most important forces behind the abilities of countries to innovate as both openness and hightech exports are positive and significant when patents granted at USPTO are considered; instead no significant results are found when patent applications to EPO are considered.

# 3 Measuring technical efficiency with SFA

While multivariate empirical analysis find 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

Table 2: Determinants of innovation capacities

Dependent Variable: $lnPATENTS(t+4)_{EPO}$

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| | FGLS | FGLS | FGLS | FGLS | NEWEY | NEWEY | NEWEY | NEWEY |
| GOVERD | 1.089*** | 1.270*** | 1.406*** | 1.159*** | 2.106*** | 2.066*** | 2.324*** | 1.704*** |
| | (0.26) | (0.26) | (0.24) | (0.26) | (0.60) | (0.48) | (0.50) | (0.50) |
| HTEXP | 0.006 | 0.003 | 0.003 | 0.000 | 0.017** | 0.006 | -0.002 | -0.005 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.01) | (0.01) | (0.01) |
| OPEN | 0.527*** | 0.653*** | 0.691*** | 0.602*** | 0.375 | 0.579*** | 0.600*** | 0.523*** |
| | (0.09) | (0.09) | (0.08) | (0.09) | (0.23) | (0.20) | (0.19) | (0.19) |
| JART | 0.709*** | 0.551*** | 0.519*** | 0.548*** | 0.825*** | 0.585*** | 0.590*** | 0.610*** |
| | (0.07) | (0.07) | (0.08) | (0.08) | (0.19) | (0.16) | (0.16) | (0.15) |
| GDP | 0.922*** | 0.717*** | 0.689*** | 0.976*** | 0.827*** | 0.575*** | 0.551*** | 0.832*** |
| | (0.07) | (0.08) | (0.07) | (0.10) | (0.13) | (0.11) | (0.11) | (0.15) |
| BERD | | 0.374*** | 0.428*** | 0.346*** | | 0.680*** | 0.743*** | 0.674*** |
| | | (0.06) | (0.06) | (0.06) | | (0.12) | (0.14) | (0.14) |
| FDI | | | 0.001 | 0.000 | | | 0.006* | 0.005 |
| | | | (0.00) | (0.00) | | | (0.00) | (0.00) |
| CHINA | | | | 1.458*** | | | | 1.447*** |
| | | | | (0.38) | | | | (0.50) |
| Wald $\chi^2$ | 2711.257*** | 51885.714*** | 64540.153*** | 62105.303*** | | | | |
| F | | | | | 47.12*** | 69.74*** | 70.51*** | 65.51*** |
| N | 358 | 352 | 349 | 349 | 358 | 352 | 349 | 349 |

***,**,* denote significance at the 1%, 5%, 10% level, respectively. Regressions with Newey-West standard errors use autocorrelation up to the 5 lag to compute standard error. The calculation of the correlation structure is obtained following the usual rule of thumb (0.75*(N$\hat{1}$/3)).

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

[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.

countries because of differences in the efficient use of innovation inputs, such 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 $\epsilon_{it}$ is decomposed in the two terms referred above:

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

where $\nu_{it}$ represents an independent normally distributed measurement error and $\mu_{it}$ 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):

$$PAT_{j,t+4} = \beta_0 + \beta_1 GOVERD_{jt} + \beta_2 HTEXP_{jt} + \beta_3 OPEN_{jt} + \beta_4 JART_{jt} + \epsilon_{it} \tag{2}$$

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 $t$ 4 years later[3]. 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.

[3]The specification is robust to changes in the lag in patenting activity and utilizing patents applications at EPO

- Openness (OPEN): it is measured as the sum of imports and exports of goods and services (in 2000 costant US$) and it is the main variable linked to external relationships that we have considered. The main reason is that both learning by importing and learning by exporting effects are present at the same time: indeed, demanding customers for advanced goods and services may improve a country's ability to satisfy them and thus to capture relevant shares of world trade by producing an ever increasing number of new–to–the–world goods and services. Hence, on the demand (export) side, high–quality exports pull for increasing technologies of production to meet global quality standards, and, on the import side, import substitution, within this scheme acts as a powerful development block which pushes technology to higher levels.

- 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:

$$TEIN_{it} = \beta_0 + \beta_1 BERD_{jt} + \beta_2 BERD^2_{jt} + \beta_3 GDP_{jt} + \beta_4 FDI_{it} + \gamma \qquad (3)$$

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 other two covariates on patenting efficiency is difficult to assess a priori. Indeed, whether they could be superficially thought to have positive impact, however, is must be underlined that, as far as BERD is concerned, although a positive impact should be expected, there is abundant evidence on the non–linear impact that R&D has on innovative activities, especially if it is evaluated at country level. We will thus enter also the quadratic form ($BERD^2$) in order to test for this kind of linearity. Finally, because of what has been previously said, we do not expect a priori a certain particular direction in the relationship between FDI and patenting efficiency.

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.[4]

The sample used for our empirical analysis is constituted by 31 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 1990-2007. 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 data (both patents application to EPO and patents grants

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

at the USPTO) considering the applicant as reference country and priority date as reference date. We also obtained data measuring Government Intramural Expenditure on R&D (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 dollars), the amount of exports and imports of goods and services (in constant 2000 Us dollars) 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 3.

Table 3: Summary statistics

| **Variable** | **Mean** | **Std. Dev.** | **Min.** | **Max.** | **N** |
|---|---|---|---|---|---|
| $PATENTS_{Uspto}$ | 4133.753 | 14839.165 | 0 | 111152.273 | 576 |
| $PATENTS_{Epo}$ | 2889.529 | 6164.992 | 0 | 34658.363 | 576 |
| $GOVERD(\%GDP)$ | 0.25 | 0.125 | 0.021 | 0.746 | 498 |
| $BERD(\%GDP)$ | 1.025 | 0.739 | 0.01 | 3.844 | 504 |
| $Htexp(\%manexp)$ | 15.747 | 9.84 | 1.044 | 57.125 | 551 |
| OPEN | 342748579 | 473062423 | 3998204 | 3398300074 | 568 |
| JART | 17218.567 | 35088.146 | 10 | 209694.703 | 571 |
| $FDI_{Stock}$ (%GDP) | 25.209 | 24.214 | 0.169 | 176.911 | 559 |
| $GDP_{PC}$ | 18146.33 | 10335.482 | 391.655 | 41900.793 | 576 |

# 5 Empirical results

The empirical results for the SFA analysis are showed in Tables 4, where the first and the second step of the empirical analysis are presented. Two sets of results for both patents at USPTO and EPO have been produced in order to check for consistency.

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 1 of Table 4) we note the both Government spending in R&D, the share of Hi–tech export, the degree of openness 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 0.3%, 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 seems to confirm that, although the role of the Government is certainly positive and important, its impact is the smaller among the selected co–variates. Indeed, the bigger role in determining the innovative capacity of a country is not surprisingly associated to the share of hi–tech exports (a one percent increase in this co–variate increases patenting by 0.9%), which together with openness (for which one point increase determines a 0.5% increase in patenting activities) confirms that a country is increasingly less able to rely on its internal capacities, but it must be aware of the fact that it is part of a global network through which the relevant knowledge is channelled. Finally, innovative activity is enhanced by the number of journal articles published in a country. This co–variate has a quite high elasticity (a one percentage point increase enhance patenting by 0.8%), thus confirming that in order to perform sustained innovative activity, a country must develop, side by side to an external capacity, also an internal one, which can be conceived as a sort of absorptive capacity.

The results for patenting activity at the European Patent Office (reported in column 4 of Table 4) are quite different, highlighting only two significant co–variated (hi–tech exports and journal articles), of which only one has a very high elasticity: a one percent increase in journal articles increases patenting at EPO by 1.2% showing a very high impact. This seems to stress fundamental differences in the structure of incentives in patenting activities related to the two most important world markets. This result is further confirmed by the different signs and values of $\eta$, which indicates how efficiency changes over time: while $\eta$ for patenting at USPO is significant and negative, which means that if $\eta < 0$, the degree of inefficiency increases over time, it is positive and very small for patenting at EPO.

With respect to the second step, which indicates the efficiency with which a country are able to innovate thus decreasing their distance from the frontier, results for patenting efficiency at USPTO and EPO are shown in column 2 and 4 of Table 4 respectively. In this case, results for USPTO and EPO are substantially similar, and both 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 30%, while GDP has a smaller increasing patenting by 10%. The results for R&D have been deepened by adding their square values of BERD in order to check for non–linearities, which emerge highlighting how the closer a country gets to the frontier, the more likely decreasing marginal productivity will occur. 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, and the effect is sensible, as one standard deviation increase decreases efficiency by 10%.

When a dummy variable for China is added to the second step regression, this dummy variable turns out to be statistically significant and negative (column 3 and 6 of Table 4) that is, it implies an increases in efficiency. Together only with South Korea, this is the only significant country dummy. Moreover, by looking at the plot of the patenting capacity scores of our set of countries (Figure 1) it clearly emerges how China is the only country showing a constant increase in patenting capacity, moreover it shows also a parallel trend with South Korea from which it starts diverging from year 2000 onward.

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 the three co–variates with the Chinese country dummy (results are shown in Table 5). From Table 5 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. This result is is also robust as it emerges for both patents at USPTO and EPO. Therefore it is 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 as a an increase of one standard deviation increases patenting efficiency by 5%. This indicates that the patterns followed by China in the last decade is usually not properly recognized when Chinese technological system is analysed. A second result emerges from a comparison between USPTO and EPO patenting activities, as for the former private R&D activity is significant and a one standard deviation increase generate an average increase of 3.5% in patenting, while GDP and FDI are significant for both but the elasticities are bot higher (almost double) for EPO patenting: an increase in GDP

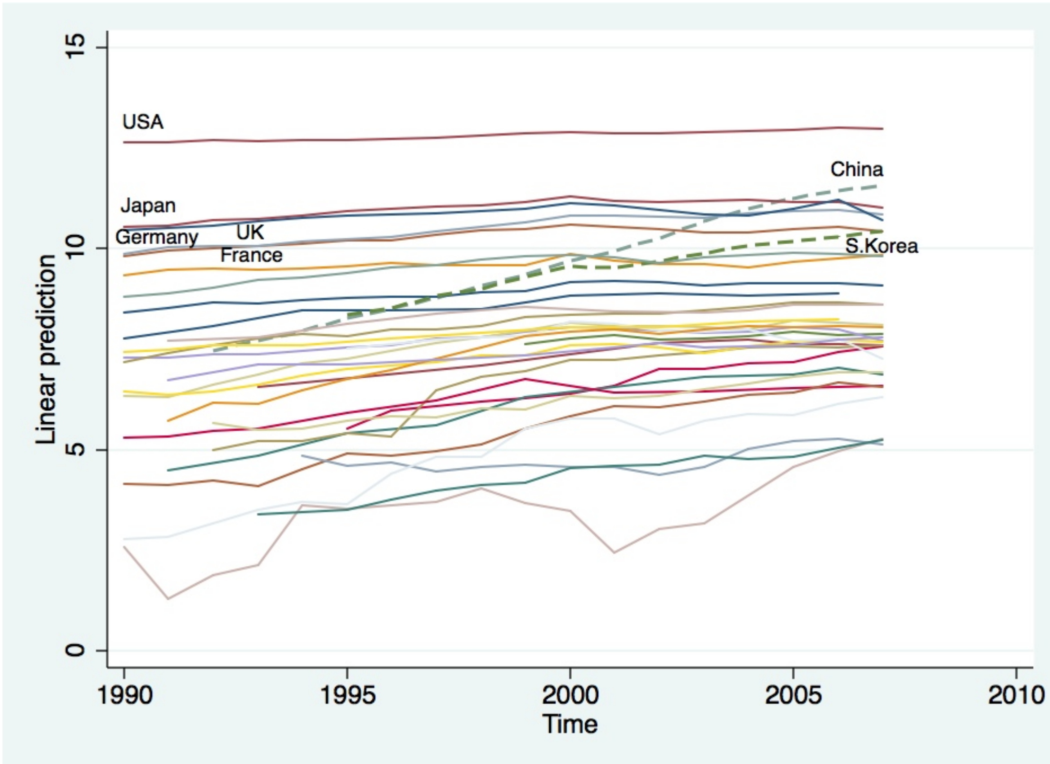


Figure 1: Patenting capacity

or FDI generates an average increase in patenting at EPO by 9%, while if generates an increase of 5% in patenting at USPTO. Therefore, two different patterns emerge regarding the generation of knowledge as related to different end user purposes: more trade related with respect to Europe, more R&D based with respect to USA.[5]

# 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 fueled by increasing the use of inputs, and this has prompted

[5]For an analysis of the motivation behind R&D choices from foreign firms with respect to China, see Motohashi (2010).

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 (the same results are confirmed with respect to patent application at EPO). The Chinese dummy which is significant confirms that this country is moving towards an innovation path 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.

# References


Altenburg, T., H. Schimtz, and A. Stamm (2008). Breakthrough? China's and India's transition from production to innovation. *World Development 36*, 325–344.

Archibugi, D. (1992). Patenting as an indicator of technological innovation: A review. *Science and Public Policy 19*, 357–368.

Barro, R. (1999). Notes on growth accounting. *Journal of Economic Growth 4*, 119–137.

Caselli, F. (2005). Accounting for cross-country income differences. In P. Aghion and S. Durlauf (Eds.), *Handbook Of Economic Growth*. Elsevier, Amsterdam.

Dekle, R. and G. Vandenbroucke (2010). Whither Chinese growth? A sectoral growth accounting approach. *Review of Development Economics 14*(3), 487–498.

Denison, E. F. (1962). The sources of economic growth in the united states and the alternatives before us. Technical report, Washington, DC: Committee for Economic Development.

Dosi, G., C. Freeman, R. Nelson, G. Silverberg, and L. Soete (Eds.) (1988). *Technical Change and Economic Theory*. Pinter, London.

Elwell, C. K., M. Labonte, and W. M. Morrison (2007). Is China a threat to the U.S. economy? Technical report, CRS Report for Congress.

Furman, J. and R. Hayes (2004). Catching up or standing still? National innovative productivity among 'follower' countries, 1978-1999. *Research Policy 33*(9), 1329–1354.

Furman, J., M. Porter, and S. Stern (2002). The determinants of national innovative capacity. *Research Policy 31*(6), 899–933.

Gabriele, A. and A. H. Khan (2008). Enhancing technological progress in a market-socialist context: China's national innovation system at the crossroads. mimeo.

Gu, S. and B. Lundvall (2006). China's innovation system and the move toward harmonious growth and endogenous innovation. *Innovation: Management, Policy & Practice 8*(1), 1–26.

Hiebert, L. (2002). The determinants of the cost efficiency of electric generating plants: a stochastic frontier approach. *Southern Economic Journal 68*, 935–946.

Jorgenson, D. W. and Z. Griliches (1967). The explanation of productivity change. *Review of Economic Studies 34*, 249–280.

Kostoff, R. (2008). Comparison of China/USA science and technology performance. *Journal of Informetrics 2*(4), 354–363.

Krugman, P. (1994). The myth of Asia's miracle. *Foreign Affairs 73*, 62–78.

Kumar, S. and R. Russell (2002). Technological change, technological catch-up, and capital deepening: relative contributions to growth and convergence. *American Economic Review 92*, 527–548.

Kumbhakar, S. and C. Lovell (2000). *Stochastic Frontier Analysis.* Cambridge University Press, Cambridge.

Kumbhakar, S. and H. Wang (2005). Estimation of growth convergence using a stochastic production frontier approach. *Economics Letters 88*, 300–305.

Liu, X. and S. White (2001). Comparing innovation systems: a framework and application to China's transitional context. *Research Policy 30*(7), 1091–1114.

Lundvall, B. (1992). *National Systems of Innovation. Towards a Theory of Innovation and Interactive Learning.* Pinter, London.

Morrison, W. and M. Martin (2008). How large is China's economy? Does it matter? Congressional Research Service, Library of Congress.

Motohashi, K. (2010). R&D Activities of Manufacturing Multinationals in China: Structure, Motivations and Regional Differences. *China & World Economy, Vol. 18, No. 6, pp. 56-72, November-December 2010 18*(6), 56–72.

Nelson, R. and N. Rosenberg (1993). Technical innovation and national systems. In R. Nelson (Ed.), *National Innovation Systems. A Comparative Analysis*, pp. 3–21. Oxford University Press, New York.

Renuka, M. and K. Kalirajan (1999). On measuring total factor productivity growth in Singapore's manufacturing industries. *Applied Economics Letters 6*, 295–298.

Solow, R. (1957). Technical change and the aggregate production function. *Review of Economics and Statistics 39*, 312–320.

Young, A. (1995). The tyranny of numbers: confronting the statistical realities of the East Asian growth experience. *Quarterly Journal of Economics 110*, 641–680.

Zhou, P. and L. Leydesdorff (2006). The emergence of China as a leading nation in science. *Research Policy 35*(1), 83–104.

Table 4: SFA: First and Second Step

| | USPTO | | | EPO | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| GOVERD | 0.2871** | | | -0.0933 | | |
| | (0.14) | | | (0.08) | | |
| HTEXP | 0.8602*** | | | 0.1047* | | |
| | (0.10) | | | (0.06) | | |
| OPEN | 0.4602*** | | | -0.0364 | | |
| | (0.16) | | | (0.10) | | |
| JART | 0.8444*** | | | 1.1964*** | | |
| | (0.12) | | | (0.10) | | |
| BERD | | -0.3907*** | -0.3108*** | | -1.6068*** | -1.6258*** |
| | | (0.07) | (0.09) | | (0.14) | (0.17) |
| $BERD^2$ | | 0.0461*** | 0.0273 | | 0.3557*** | 0.3602*** |
| | | (0.02) | (0.02) | | (0.04) | (0.04) |
| GDP | | -0.1162*** | -0.1716*** | | -0.2110*** | -0.1978*** |
| | | (0.02) | (0.04) | | (0.04) | (0.07) |
| FDI | | 0.0040*** | 0.0041*** | | 0.0019* | 0.0019* |
| | | (0.00) | (0.00) | | (0.00) | (0.00) |
| CHINA | | | -0.2717*** | | | 0.0645 |
| | | | (0.10) | | | (0.19) |
| CONST | -13.1786*** | 2.7280*** | 3.2127*** | -2.0991 | 2.9958*** | 2.8808*** |
| | (2.86) | (0.19) | (0.33) | (2.44) | (0.32) | (0.55) |
| $\sigma^2$ | 1.0621*** | | | 0.6861 | | |
| | (0.25) | | | (0.64) | | |
| $\gamma$ | 1.8272*** | | | 3.2688*** | | |
| | (0.30) | | | (0.66) | | |
| $\mu$ | 4.2417*** | | | 0.4780 | | |
| | (0.39) | | | (1.02) | | |
| $\eta$ | -0.1165*** | | | 0.0227*** | | |
| | (0.01) | | | (0.00) | | |
| $R^2$ | | 0.515 | 0.523 | | 0.503 | 0.503 |
| N | 355 | 490 | 490 | 358 | 490 | 490 |

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

Table 5: SFA: Second step — Dummy China interacted

| | USPTO | | | EPO | | |
|---|---|---|---|---|---|---|
| BERD | -0.2416*** | -0.2267*** | -0.2287*** | -0.5274*** | -0.4982*** | -0.5017*** |
| | (0.03) | (0.03) | (0.03) | (0.08) | (0.08) | (0.08) |
| GDP | -0.1558*** | -0.1874*** | -0.1844*** | -0.3864*** | -0.4471*** | -0.4416*** |
| | (0.03) | (0.03) | (0.03) | (0.05) | (0.06) | (0.06) |
| FDI | 0.0040*** | 0.0041*** | 0.0041*** | 0.0017 | 0.0018 | 0.0018* |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| BERD*CHINA | -0.2337** | | | -0.3170 | | |
| | (0.11) | | | (0.23) | | |
| GDP*CHINA | | -0.0440*** | | | -0.0749*** | |
| | | (0.01) | | | (0.02) | |
| FDI*CHINA | | | -0.0221*** | | | -0.0375*** |
| | | | (0.00) | | | (0.01) |
| CONST | 3.0314*** | 3.3220*** | 3.2944*** | 4.1460*** | 4.7048*** | 4.6549*** |
| | (0.23) | (0.25) | (0.25) | (0.46) | (0.50) | (0.49) |
| $R^2$ | 0.512 | 0.519 | 0.519 | 0.441 | 0.445 | 0.445 |
| N | 490 | 490 | 490 | 490 | 490 | 490 |

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