LUND UNIVERSITY
School of Economics and Management

Master Programme in International Economics with a Focus on China

R&D Efficiency in China: Can State-owned Firms Compete?

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Abstract: Can state-owned firms' R&D compete with that of more nimble private and foreign innovator firms? This paper analyzes R&D efficiency in China's high tech industries (i) theoretically, based on previous studies, and (ii) empirically, through Data Envelopment Analysis under both Constant and Variable Returns to Scale. Though Chinese state-owned firms can theoretically be R&D efficient in industries where the underlying science is well understood, a myriad of factors including persistent soft budget constraints and policy burdens mitigate the potential advantages – bureaucratic pre-screening and access to finance – that characterize state-owned firms. Using Chinese national statistics on high-tech industries, foreign firms are found to be R&D scale-efficient in the medical, aerospace, and computer industries. Private Chinese firms are shown to be scale efficient in computers and electronics. Though generally the least efficient of the firm types, state-owned firms are more efficient in aerospace than other domestic Chinese firms, showing that state-owned firms can be moderately efficient in some industries. The findings of this paper lend support to the notion that SOEs are inefficient and that privatization and competition stimulate innovation.

Key words: China, R&D Efficiency, Aerospace, Data Envelopment Analysis, SOE

EKHR81
Master thesis, first year (15 credits ECTS)
June 2013
Supervisor: Kerstin Enflo
Examiner: Christer Gunnarsson

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Acronyms:

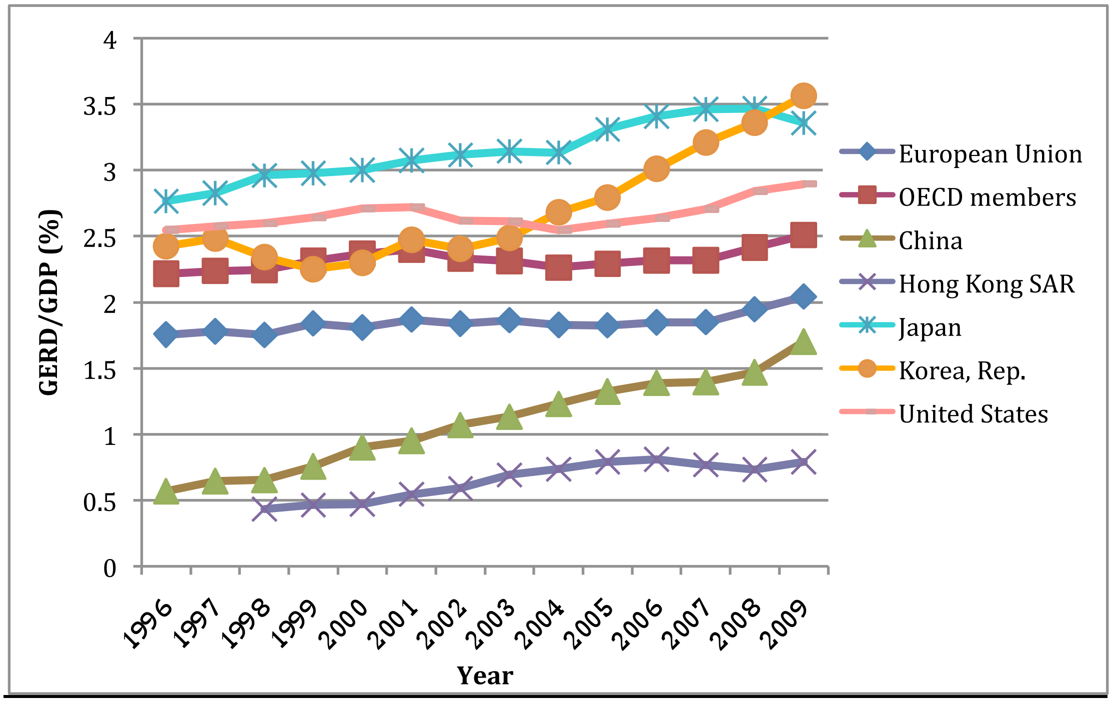
- R&D – Research and Development
- S&T – Science and Technology
- GERD – Gross Domestic Expenditure on R&D
- SOE – State-owned enterprise
- DEA – Data Envelopment Analysis
- DMU – Decision-making Unit
- CRS – Constant Returns to Scale
- VRS – Variable Returns to Scale

1. Introduction

Can state-owned firms compete with the R&D efficiency of private and foreign firms? Or are they too cumbersome and burdened by policy directives? Using efficiency analysis backed by interviews and lectures conducted in China, this paper fills a gap in existing Chinese economy studies by analyzing relative R&D efficiencies of various firm types across Chinese high tech industries. Several studies have shown that private R&D is superior to state-backed R&D, however few have compared firm types across multiple industries. The topic of R&D efficiency in China is particularly relevant to current events because the sources of economic growth in China are changing. The traditional investment-driven, export model of growth can no longer be relied upon. The supply of manufacturing labor is falling, real salaries are rapidly rising, the cost of land has increased dramatically, especially since the 2008 stimulus, and energy costs are rapidly rising on escalating demand (Fabre & Grumbach 2012). In addition to stimulating domestic infrastructure and consumption, Chinese policymakers have aggressively targeted domestic S&T innovation as a source of sustainable economic growth. In 2012, two percent of the country's GDP, or over 1 trillion RMB ($161 billion US), was spent on research and development activities (*Xinhua News* 2013). Of this total figure, businesses accounted for 74% and government activities for the remaining 26%. The historical prominence of state-owned enterprises (SOEs) in China is increasingly endangered by the emergence of private and foreign firms. Therefore, the ability of SOEs versus private and foreign firms to innovate efficiently is central to China's economic future, and perhaps to survival of the institution of state-owned firms in China.

Though the US and OECD member countries still exceed China in GERD/GDP, with 3% and 2.5% respectively, China and South Korea represent the steepest upward trajectories in Figure 1, below. This trend has continued in the most recent years, with China's GERD/GDP ratio reaching two percent in 2012. The increase in R&D expenditure is drastic and shows no signs of slowing.

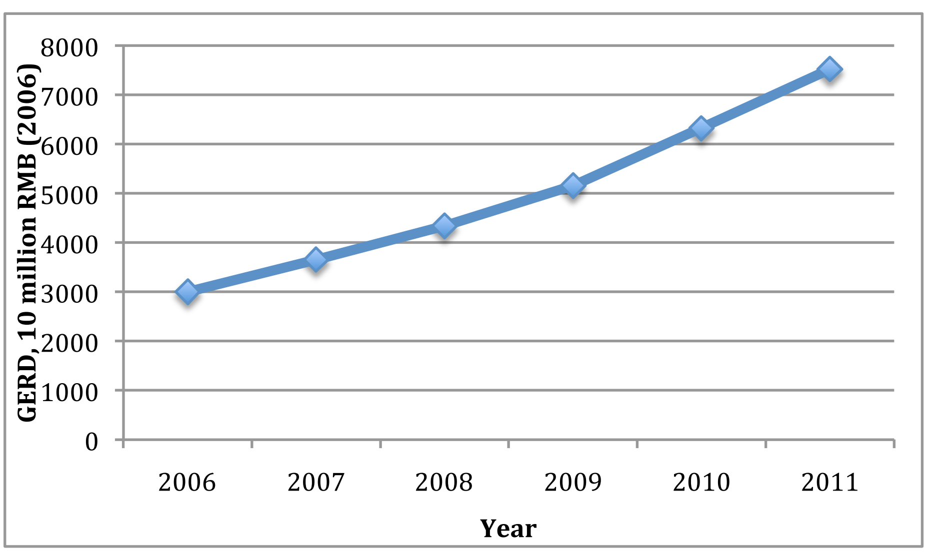
Figure 1: Gross Domestic R&D Expenditure (GERD) to GDP ratios, 1996-2009



Source: World Bank *World Development Indicators*

In absolute terms, China's gross domestic R&D expenditure has nearly tripled since 2006 after accounting for inflation. The GERD numbers in Figure 2, below, are presented in constant 2006 RMB values:

Figure 2: Gross Domestic R&D Expenditure, China 2006-2011



Source: *China Science & Technology Statistics Data Book, 2012;* author's calculations

In spite of the rapid growth and liberalization of the Chinese market, state-owned enterprises still hold over 30 percent of all Chinese assets and tend to be 13.4 times larger than non-SOEs in China in terms of assets (Xu 2010). Given the continuing prominence of state-owned firms and China's proposed target of reaching an R&D intensity of 2.5% of GDP by 2020, this paper answers the following question:

> *Can state-owned firms be more R&D efficient than private or foreign firms in specific high tech industries in China?*

This study identifies industries where state-owned firms may demonstrate superior R&D efficiency than private and foreign firms. This will support either the notion that decentralization and marketization lead to more efficient innovation in all industries in China, or that innovation in certain industries should remain state-driven. Following the introduction, a theoretical framework of R&D efficiency and different firm types is presented, followed by a synopsis of existing R&D efficiency literature. Section 4 presents the data and quantitative method, Data Envelopment Analysis (DEA), used in this study. Finally, Sections 5 and 6 conclude with discussions of the DEA results and their implications for firms and policymakers alike.

2. Theory – The Potential of State-owned R&D

While the majority of studies on Chinese R&D find that SOEs are less R&D efficient than foreign and private firms, Bolton and Farrell (1990) construct a game-theoretical model where decentralization leads to redundancies in productivity and stunted innovation. They posit that decentralization leads to coordination problems, where many firms expend duplicitous resources to produce the same goods, thereby producing, or innovating, more slowly than in centralized systems. They also suggest that centrally planned systems are superior at making rapid and arbitrary choices due to a lack of a lack of opposition but inferior to market economies in gathering and employing dispersed information (Bolton & Farrell 1990). Although China is more of a hybrid centrally planned, capitalist state, the largest firms remain state-owned and the communist leadership issues 5-year plans, targeting specific sectors for state-backed or private led growth.

Building on Bolton and Farrell's (1990) duplication and delay model, Qian and Xu (1998) posit that bureaucracy can act as a sieve, filtering out duplicitous R&D projects as well as those with less certainty of success. In their model, projects financed by the state are subject to soft budget constraints, so high-cost projects are rarely canceled *ex post*, or after starting; by contrast, in decentralized economies, projects financed by private banks are subject to hard budget constraints. Hence these projects are frequently canceled *ex post* due to both internal factors such as unanticipated project costs, and external factors like increasing interest rates. As a result, soft budget constraints leads to more bureaucratic pre-screening, which enables better results in R&D projects with fewer scientific uncertainties. Qian and Xu (1998) conclude that state-backed R&D, subject to bureaucracy and softer budget constraints, may be superior in fields where the underlying science is well known – such as aerospace and most heavy industries. The converse is also posited, that private R&D is more efficient and nimble for higher risk projects with less certain outcomes.

As a result of hard budget constraints, private and foreign innovators must frequently rely on external financing. Huang and Xu (1998) develop a theory of optimal R&D financing based on budget constraints and project uncertainty. Similar to the suppositions of Qian and Xu (1998), the lack of an *ex post* screening mechanism in centralized economies – as is the case with SOEs in China – leads to the continuation of ineffective R&D projects past the point of cancellation as compared to similar projects in decentralized economies. This was seen with the Soviet Union's costly and unsuccessful catching up in consumer electronics and computers. In heavy industries, with previously grounded science, centralized economies performed as well as decentralized market economies. The USSR and

China, as compared to the US, for example, fared equally as well in the aerospace, nuclear, and natural resource extraction industries (Qian & Xu 1998).

When the underlying science of an R&D project is poorly understood, as with computers in the 1970's and 80's, smaller private and foreign firms are more likely to be the efficient sources of innovation than large corporations and state-backed firms. This is because larger corporations and state-run firms employ more bureaucratic pre-screening than smaller firms. Therefore, larger firms and SOEs may reject projects with high values of γ – those with a high degree of scientific uncertainty – before even starting them (Qian & Xu 1998). In addition, bureaucrats and corporate leaders run the risk of being perceived as wasting public or shareholder funds if R&D projects fail or if costs balloon beyond initial projections.

This contrasts with the contained risks of a small innovator firm with few employees, where entrepreneurs risk losing only their personal funds or the funds of one or two investors when a project fails. Therefore bureaucrats and large corporations may be more cautious of approving R&D projects that are not based on existing scientific knowledge. One could argue that this was not the case with the government space programs of the US and Soviet Union. In the mid 20th century, space was an entirely unexplored frontier. Even though the success of sending astronauts into space or to the moon was far from guaranteed, the underlying theories of physics and aerospace engineering and gravity were already well understood. Therefore, the massive R&D projects associated with US and Soviet space programs were approved by their respective governments. These projects were also perceived to be of paramount importance to national security, increasing the inputs allocated these projects by the state. Additionally, governments – especially those in single-party systems like in China – can have longer planning horizons and can absorb externalities at the risk of irking the public.

Given the range of factors that impact R&D efficiency, a basic empirical model can be constructed to put these factors in relation to one another and reflect the suitability of state-owned firms to conduct R&D efficiently.[1] Consider an arbitrary variable, Ψ_i, which represents the suitability of a state-backed firm to conduct R&D efficiently in industry *i*. This variable is impacted by the length of the proposed R&D project (λ_i), the proposed cost of inputs ($\chi_{i(t-n)}$), the scientific uncertainty of the project (γ_i), and the softness of budget constraints in the country (θ) (Bolton & Farrell 1990, Qian & Xu 1998, and Huang & Xu 1998). Firms with limited access to capital are less likely to undertake longer R&D projects, as capital constraints are prevalent with R&D (Hu & Jefferson 2005). Similarly, capital-constrained firms are unable to see expensive innovation projects through to completion, and hence less likely to undertake them from the outset. Thus determining Ψ_i relies on some key theoretical assumptions:

- Due to greater access to financing, project length (λ_i) is positively correlated with a SOE's suitability to conduct R&D.
- Similarly, input costs ($\chi_{i(t-n)}$) are positively correlated with Ψ_i because SOE's possess greater financial resources as compared to private firms.
- Ψ_i is negatively correlated with the level of uncertainty (γ_i) surrounding the R&D venture.
- The softness of the budget constraint (θ) is a predetermined value between 0 and 1, with 1 indicating a very soft budget constraint (essentially guaranteed blank checks from the state for SOEs). θ is negatively correlated with an SOE's ability to conduct R&D efficiently, though not correlated with the likelihood of an SOE carrying out a particular R&D venture.

Furthermore, a threshold value of Ψ_i can be established prior to calculation for the industry in question, above which SOEs are better suited to conduct R&D

[1] Based on the five high tech industries outlined in the *China Yearbook on High Technology* and *China Statistical Yearbook*, both published annually. They consist of: Medical (pharmaceuticals), Aerospace, Electronics and electronic components, Computers and their components, and Medical Meters and medical equipment

efficiently, and below which private and foreign firms are better suited. Given the assumptions above, Ψ_i can be estimated with the following:

(1)

$$\Psi_i = \frac{\lambda_i}{\theta \times \gamma_i} \times \left(\frac{\sum \chi_{i(t-n)}}{1} \right)$$

Because absolute input costs do not capture any measure of efficiency, the aggregate cost of inputs per one unit of output, $\left(\frac{\sum \chi_{i(t-n)}}{1} \right)$, is a superior measure for this model's purposes. The output units are arbitrary, and may be one patent application, or one new product sale, or revenue from one new product sale. By holding the output fixed at one unit, the model is thus input-oriented. It could also be converted to output orientation by including the output yield per fixed unit of input (Coelli 1996). Additionally, because there is a time lag between R&D inputs and R&D outputs, *Output* in year t is the direct product of inputs (χ) in year t minus n years of R&D (Lee & Park 2005). The formula can be further simplified by substituting 1 for $Output_{it}$:

(2)

$$\Psi_i = \frac{\lambda_i}{\theta \times \gamma_i} \times \left(\frac{\sum \chi_{i(t-n)}}{1} \right)$$

And finally, reduced to the following:

(3)

$$\Psi_i = \frac{\lambda_i \times \sum \chi_{i(t-n)}}{\theta \times \gamma_i}$$

Thus, the higher the value of Ψ_i, the better-suited SOEs are to conduct R&D efficiently. If λ_i is high, $\chi_{i(t-n)}$ is high, γ_i is low, and state-backed firms operate with relatively hard budget constraints (low θ), Ψ_i will be high and state-owned firms in industry i are theoretically better suited to fulfill R&D projects efficiently. A low value of Ψ_i would indicate that private or foreign firms are better suited to fulfill R&D projects efficiently in industry *i*. This paper does not empirically test all aspects of this model due to data insufficiencies. The data used in this paper is from the annual *Statistical Yearbooks on High Technology*, published by the Chinese National Bureau of Statistics. It does not include data on average R&D projects lengths or costs or how well the underlying science of a high tech industry is understood. In addition, θ is an arbitrary variable that must be estimated based on research of China and Soft Budget Constraints.

However, this theoretical model is still valuable even if it remains untested. The relationship of the variables in the model – those influencing R&D projects – are key to why SOEs might be more R&D efficient in some industries, and less so in others. Consider the aerospace industry; developing new aircraft can take several years and R&D costs can soar to hundreds of millions of dollars. In the US, for example, R&D costs per R&D scientist or engineer in aerospace are nearly twice that of the average R&D costs in all high tech industries (*AIA Aerospace*). Thus, λ_i is high and $\chi_{i(t-n)}$ is high. Though soft-budget constraints do still exist for state-owned firms in China, there is evidence that budget constraints are hardening, meaning that θ may be moderate or low. The uncertainty, γ_I, of aerospace is low as the laws of physics regarding plane flight are well understood. Thus, using the aforementioned model, the aerospace industry may have a high value of Ψ_i, and state-owned firms can indeed be R&D efficient. This would not necessarily be the case in the medical, computer, or electronics industries, where R&D projects tend to be less costly, shorter, and experimental in terms of underlying science (Qian & Xu 1998, and Huang & Xu 1998).

Given the theoretical supposition that state-owned R&D can be more efficient than foreign and private R&D in China, the following hypothesis is tested:

H_A: Private and foreign firms are not more R&D efficient than state-backed firms in all industries; SOEs are efficient in the aerospace industry – as well as those with well-understood scientific underpinnings and long term, large-scale R&D projects.

3. Previous Studies – Budget Constraints, Competition and Efficiency

Many scholars have studied R&D efficiency, at both the national and firm level. Using national statistics, Lee and Park (2005) employ data envelopment analysis (DEA) to compare R&D productivity across 27 countries. Using patent applications as the output variable and number of R&D personnel, R&D intensity and number of PhDs as inputs, they find China, South Korea and Taiwan to be relatively inefficient compared with more developed western nations. In a similar study, Sharma & Thomas (2008) analyze the relative efficiency of R&D in 22 developing countries using DEA. The number of qualified researchers and gross domestic expenditure on research are used as inputs, and as in Lee & Park's (2005) study, the number of patents granted is the output variable. Sharma and Thomas find that, assuming constant returns to scale, China is R&D efficient. Although this contrasts Lee and Park's (2005) finding that R&D in China is relatively inefficient, the basket of countries in Sharma and Thomas' study is only those with developing economies, so the findings are not necessarily mutually exclusive.

In comparing efficiencies, scholars commonly use production functions and Data Envelopment Analysis. Though not inherently probabilistic or predictive, DEA is useful for comparative analysis because it aggregates inputs and outputs into a production frontier of relative efficiency. Kumar & Russell (2002) highlight the advantages of DEA in analyzing technological catch-up, or convergence, among 57 countries between 1965 and 1990. Creating world production frontiers during the two periods, Kumar and Russell (2002) find that both developed and developing countries have benefitted from technological improvements and increases in efficiency between 1965 and 1990. Expanding the notion of technological catch-up, a small handful of R&D efficiency studies focusing specifically on China have been conducted. David, Hall, and Toole (2000) conduct a meta-study of existing studies on the effectiveness of public versus private R&D, giving emphasis to China. Their findings are mixed as to whether public R&D complements (adds to) or substitutes (crowds out) private R&D. They posit that both state and civilian R&D expenditures may have spillover effects, creating social and economic benefits. In spite of their ambiguous findings, they conclude that some industries provide greater technological opportunities than others, which either public or private R&D may be better suited to address in certain cases depending on scale. Innovation in heavy industries, for example, may be better suited for public R&D, as was the case in the Soviet Union.

Given that state owned firms are larger and less nimble than private or foreign firms, state owned enterprises (SOEs) cannot be sustained by market forces alone – they must receive preferential government treatment in order to continue providing goods and services at competitive prices. Kornai (1986) defines this phenomenon – the soft budget constraint – as when a firm or decision-maker can expect "external financial assistance with high probability and this probability is firmly built into his behavior" (Kornai 1986). A hard budget constraint then, describes the converse, when external financial assistance is not expected and a firm's behavior is based on this expectation. In return for preferential government treatment and easily accessed loans, Chinese SOEs are commonly burdened with furthering certain government policies (Lin & Tan 1999). Recognizing the incentive problem created by state ownership of firms and soft budget constraints, Chinese government leaders passed a bill in 1997 that privatized small SOEs (Dong & Putterman 2003). The government, however, retained control of large- and medium-sized enterprises. This policy, known as *zhuada fangxiao*, or 'grasp the large, release the small' enabled the government to marketize many SOE's while still retaining control of the largest firms in key strategic industries. In so doing, the Chinese government has allowed some limited outside investment in SOEs by listing many of the largest firms on both domestic and foreign stock exchanges.

In socialist and transition economies like China, SOEs that incur losses rely on the government to provide funding, tax benefits, or other preferential treatment (Lin & Tan 1999). Furthermore, Victor Nee and Sonja Opper (2012) stipulate that state-owned banks currently appropriate over 60 percent of lending in China. Because private firms are still essentially excluded from financial support in the form of subsidies or low-interest loans, the vast majority of the big four Chinese state-owned banks' lending is to state-backed enterprises (Nee & Opper 2012: 97). This is a significant constraint for private and foreign innovators in China.

R&D projects initially require significant capital infusions to purchase high-tech equipment and pay scientists and well-educated employees (Hall 2002). Using firm level data from French firms between 1994 and 2004, Aghion et al (2012) examine the relationship between access to loans, interest rates and firms' R&D expenditure. They find that among credit-constrained firms, R&D expenditure drops dramatically during recessions but does not proportionately rise during upturns (Aghion et al 2012). The authors posit that macroeconomic policies in response to economic downturns, such as raising and lowering of central interest rates, significantly impact the likelihood of firms' choosing to acquire external financing, and hence propensity to conduct R&D. Thus, Chinese SOEs may be better suited to conduct R&D than private and foreign firms in adverse market conditions – including downturns when liquidity diminishes. As a result, policymakers may feel more secure steering R&D projects in critical industries, such as transportation infrastructure, aerospace, and energy towards state-backed firms with softer budget constraints, regardless of their relative R&D efficiency. This could explain the continued prominence of SOEs in China's economy, in spite of their poor performance in biotech and related industries (Berg 2012).

To incentivize innovation, a common path for policymakers is to provide tax benefits for high-tech firms. Yang, Huang and Hou (2010) demonstrate that firms receiving R&D tax credits in Taiwan appear on average to have 53.8% higher R&D expenditures than they would without tax incentives. As in Taiwan, China offers tax incentives to foreign and private firms for conducting R&D. Favorable policies for innovation are not limited to foreign and private tax breaks, however. The fact that SOEs are more likely to receive external financing in China may allow state-backed firms to absorb the costs associated with both "riskier" and longer-term R&D projects. However, given the substantial tax benefits to all firms conducting high tech R&D in China, state-backed firms do not necessarily possess an advantage in having funds to devote to R&D; rather, the advantage lies in their ability to access external financing.

Table 1: R&D Advantages and Disadvantages of Various Firm Types in China

	Advantages	*Disadvantages*
Private	- Few shareholders allow decisions to be made quickly and without shareholder opposition - Tax incentives to level the playing field - Strong incentives to innovate	- Capital constraints – difficult to access loans and external financing - R&D projects can be constrained by size
State-Owned	- Ease of access to finance - Large size, extensive government resources - Lack of opposition in Chinese bureaucracy leads to quick decision-making	- Policy burdens, which cause labor redundancies - Lack of incentives, no 'innovate or die' mentality
Shareholding Corporation	- Diversified ownership - Capital markets provide resources apart from government or bank funds	- Relatively slow decision-making - Importance of short term revenue generation may trump innovation
Foreign	- Experience conducting R&D in other countries - Access to foreign human capital and foreign equipment	- Relocation costs, fixed costs associated with establishing R&D labs in China - Higher wages, and must meet laws/standards of both China and home country

Sources: Nee & Opper (2012), Yang Huang & Hou (2010), Kornai (1986), Hu & Jefferson (2003)

Hu and Jefferson (2005) demonstrate that firms performing R&D in China tend to be much larger than non-R&D performing firms because R&D is so cash-intensive. In their study, Chinese entrepreneurs cite lack of funding as the main constraint to conducting R&D. Furthermore, Hu and Jefferson show that foreign investors are five times more likely to take out invention patents – as opposed to utility, or incremental innovation patents – than their domestic Chinese counterparts, indicating that due to difficulty acquiring financing, Chinese firms innovative efforts are more focused on incremental technological improvements, rather than new technology development. In a previous study, Hu and Jefferson (2003) find that R&D expenditure does not increase proportionately with firm size, and that it is not clearly related to a firm's cash flow. They analyze OLS regressions with firm ownership as the key independent variable and patent applications as the dependent variable and find that private enterprises exhibit the highest propensity to patent, followed by stock-incorporated enterprises and collective-owned enterprises. However, they do not account for the fact that private firms conducting R&D are primarily active in industries with high patent output, such as consumer electronics and electronic components. Additionally, they leave significant room for further analysis of innovation on an industry-by-industry basis. Foreign invested enterprises (FIEs) and state-owned enterprises (SOEs) are among the least active in patenting in China across all industries, not just high tech industries, where R&D is focused. Hu and Jefferson posit that FIEs likely do not patent less than private or stock-incorporated firms, they simply patent less in China, as FIE headquarters may be responsible for most of the patents granted to multinational corporations. This lack of SOE patenting is consistent with the findings of Jefferson, Huamao, Xiaojing, and Xiaoyun (2004) that SOEs are relatively less efficient in producing new products. It should be noted that these studies compare patenting across all industries, not only high tech industries.

In a related study, Berg (2012) examines the impact of firm ownership structures on R&D efficiency in the biotech industry. Using DEA, he finds that private, foreign, and Hong Kong- and Taiwan-funded R&D biotech is scale efficient, though R&D conducted by state-owned enterprises is significantly less efficient. As in similar DEA studies, Berg uses patent applications as the output variable and finds that private and foreign firms conducting R&D in China are more input efficient per patent. These findings are in line with those of Zhang, Zhang and Zhao (2003) as well as with proposed theories of soft-budget constraints. Because they face tighter capital restrictions, private and foreign firms have stronger incentives to operate efficiently. As a result, they may focus their limited R&D capital on projects with the low scientific uncertainty, high market potential, and short timeframe between research and revenue generation.

4. Empirical Method

4.1 – Data Envelopment Analysis

Using data drawn from the Chinese government's *Statistical Yearbook on High Technology 2012*, the efficiencies of different property arrangements in each high tech R&D industry are compared. In order to aggregate the data into a measure enabling comparison of relative efficiencies, Data Envelopment Analysis (DEA) is used. A crucial strength of DEA is that it can encapsulate multiple inputs and outputs to yield a single figure for comparison of efficiencies. Originated by Farrell (1957) and operationalized by Charnes, Cooper, and Rhodes (1978), DEA is a non-parametric method where efficiencies of different firms or firm ownership categorizations can be compared based on ratios of inputs to outputs. Each firm type is categorized as a decision making unit (DMU), with the most efficient firm types – those which produce a fixed number of outputs given the most efficient combination of inputs – falling on the efficiency frontier. In the simplest, two-dimensional DEA model, DMUs are compared using one input and one output. For example, the input could be intramural R&D expenditure and the output could be new product sales. The most efficient DMU (on the efficiency frontier) is the one possessing the lowest ratio of R&D expenditure to new product sales. In the case where more inputs are used, DEA assigns relative weights to each input in order to aggregate the varying amount of inputs used by each DMU per unit of output into a single efficiency score. Those with efficiency scores of 1 define the efficiency frontier. Less efficient DMUs are thus "enveloped" by the efficiency frontier, and relative efficiencies can be compared (Coelli 1996).

The free DEA analysis program DEAP 2.1, developed by the Centre for Efficiency and Productivity Analysis at the University of Queensland, is used in this study. The program creates efficiency scores under both constant returns to scale (CRS) and variable return to scale (VRS) assumptions, and also calculates changes in total factor productivity (Coelli 1996). Both CRS and VRS models are used in this study. Constant returns to scale refers to the assumption that increases in inputs yield constant proportional increases in output, regardless the DMU's size. However, due to productivity constraints in the real world, CRS assumptions are not appropriate for firms operating at their optimal scale (Coelli 1996). The variable returns to scale model was therefore conceived, which tightens the efficiency frontier by allowing for increasing or decreasing returns as the DMU's scale changes. A two-dimensional graphical representation of the difference between CRS and VRS is presented in the Figure 4 in the Appendix.

Data Envelopment Analysis consists of four possible measures of efficiency (Coelli 1996):

(i) Technical Efficiency – The amount of output is given and fixed, and produced with lowest amount of inputs.

(ii) Allocative Efficiency – A measurement of the most efficient combination of inputs to produce a fixed output amount.

(iii) Economic efficiency – A cost-oriented measure where a given amount of output is produced with minimal monetary cost.

(iv) Scale efficiency – A measure of the most efficient scale size, where maximal output productivity is achieved given a set amount of inputs. It is found by dividing the technical efficiencies of CRS by those of VRS:

Because the costs associated with each R&D employee and R&D projects vary, economic efficiency is a less appropriate comparative measure than technical and allocative efficiencies. This study calculates technical efficiencies to find the scale efficiencies of the four firm registration types in the *Statistical Yearbooks.*

To compare R&D efficiency across different firm registration types in China, this study employs technical and scale efficiencies to compare R&D efficiencies of differing firm types. All efficiency scores are between 0 and 1, with 1 corresponding to DMUs on the efficiency frontier and measures less than 1 representing those beneath the frontier. The DEA models used in this paper are input-oriented because firm decision makers can choose the number and proportion of R&D expenditures, personnel, and other inputs, but cannot dictate the resulting number of patentable results. Thus, by keeping the number of patent applications fixed and measuring the comparative usage of inputs, relative efficiencies can be compared (Coelli 1996). Efficiency scores less than 1 indicate the distance of a DMU from the efficiency frontier. In other words, the proportion by which inputs must be decreased to reach the efficiency frontier is calculated by subtracting a DMU's efficiency score from 1.

Data envelopment analysis is advantageous in that assumptions about the distribution of the production function – whether it is convex, concave, or linear – need not be known prior to analysis. The underlying assumption of CRS is that efficiency remains constant, regardless of size. With VRS, efficiency is assumed to change as the size of the DMU changes. Although theoretically useful, CRS may not reflect the reality of R&D. Rather Graves and Langowitz (1996) demonstrated in an international, multi-industry study that R&D expenditure has clear and consistent decreasing returns to scale.[2] In addition, VRS tends to raise efficiency scores. Ideally, to yield more robust results, the number of decision-making units should adhere to the Dyson rule, where the number of DMUs equals at least twice the number of inputs multiplied by the number of outputs (Dyson et al., 2001). At minimum, for a DEA model to have discriminatory power and yield accurate results, the number of DMUs should be equal to the number of inputs to number of outputs (Boussofiane et al. 1991). Given the limitations of only four firm registration categories in the *China Statistical Yearbook on High Technology Industry 2012*, Boussofiane et al.'s lower threshold is followed here.

4.2 – Data: *China Statistical Yearbook on High Technology Industry, 2012*

The question of whether or not official Chinese statistics are reliable is an area of heated debate among economists. The Chinese National Bureau of Statistics has published the *China Statistical Yearbook*, used in this paper, every year since 1981 (Chow 2006). Rawski (2001) argues that national Chinese statistics, particularly regarding GDP growth, are overstated based on energy use and consumer price index data. However Chow (2006) conducts a meta-analysis of empirical China studies using official data and finds no consistent evidence indicating data falsification in China's national statistics. Chow also contends that Premiers in the Chinese Communist Party have no incentive to falsify statistics, as the data in the Yearbooks is also that which the Communist Party uses for internal review and government planning. Furthermore, Chow (2006) states that falsifying data would be nearly impossible given the extended timescale – from 1981 until the present – of the annual publication of statistics. Hence there is no clear evidence that there would be biases or inconsistencies in the R&D data presented therein. Though the *China Statistical Yearbook* may not be entirely accurate, it is the most comprehensive and accessible source of Chinese innovation data available.

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[2] Although decreasing returns to scale are consistent for all industries and regions, the rate of decreasing returns vary by region and industry (Graves & Langowitz 1996).

4.3 – Decision Making Units (DMUs)

In the *China Yearbook on High Technology 2012,* four major R&D conducting firm types are delineated:

1. *Domestic Funded*:

This category encompasses both private Chinese firms as well as LLCs. In short, it includes all Chinese firms that are not state-owned. As can be seen in Figure 3 (in the Appendix), non state-owned Chinese firms now make up the largest share of R&D activities in the country. Historically, private Chinese firms such as Huawei, the world's largest ICT company, have relied on copying leading innovators in the US and Europe to catch up. As the Chinese domestic market has developed, these companies are now transitioning to in-house development (Lindskog 2013). This reflects not only the growth of the company but also the increasing effectiveness of IPR protection in China.

2. *State-owned Enterprises (SOEs)*:

State-owned Enterprises are those that are owned either wholly or in majority by the Chinese government. SOEs act as a conduit between the government and the public, providing employment and implementing government policies. These policy burdens have traditionally resulted in SOEs operating with systemic, inefficient labor surpluses. Prior to the SOE reforms of the 1980's, state-owned firms operated without competition, as private and foreign firms were essentially nonexistent (Morel 2006). The gradual marketization of SOEs in the 1980's began with managerial incentives, whereby managerial pay was benchmarked with enterprise performance. This incentivization also, at least in theory, reduced SOE reliance on soft budget constraints.

The second main SOE reform of the 1980s was the decentralization of SOEs, shifting primary ownership from the central government to provincial governments. This second overhaul also converted many SOEs into shareholding companies with several owners of diverse interests. As was previously mentioned, the government only maintained control of the largest, most influential SOEs, according the policy of *zhuada fangxiao*. In 1988, the Chinese Communist Party implemented the Torch Program, which promoted R&D in small and medium sized enterprises and conversion of R&D projects into direct consumer benefits. The Torch Program also mandated the establishment of high-tech development parks, where participating firms receive preferential loans, subsidies, and tax regulations (Morel 2006).

3. *Firms with funds from Hong Kong, Taiwan, and Macau:*

Several of the largest innovators in China are based in the special administrative regions of Macau, Hong Kong, and Taiwan. For example, Foxconn International Holdings, a Taiwanese firm and the world's largest electronics manufacturer, conducts the bulk of its R&D and assembly in China (Zheng et al. 2010).

4. *Foreign Firms:*

As with private firms in China, the presence of foreign companies has grown drastically in China (Nee & Opper 2012). Though foreign firms from the West hold advantages over Chinese firms in terms of development and advanced technology, domestic Chinese firms hold an advantage over foreign firms with regards to R&D costs – particularly equipment and labor. This advantage stems from the fact that foreign firms tend to cluster in higher cost areas, and foreign firms' R&D frequently involves the use of foreign-made, more expensive equipment. Eric Brubaker, Manager of Global Technical Centers at SKF (Svenska Kullagerfabriken), asserted that foreign firms do not necessarily conduct R&D in China because of tax incentives; rather, they do R&D in China to be close to customers and shorten the supply chain. SKF, for instance, is allocated land from the Chinese government for the purpose of building R&D labs and factories, without ongoing monitoring by the government to ensure that SKF does in fact use the facilities for R&D (Brubaker 2013).

Another attractive feature luring foreign firms to conduct R&D in China is the lack of red tape; because there is only one political party, government decisions happen quickly and there is rarely any "analysis paralysis." A main constraint of R&D in China is a lack of human capital with practical experience and hands-on training. With R&D there is a significant depreciation of capital and equipment over time. Not considering the sunk costs of equipment and physical capital, R&D in China is not necessarily cheaper than R&D in Europe and the West (Brubaker 2013). Foreign firms are also encouraged with special tax breaks or subsidies, or constrained by the three types of industry, as highlighted by the Chinese government: encouraged industries, like education and environmental conservation, permitted industries, like banking, and prohibited industries, such as arms manufacturing (Tong 2013).

4.4 – R&D Inputs

Non state-owned Chinese firms make up the largest share of R&D activity in China (see Figure 3 in Appendix). The four main DEA inputs are as follows:

- *R&D Personnel, 2011:* A widely used input in R&D efficiency measurement, this is an aggregation of the number of trained engineers, researchers and scientists employed in R&D projects in 2011.
- *Intramural R&D expenditure, 2011*: This is the most widely used indicator of a firm's R&D activities. It refers to spending on high-tech R&D. This can be further split into funds of government origin and firm-raised funds. All R&D expenditures are reported in 10,000 RMB.
- *Equipment expenditure, 2011:* This input represents expenses on equipment and lab machinery needed for R&D. It is also measured in 10,000 RMB.
- *External expenditure, 2011:* This is the outlay of R&D-conducting firms on licensing or purchasing equipment from universities, the government, or other enterprises. It is also measured in 10,000 RMB.

Table 2: Input data by Firm Type and Industry, China 2011

	Inputs (units: people and 10,000 RMB)	*Domestic Funded*	*SOE*	*HK-, Taiwan-, Macau-funded*	*Foreign*	*Total*
Medicine	R&D Personnel	88,317	4,947	14,369	15,872	123,505
	R&D Expenditure	1,505,888	88,4466	271,812	334,761	2,996,927
	Equipment	1,002,046	17,664	36,890	51,817	1,108,417
	Extl. Expenditure	841,260	4,303	41,194	43,793	930,550
Aerospace	R&D Personnel	39,068	5,349	1,440	310	46,167
	R&D Expenditure	1,480,962	149,707	6,443	8,490	1,645,602
	Equipment	73,706	14,394	498	250	88,848
	Extl. Expenditure	194,854	1,478	487	2	196,821
Electronics	R&D Personnel	205,162	13,324	58,127	59,983	336,596
	R&D Expenditure	5,189,955	449,784	1,043,268	1,671,647	8,354,654
	Equipment	558,199	31,507	114,071	235,812	939,589
	Extl. Expenditure	221,273	30,427	26,290	71,425	349,415
Computers	R&D Personnel	20,157	310	13,311	23,453	57,231
	R&D Expenditure	396,673	8,378	446,210	737,699	1,588,960
	Equipment	23,794	1,529	20,057	110,405	155,785
	Extl. Expenditure	13,014	1	12,339	8,391	33,745
Medical Equipment	R&D Personnel	59,965	6,916	6,022	12,798	85,701
	R&D Expenditure	938,654	135,644	93,566	283,105	1,450,969
	Equipment	132,883	25,287	7,759	28,437	194,366
	Extl. Expenditure	44,177	11,356	897	23,993	80,423
Total	R&D Personnel	412,669	30,846	93,269	112,416	649,200
	R&D Expenditure	9,512,132	1,627,979	1,861,299	3,035,702	16,037,112
	Equipment	1,790,628	90,381	179,275	426,721	2,487,005
	Extl. Expenditure	1,314,578	47,565	81,207	147,604	1,590,954

Source: *Statistical Yearbook on High Tech Industry, 2012*, National Bureau of Statistics

As can be seen in Table 2, above, domestic Chinese enterprises make up the largest share of inputs among the sampled firms. Intramural R&D expenditure makes up the largest share of innovation spending, far outweighing the costs of equipment and licensing (external expenditure) in all five industries.

4.5 – R&D Outputs

Patent Applications, 2011:

Patent applications are the most common dependent, or output, variable in existing innovation studies. As can be seen in Table 3, below, patent applications vary across different industries, with many more patents per firm in the computer and electronics industries as compared to medical industries. Though R&D-conducting state-owned firms are far outnumbered by other domestic Chinese firms in most other R&D industries, the number of patents per firm is not clearly higher or lower in all industries for any single registration type, indicating that firms of all types are approximately the same scale.

Since 2001 and China's accession to the WTO, provincial patent subsidy programs have caused patent application numbers in China to escalate. Intended to spur innovation through subsidies, the effectiveness of these programs is unclear. In the last decade, the rise in patents has far outpaced the rise in R&D expenditures. This has led some scholars (Hu & Jefferson, 2003) to question China's patent quality. Li (2010) investigates the validity of patent data in China and assesses whether it is appropriate for academic studies. He finds that increasingly large proportions of applications are granted patent rights since patent subsidy programs were introduced 10 years ago. He argues that application quality, and hence innovation, has risen, which is the cause for increasing patent granting rates. He further asserts that unless the standards used for patent examination have been lowered, which the government has no motivation to do, deteriorating patent quality in China is not a serious concern. In addition to increasing in number, Geir Sviggum, of the law firm Wikborg Rein, emphasized that patents have increasing practical benefit in China with rapidly improving protection of intellectual property rights, especially for foreign firms which Chinese policymakers are concerned about not alienating (Sviggum 2013). This is another reason for rapidly growing patent numbers, complementing increasing innovation in China. Foreign firms are increasingly patenting in China. Although the process still takes longer than in Europe, or in the US, Lars Fabricius, site manager for Alfa Laval in Kunshan, described patenting in China as "relatively easy and straightforward," and lawsuits against patent infringement in China are indeed effective (Fabricius 2013).

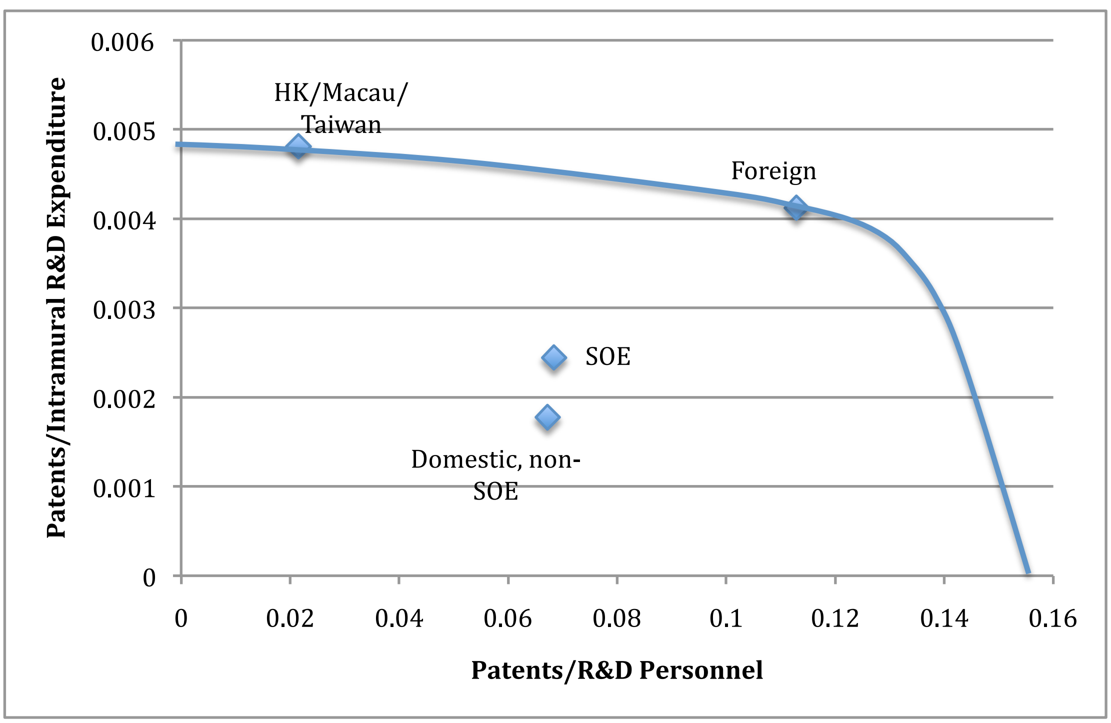
Table 3: Number of R&D Firms and High Tech Patent Applications by Firm Type, China 2011

		Domestic Funded	*SOE*	*HK-, Taiwan-, Macau-funded*	*Foreign*	*Total*
Medicine	R&D Firms	1,512	45	191	234	1,982
	Patents	8,616	129	1,026	1,473	11,244
	Patents/Firm	5.70	2.87	5.37	6.29	5.67
Aerospace	R&D Firms	100	24	3	8	135
	Patents	2,627	366	31	35	3,059
	Patents/Firm	26.27	15.25	10.33	4.38	22.66
Electronics	R&D Firms	1,699	54	559	569	2,881
	Patents	42,089	2,066	6,956	11,290	62,401
	Patents/Firm	24.77	38.26	12.44	19.84	21.66
Computers	R&D Firms	203	3	77	94	377
	Patents	3,174	20	2,290	6,661	12,145
	Patents/Firm	15.64	6.67	29.74	70.86	32.21
Medical Equipment	R&D Firms	1,206	50	111	221	1,588
	Patents	11,365	768	1,645	1,989	15,767
	Patents/Firm	9.42	15.36	14.82	9.00	9.93
Total	R&D Firms	4,720	176	941	1,126	6,963
	Patents	67,871	3,349	11,948	21,448	104,616
	Patents/Firm	14.38	19.03	12.70	19.05	15.02

Source: *Statistical Yearbook on High Tech Industry, 2012*, National Bureau of Statistics; author's calculations

As per Table 3, above, domestic Chinese enterprises – private firms, LLCs, corporations – represent the largest share of active R&D firms and patent applicants in China. The aerospace, electronics, and computer industries have the highest patent per firm ratios, with 22.66, 21.66, and 32.21, respectively. The Medicine industry averages 5.67 patents per firm, which may reflect the theory that smaller firms are those best suited to develop medicinal advances, where the underlying science is not perfectly understood (Qian and Xu 1998). Of the four firm types, SOEs make up the smallest contingent of total patent applications and R&D enterprises, with only 176 in the dataset. However, SOEs have a much higher patent applications per firm ratio than domestic or Hong Kong-, Taiwan-, and Macau-funded firms. SOEs and foreign firms produce 19.03 and 19.05 patent applications, respectively, per firm. This is consistent with the reform history of SOEs in China, where the government retained control of only the largest and most influential firms. For foreign firms, this statistic may represent the notion that multinationals operating in China must be large in order to have the resources to conduct R&D abroad.

Figure 2: Two-input Technical Efficiency Frontier, Chinese Aerospace, 2011



Source: *Statistical Yearbook on High Tech Industry*; author's calculations

Based on the inputs and patent outputs in the aerospace industry, an approximated technical efficiency frontier can be constructed. As is evident in Figure 2, foreign firms and firms from Hong Kong, Macau and Taiwan are most efficient with two inputs, and consequently define the efficiency frontier. State-owned and domestic non state-owned firms lie below the frontier, and are therefore R&D inefficient, or enveloped, in aerospace given the two chosen inputs (intramural R&D expenditure and R&D personnel). However, because DEA is highly sensitive to the chosen inputs, the relative efficiencies are prone to change by adding additional inputs. The efficiency scores presented in Section 5 are calculated using the four inputs previously mentioned: R&D personnel, intramural R&D expenditure, equipment expenditure, and external expenditure. As can be gleaned from Figure 2, DEA is also highly sensitive to DMUs with outlying data, which can skew the efficiency frontier (Coelli 1996).

5. Results

5.1 – Four Input Results

The results from Data Envelopment Analysis with four inputs, presented in Table 4, below, reveal that in 2011, SOE's were not more R&D efficient than foreign or Hong Kong-, Taiwan-, and Macau-funded firms in any industry, and only more efficient than domestic firms in the aerospace industry. In the medical and pharmaceutical industries, domestic Chinese and foreign firms are scale efficient, while Hong Kong-, Taiwan-, and Macau-funded firms have an efficiency score of 0.978. This indicates that these firms need to proportionately reduce R&D inputs by 2.2% to reach the efficiency frontier for patent applications. In other words, these firms are 97.8% as efficient as domestic Chinese and foreign firms at producing patent applications based on the four inputs identified – R&D personnel, intramural R&D expenditure, equipment expenditure, and external expenditure.

Table 4: DEA Results, Four Inputs – China 2011

DMU	*CRS*	*VRS*	*Scale Efficiency*[3]
Medical and Pharmaceutical			
Domestic	1.0	1.0	1.0
SOE	0.891	1.0	0.891 (irs)
HK, Taiwan, Macau	0.978	1.0	0.978 (irs)
Foreign	1.0	1.0	1.0
Medical Meters			
Domestic	0.694	1.0	0.694 (drs)
SOE	0.407	0.871	0.467 (irs)
HK, Taiwan, Macau	1.0	1.0	1.0
Foreign	0.569	0.620	0.918 (drs)
Aerospace			
Domestic	0.596	1.0	0.596 (drs)
SOE	0.606	1.0	0.606 (drs)
HK, Taiwan, Macau	1.0	1.0	1.0
Foreign	1.0	1.0	1.0
Electronics			
Domestic	1.0	1.0	1.0
SOE	0.87	1.0	0.870 (irs)
HK, Taiwan, Macau	1.0	1.0	1.0
Foreign	0.917	0.999	0.918 (irs)
Computers and Office Equipment			
Domestic	1.0	1.0	1.0
SOE	1.0	1.0	1.0
HK, Taiwan, Macau	1.0	1.0	1.0
Foreign	1.0	1.0	1.0

Source: *Statistical Yearbook on High Tech Industry*; author's calculations

[3] Note: Increasing returns to scale indicated by (irs) and decreasing returns to scale by (drs). All efficient DMUs operate with constant returns to scale

State-owned firms in the medical and pharmaceutical industries have an efficiency score of 0.891, indicating that SOEs would need to proportionately reduce these four inputs by 10.9% while producing the same number of patent applications in order to be R&D efficient. The finding that SOEs are less efficient in an industry with many smaller firms producing incremental pharmaceutical improvements is consistent with previous literature (Zhang, Zhang & Zhao 2003, Berg 2012).

The aerospace industry is that in which the theoretical propositions of Bolton & Farrell (1990), Qian and Xu (1998), and Huang and Xu (2008) can be evaluated. Under CRS assumptions SOEs are not efficient, with an efficiency score of 0.606, yet they are still slightly more efficient than Chinese domestic firms (with an efficiency score of 0.596) for the given 4 input-1 output combination. This may reflect a lower general level of technological advancement among Chinese SOEs and private firms alike as compared to foreign firms. Therefore SOEs in aerospace, an industry with low scientific uncertainty (γ), do not hold an efficiency advantage in R&D as was hypothesized. SOE's R&D inefficiencies may be due to continuing soft budget constraints for SOEs in China, or SOE's taking on projects with larger innovative payoffs that are fewer and farther in between. Because the output, patent applications, does not measure any element of cost or duration of R&D projects, it is possible that SOEs would lie on the aerospace efficiency frontier with a different output – such as new product sales or number of invention patents, rather than simply patent applications or utility patents.

In DEA, input slacks refer to the distance, or amount by which each input needs to be decreased while holding output constant in order to reach the efficiency frontier (Coelli 1996). Although SOE's operate with efficient numbers of R&D personnel in aerospace, intramural expenditure would need to decrease 19.47 million RMB, equipment expenditure would need to decrease by 61.1 million RMB, and external expenditures would need to decrease by 8.75 million RMB while holding output constant in order for SOE's to reach the efficiency frontier for aerospace.[4] That SOEs operate with efficient levels of R&D personnel in aerospace is particularly striking in the context of Kornai's (1986) discussion of soft budget constraints causing systemic labor surpluses. As compared with domestic and HK-, Macau-, and Taiwan-invested aerospace firms, SOEs employ relatively fewer researchers per firm. Labor surpluses may still be present but simply not represented by higher skilled workers. Well-educated scientists would be among the last to be unemployed because of their qualifications. Therefore, labor surpluses would likely be reflected in low-skilled labor positions in aerospace, and indeed most state-owned high tech firms.

5.2 – Five Input Results

Extending the suppositions of David, Hall, and Toole (2000), the intramural expenditure input can be divided into two sources: public R&D funds and firm-raised R&D funds. The other inputs remain the same, and patent applications are once again used as the output. Although increasing the number of inputs with very few decision making units reduces the discriminatory power of the DEA model, delineating public and self-raised funds for R&D may yield a more complete picture of firms' patent output (Boussofiane et al. 1991). The results from the 5 input-1 output model are presented in Table 5, following.

With the intramural expenditure input divided into government funds and firm-raised funds, SOEs have a higher efficiency score in aerospace, and are further efficient than other domestic aerospace R&D firms as compared to the 4 input model. SOE's have an efficiency score of 0.859 and that of domestic firms is 0.689, which is a significantly larger gap in efficiency than in the 4-input model. Both operate with decreasing returns to scale, with patent applications increase at a declining rate as inputs increase. As can be seen in Table 3 above, SOEs would need to proportionally reduce inputs by 14.1% while holding patent applications constant in order to reach scale efficiency in aerospace R&D. In the medical meters industry, only firms from Hong Kong, Taiwan, and Macau are scale efficient.

Table 5: DEA Results, Five Inputs – China, 2011

DMU	*CRS*	*VRS*	*Scale Efficiency*[5]
Medical and Pharmaceutical			
Domestic	1.0	1.0	1.0
SOE	0.891	1.0	0.891 (irs)
HK, Taiwan, Macau	0.978	1.0	0.978 (irs)
Foreign	1.0	1.0	1.0
Medical Meters			
Domestic	0.694	1.0	0.694 (drs)
SOE	0.407	0.871	0.467 (irs)
HK, Taiwan, Macau	1.0	1.0	1.0
Foreign	0.922	1.0	0.922 (drs)
Aerospace			
Domestic	0.689	1.0	0.689 (drs)
SOE	0.859	1.0	0.859 (drs)
HK, Taiwan, Macau	1.0	1.0	1.0
Foreign	1.0	1.0	1.0
Electronics			
Domestic	1.0	1.0	1.0
SOE	0.870	1.0	0.870 (irs)
HK, Taiwan, Macau	1.0	1.0	1.0
Foreign	1.0	1.0	1.0
Computers and Office Equipment			
Domestic	1.0	1.0	1.0
SOE	1.0	1.0	1.0
HK, Taiwan, Macau	1.0	1.0	1.0
Foreign	1.0	1.0	1.0

Source: *Statistical Yearbook on High Tech Industry*; author's calculations

[5] Note: Increasing returns to scale indicated by (irs) and decreasing returns to scale by (drs)

An interesting feature of both the 4-input and 5-input DEA models is that the returns to scale are not consistent. Firms in the medical/pharmaceutical industries demonstrate increasing returns to scale. This differs from the findings of Graves and Langowitz (1996), which showed clear and consistent decreasing returns to scale with R&D expenditures. One possibility for this discrepancy is that Graves and Langowitz do not directly include R&D personnel in their study. Rather, they examine R&D expenditures in dollar costs. However there is little or no theoretical basis for R&D personnel to induce increasing returns to scale. Another possibility is inherent to the medical industry. As predicted by Huang and Xu (1998) and Qian and Xu (1998), smaller firms with hard budget constraints are best suited to yield R&D-based advances in medicine. Perhaps medical firms in the data tend to be small, and thus under the scalar inflection point, at which firms tend switch from increasing to decreasing returns to scale.

5.3 – A Note on Time Lag

Due to the time-consumptive nature of R&D, there is a non-negligible delay between inputs and outputs (Lee & Park 2005). Though panel data of high tech firms over several years would enable studies to incorporate this, Chinese government statistics unfortunately do not track firms entering or exiting the sample. Therefore input data from 2008 would be incompatible with output data from, for example, 2011 because the composition of sampled firms has changed. Input and output data from the same year, while not ideal, is superior to using data from different years where changes in inputs and outputs could be drastically confounded by the entry of new firms and the exit of bankrupt or purchased firms in the sample. In addition, the lag between R&D inputs and outputs is not fixed, varying between not only firms but also industries (Lee & Park 2005). Therefore using input and output data from the same year is appropriate given the nature of the Chinese government statistics.

5.4 – A Note on Bootstrapping

Because DEA measures efficiency relative to an estimated frontier, it is prone to significant uncertainty based on sampling variation (Daraio & Simar 2007). There is always an element of inherent randomness, or background noise, in reality that impacts the data. Ideally, the estimated efficiency frontier would remain the same regardless of the sample size (number of DMUs). However because this study only employs 4 DMUs, variation in the efficiency frontiers in reality and those represented in this study may vary to some degree. Enflo and Hjertstrand (2009), in a study of European productivity convergence, employ a bootstrap production frontier approach to DEA. DEA's inherent flexibility (not needing to know the production function or market structure) means inputs may not be compared according to their relative importance in yielding a certain output. For example, R&D personnel may be a more influential input than R&D expenditure on a firm's patent applications, however DEA does have a mechanism to reflect this.

Additionally, the efficiency frontier is constructed using the best-practice DMU, when there may in fact be several other more efficient DMUs that are not included in the dataset. As a result, bootstrapping methods can be used to account for natural variance in the data. By using repeated Monte Carlo simulations to generate asymptotic production functions, Enflo and Hjerstrand (2009) provide both biased and bias-corrected, or bootlegged, technological frontiers. By making the production function asymptotic, all of the bias-corrected efficiency scores are lower than their corresponding uncorrected scores. This is due to the bias-adjusted efficiency frontier accounts for simulated combinations of inputs and outputs within an acceptable range of statistical variance that are more efficient than the most efficient DMUs in the data, thus increasing the attainable efficiency frontier (Badunenko, Henderson & Russell 2008). Because the Chinese data yearbooks only allow for four firm-type DMUs, bootstrapping is not appropriate to yield robust results in this paper. Conducting Monte-Carlo simulations to generate normally distributed input and output data around the existing observations with only 4 DMUs would not fix the inherent "background noise" problem in a robust way.

6. Conclusions

The findings of this study are mixed. While SOEs can theoretically be R&D efficient in heavy industries and large-scale projects (Bolton & Farrell 1990, Qian and Xu 1998, and Huang and Xu 2008), the DEA results indicate that domestic, Hong Kong- Taiwan- and Macau-invested, and foreign firms tend to be more efficient in terms of patent production in high tech industries. Thus the hypothesis that SOEs are more R&D efficient than private and foreign firms in aerospace is not supported. One possible explanation for this is that Chinese policymakers mandate SOEs to tackle only larger, longer-term R&D projects with fewer patent opportunities, leaving incremental innovation projects to private and foreign firms. This paper also confirms the findings of Berg (2012); foreign firms are indeed scale efficient in the medical and pharmaceutical industry. Furthermore, SOEs are more R&D efficient than domestic firms in the aerospace industry, but less so than HK-, Macau, or Taiwan-invested, or foreign firms. This may indicate that SOEs are either better suited to tackle large projects where the underlying science is well understood than other domestic firms. It may also be evidence that there is still a technology gap between Chinese aerospace R&D, and foreign aerospace R&D, though SOEs may be catching up to first tier aerospace companies, like Boeing and Airbus, faster than domestic Chinese firms.

Although state-backed R&D cannot be said to be more efficient than private or foreign R&D, this paper presents the most recent Chinese R&D data and uses a DEA framework that can be applied to future studies, with newer or more complete data. In addition, this paper isolates and puts into relation the key determinants of a state-owned R&D efficiency – length of projects, input costs, softness of budget constraints, and the scientific uncertainty of the projects. Another contribution of this study is its synthesis handful of empirical data with interviews and lectures conducted with innovation industry experts in China. That said, the robustness of this study could be improved with more comprehensive data. First, panel R&D data from multiple years would enable use of the Malmquist productivity index, which measures changes in DMU efficiency over time. Second, as previously discussed, data drawn from the same firms over time would enable the use of time lags between inputs and outputs, which is the case with R&D in reality (Lee & Park 2005). Third, national statistics sorted into more firm types would enable the use of more DMUs, thus increasing the robustness and discriminatory power of the DEA model to show input efficiency. Finally, firm-level data on R&D would fill in gaps in industry trends, industry firm sizes, and human capital.

This study bridges a rift in existing China literature. While several studies have found that private R&D and marketized innovation is superior in consumer industries, few have compared firm types across several industries. The policy implications of this paper are somewhat ambiguous, however three facts are clear: (i) competition spurs innovation, particularly in industries with frequent, incremental improvements, such as biotech, (ii) access to financing is a key determinant of firms' R&D, and finally (iii) hardening budget constraints for SOEs should be a top priority of Chinese policymakers to spur competition and innovation between state and private sectors. As per the suggestions of Huang and Xu (1998), one way to harden budget constraints in the state sector is for Chinese policymakers to open uncertain projects to more sources of financing, or even require R&D projects to be co-financed by multiple independent investors. Consequently, SOEs would have stronger incentives to innovate efficiently.

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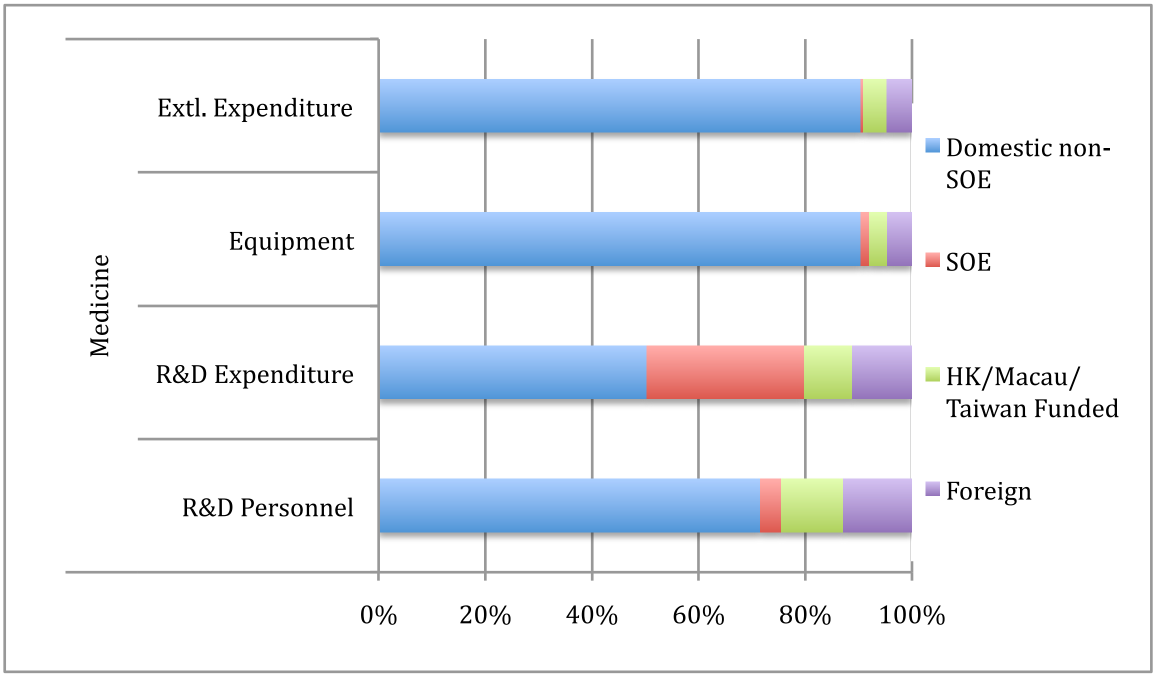
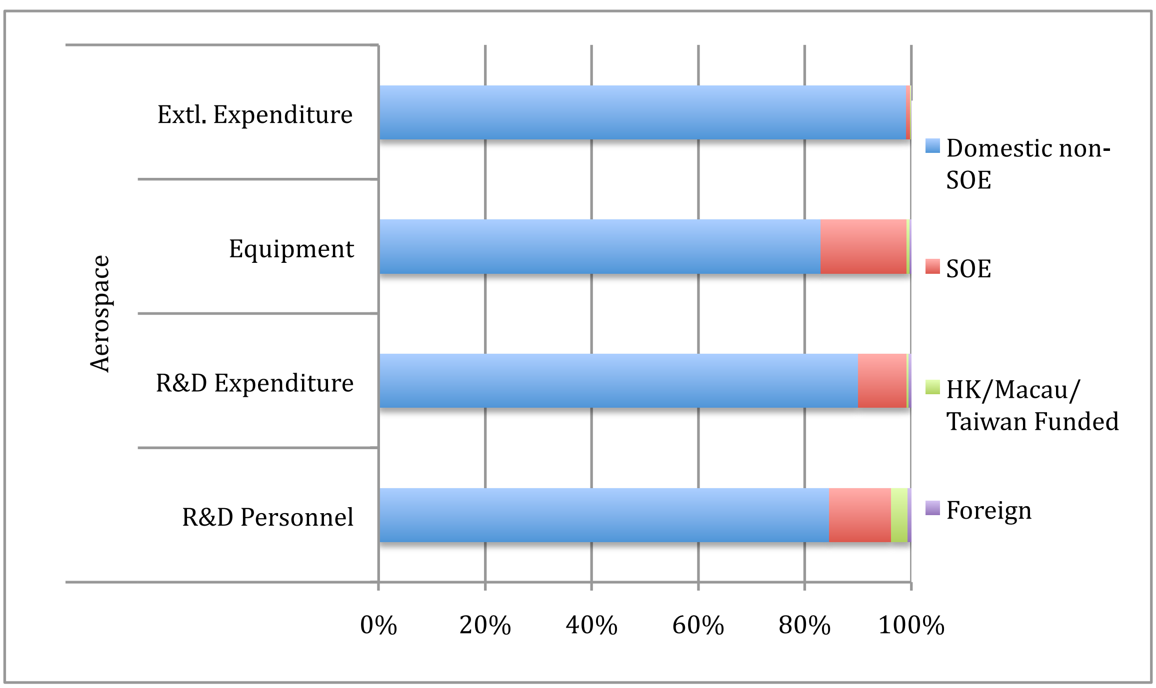
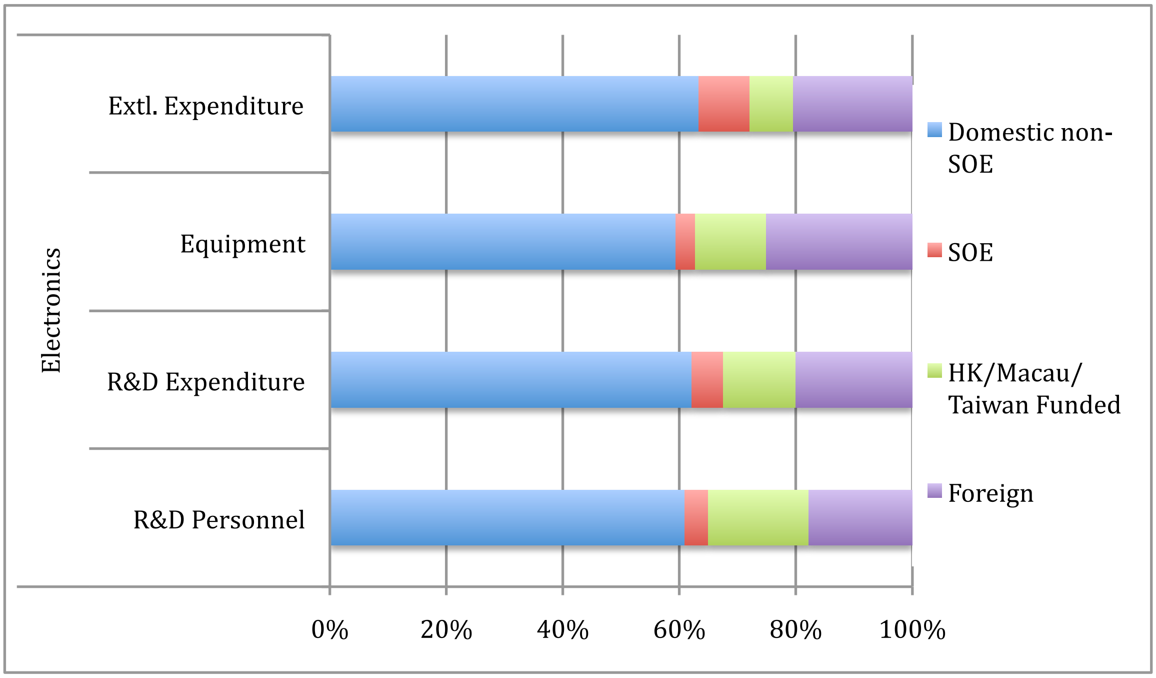
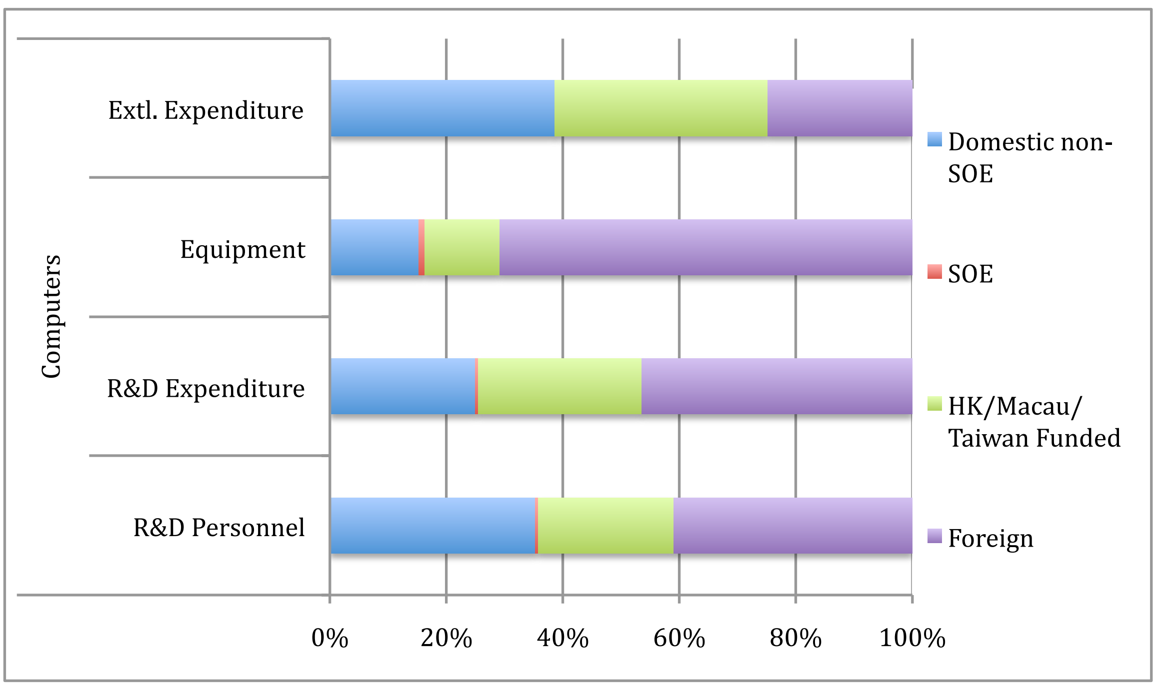
Appendix

Figure 3: Input Proportions by Firm Type and Industry, China 2011






Electronics
Extl. Expenditure
Equipment
R&D Expenditure
R&D Personnel
0%
20%
40%
60%
80%
100%
Domestic non-SOE
SOE
HK/Macau/ Taiwan Funded
Foreign


Computers
Extl. Expenditure
Equipment
R&D Expenditure
R&D Personnel
0%
20%
40%
60%
80%
100%
Domestic non-SOE
SOE
HK/Macau/ Taiwan Funded
Foreign

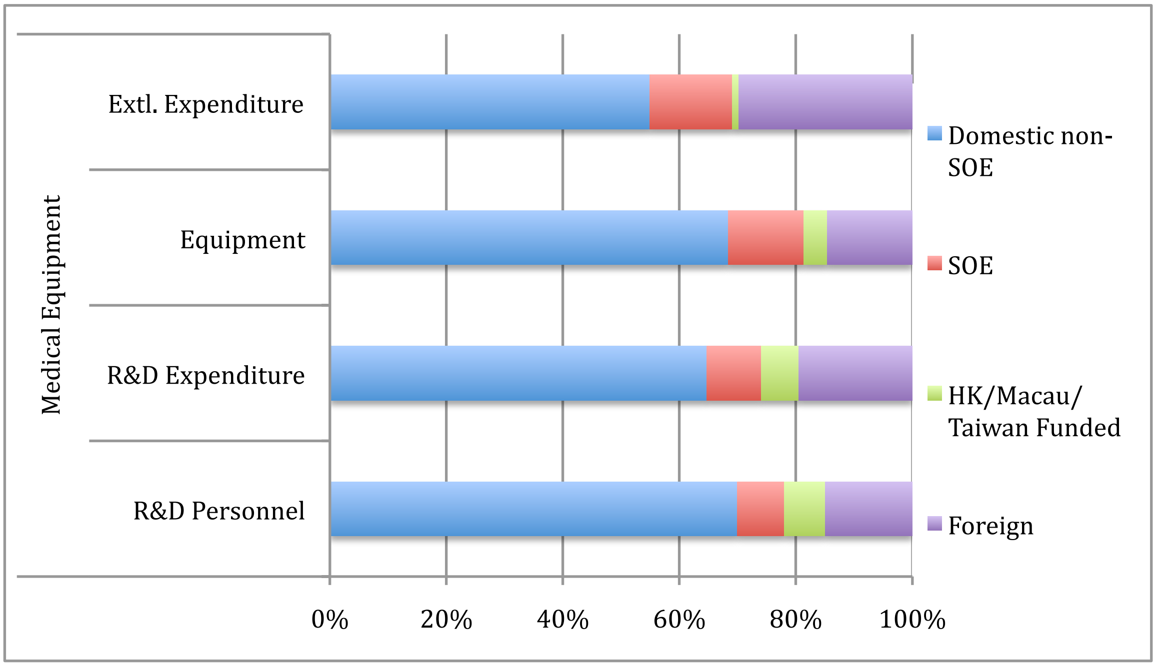


Figure 4: Example Efficiency Frontier, CRS vs. VRS (Coelli 1996)