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The impacts of academic and industry research on high-tech manufacturing: Evidence from supercomputer usage

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It is widely accepted that research in the high-tech sector is considered a key to maintain advanced economies' competitiveness at the face of their emerging counterparts' rising technological sophistication. Yet, the impact of research on high-tech output has never been quantified. In this paper, we empirically examine the impact of frontier research on high-tech manufacturing production. Standard R&D expenditure measure is found to be too general to capture the input in frontier research. To overcome this problem, we propose a novel proxy for frontier research investment – the supercomputing capacity. Empirical evidence strongly supports this choice of variable. We also find that academic research exerts a larger growth effect on high-tech manufacturing output than its industrial counterpart.

JEL Classifications: O14, O39

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Abstract

It is widely accepted that research in the high-tech sector is considered a key to maintain advanced economies' competitiveness at the face of their emerging counterparts' rising technological sophistication. Yet, the impact of research on high-tech output has never been quantified. In this paper, we empirically examine the impact of frontier research on high-tech manufacturing production. Standard R&D expenditure measure is found to be too general to capture the input in frontier research. To overcome this problem, we propose a novel proxy for frontier research investment – the supercomputing capacity. Empirical evidence strongly supports this choice of variable. We also find that academic research exerts a larger growth effect on high-tech manufacturing output than its industrial counterpart.

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1- Introduction

Technological progress has long been considered as a key to long-run growth (see, e.g., Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992). While technology is typically protracted as *one* (though important) piece of production element in economic textbooks, in reality it is highly heterogeneous in terms of both content and level. Different industries can have vastly different levels of technological sophistication. High-tech industries such as information and communication technology, which employ the most advanced technologies in production, are believed by many as the key driving force of modern economies.

The high-tech competition among countries is fierce. History has evidenced that at every stage, there is a distinct leading country which maintains technological leadership: the Netherlands (around 1600 to the Napoleonic wars), Great Britain (from 1820 to the first industrial revolution) and the US (from 1890 to present). In modern time, we have witnessed the competition between Japan and the US in the 1980s, and the emergence of China as a future challenger to the US's hegemony more recently.

The high-tech sector is not only important in the fighting for technological supremacy amongst developed countries themselves, but is also important for them to deter imitation by their developing counterparts. Stylized facts indicate that almost all high-tech products were originated from developed countries, and developing countries only get involved in their production at some later stage when the products become standardized and the technology has spilled over to them – a phenomenon known as the international product life cycle (Vernon 1966). Multinational corporations are traditionally a key conductor of this cooperative process of technology transfers. However, international production cycle could also be a result of unintended technology transfers, of which trade is the most important channel. By importing more advanced products from their developed counterparts, developing countries can copy or backward engineer the product designs. When the imitation is perfected, monopoly profits earned by the original innovators will be eroded due to their high labour costs. Focusing on high-tech exports is one way for developed countries to deter imitation as technologically sophisticated products are by nature much harder to copy or reverse engineer.

As technological advantage becomes synonymous to national competiveness, countries are compelled to constant investment in high-tech research if they want to stay competitive globally. Frontier research,[1] due to its cutting edge nature, is expensive and risky. Furthermore, the road of turning research output into marketable products itself is also full of hurdles and uncertainties. As a result, how much of frontier research investment will precipitate into actual high-tech output is not a trivial question. Against this background, *the first objective of this paper is to quantify the effects of research and development (R&D) in affecting high-tech manufacturing output.*

To quantify research efforts, the literature often uses the measure of R&D expenditure provided by the United Nations Educational, Scientific, and Cultural Organization (UNESCO) Institute for Statistics. According the Institute, the measure is defined as "… current and capital expenditures (both public and private) on creative work undertaken systematically to increase knowledge, including knowledge of humanity, culture, and society, and the use of knowledge for new applications. R&D covers basic research, applied research, and experimental development." Clearly, this measure of R&D is too broad to be relevant for the high-tech manufacturing sector. To address this problem, this paper proposes a novel proxy measure of R&D input that is unequivocally associated with high-tech: the capacity of

[1] By frontier research, we refer to research that leads to an improvement in the state-of-the-art technology. Given that high-tech industries employ the most advanced technologies for their production, research in these industries are very much 'frontier' in this aspect. As a result, in this paper we use the term 'frontier research' and 'high-tech research' interchangeably.

supercomputers used in a country. While this proxy measure may seem to be as bold as innovative, obtained results validate our choice.

It is necessary to be upfront about the limitation of our approach. First of all, the concept of high-tech research is not limited to manufacturing and even in the manufacturing sector high-tech research may not require supercomputer capacity. Moreover, the Top500 supercomputers do not necessarily capture all the high power computing capability. Distributed or grid computing systems can make use of the network of a large number of personal computers to generate an aggregate computer capability exceeding many supercomputers, and this practice has been used in frontier research in various scientific programs (e.g. see Berkeley Open Infrastructure for Network Computing (BOINC) platform). Here we do not intended to claim that supercomputer capacity is an ideal measure of research input into the high-tech manufacturing sector, but rather it is an improved proxy of such research input compared to the commonly used R&D expenditure measure.

The upgrading of old products as well as the generating of new products is commonly considered primarily the task of the industry. However, the role played by academic institutions in this process could be equally, if not more, important. Throughout history, universities have actively participated in many significant innovations, ranging from pharmaceuticals to information technology, from aero-space engineering to genetic food.[2] A conventional view is that industrial research and academic research are two different knowledge production mechanisms: the academia focuses on publications while the industry focuses on patentable or excludable outputs. This implies that knowledge produced by the academic sector is more like a public good while that produced by the industrial sector is mostly a private good (e.g. Stephan, 1996; Sauermann and Stephan, 2010). This view is

[2] For example, blood preservation technology was invented by (scientists at) the University of Columbia in 1940, liquid crystal display (LCD) by the Kent State University in 1967, and hepatitis B vaccine by the University of Pennsylvania in 1969.

obviously very narrow in that many academic institutions have their outputs commercialized[3] and many enterprises make their research findings available to the public. Also, it is increasingly common for universities to commercialize their research output, blurring the conventional border between academic and industrial research. Notwithstanding, in general it is reasonable to say that academic research is likely to have broader but less direct effect on high-tech manufacturing output, while industry research is likely to have narrower but more direct impact. Overall which sector has a bigger impact on high-tech output is a question begging for an answer. In view of this, *the second objective of this paper is to test and quantify any impact differentials between academic research and industrial research on high-tech manufacturing output.*

This paper makes several contributions to the literature. Firstly, to the best of our knowledge it is the first empirical attempt to explain differences in high-tech manufacturing output across countries. More specifically, it examines the impact of high-tech research on high-tech output. Secondly, it explores whether supercomputing capacity (SCC) is a better measure for high-tech research input than the commonly used R&D expenditure. Through doing so, it proposes a brand new proxy for this kind of investment. Thirdly, given that existing studies only examine the division of Highly-skilled labour between industry and academia (e.g. Aghion *et al.*, 2008; Sauermann and Stephan, 2010), this paper complements the literature by considering the physical capital aspect.[4] Our panel dataset has SCC measures for a number of segments within countries, including industry and academia. Since SCC is measured in processing speed, there are no price conversion issues like R&D expenditure. This therefore facilitates making comparisons between segments, across countries, and over time.

[3] According to Lach and Schankerman (2003), the number of patents granted to US university scientists increased from 500 in 1982 to more than 3100 in 1998.

[4] We acknowledge a rich literature on the economic impacts of university and industrial research such as Jaffe (1989), Berman (1990), Anselin et al. (1997), Martin (1998), Goldstein and Renault (2004).

The main findings of the paper are quite encouraging. There is robust evidence that SCC is a better measure of high-tech research investment than the more general R&D expenditure. It is found that accumulated research capital based on the SCC measurement exerts a statistically significant, positive impact on a country's high-tech manufacturing output. Also, academic high-tech research is shown to contribute more to the growth of high-tech output than its industrial counterpart. Furthermore, very similar results are obtained when high-tech exports are used in place of high-tech manufacturing output.

The paper is structured as follows. Section 2 develops a theoretical model of economic growth with industrial and academic science. Section 3 briefly describes the methodology, measures and data for the empirical analysis. Section 4 presents the results and section 5 concludes the paper.

2- The theoretical model

The final goods sector

A representative country consists of a large number of competitive final goods producers of high-tech products. The production of these products takes the following Cobb-Douglas form:

$$Y_t = A_t^{1-\alpha} \sum_{i=1}^{N} q_{i,t} x_{i,t}^{\alpha}, \qquad 0 < \alpha < 1 \tag{1}$$

where Y_t is the industry-wide aggregate output level at time t, A_t is the existing stock of general knowledge, N denotes the fixed range of intermediate inputs used for production of final goods, $x_{i,t}$ is the amount of intermediate capital used in industry i, and $q_{i,t}$ is its attached quality grade. Here, A_t is produced through academic research while industrial research enhances $q_{i,t}$. Capital goods are produced by specialised intermediate firms.

The market for final high-tech consumption good is perfectly competitive. So equating the marginal product of a particular capital good with its price gives the inverse demand for that intermediate good:

$$\frac{\partial Y_t}{\partial x_{i,t}} = A_t^{1-\alpha}\alpha\theta_{i,t}x_{i,t}^{\alpha-1} = p_{i,t} \tag{2}$$

The intermediate goods sector

The intermediate goods sector is monopolistically competitive. For simplicity, we assume that producing one unit of intermediate goods $x_{i,t}$ requires only human capital and a fixed production factor:

$$x_{i,t} = h_{i,t}Z^{\beta} \tag{3}$$

where $h_{i,t}$ is the amount of human capital employed in industry i and Z is the fixed production factor (which is normalized to 1).

As a result, total human capital devoted to intermediate goods production is:

$$H_t = \sum_{i=1}^{N} h_{i,t} = \sum_{i=1}^{N} x_{i,t} \tag{4}$$

Given the symmetry between firms, in equilibrium $x_{i,t} = x_t \ \forall i$. Therefore:

$$H_t = \sum_{i=1}^{N} x_{i,t} = N x_t \tag{5}$$

Using this result, the final goods production function can be rewritten as:

$$Y_t = \frac{1}{N^{\alpha}}\Theta_t A_t^{1-\alpha}H_t^{\alpha},\ \alpha < 1 \tag{6}$$

where $Q_t = \sum_{i=1}^{N} q_{i,t}$ denotes the industry-wide aggregate stock of firm-specific knowledge.

Along the balanced growth path, the fraction of human capital devoted to intermediate goods production is constant so that:

$$g(Y) = g(Q) + (1 - \alpha)g(A) + \alpha g(H) \tag{7}$$

where $g(X) \equiv \dot{X} / X$ denotes the growth rate of variable X .

The research sector

Knowledge production requires physical capital investment like building laboratory as well as human capital investment like placing researchers. Since inputs into high-tech research are typically highly specialized, the substitutability between physical and human capitals in knowledge production is expected to be very low. Thereby, for simplicity we can assume that the production function of high-tech knowledge takes the Leontief form. In further assuming no excess (i.e. wasteful) deployment of physical capital, this implies that we only need to account for physical capital in the production of knowledge.

Academic research performed by universities is assumed to enhance general knowledge. The academic knowledge evolves as follows:

$$\dot{A}_t = \frac{K_{A,t} A_t^{\gamma_1} Q_t^{\gamma_2}}{A_t Q_t}, \ \gamma_1 > 0, \gamma_2 > 0 \tag{8}$$

where $K_{A,t}$ is physical investment devoted to academic research, and $A_t^{\gamma_1}$ and $Q_t^{\gamma_2}$ denote the externalities of, respectively, academic and industry R&D activities. The research inputs are deflated by $A_t Q_t$ to indicate that R&D difficulty grows as the technology becomes more complex.

Industry research activities are firm specific. Each firm's technological level is enhanced according to a procedure similar to the one in academia:

$$\dot{q}_{j,t} = \frac{k_{j,t} A_t^{\delta_1} Q_t^{\delta_2}}{A_t Q_t}, \delta_1 > 0, \delta_2 > 0 \tag{9}$$

where $k_{j,t}$ is the physical investment in research by firm j at time t.

Summing over j noting that $\int_0^N k_{j,t} dj = K_{Q,t}$ and $\int_0^N \dot{q}_{j,t} dj = \dot{Q}_t$ gives;

$$\dot{Q}_t = \frac{K_{Q,t} A_t^{\delta_1} Q_t^{\delta_2}}{A_t Q_t} \tag{10}$$

Along the balanced growth path, g_A and g_Q are both constant so that:

$$g(K_A) + \left(\gamma_1 - 2\right) g(A) + \left(\gamma_2 - 1\right) g(Q) = 0 \tag{11}$$

$$g(K_Q) + \left(\delta_1 - 1\right) g(A) + \left(\delta_2 - 2\right) g(Q) = 0 \tag{12}$$

Solving this system of equations for $g(A)$ and $g(Q)$ and plugging the results into (7) yields:[5]

$$\begin{aligned} g(Y) = {} & \frac{[(2-\gamma_1) - (1-\alpha)(1-\gamma_2)]}{(2-\delta_2)(2-\gamma_1) - (1-\delta_1)(1-\gamma_2)} g(K_A) \\ & + \frac{[(1-\alpha)(2-\delta_2) - (1-\delta_1)]}{(2-\delta_2)(2-\gamma_1) - (1-\delta_1)(1-\gamma_2)} g(K_Q) + \alpha g(H) \end{aligned} \tag{13}$$

This can be simplified into

$$g(Y) = \beta_1 g(K_A) + \beta_2 g(K_Q) + \alpha g(H) \tag{14}$$

[5] Here we assume that the parameters are such that the unique solution to the system exists.

where $b_1 = \dfrac{(2-g_1)-(1-a)(1-g_2)}{(2-d_2)(2-g_1)-(1-d_1)(1-g_2)}$ and $b_2 = \dfrac{(1-a)(2-d_2)-(1-d_1)}{(2-d_2)(2-g_1)-(1-d_1)(1-g_2)}$.

Equation (14) suggests that the growth rate of high-tech output in a country is a function of the growth rates of its respective investments in academic and industrial research as well as human capital. It essentially denotes a production function expressed in terms of growth rates instead of levels. Even if restrictions are imposed on the parameters so that $b_1 > 0$ and $b_2 > 0$ based on a prior expectations, there is still no definite order between b_1 and b_2. However, using the equation as a platform we can empirically examine the relative impacts of academic and industrial frontier research on high-tech output, as explained next.

3- The methodology and data

3.1 The methodology

The strategy of our empirical work, however, is not to estimate (14) straight away. Instead, we will first establish if a country's SCC is a better proxy for its input into high-tech research than the commonly used R&D expenditure measure. Once the relevance of the SCC measure has been validated, we can then use it to examine the differential impact of academic and industrial research on high-tech manufacturing output.

Our dataset is an unbalanced panel, covering 27 to 28 countries, depending on model specifications. The list of countries is provided in the Appendix. As expected, the vast majority of the countries are OECD countries. The remaining countries are emerging economies, including Brazil, China, Russia, Saudi Arabia, South Africa and Taiwan. The time coverage is from 1991 to 2010.

3.2 Supercomputer capacity measures and data

The data of supercomputer capacities of different countries are sourced from the TOP500 project, which started in 1993 to provide a platform for tracking and detecting trends in high-performance computing. The project produces twice a year a list of the 500 most powerful computer systems around the globe. The performance measure is based on the LINPACK benchmark by solving a system of 1000 linear equations. According to the project organization, “This performance does not reflect the *overall performance* of a given system, as no single number ever can. It does, however, reflect the *performance of a dedicated system for solving a dense system of linear equations.* Since the problem is very regular, the performance achieved is quite high, and the performance numbers give a good correction of peak performance” (italic original). The maximal LINPACK performance achieved by a supercomputer is referred to as Rmax, which has the unit of Tflops. A supercomputer that has a higher Rmax value is supposed to be of more powerful. We use the accumulated Rmax values of countries to measure their supercomputer capacity.

An alternative measure of computing power, the theoretical peak performance Rpeak is also reported in the TOP500 list. According to the project organization, “Rpeak is a theoretical peak performance. It is determined by counting the number of floating-point additions and multiplications (in full precision) that can be completed during a period of time, usually the cycle time of the machine.” Since Rpeak is a theoretical peak performance while Rmax is the actual peak performance, the former is noticeably larger than the latter. We use Rmax as our main supercomputing power measure, but also use Rpeak for robustness check.

The Top500 list contains a range of information about each of the TOP500 supercomputers, including system specifications, the major area of application, and the country and year of instalment. A particular important aspect of the dataset is that it stratifies the supercomputers not only by countries but also by segments in which the supercomputers are used. The six segments are respectively, academic, research, industry, vendor, government, and classified.

Since vendors are manufacturers of supercomputers, they can also be considered as part of a broader industry segment. Classified segment typically consists of national security agencies and thereby can be considered as part of a broader government segment. The academic segment typically consists of universities. The research segment normally consists of national research institutes such as space science research institutes or medical research institutes. Due to this nature, it can be considered as part of a broader academic segment. In the empirical analysis, we will examine whether the results are robust to the aggregation of related segments.

The rapid advancement of computing power is well known. This is true also for those in the top of the rank – supercomputers. However, even amongst supercomputers there is a wide range of capacity. On average, a leading edge supercomputer – known as 'tier-0' supercomputer in the industry – can stay at that tier for roughly three years. This is reflected in the TOP500 data as well. For example, in the June 2010 list,[6] only two out of the TOP500 supercomputers in the world were installed in 2005, six in 2006 and 18 in 2007; the remaining 95% were all installed in the last 3 years. In comparison, according to the 1993 list, only four out of the TOP500 supercomputers were installed between 1991 and 1993, all the rest were much 'older' vintages. In fact, the oldest supercomputer recorded in the 1993 list was installed in 1984 – almost a decade ago! This temporal comparison indicates that the advancement cycle of supercomputing power and thus the lifespan of being a TOP500 has been shortened substantially in the past two decades.

In this paper we use the accumulated SCC as a proxy measure of high-tech R&D activities for countries and segments. For instance, the SCC of a country in the first year, 1993, will be equal to the sum of the computing power of its TOP500 supercomputers in 1993. Its SCC in 1994 will be equal to the sum of the computing power of its *new* TOP500 in 1994 plus its

[6] The TOP500 list is updated twice a year. All data used in this paper are from the mid-year June list.

SCC in 1993. Likewise, its SCC in 1995 will be equal to the sum of the computing power of its new TOP500 in 1995 plus its SCC in 1994. In doing so, we include the computing power of the supercomputers that have dropped out of the TOP500 list. This is appropriate because the competition of TOP500 is increasingly fierce with a lifecycle of about 3 years, but a supercomputer obviously has a much longer lifespan than that. We also consider the impact of deterioration in capacity in robustness tests.[7]

Although the TOP500 project was started in 1993, the first list contains information of supercomputer installed as early as 1984. However, the number of observations for earlier years is too small. As a result, we choose to use 1991 as the starting year (i.e. SCC from 1984 to 1991 will be counted toward the accumulated SCC in 1991).

Figure 1 shows the sectoral shares of supercomputer capacity of the 28 countries in our data over 1991-2005. Year 2005 is the latest year in which we have data for other variables used in the regressional analysis. For most countries, academic, research and industry segments account for the bulk of the countries' SCC. However, it does not mean that the supercomputing capacities of the classified and government segments are negligible in absolute terms. Figure 2 shows the time trend of the total computing power of Top500 supercomputers as measured by ln(Rmax). It can be seen that, there is a rapid growth of supercomputing capacity in all segments. Although the classified and government segments are of the smallest shares (so is the vendor segment), they maintain a similar growth trend as the other much larger segments.

[Figure 1]

[Figure 2]

[7] One needs to distinguish between the depreciation in market value and deterioration in capacity. The market value of a computer can depreciate very rapidly. However, it does not mean that the capacity of the computer has deteriorated even though new software may require much bigger processing power so that older computers could become insufficient.

3.3 Measures and data for other variables

The main dependent variable in the regression analysis is the growth rate of high-tech manufacturing value-added. As an extension, we have also examined the impact of frontier research on high-tech manufacturing export growth. Data on value added and export of high-tech manufacturing sector are extracted from US National Science Foundation's databases.

The five manufacturing industries constituting the high-tech manufacturing sector are: communications and semiconductors, pharmaceuticals, scientific instruments, aerospace, and computers and office machinery.

The figures are measured in million of constant US dollars (the base year is 2000).

Based on the theoretical model presented in section 2, the independent variables include the growth rate of R&D expenditure, the growth rate of SCC, and the growth rate of human capital. R&D expenditure data from OECD STAN databases (2008) are used to generate R&D capital stocks using the method as described in Coe and Helpman (1995). The figures are also measured in million of constant US dollars (the base year is 2000). For human capital, it is highly-skilled labour that is most relevant here and thus we use the proportion of population with tertiary education. Data on percentage of population aged 25 and over completed tertiary education come from Barro and Lee (2010) database.

4- Empirical results

In all regressions reported in this section, the dependent variable is high-tech manufacturing value-added growth rate unless stated otherwise. The use of the value-added measure means that we have accounted for the fact that countries may import a high-tech intermediate goods for domestic production which itself could be of low to mid-tech nature only.

4.1- Comparing R&D expenditure and supercomputer capacity

We start with models using the conventional R&D expenditure measures. The results are reported in the first three columns of Table 1. Models (1a) to (1c) are estimated using respectively, the OLS, the fixed effects, and the random effects estimators. The numbers in the parentheses are cluster robust standard errors.[8]

[Table 1]

The growth rate of R&D expenditure has the expected positive sign across all three models. It is highly significant in the OLS and random effects regressions, but not in the fixed effects one. However, results from the Hausman test strongly reject the hypothesis of the random effects model being consistent (p-value < 0.01), and the fixed effects model controls for country heterogeneity and therefore is preferred to the OLS model. According to the fixed effects model, the growth rate of R&D expenditure is not significant at any standard levels. The results therefore support our argument that standard R&D expenditure measures might not be precise enough to capture the specific, frontier research that are required for the high-tech manufacturing sector. Highly-skilled labour measured by the proportion of population with tertiary education has the wrong sign but is highly insignificant across all three regressions.

In models (1d) to (1f) the growth rate of supercomputing capacity is added as an additional explanatory variable. The SCC variable is significant at the 10% level of significance across three models and the coefficients are virtually identical across the three models. The OLS and random effects estimation results for the R&D expenditure variable are qualitatively similar to the previous ones, but the fixed effects estimation returns a wrong sign. But once again, results from the Hausman test indicate that the fixed effects model is overwhelmingly preferred to the random effects model.

[8] Unobserved random shocks that hit a country at time t might also influence the country's output at t+1, leading to correlated errors within countries. Using cluster-robust standard errors takes care of that. Furthermore, it is robust to heteroskedasticity (Stock and Watson 2008).

In models (1g) to (1i) a squared term of SCC growth rate is added to the model. The purpose is to test if there is a diminishing effect of SCC growth on the high-tech manufacturing value-added growth. Results from the Hausman test continue to reject the random effects model in favour of its fixed effects counterpart. According to the fixed effects model (1h), not only that the SCC growth rate has become significant at the 1% level and its coefficient has increased, but also that its squared term is significant at the 1% level.

R&D expenditure growth and highly-skilled labour growth are not jointly significant at any standard levels (p-value = 0.81) in model (1h). Given this, we test for the sensitivity of the model with respect to their exclusion. The results are shown in Table 2. All models are estimated using the fixed effects estimation method. Models (2a) to (2c) exclude either R&D expenditure growth or highly-skilled labour growth or both. All these alternative specifications have little effects on all other variables in terms of their coefficient magnitude, sign and significance. Given the robust results for the SCC growth rate and its squared term, we exclude the R&D expenditure and highly-skilled labour growth variables in all other estimations and designate model (2c) as our baseline model.

[Table 2]

As another type of robustness test, we experiment with alternative measures of SCC and the results are also reported in Table 2. In model (2d), a 5% annual deterioration rate of the computing capacity is assumed in the calculation of the accumulated SCC. This has little effect on the results, largely because SCC is increasing very rapidly over time. For instance, the topmost supercomputer in 2005 is of a power roughly 2300 times that of its counterpart in 1993; as a result, unless we assume a very large deterioration rate in estimating the accumulated SCC it would have made little differences. In model (2e), the SCC of the classified segment is removed, while in (2f) the capacity of the government segment is removed as well. The use of supercomputer in these two segments is mostly related to defence purpose. Expectedly countries would try to conceal their defence technologies as much as possible. However, relatively less sensitive defence technologies are regularly turned into civilian applications. Therefore, whether defence research has any impact on high-tech manufacturing output growth is an empirical question. The results show that excluding the classified and government segments has virtually no effect on the two SCC variables. This is perhaps related to the fact that the two segments only account for a very small share of supercomputing capacity in most countries in our dataset for most of the years (referring to Figure 2). Lastly, in model (2g), an alternative measure of supercomputer performance, Rpeak, is used. Once again, this barely affects the original findings. This is expected because the two measures of SCC are highly correlated (correlation > 0.98). Overall, results from Table 2 demonstrate that the baseline model (2c) is very robust. According to the baseline model, when evaluated at the mean value of the SCC growth rate, for every percentage point increase in the growth of SCC, the growth of high-tech manufacturing value-added increases by 0.05 percentage point.

4.2- Comparing the impacts of academic and industrial research

In the regressions in Table 3 we add segmental shares of SCC to the baseline model (2c). In all models, the additional variables do not affect both the quantitative and qualitative findings for the SCC growth variables as compared to the baseline case. Notwithstanding, the results for various segmental shares are quite different.

[Table 3]

Results from models (3a) and (3b) show that increasing the SCC shares of the academic and research segment (relative to all other segments combined) is expected to have positive effects on the growth rate of high-tech manufacturing value-added. However, between the two only the share of academic segment is significant. On the contrary, results from models

(3c) to 3(f) show that increasing the SCC shares of all other four segments is expected to have negative effects on high-tech manufacturing value-added growth. However, the shares of classified and government segments are not significant at any standard levels. Combining the academic and research segments into a broader academic segment, industry and vendors into a broader industry segment, and classified and government into a broader segment does not change the conclusions.

While the results from Table 3 seem to suggest that research in the academic segment is more productive than that in the industry segment in terms of boosting high-tech manufacturing value-aded, the conclusion is not defined. This is because, in model (3g) for instance, we do not control for the effect of the broader industry segment in assessing the impact of the broader academic segment. Incorporating both shares into a single equation, however, is found to be unproductive due to multicollinearity problems – as shares of all segments must sum to one. To circumvent this problem, we examine the 'substitution effects' between any two segments when their combined share (or in equivalent the remaining segments' combined share) has been controlled for. The results are reported in Table 4.

[Table 4]

In all the models in Table 4, the results for the SCC growth variables remain virtually identical to those in the baseline model. In models (4a) to (4d), we include various ratios of academic and industry segments, either narrowly or broadly defined. The models also control for the sum of the remaining segments' shares. For instance, in (4a), the remaining segments are research, vendor, classified and government; while in (4d), the remaining segments are classified and government only. Results from all four models indicate that after controlling for the shares of other segments, substituting the share of academic segment for that of industry segment, either narrowly or broadly defined, will have a positive impact on high-tech manufacturing value-added growth. The finding therefore supports the hypothesis that frontier research in the academic segment has a bigger impact on high-tech manufacturing production than frontier research in the industry segment.

In models (4e) and (4f), we test the ‘substitution effects’ between respectively, academic and government segments, and industry and government segments, all broadly defined. However, there are no statistically discernible effects between these two pairs of segments.

4.3- Impacts of frontier research on high-tech exports

As an extension, we re-do the estimation after replacing value-added growth with export growth as the dependent variable. The impact of frontier research on high-tech export itself is a worthwhile topic given that high-tech exports are where advanced economies’ comparative advantage lies. The main results are reported in Table 5.

[Table 5]

All the models are estimated using the fixed effects estimator, except for (5c) which is estimated using the random effects estimator. At the outset it is not clear if we will get similar results as the growth rates of the two have a very small correlation coefficient of 0.125 only. Notwithstanding, the results turn out to be qualitatively very similar to those for value-added growth. Model (5a) includes once again, both R&D expenditure and Highly-skilled labour growth, but the former is of a wrong sign despite being highly significant and the latter is highly insignificant. In model (5b) we estimate the same baseline model as for value-added so we can compare their results. The results are qualitatively similar to those in (2c). In particular, the growth rate of SCC has a positive coefficient while its squared term has a negative one, signalling diminishing returns. The random effects model (5c) yields similar estimations to (5b), but result from the Hausman test rejects it in favour of the fixed effects model. Results from models (5d) and (5e) show that research in the academic segment also has a bigger impact on high-tech export growth than research in the industry segment, either narrowly or broadly defined. Lastly, results from models (5f) and (5g) indicate that there are no statistically discernible impact differentials between the broader academic and government segments, or between the broader industry and government segments. The strong similarity between the findings for value-added growth and export growth despite their low correlation goes some way strengthening our confidence in drawing conclusions from the whole analysis.

Overall, our empirical findings suggest that while frontier research as proxied by SCC has a statistically significant impact on high-tech manufacturing value-added, there are impact differentials between different segments of high-tech research. It was found that input into academic research has a statistically discernible, stronger effect on high-tech manufacturing value-added growth than that into industrial research. There are a number of possible explanations for this finding. Firstly, knowledge produced by universities is much more of a public good than that produced by industrial firms where their results are not often made public. This public good nature of academic research and its resulting positive externalities to the private sector (knowledge spillovers) stimulates technological innovations and leads to higher productivity. Secondly, academic research helps create human capital in the form of Highly-skilled labour which is more likely to create technological innovation.

The above findings obviously should be interpreted with caution due to the proxy nature of various measures and other data limitation. Furthermore, due to data limitation, we did not control for highly-skilled labour input in individual segments.

5- Conclusion

High-tech is widely regarded as the crown of industrialization and the key to long term national competiveness. As such ‘wisdom’ taking hold, stakeholders will expectedly start to enquire if any policy can be put in place to boost the nation’s high-tech sector. The notion of high-tech however, turns out to be too malleable and too fast changing to be pinned down by statistics precisely. When the object cannot be clearly defined, it is not quite clear to what extent it matters, not to mention what needs to or should be done about it. As succinctly summarized by Wirtz (2001), “we know high-tech is important in today's economy, but don't ask us how we know. Please.”

This paper took a bold step into this murky world of high-tech. It empirically examined the impacts of frontier research on high-tech manufacturing value-added, as well as the differential effects between the academic and industry segments. The lack of precise measures for high-tech research input presents one of the biggest hurdles. Standard R&D expenditure is too general to capture the input in high-tech research. To overcome that hurdle, this paper proposes an innovative measure of frontier research investment – the supercomputer capacity.

The empirical findings in this paper demonstrated that SCC is a good proxy for high-tech research input in that it is useful to explain both within and between countries variation in high-tech manufacturing value-added. It was also found that the composition of high-tech research also has an impact on high-tech manufacturing value-added growth. Academic research was shown to have a bigger growth effect on the high-tech manufacturing sector than industrial research.

Without doubt, SCC remains a very partial estimate of frontier research input. As such, we consider the current paper as an explorative study and aim to use it to highlight both measurement and policy issues in relation to high-tech research and high-tech output.

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Figure 1- ***Sectoral shares of Top500 supercomputer capacity by country, 1991-2005***

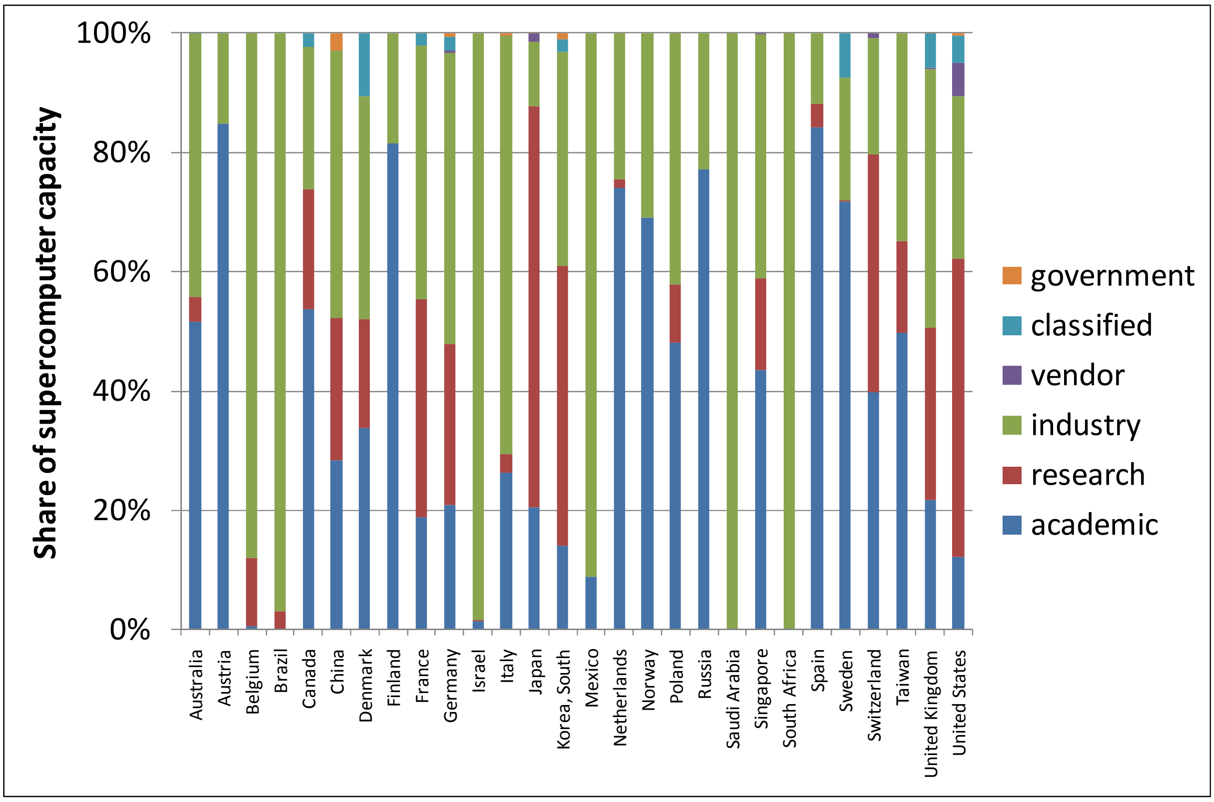

Figure 2 - ***Time trend of the Top500 supercomputer capacity, 1991-2005.***

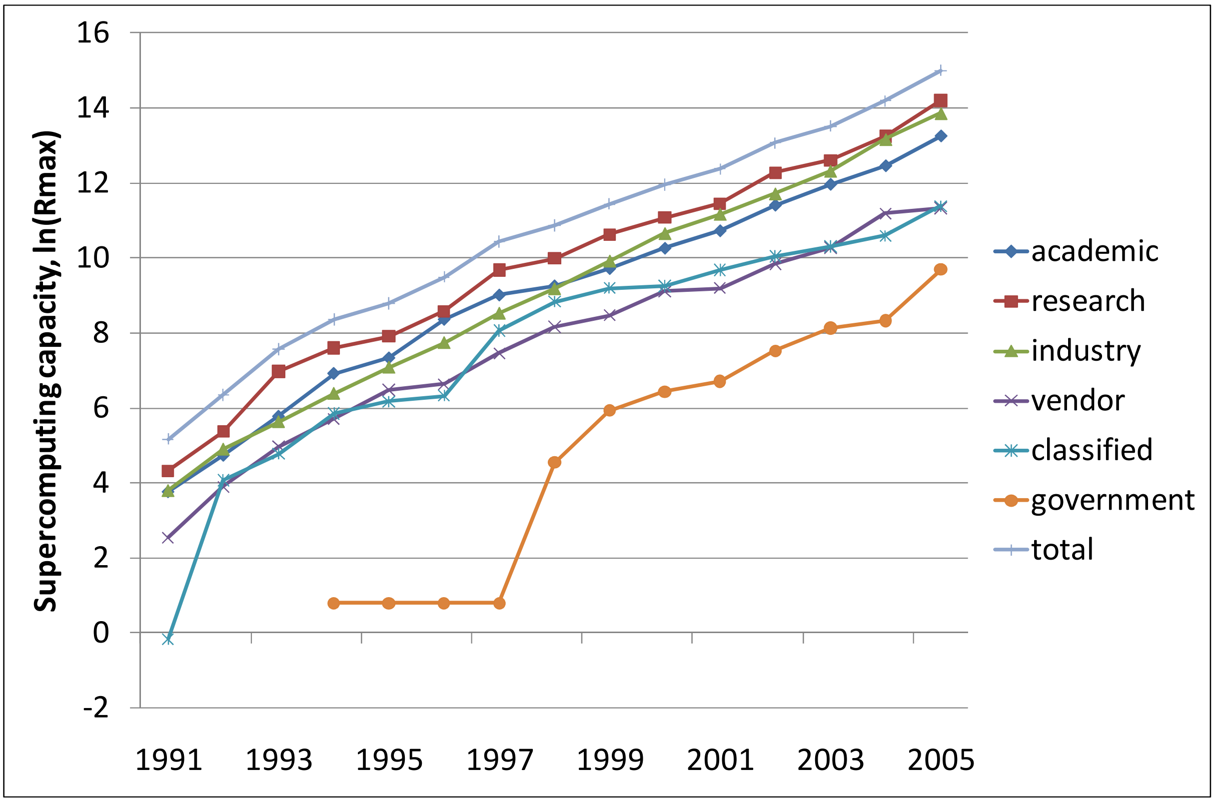

Table 1- ***Regression results for manufacturing value-added growth rate***

	1a	1b	1c	1d	1e	1f	1g	1h	1i
Estimator	OLS	Fixed effects	Random effects	OLS	Fixed effects	Random effects	OLS	Fixed effects	Random effects
R&D expenditure growth	0.248***	0.206	0.248***	0.191*	-0.129	0.190**	0.195*	-0.099	0.192**
	(0.067)	(0.193)	(0.067)	(0.097)	(0.211)	(0.097)	(0.100)	(0.199)	(0.100)
Highly-skilled labour growth	-2.157	-1.470	-2.157	-1.915	-1.096	-1.898	-1.889	-0.960	-1.833
	(2.245)	(2.323)	(2.245)	(2.218)	(2.181)	(2.216)	(2.269)	(2.129)	(2.257)
SCC growth				0.026*	0.025*	0.026*	0.057**	0.068***	0.058***
				(0.014)	(0.014)	(0.014)	(0.023)	(0.023)	(0.023)
SCC growth squared							-0.012**	-0.017***	-0.012**
							(0.005)	(0.005)	(0.005)
Hausman test (p-value)			0.711			0.340			0.276
R-squared	0.040			0.058			0.066		
r2_o		0.039	0.040		0.025	0.058		0.036	0.066
r2_b		0.289	0.294		0.034	0.372		0.069	0.303
r2_w		0.020	0.019		0.041	0.035		0.055	0.048
N	431	431	431	395	395	395	395	395	395

Note: All estimations include a constant term and a time trend. Cluster robust standard errors are in parentheses. *, ** and *** denote significance at the 10, 5 and 1% levels respectively.

Table 2 - ***Sensitivity tests for the baseline model***

	2a	2b	2c	2d	2e	2f	2g
Modification to SCC measure			(Baseline)	5% deterioration	Excluding classified	Excluding classified & government	Replacing Rmax with Rpeak
SCC growth	0.0681***	0.0690***	0.0694***	0.0642***	0.0689***	0.0687***	0.0610***
	(0.0226)	(0.0211)	(0.0210)	(0.0196)	(0.0212)	(0.0210)	(0.0207)
SCC growth squared	-0.0167***	-0.0169***	-0.0170***	-0.0152***	-0.0166***	-0.0164***	-0.0143***
	(0.0048)	(0.0046)	(0.0046)	(0.0042)	(0.0048)	(0.0048)	(0.0050)
R&D expenditure growth	-0.0959						
	(0.1988)						
Highly-skilled labour growth		-0.9387					
		(2.1153)					
r2_o	0.035	0.054	0.051	0.051	0.051	0.052	0.050
r2_b	0.100	0.026	0.011	0.007	0.009	0.011	0.031
r2_w	0.054	0.057	0.057	0.057	0.057	0.057	0.053
N	395	411	411	411	411	411	410

Note: As above.

Table 3 - ***Regression results with segment share of supercomputer capacity***

	3a	3b	3c	3d	3e	3f	3g	3h	3i
SCC growth	0.066***	0.071***	0.073***	0.069***	0.069***	0.070***	0.073***	0.072***	0.070***
	(0.019)	(0.022)	(0.020)	(0.021)	(0.021)	(0.021)	(0.019)	(0.019)	(0.021)
SCC growth squared	-0.016***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
Academic	0.091**								
	(0.037)								
Research		0.021							
		(0.040)							
Industry			-0.093*						
			(0.046)						
Vendor				-0.100***					
				(0.037)					
Classified					-0.202				
					(0.193)				
Government						-0.191			
						(0.120)			
Academic + research							0.104**		
							(0.043)		
Industry + vendor								-0.101**	
								(0.045)	
Classified + government									-0.221
									(0.158)
r2_o	0.056	0.049	0.049	0.056	0.054	0.052	0.055	0.053	0.055
r2_b	0.006	0.003	0.000	0.036	0.015	0.007	0.001	0.001	0.010
r2_w	0.081	0.057	0.080	0.059	0.060	0.058	0.088	0.084	0.062
N	411	411	411	411	411	411	411	411	411

Note: As above.

Table 4 - ***Regression results with ratios of segment shares of supercomputer capacity***

	4a	4b	4c	4d	4e	4f
SCC growth	0.070***	0.072***	0.070***	0.072***	0.072***	0.072***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
SCC growth squared	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Academic/industry	0.056**					
	(0.023)					
(Academic+research)/industry		0.049**				
		(0.023)				
Academic/(industry+vendor)			0.056***			
			(0.022)			
(Academic+research)/(industry+vendor)				0.050**		
				(0.022)		
(Academic+research)/(classified+government)					0.105	
					(0.078)	
(Industry+vendor)/(classified+government)						0.055
						(0.080)
Sum of remaining segments' shares	-0.001	-0.112*	0.012	-0.159	0.005	0.154*
	(0.041)	(0.059)	(0.046)	(0.156)	(0.088)	(0.081)
r2_o	0.055	0.059	0.056	0.058	0.058	0.058
r2_b	0.002	0.004	0.003	0.002	0.002	0.002
r2_w	0.085	0.089	0.087	0.089	0.089	0.089
N	411	411	411	411	411	411

Note: As above.

Table 5 - ***Regression results with export growth of high-tech manufacturing as the dependent variable***

	5a	5b (baseline)	5c (random effects)	5d	5e	5f	5g
SCC growth	0.056***	0.127*	0.108*	0.134**	0.132**	0.132**	0.132**
	(0.016)	(0.063)	(0.059)	(0.066)	(0.064)	(0.064)	(0.064)
SCC growth squared	-0.015***	-0.031**	-0.023*	-0.032**	-0.032**	-0.032**	-0.032**
	(0.004)	(0.015)	(0.013)	(0.015)	(0.015)	(0.015)	(0.015)
R&D expenditure growth	-0.899***						
	(0.296)						
Highly-skilled labour growth	-1.482						
	(3.113)						
Academic/industry				0.055***			
				(0.018)			
(Academic+research)/(industry+vendor)					0.061***		
					(0.021)		
(Academic+research)/ (classified+government)						0.063	
						(0.060)	
(Industry+vendor)/ (classified+government)							0.003
							(0.068)
Sum of remaining segments' shares				0.090	-0.066	-0.058	0.124**
				(0.063)	(0.126)	(0.080)	(0.059)
Hausman test (p-value)			0.720				
r2_o	0.001	0.010	0.011	0.010	0.011	0.011	0.011
r2_b	0.117	0.001	0.002	0.002	0.005	0.005	0.005
r2_w	0.088	0.012	0.011	0.016	0.016	0.016	0.016
N	341	355	355	355	355	355	355

Note: As above.

Appendix - *Country list*

Australia	Finland	Mexico	South Africa
Austria	France	Netherlands	Spain
Belgium	Germany	Norway	Sweden
Brazil	Israel	Poland	Switzerland
Canada	Italy	Russia	Taiwan
China	Japan	Saudi Arabia	United Kingdom
Denmark	Korea, South	Singapore	United States