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International protection of intellectual property rights: a stochastic frontier index

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Abstract

This paper combines two bodies of work: the literature regarding the measurement of the strength of intellectual property rights (IPR) protection systems and stochastic production frontier efficiency analysis. We propose measuring the efficiency of IPR protection systems by comparing optimal production frontier of innovation to real results, through a measure based on the existing Stochastic Frontier Analysis of technical efficiency. Our results indicate that, despite imperfect datasets, this approach provides interesting results comparable to measures in Park (2008) and other IPR strength indicators. Some issues to be further explored longer datasets and richer information, and innovation measurements. This paper also adds some evidence to the idea of an inverted U relationship between innovation output and IPR protection system strength.

Keywords: intellectual property, innovation, Global Innovation Index, patent applications, economic development, stochastic frontier analysis, fixed effects.

I. Introduction

In an ideal world, innovation activity flourishes as firms exploit their new inventions and intellectual property, while free-riding[1] is curtailed by a system of legal protections and attributions regarding the use of these intangible properties. This system would be based on judges capable of discerning novelty from repetition or minor modifications to existing technologies. That is, only discernibly new inventions would receive protection through intellectual property rights protection mechanisms such as patents. It would require the

[1] In this context, free-riders are firms that exploit the new product or process, but do not attribute royalties to the innovating firm. This is an example of a positive externality.

disclosure of the new product or process' formula while offering legal mechanisms to pursue copycats in courts in order to obtain full retributions for its innovative process. The result would be knowledge transfers amongst firms creating new processes and products to other firms, placing the correct[2] incentive to sustain continued innovation and growth. In that sense, an intellectual property rights system is a set of protections for innovators over the economic benefits involving the use and reproduction of their products and processes [12].

One can imagine then, that there is an optimal level of where IPR protection. That is to say, there may be over or under protection of IPRs, stifling innovation in both cases. Too strong an IPR system and the incentives to innovate may be eroded by the stresses of cumbersome litigation processes and costs; too weak a system and imitators would easily free-ride the costs of the innovative process and the innovator's rents would not justify the new product or process. There seems to be a non-linear relationship between the strength of intellectual property rights and innovation in the form of an *inverted-U* [19].

This may also imply that competition may not stymie innovation but rather, stimulate it. Intuitively, this means that the post and the pre innovation rents is the incentive to innovate (innovate to survive) rather than need to secure only post innovation rents. Here the innovator, the industry leader, innovates to affect productivity/costs to sustain their position, even if competition degrades all of the firms' profits [1].

What is crucial to a good intellectual property rights system is the quality of the institutions which manages the system and settles disputes. Good intellectual property rights systems will stimulate the production of patent applications and output innovation. It should stimulate the sharing and retribution of new ideas, taking incentives away from more informal forms of IPR protection such as secrecy or lead-time. It should also not promote unscrupulous patenting as a competitive mechanism. There is a balance between protection and enforcement by the institutions and the rule of law, and, firm-level incentives to innovate. Which is why moving away from a linear thought on metrics of the relationship between IPRs and innovation is key.

Measuring the efficiency with which this process is done is a hard task. One of the main issues is the information available. To start, the meaning of innovation output is abstract, since there is no perfect measurement of it. Regardless, any samples available may be biased in terms of the size or type of the firms selected, and consistent longitudinal cross country data is hard

[2] That is, correcting the positive externality by attributing the uncaptured benefits of the new processes or products to the innovative firm.

to come by [11]. Intellectual Property Rights indexes are mostly composed of sums of unweighted factors believed to be determining the innovation process, capturing for the most part the quality of the IPR system. The intent behind these sort of indexes is to have a robust metric of patent protection systems across countries which captures attributes of the complex dynamic system underlying the production and protection of patents, and intellectual property.

This work is pointed at opening a new door for measuring the strength of intellectual property protection systems. We propose a simple stochastic frontier fixed effects model using panel data on countries' patent applications controlling for innovation output. We postulate that variations from estimated optimal patent application production, for a given level of output index, can be interpreted as technical inefficiency measures. In turn this may signal preferences towards informal protection mechanisms due to prohibitive legislative costs or poorly enforced rule of law. Another hypothesis not explored in this paper, but touched on by [19], may be an inverted U relationship between patent applications and the complexity and severity of patent protection laws, suggesting that too stringent IPRs may curtail the production of innovation (and patents).

We find that, given the difficult task of finding adequate quantifiers of the factors behind the dynamics of intellectual rights protection, our metric is comparable with the ranking results of our benchmark index proposed in [9] and updated in [18]. Additionally, we are able to establish strong and significant correlations between measures of a country's rule of law and quality of public institutions, and our index. This strengthens our hypothesis that an important driver in patent use is the quality of the legal system and institutions backing the patent system. Finally, we suggest that this avenue of research needs to be further explored, fine-tuning the data used in order to produce more explicative results. It is important to note that this work does not attempt to explain the reasons why countries may be more or less efficient, which in it of itself is a daunting task.

The remainder of this paper is organized as follows. Section 2 reviews the literature on patents protection metrics and section, intellectual property protection strategies, and efficiency analysis through stochastic frontier. Section 3 reviews the results of our findings and discusses the possible factors which may be operating behind our index. Section 4 presents our concluding comments and suggests areas for further exploration.

II. IPR Protection, measurement, and efficiency analysis

In this section, we begin by reviewing the literature on intellectual property rights and protection strategies. We explore the choice of different IP protection strategies and what are some of the stylized facts regarding the choice for strategies such as patenting or secrecy. Next, we delve into intellectual property rights metrics and indexes. A discussing of some of the main aspects of such metrics and the difficulties surrounding the empirical work on patent protection. Lastly, we review the body of work which entails stochastic frontier analysis as a measure of efficiency and tie it to the literature on IPR indexes.

i. Intellectual Property Protection

Intellectual property protection mechanisms allow firms to appropriate the returns on investment in new ideas, making the innovative process worthwhile. There is a trade-off, for both firms and society as a whole, between the incentives to continue innovation and widespread disclosure of these new ideas to the public [15]. Between full disclosure (due to the patenting process) and full secrecy of the innovation, there are strategies which combine patents and secrecy, lead time, or complexity to maximize the returns on their investment on innovation. We will find that the choice of the strategy is not a straight forward, and the simplistic narrative of one strategy over another hides intrinsic complexities within the IPR system [11].

In a broad sense, firms choose amongst formal and informal strategies to protect their IP. Formal strategies include patents, trademarks, designs, and copyrights; informal strategies include secrecy, confidentiality agreements, lead-time and complexity. That formal and informal strategies are mutually exclusive is debatable; firms may choose to exclusively use patents or secrecy to keep others from exploiting their innovations, or they may employ a mix of patents and complexity to stymie imitation or unauthorized use [11], or even choose to issue targeted disclosures in order to fend off potential rival firms from filling future patents [5].

A firm that comes up with a brand new idea has the choice of protecting their idea through, say, a patent, trademark, copyright, secrecy, lead time, or complexity. Patents usually require a level of disclosure of their idea and the process includes a series of occasions where the patent application can be challenged throughout the process by third parties[3], not to mention there is a minimum level of novelty required to patent [11]. Disclosure is a good mechanism of disseminating a new idea to third parties, exploiting a positive

[3] See Jaffe and Lerner (2006) for comments regarding the implications of challenging patents during the pre-patent grant process.

externality in the form of knowledge spillover [5][19]. However, the costs to innovate are assumed mostly by the innovating firm. So a patent system provides, once the idea is patented, mechanisms to protect such innovation from third party firms who reproduce the technology without prior authorization, through either litigation and/or indemnifications.

In some cases, firms may want to avoid the patent system as a protection strategy specifically because of the requirement to disclose their innovation [11][19]. Patent protection may also be of limited scope, perhaps weakening as globalization allows firms from different countries to reverse engineer or blatantly reproduce a patent protected innovation. In these cases, the firm may decide to use secrecy as a form of protecting their IP [12]. This entails some form of enforceable confidentiality agreement. Clearly, the efficiency of the secrecy is based on the ability of the firm to sustain the agreement [11].

Secrecy has its advantages, mainly that it is less costly to set-up and maintain than a patent and most importantly, there is no disclosure required. However, labor mobility may be an issue when trying to sustain confidentiality agreements. Also, agreements are subject to weaker legal protection [11]. A social outcome of secrecy is less disclosure of new ideas, which hinders the creation of newer ideas which build upon the innovations being kept secret [5].

Other forms of informal protection such as lead-time play a more competitive strategy role, since firms will want to prove its status as first innovator in order to establish precedent in future IP litigations. Also, they may use lead-time to act as barriers of entry for imitators and late adopters [11]. Empirically speaking, lead time seems to be the choice of protection strategy amongst survey data findings.

Most of the literature surrounding patents and knowledge transfer is related with the choice of IP strategy and the welfare and equilibrium result under different information structures. Empirical data shows a marked heterogeneity in the use of patents, depending on the market structure, competitiveness, and the product's complexity. Also as mentioned in the previous paragraph, lead time seems to be a common strategy to upend the competition by being the first in a market, establishing precedent in future IP disputes [11].

There patterns surrounding the use different protection strategies. Industries such as chemicals and pharmaceuticals, where discretion is key to competition and there is little ambiguity regarding the innovation and its codification is possible, rely heavily on patents in order to block the development of new rivals. Likewise, complex industries may patent more in order to force rival firms into negotiating the release of the innovation. The size of the firm has been found to be a determinant in the use of patents, where larger firms are more inclined towards the use of patents than smaller firms [6]. Overall, secrecy and other forms of informal IP protection are preferred by most firms of all characteristics over patents [6], [4], [11]. This may be explained by the legal and economic costs of implementing and sustaining a patent, not to mention In general, the characteristics of the innovation at hand and the market competing dynamics which the innovator faces determine the choice between patents (formal strategies) and secrecy (informal strategies) [11].

So while available evidence suggests that informal strategies and mixed strategies may be dominant over formal protection strategies, the data is riddled with measurement and methodological issues which challenges researchers to build more robust explicative models. Not to mention, the impact of policy decisions regarding protection will depend in large part on to what degree companies believe there to be a trade-off or complementary relationship amongst the IP protection strategies available [11].

ii. Measures of IPR strength

Measuring the effectiveness or even firm-level trends is a difficult task myriad with imperfect data sets and inconsistent cross country evidence [11], [3]. Patents may be easy to trace and evaluate, but the effectiveness of secrecy or other informal mechanisms may be more difficult to quantify. So it makes sense that metrics of how well patents works may not be capturing the actual efficiency of patent systems in a relative sense, rather they may just be capturing the macroeconomic, institutional, and legal conditions surrounding the patent system in place.

Several works have focused on capturing the firm-level perception of IP protection strategies, where the results are heavily influenced by the datasets employed, not to mention an endogeneity existing in surveys of research and development, and competition [11]. Mansfield (1994), for example, surveyed 100 major U.S. firms from 6 different industries to evaluate the perception of IP protection [16]. As mentioned earlier, although the findings may shed a light on the types of patent behavior across industries, it may censor the effects of firm's size regarding the choice between formal and informal strategies. The possibility of patenting an idea is also subject to national standards of novelty, while certain types of products or processes cannot be patented at all. This cross-country inconsistency presents a challenge, not to mention selected sampling may complicate when analyzing datasets [11].

III. Measuring IPR efficiency using stochastic frontier

There is a vast literature on measuring technical or productive efficiency using the stochastic frontier approach, starting with the seminal works from Farrell (1957), to the explicit formulation of the stochastic frontier model in Aigner et al (1977) and Meeusen and Broeck (1977). The basic notion underlying these works is to estimate the optimal level of output conditioned on input levels and a measure of technical efficiency [2]. This measure is defined hence as the ratio between the estimated optimal level of output and the actual level of production [14]. What follows is an exploration of the basics of Stochastic Frontier Analysis and we set-up our fixed effects model to be used in the following section.

i. The basics of stochastic frontier analysis using panel data

The stochastic production frontier starts with a production function where the efficient level of output y_i for each $i = 1, 2, ..., N$ productive unit (e.g. in our case countries) depends on x_i inputs and an error term composed of a stochastic component and an inefficiency term, such that

$$y_{it} = f(x_{it}, \beta) TE_i exp(v_{it} \tag{1}$$

Where the βs are estimated parameters of the production function and TE_i[4] is a measure of technical efficiency, defined as the deviation of the real production output from the optimal production schedule[5] [13]. Taking the natural log of both sides of the equation (1) we arrive at the basic stochastic frontier model for panel data, following Kumbhakar and Lovell (2000)

$$ln(y_{it}) = \beta_0 + \sum_n ln(x_{nit}) + v_{it} - u_i \tag{2}$$

$$TE_i = exp(-u_i) \tag{3}$$

Where v_{it} is the statistical noise assumed to be normal, independently and identically distributed two-sided error term taking on random deviations from optimal production levels noise due to random occurrences such as natural disasters. The technical inefficiency term, u_i captures the actual deviations from the optimal production schedule.

Estimates of the production function's parameters are not the main interest of research. Rather, the main focus is to obtain efficiency measures based on the estimated values of u_i. Once the parameters of the model are estimated,

[4]Technology change may be time invariant or variant, where in the latter case we write TE_{it}.

[5]See Kumbhakar and Lovell (2000) for a detailed summary of the various set-ups tested, including a half-normal and exponential distributions

including the standard errors of both the statistical noise and the inefficiency term, the following normalization is done such that

$$\widehat{\beta_0} = \max_i \{\widehat{\beta_{0i}}\} \tag{4}$$

We are able to estimate the inefficiency measure as

$$\widehat{u_i} = \widehat{\beta_0} - \widehat{\beta_{0i}} \tag{5}$$

Where by construction $\widehat{u_i} \geq 0$. Finally, the average technical efficiency for each form is estimated as

$$\widehat{TE_i} = exp(-\widehat{u_i}) \tag{6}$$

Stochastic frontier models allow for time varying and time invariant technology. That is, the models can incorporate technological change, typical of longer panels where the technological state is allowed to change over time. The assumptions made over the technology change will condition the estimations of the inefficiency term since assuming time invariant technology is a strong assumption, especially for longer panel data sets. Regulatory, policy, and productive innovations may produce exogenous shocks to the production technology. If the model assumes incorrectly the nature of technological change, than the effects captured by u_i may be confounded.

ii. Fixed stochastic frontier models

The availability of panel data allows for repeated observations of the same productive unit allow for more relaxed distributional assumptions when estimating JLMS; these can be estimated consistently as $T \to \infty$ [14]. Additionally, the fixed effects set-up relaxes the zero-conditional mean of the inefficiency term regarding the regressors [**wooldridge2005fixed**]. We assume that v_{it} the stochastic disturbance which varies through time and productive unit, is *iid* across all observations and is uncorrelated with the vector of inputs and that u_i is *iid*$\sim N(\mu, \sigma_\mu^2)$, but as mentioned, this set-up does not require that $E(u_i|x_{it}) = 0$.

Unbiased and consistent estimators for the production's parameters result only if $E(v_{it} - u_i^*)$ is consistent [20], [14]. This condition can be easily met if $T \to \infty$ since longer panels are able to better capture unobserved heterogeneity [14]. Perhaps the first red flag with this panel approach is the notion of whether there exists time-varying effects which could be confounded with the inefficiency measures in panel data with high levels of heterogeneity and/or large T. We will return to this point later and assume time invariant technical efficiency.

The parameters of the fixed effects model are estimated using dummy variables (intercepts) specific for each productive unit and suppressing the constant term. Once the parameters of the model have been estimated, the inefficiency term is obtained following equations (5) and (6). The parameters for this model and the efficiency terms are consistent not only as $N \to \infty$, but also as $T \to \infty$ assuming time invariant technical efficiency.

In this specification, the inefficiency term is bounded to the individual intercepts, so that the technical efficiency is conditioned to the most efficient productive unit in the sample. We interpret the technical efficiency as a percentage deviation from the optimal production schedule with regards to the most efficient unit in the sample. An issue with this model may be that the selection of a specific sample may condition the efficiency measures.

The advantages of this model are first and foremost its simplicity in separating the stochastic disturbance from the inefficiency term, consistently estimating unit specific efficiency measures. Also, assuming that $E(u_i|x_{it}) \neq 0$ provides greater flexibility regarding the specification of the model, versus perhaps the random effects set-up where it is assumed a priori that $E(u_i|x_{it}) = 0$.

However, a trade-off for its simplicity is the potential for confounding effects resulting from time-invariant non-technical effects captured by (the fixed effects) [14], [10]. That is to say, it is impossible to separate firm specific technical efficiency measures from effects such as policy rules and regulations which vary across productive units but are invariant through time. Needless to say, there is plenty of work to be done in this respect.

IV. Empirical Analysis

We present the results for the estimation of the fixed and random effects stochastic frontier technical efficiency measures. We do make a note that, from this point forward, we will interpret the technical efficiency measure as an Intellectual Property Rights Index.

i. Data employed

We use total patent application data from the World Intellectual Property Organization (WIPO) and the Global Innovation Index's Innovation Output Sub-Index. Using this data, we built a balanced panel of 108 countries spanning through the years 2012 and 2015.

Total patent applications per year (P_{it}) were first transformed into a size dependent variable, where we normalize in terms of population size. We used a size dependent normalization in [8], in order to remove the effect from the country size. This allows us to interpret patent applications net of the country size; China will inherently have more patent applications than Uruguay since the former is a significantly larger country than the latter. So in lieu of a size dependent variable, China might seem as a highly innovative country compared to Uruguay.

The Innovation Output Sub-Index (IOS) [7] is a measure a country's innovation output activity. It combines two pillars containing information on knowledge, technology, and creativity innovation [21]. It contains information on knowledge creation, knowledge impact, and knowledge diffusion. A note, inside the output index, there are measures of patent activity, which is an issue within our model. Future explorations will take into consideration better data points and longer panels.

Strictly speaking, the GII can be decomposed and the innovation output components can be captured individually. Unfortunately, there is incomplete information for the countries selected through the time period used. To obtain a larger sample of countries and a longer panel, implies the trade-off of reducing the number of countries. The IOS may be a too holistic measure of innovation output, but the gains of a balanced panel with a larger number of countries allows us to better test the overall fit of this methodology as an IPR measure of efficiency.

We use as a dependent variable the level of size-dependent total patent applications for each country and year from the World Intellectual Property Organization [17]. We employ size dependency because it is ludicrous to compare smaller more productive countries with larger more populous countries (and hence probably equally as productive in absolute terms). Normalizing countries by their size is a simple process, wherein we divide the total patent applications by the population of the country. Population estimates were taken from the World Bank's Database. Such procedure allows us to compare individual contributions to innovation output, instead of country-level contributions [8].

ii. Econometric Model

Stochastic frontier models employing fixed effects have a strong trade-off between the flexibility of its assumptions surrounding the disturbance and technical efficiency measure, and the confounding effects within the technical inefficiency estimations. As a first approximation to this methodology we assume time-invariant technology. We believe that because of the length of the panel and the nature of the data, we are safe to assume a constant technology; however, we note that our ignoring of the confounding effects amongst policy and efficiency factors is relevant and must be further addressed in future iterations.

Since we are interested in measuring the efficiency of patent application production given a measure of innovation output, we must first estimate a fixed effects regression model in the likes of equation (2) using the natural log of size-dependent total patent applications as the input and the natural log of the Innovation Output Sub-index as the output.

iii. Results

We estimated an Intellectual Property Rights Index for each country for a period between 2012 and 2015. As discussed, this index places the most efficient country of the sample as the most efficient of the index, so that the interpretation is relative. The results for the fixed estimations of the IPR Index are shown Tables 1. The fixed effects model, due to the normalization of the inefficiency term, is sensitive to the sample chosen. For example, we compared the estimates for the entire sample of 108 countries with an estimate of a sub sample of countries including only those in the OECD, as shown in Table 2.

The results show that the order or rank of the countries is mostly unaffected, while the magnitude of efficiency varies as less efficient countries are left out of the sample. That is, a sample with more efficient countries may improve the IPR index most efficient countries in the sample in a greater magnitude that the trailing countries. The IPR Index may overestimate efficiency for smaller samples; a clear trade-off between the size of the sample and the quality and quantity of data available.

An interesting result of our Index is the fact that it resembles diminishing returns to greater efficiency. Marginal efficiency of an IPR index decreases as the country reaches the most efficient country in the sample. Countries with the worst IPR systems will see greater improvements in their Innovation Output Index and their level of patent applications. This may also hint at the fact that overzealous IPR systems may add little to changes in Innovation Output and total patent applications.

We compared our results with the IPR index in [18] and found a significant and positive pair-wise correlation[6] Compared with Park (2008), we are able to capture diminishing returns to stronger IPR systems, as seen in , meaning there may be an optimal level of IPR strength and too much IPR may hinder innovation output. This was implied by the “inverted U” hypothesis regarding

[6]Our index and that of [18] does not contain the same sample of countries, so the correlation analysis may be affected. For example, when comparing the full sample with the smaller OECD country samples, our correlation falls (r = 0.30; p = 0.01) with respect to not only [18], but also the Rule of Law Index

the relationship between innovation output and IPR system's strength.

To test our measure of institutional and rule of law quality over our IPR index, we analyzed pair-wise correlations between the World Bank's CPIA Index[7] measuring the quality of public administration and the Rule of Law Index to measure the quality of the legal system. As shown in Graph 6 and 7, the IPR Index significantly correlates a direct relationship between these indicators. As a proxies, they may signal that countries with better institutions and better legal management may be inclined to present a more efficient IPR system. This goes hand in hand with out hypothesis of an optimal level of IPR, which requires richer data to test.

V. Conclusions

The IPR Index using stochastic frontier fixed effects model produces interesting results. It is able to rank countries according to their measure of IPR system efficiency. The efficiency of each country's IPR system is relative to the most efficient country in the sample. Stochastic frontier analysis seems to be an adequate measure of an IPR index, seemingly comparable to those obtained by [18]. A further look into alternative stochastic frontier techniques including country level heterogeneity of the stochastic term and of the inefficiency measure need to be incorporated into further estimates, as well as additional methods of testing robustness.

Though the limitations regarding the data may tax the unbiased estimation of this index, we believe that it is an avenue which deserves further research. Ideally, perfect information should exist regarding the legal and administrative characteristics of the IPR system, as well as the quality of the public administration and legal system. In lieu of such data, estimates of the stochastic frontier IPR Index panel data model will produce the best results the longer the panel data set.

Extensions, asides from the already mentioned, may further explore the hypothesis of the inverted U relationship between innovation output and the IPR index. Other methods such as DEA may be interesting methods to test, exploiting the nonparametric nature of such techniques. There is plenty to explore regarding the stochastic frontier method of measuring efficiency of IPRs.

[7] ROLI is a metadata measure of the quality of the Rule of Law. We took the average score for each year of the sample. We applied the same procedure for the CPIA-PADMIN index.

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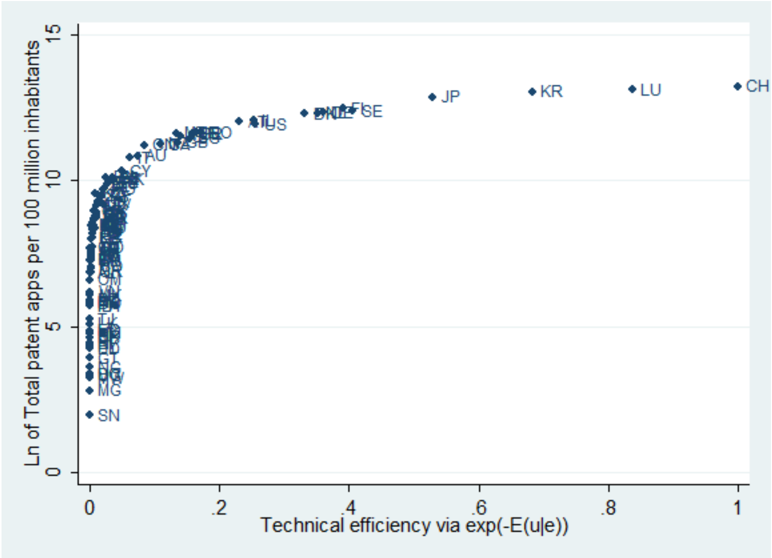

Figure 1: *IPR Efficiency and LN Total Patent Applications per capita using 108 country sample*

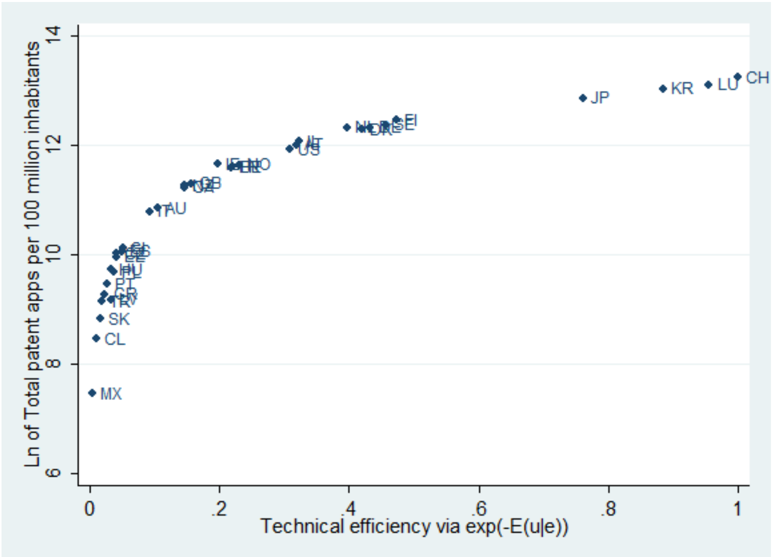

Figure 2: *IPR Efficiency and LN Total Patent Applications per capita using OECD country sample*

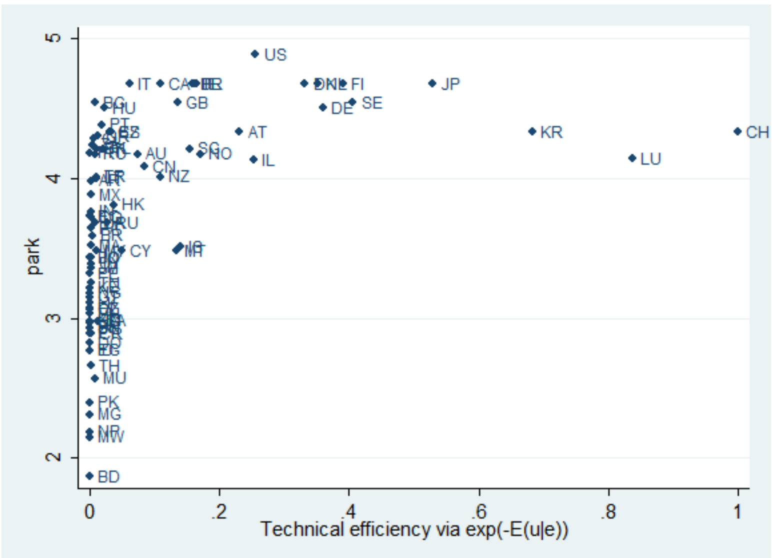

Figure 3: *Park (2007) and SFA IPR Measure*

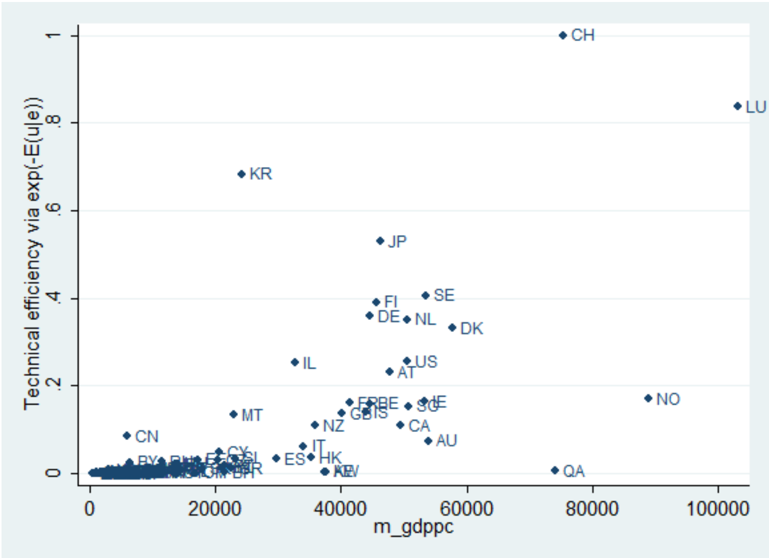

Figure 4: *Mean GDP per capita and SFA IPR Measure*

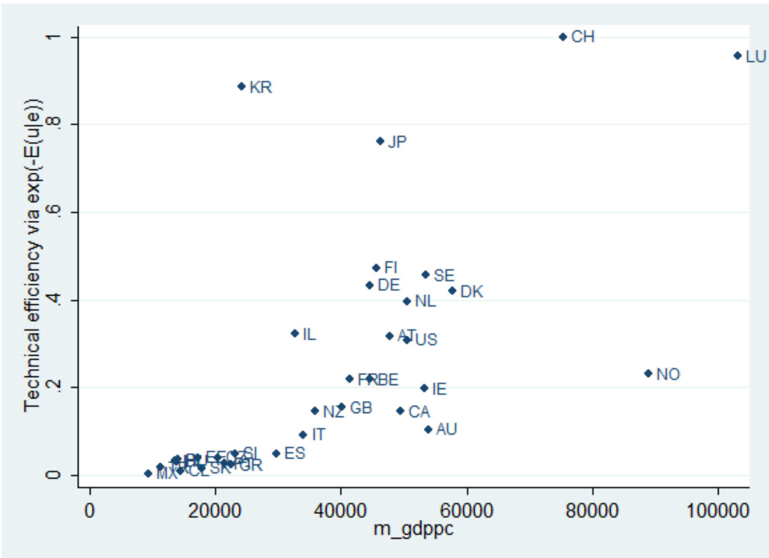

Figure 5: *Mean GDP per capita and SFA IPR Measure OECD Sample*

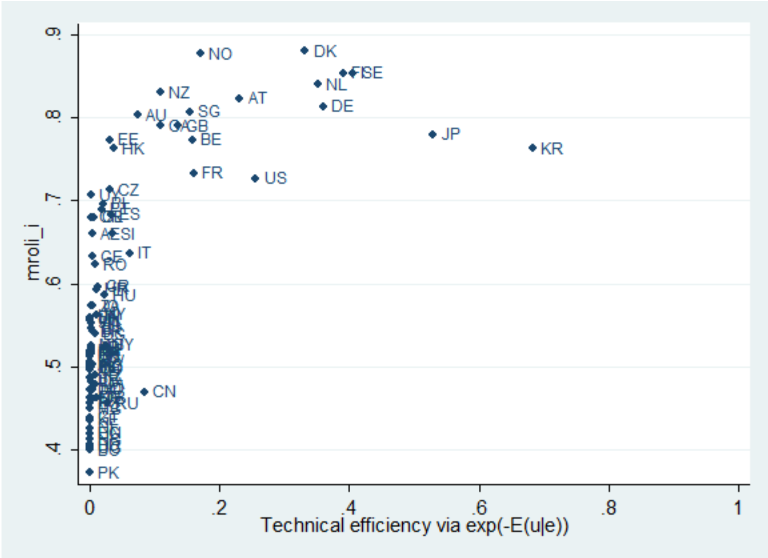

Figure 6: *Mean Rule of Law Index & SFA IPR Measure, 108 country sample*

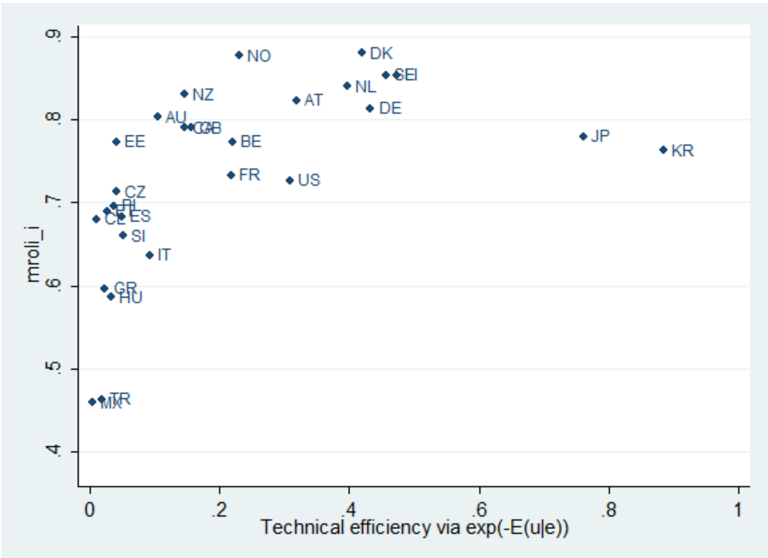

Figure 7: *Mean Rule of Law Index & SFA IPR Measure OECD Sample*

Table 1: *IPR System Efficiency Index, 108 countries*

Country	ID	IPR1
Switzerland	CH	1,00000
Luxembourg	LU	0,83673
Korea, Rep.	KR	0,68342
Japan	JP	0,52957
Sweden	SE	0,40602
Finland	FI	0,39064
Germany	DE	0,35913
Netherlands	NL	0,35137
Denmark	DK	0,33207
United States	US	0,25593
Israel	IL	0,25236
Austria	AT	0,23113
Norway	NO	0,17017
Ireland	IE	0,16471
France	FR	0,16036
Belgium	BE	0,15879
Singapore	SG	0,15338
Iceland	IS	0,13979
United Kingdom	GB	0,13608
Malta	MT	0,13334
New Zealand	NZ	0,10940
Canada	CA	0,10915
China	CN	0,08481
Australia	AU	0,07344
Italy	IT	0,06171
Cyprus	CY	0,04847
Hong Kong SAR, China	HK	0,03645
Slovenia	SI	0,03401
Spain	ES	0,03360
Estonia	EE	0,03102
Czech Republic	CZ	0,03018
Russian Federation	RU	0,02742
Belarus	BY	0,02534
Hungary	HU	0,02176
Latvia	LV	0,02138
Poland	PL	0,02015
Portugal	PT	0,01739
Saudi Arabia	SA	0,01295
Greece	GR	0,01238

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Table 1 – *Continued from previous page*

Country	**ID**	**IPR1**
Turkey	TR	0,01054
Malaysia	MY	0,01041
Slovak Republic	SK	0,01025
Lithuania	LT	0,00985
Croatia	HR	0,00925
Kazakhstan	KZ	0,00876
Ukraine	UA	0,00847
Bulgaria	BG	0,00843
Mauritius	MU	0,00817
Romania	RO	0,00781
Armenia	AM	0,00690
Qatar	QA	0,00632
Chile	CL	0,00586
Montenegro	ME	0,00495
United Arab Emirates	AE	0,00466
Serbia	RS	0,00450
Kuwait	KW	0,00446
Azerbaijan	AZ	0,00441
South Africa	ZA	0,00439
Moldova	MD	0,00438
Georgia	GE	0,00385
Brazil	BR	0,00365
Bahrain	BH	0,00251
Argentina	AR	0,00244
Kyrgyz Republic	KG	0,00229
Uruguay	UY	0,00221
Lebanon	LB	0,00218
Jordan	JO	0,00218
Mexico	MX	0,00212
Tunisia	TN	0,00201
India	IN	0,00193
Thailand	TH	0,00190
Mongolia	MN	0,00178
Panama	PA	0,00169
Costa Rica	CR	0,00154
Jamaica	JM	0,00152
Colombia	CO	0,00100
Morocco	MA	0,00096
Vietnam	VN	0,00074

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Table 1 – *Continued from previous page*

Country	**ID**	**IPR1**
Macedonia, FYR	MK	0,00070
Egypt, Arab Rep.	EG	0,00056
Philippines	PH	0,00052
Senegal	SN	0,00050
Cote d'Ivoire	CI	0,00050
Sri Lanka	LK	0,00047
Bosnia and Herzegovina	BA	0,00044
Kenya	KE	0,00041
Oman	OM	0,00037
Peru	PE	0,00033
Albania	AL	0,00032
Dominican Republic	DO	0,00027
Algeria	DZ	0,00026
Namibia	NA	0,00024
Indonesia	ID	0,00021
Paraguay	PY	0,00019
Tajikistan	TJ	0,00015
Burkina Faso	BF	0,00012
Ecuador	EC	0,00010
Pakistan	PK	0,00010
Guatemala	GT	0,00007
Honduras	HN	0,00006
Bangladesh	BD	0,00004
Bolivia	BO	0,00004
Nicaragua	NI	0,00004
Malawi	MW	0,00003
Nepal	NP	0,00003
Nigeria	NG	0,00002
Uganda	UG	0,00002
Madagascar	MG	0,00002

Table 2: *IPR System Efficiency Index using OECD data*

Country	**ID**	**IPR2**
Switzerland	CH	1,000
Luxembourg	LU	0,955
Korea, Rep.	KR	0,885
Japan	JP	0,761
Finland	FI	0,473
Sweden	SE	0,457
Germany	DE	0,433
Denmark	DK	0,420
Netherlands	NL	0,398
Israel	IL	0,323
Austria	AT	0,318
United States	US	0,309
Norway	NO	0,230
Belgium	BE	0,219
France	FR	0,218
Ireland	IE	0,197
United Kingdom	GB	0,155
Canada	CA	0,146
New Zealand	NZ	0,146
Australia	AU	0,104
Italy	IT	0,093
Slovenia	SI	0,050
Spain	ES	0,050
Czech Republic	CZ	0,041
Estonia	EE	0,041
Poland	PL	0,037
Latvia	LV	0,033
Hungary	HU	0,032
Portugal	PT	0,027
Greece	GR	0,023
Turkey	TR	0,018
Slovak Republic	SK	0,017
Chile	CL	0,011
Mexico	MX	0,004

Table 3: *PW Correlation Matrix*

	IPR1	IPR2	Park (2007)	ROLI	CPIAPAD
IPR1	1.000				
IPR2	0.9929	1.000			
Park	0.4668	0.3000	1.000		
ROLI	0.6714	0.5709	0.7159	1.000	
CPIAPAD	0.4373	.	0.2085	0.2778	1.000
IOS	0.6762	0.6837	0.7284	0.08085	0.04047