# Are There Laws of Innovation? (Part II)

by

**Lawrence J. Lau and Yanyan Xiong**

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Lau Chor Tak Institute of Global Economics and Finance
The Chinese University of Hong Kong
13/F, Cheng Yu Tung Building, 12 Chak Cheung Street, Shatin, Hong Kong

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# Are There Laws of Innovation? (Part II)[§]

**Lawrence J. Lau[1] and Yanyan Xiong[2]**

September 2021



[1] Lawrence J. Lau is Ralph and Claire Landau Professor of Economics, The LAU Chor Tak Institute of Global Economics and Finance, The Chinese University of Hong Kong, and Kwoh-Ting Li Professor in Economic Development, Emeritus, Stanford University. The opinions expressed herein are those of the authors and do not necessarily reflect the views of the Institute.

[2] Yanyan Xiong is ZJU100 Young Professor, School of Economics, and Research Fellow, Center of Social Welfare and Governance, Zhejiang University, Hangzhou, China, and Research Fellow (Honorary), The LAU Chor Tak Institute of Global Economics and Finance, The Chinese University of Hong Kong.

Dedication

To Ayesha, my muse, my love and my life, LJL

To my beloved grandparents who enlightened me with endless love, YX

## Preface

The objectives of this book are threefold: first, to identify the determinants of innovation at the economy-wide level; second, to ascertain whether they are the same across different economies; and third, to find suitable metrics for comparing the relative success in innovation across different economies. In other words, we try to discover whether there is a common law of innovation that applies across different economies. We also try to develop indicators of relative success in innovation across different economies.

An important innovation input is Research and Development (R&D). While discoveries and inventions are brought about by R&D activities, they are not brought about by only R&D activities in the current period. They can result from R&D activities initiated a long time ago. We therefore measure the innovation input of an economy by the quantity of its real R&D capital stock, defined as the cumulative past real expenditures on R&D, less a depreciation of 10 percent per annum. Important innovation outputs are patent applications submitted to and patent grants awarded by different official patent authorities, such as the U.S. Patent and Trademark Office (USPTO), the European Patent Office (EPO) and the China National Intellectual Property Administration (CNIPA), and other domestic patent authorities. We try to establish systematically the positive relationship between innovation outputs and innovation input of different economies.

The economies included in our study consists of the Group-of-Seven (G7) countries (Canada, France, Germany, Italy, Japan, the United Kingdom and the United States), the four East Asian Newly Industrialised Economies (EANIEs) (Hong Kong, South Korea, Singapore and Taiwan), and the Mainland of China.

We wish to express our deepest gratitude to Professor XU Guanhua, who served as Minister of Science and Technology of the People's Republic of China from 2001 to 2007, for writing a Preface for our book. We are most grateful to Mrs. Ayesha Macpherson LAU and Prof. Jungsoo PARK for their helpful comments and suggestions on earlier drafts. The authors also wish to thank Dr. Paul AIELLO, Prof. Michael J. BOSKIN, Prof. Cyrus CHU, Prof. Dale W. JORGENSON, Prof. Lang KAO, Prof. Chung-Ming KUAN, Prof. Masahiro KURODA, Prof. Jiadong SHEA, Mr. Kenny SHUI, Mr. Junjie TANG, and the late Prof. John WONG of the National University of Singapore for their advice and assistance. We also wish to thank the Lau Chor Tak Institute of Global Economics and Finance of The Chinese University of Hong Kong for its financial support of this research project. Finally, Ms. Nicole ONG and her colleagues at the World Scientific Publishing Company deserve our special thanks for their advice and assistance. Responsibility for any errors remains with the authors.

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and

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## Chapter 8: Indicators of Relative Success in Innovation across Economies

In previous chapters, we have compared the economies included in our study in terms of their numbers of domestic, USPTO, EPO and CNIPA patent applications and/or grants. In this chapter, we develop several indicators of relative success in innovation based on their numbers of patent applications and grants and use them to assess the relative performance of the economies in innovation.

In Table 8-1, we tabulate the numbers of domestic, USPTO, EPO and CNIPA patent grants received by the residents of the different economies in 2019. From the tabulation, we also derive the relative rankings of each economy in accordance with the number of patent grants under each category. In 2019, Mainland China had the largest number of domestic patent grants in 2019, followed by the U.S. and Japan, with South Korea in fourth place. The U.S. had the largest number of USPTO and EPO patent grants, but only the third largest number of CNIPA patent grants, after Japan. Japan demonstrated its formidable strength in innovation by becoming the second highest recipient of respectively the USPTO, EPO and CNIPA patent grants. Germany was the strongest European country in innovation, ranking first among European countries in all three categories of patent grants—USPTO, EPO and CNIPA. (It was third in EPO patent grants, fourth in CNIPA patent grants, and fifth in USPTO patent grants.) South Korea, also an up-and-coming powerhouse in innovation, came in third in USPTO patent grants, ahead of both Mainland China and Germany, and fifth in both EPO and CNIPA grants. Singapore and Hong Kong were in the last places.[3]

[3] Hong Kong, however, was ahead of Canada in CNIPA patent grants in 2019 (592 vs 568).

**Table 8-1: The Numbers of Domestic, USPTO, EPO and CNIPA Patent Grants Received by the Residents of the Different Economies and Their Relative Ranks in 2019**

| | Domestic Patent Grants | | USPTO Patent Grants | | EPO Patent Grants | | CNIPA Patent Grants | | Weighted Rank | Weighted Rank Integerise |
|---|---|---|---|---|---|---|---|---|---|---|
| | Number | Rank | Number | Rank | Number | Rank | Number | Rank | | |
| Canada | 2,035 | 10 | 7,595 | 8 | 1,683 | 9 | 568 | 11 | 9.58 | 10 |
| France | 11,673 | 7 | 7,233 | 9 | 8,800 | 4 | 2,997 | 7 | 7.31 | 7 |
| Germany | 11,770 | 6 | 18,293 | 5 | 21,198 | 3 | 9,989 | 4 | 4.23 | 4 |
| Italy | 2,130 | 9 | 3,175 | 10 | 3,713 | 8 | 1,102 | 9 | 9.23 | 9 |
| Japan | 140,865 | 3 | 53,542 | 2 | 22,423 | 2 | 30,401 | 2 | 2.00 | 2 |
| United Kingdom | 3,081 | 8 | 7,791 | 7 | 4,119 | 7 | 1,310 | 8 | 7.48 | 8 |
| United States | 167,115 | 2 | 167,115 | 1 | 34,614 | 1 | 23,114 | 3 | 1.96 | 1 |
| Mainland, China | 354,111 | 1 | 19,209 | 4 | 6,229 | 6 | 354,111 | 1 | 2.85 | 3 |
| Hong Kong, China | 107 | 12 | 846 | 12 | 50 | 12 | 592 | 10 | 11.04 | 11 |
| South Korea | 94,852 | 4 | 21,684 | 3 | 7,247 | 5 | 9,437 | 5 | 4.25 | 5 |
| Singapore | 264 | 11 | 1,119 | 11 | 440 | 11 | 566 | 12 | 11.48 | 12 |
| Taiwan, China | 14,481 | 5 | 11,489 | 6 | 1,014 | 10 | 6,197 | 6 | 6.58 | 6 |

Sources: Data on the number of domestic and U.S. patent grants are from Table A4-2 and TableA5-2, respectively. Data on EPO patent grants were collected from the European Patent Office website. Data on CNIPA patent grants were collected from China Statistical Yearbook, various issues.

Looking simply at the aggregate total number of patent grants received by each economy from all three major patent offices—CNIPA, EPO and USPTO—in 2019, Mainland China would come in first, with 379,549 patent grants, followed by the U.S. (224,843) and Japan (106,366). However, this result is, in part, the artifact of the overwhelmingly large total number of CNIPA patent grants (452,804), the bulk of which (354,111) were awarded to Chinese applicants, even though as a group they had the lowest CNIPA grant rate. Instead, we compute a weighted rank for the twelve economies, using their ranks in each of the categories of USPTO, EPO and CNIPA patent grants in Table 8-1. The weights are the total numbers of patent grants of USPTO (354,430), EPO (137,784) and CNIPA (452,804) respectively in 2019, divided by the aggregate total number of patent grants of all three patent offices (945,018). The results, presented in the "Weighted Rank" column, indicate that the U.S. would still be number one by a hair, followed by Japan, with Mainland China in third place. Germany was ranked fourth, followed by South Korea and Taiwan, China. Four of the top ten patent-generating economies were in East Asia, four were in Europe, and two were in North America.[4] The weighted ranks have been converted into whole integer ranks in the last column of Table 8-1.

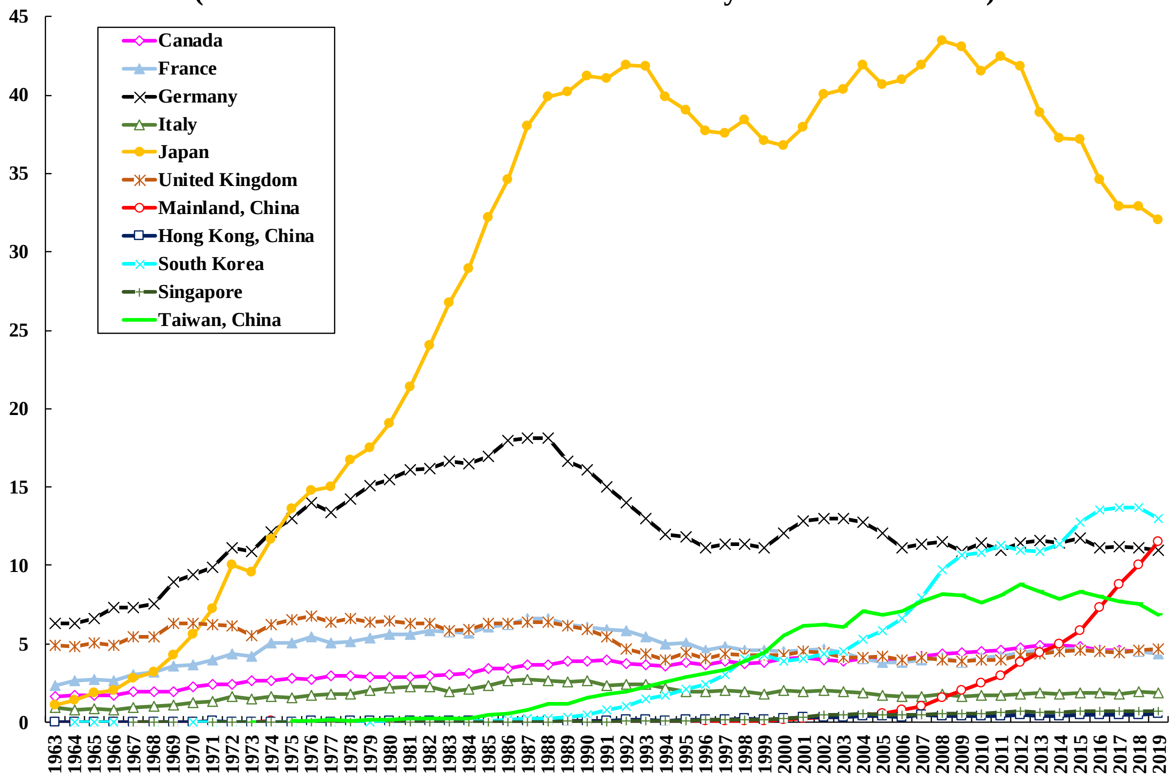
The rank correlation coefficient between the integerised weighted ranks and the USPTO ranks is a high 0.937, which means that the USPTO rank order is a good summary indicator of the relative success in innovation across economies. We have also previously established, in

[4] Israel is one of the innovative economies that has not been included in this study.

Chapter 5 above, that the procedures and standards employed by the USPTO do not appear to be biased in favour of either U.S. applicants or any of the foreign applicants. Of course, counting only the number of USPTO patent grants does penalise economies with a low USPTO patent application rate, such as Mainland China. But we expect that both the Chinese USPTO patent application rate and the CNIPA patent application rates of the U.S. and other economies will increase over time, since no enterprise in the world, whatever its geographical or national origin, can afford to ignore the huge markets of China and the U.S. in the long run.

In Chart 8-1, we compare the numbers of USPTO patent grants received by each economy each year, using the number of patent grants received by U.S. residents as a benchmark (100). Chart 8-1 shows that the U.S. has been the leader in USPTO patent grants from the very beginning. Since the mid-1970s, Japan has been a persistent number two behind the U.S., followed more recently by South Korea, which overtook Germany in the mid-2010s. However, China also managed to overtake Germany in 2019 to become the economy with the fourth highest number of USPTO patent grants. The U.S. lead in USPTO patent grants has been commanding, accounting for almost 50 percent of all USPTO patent grants. The second-placed Japan received no more than a third of the number of patent grants received by the U.S., and South Korea, China, and Germany each received approximately one-tenth of the number received by the U.S. With this as a performance indicator of innovation, the rank order is the U.S., Japan, South Korea, China, and Germany.

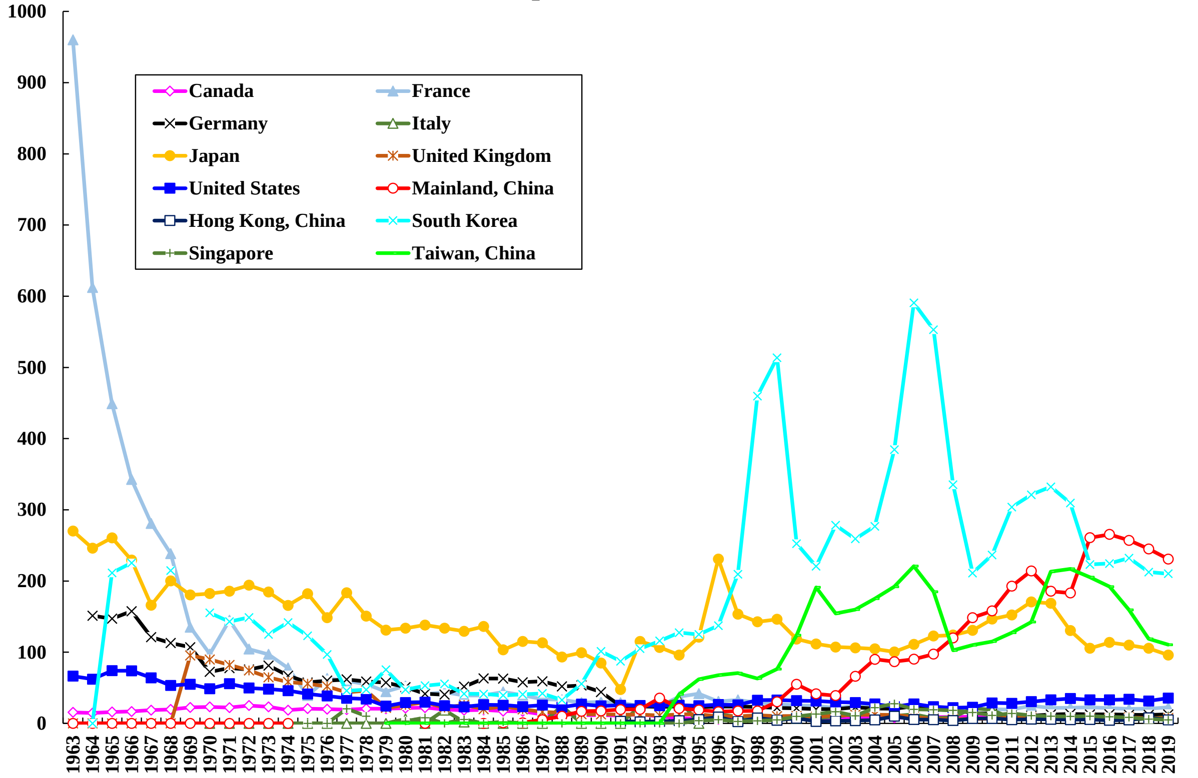
**Chart 8-1: An Index of USPTO Patent Grants**
**(The Number of Patent Grants Received by U.S. Residents=100)**




Source: Data on the number of U.S. patent grants are from Table A5-2.

A second possible indicator is the relative efficiency of the real R&D capital stock across economies. If the efficiency is the same between two economies, then the numbers of patent grants received per unit quantity of the real R&D capital stock should be identical. To the extent that they differ, they may reflect differences in R&D efficiency. In Chart 8-2, we compare the R&D efficiency in terms of the number of domestic patent grants per billion 2019 U.S. dollars of R&D capital stock, across the economies included in our study. China has had the highest R&D efficiency in the generation of domestic patent grants since 2015, despite a very low domestic patent grant rate (see Chart 7-5), followed by South Korea and Taiwan, China. Japan was the leader in R&D efficiency in domestic patent grants between 1969 and 1996, but lost out to first South Korea, then Taiwan, China and then Mainland China, ending up in fourth place in 2019. The U.S. had the highest efficiency among the G-7 countries except Japan. With this as a performance indicator of innovation, the rank order is Mainland China, South Korea, Taiwan, China, Japan, and the U.S. We should add that the quantity of R&D capital stock in 2019 U.S. dollars of an economy is sensitive to the value of the exchange rate of its currency relative to the U.S. dollar in 2019. A low value of its exchange rate would result in a lower quantity of its real R&D capital stock, and hence a higher R&D efficiency in the generation of domestic patent grants, and vice versa.

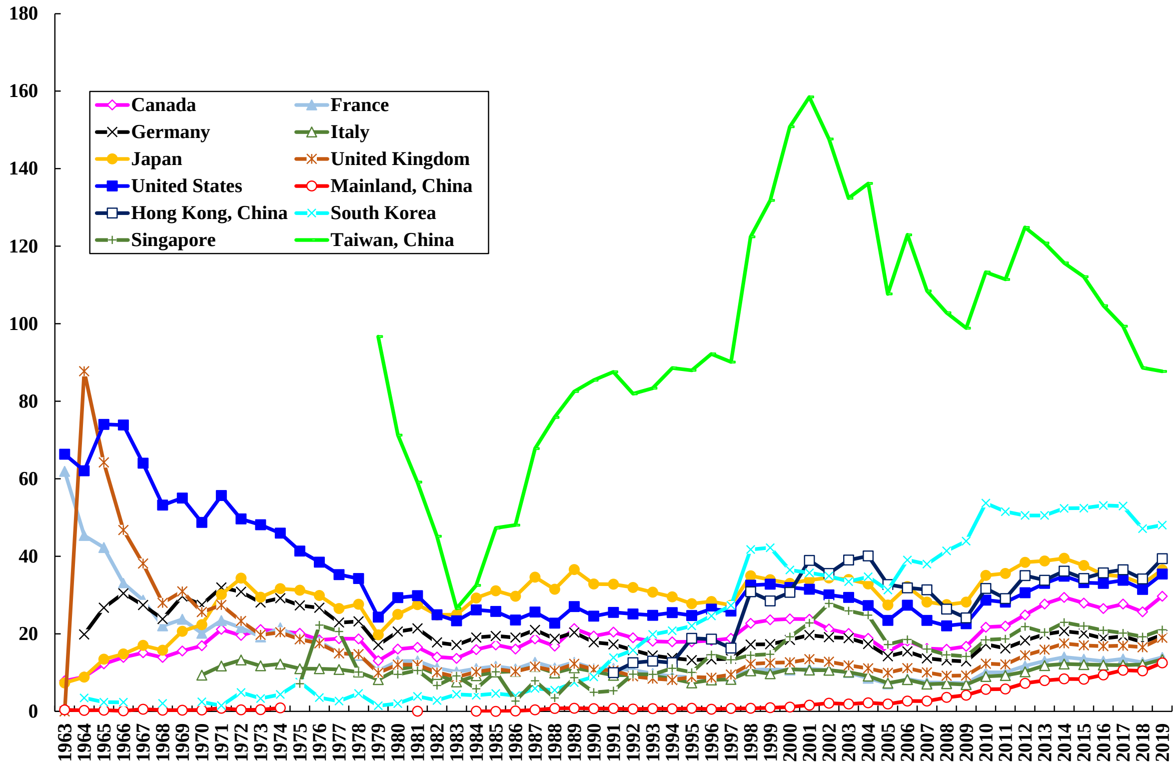
**Chart 8-2: The Number of Domestic Patent Grants per Unit Quantity of the Real R&D Capital Stock in billion 2019 US$**




Sources: Data on the number of domestic patent applications are from Table A4-2 and data on the quantity of real R&D capital stock are from Table A3-2.

In Chart 8-3, we compare the R&D efficiency in terms of the number of USPTO patent grants per billion 2019 US$ of R&D capital stock, across the economies in our study. It turns out that Taiwan, China had the highest R&D efficiency, with the largest number of USPTO patent grants per unit quantity of its real R&D capital stock. South Korea was in second place, followed by Hong Kong, China, Japan, and the U.S. The U.S. has had the highest R&D efficiency in the generation of USPTO patent grants among all G-7 countries except Japan since 1965. China has had the lowest R&D efficiency in the generation of USPTO patent grants, but this may also have to do with its low U.S. patent application rate. In any case, Chinese R&D efficiency in the generation of USPTO patent grants has been rising steadily since 2000. With this as a performance indicator of innovation, the rank order is Taiwan, China, South Korea, Hong Kong, China, Japan, and the U.S. Similar to the case for R&D efficiency in the generation of domestic patent grants, the relative efficiency in the generation of USPTO patent grants is also sensitive to the values of exchange rates in 2019. A low value of the exchange rate would result in a lower quantity of the real R&D capital stock in U.S. dollars, and hence a higher R&D efficiency in the generation of USPTO patent grants, and vice versa.

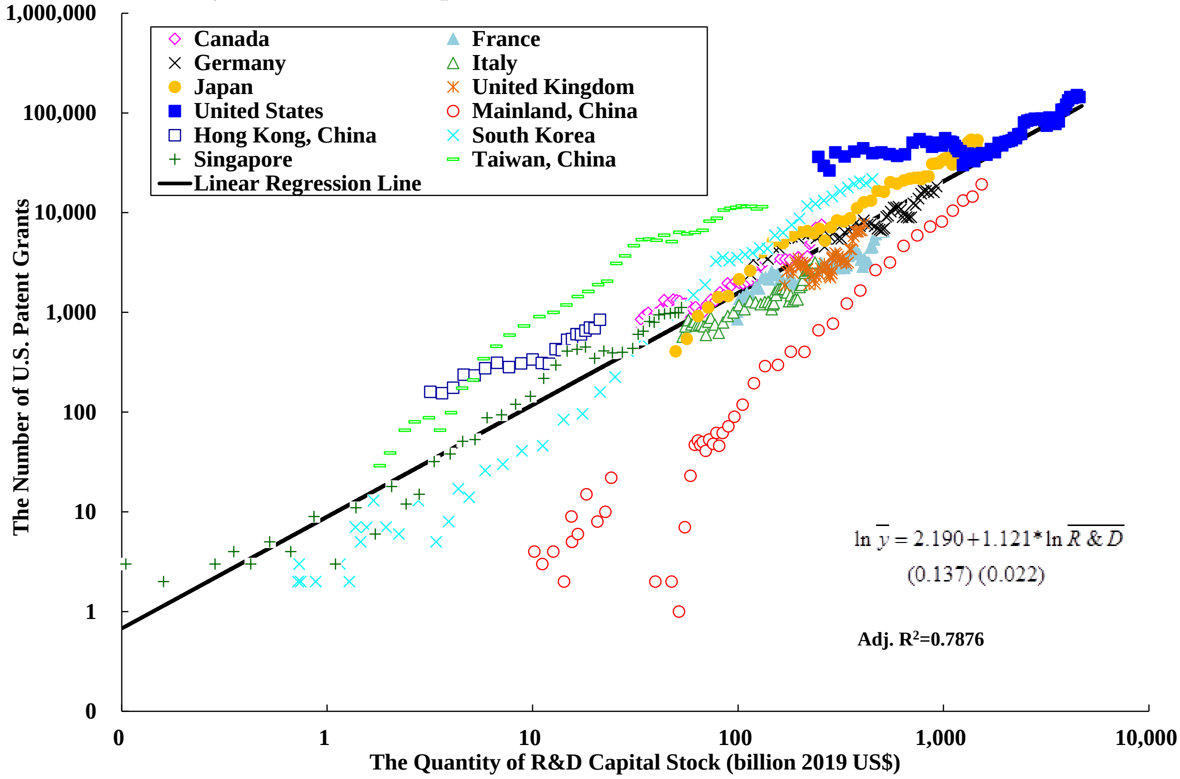
**Chart 8-3: The Number of USPTO Patent Grants per Unit Quantity of the Real R&D Capital Stock in billion 2019 US$**




Sources: Data on the number of USPTO patent applications are from Table A5-2 and data on the quantity of real R&D capital stock are from Table A3-2.

A third possible indicator is based on scatter diagram of the number of USPTO patents and the quantity of real R&D capital stock presented as Chart 5-14 and reproduced below. There is an overall linear regression line estimated from the data, which can be used to predict the number of USPTO patents that an economy with a given quantity of real R&D capital stock would be expected to be able to generate under normal circumstances. The vertical distance of each economy's data point from the linear regression line (the residual of the regression) is then a measure of its degree of under- or over-achievement. If an economy operates below the overall linear regression line, it is an "under-achiever"; if it operates above the line, it is an "over-achiever". For every economy and in every year between 2000 and 2019, we compute the additional percentage (positive or negative) of USPTO patent grants that the economy would have been awarded, given its quantity of real R&D capital stock, if it had operated on the linear regression line.

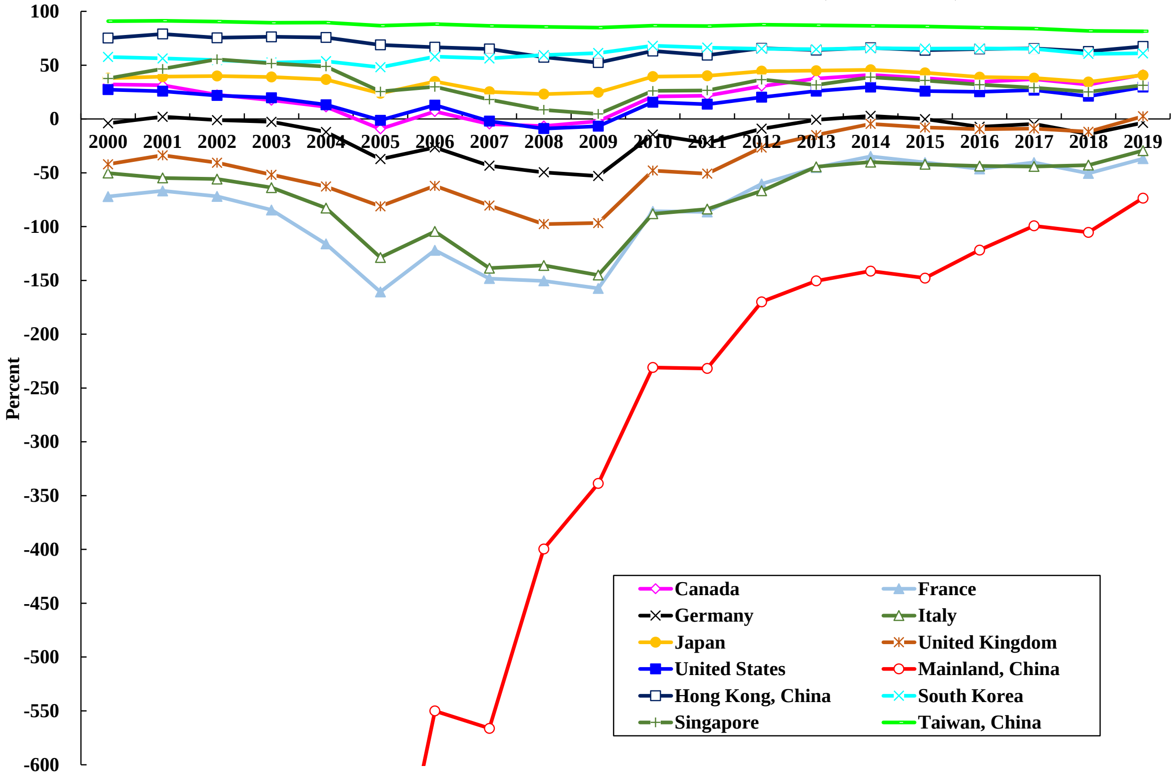
**Chart 5-14: The Number of USPTO Patent Grants and the Quantity of Real R&D Capital Stock, G-7 Countries, Mainland China, and 4 EANIEs**




Sources: Table A5-2 of the Appendix in Chapter 5 and Table A3-2 of the Appendix in Chapter 3.

The results of this exercise are presented in Chart 8-4. These results are both retrospective and prospective. Taiwan, China had the highest degree of "over-achievement", followed by Hong Kong, China, South Korea, Canada, Japan, and Singapore. The U.S. has been an "over-achiever" since 2010. However, all the European economies in our study—France, Italy, the U.K., and Germany--have been habitual "under-achievers". So has been Mainland China. However, the Chinese degree of "under-achievement" has greatly improved over time, increasing from -1,291 percent in 2000 to -73 percent in 2019. The "under-achievers" such as China, and France and Italy (both with "under-achievement" somewhere between 30 and 40 percent) have a great deal of room for further improvement. With this as a performance indicator of innovation, the rank order is Taiwan, China, Hong Kong, China, South Korea, Canada, and Japan. We should add that the degree of over- and/or under-achievement can also be sensitive to the values of the exchange rates in 2019. In the first place, the overall linear regression line itself will be affected by the changes in the quantities of R&D capital stocks in 2019 US$. Moreover, if the exchange rate was under-valued, the quantity of R&D capital stock in 2019 U.S. dollars would also be under-estimated, and this might result in an "apparent" over-achievement (the same number of patent grants with a lower quantity of real R&D capital stock), and vice versa.

**Chart 8-4: The Percentage of Over- and Under-Achievement in USPTO Patent Grants, G-7 Countries, Mainland China, and 4 EANIEs (2000-2019)**




Source: Data are taken from Table A8-1 of the Appendix to this Chapter.
Note: The graph is truncated at -600 percent in order to maintain legibility of the rest of the graph. In 2000, the under-achievement of Mainland China in USPTO patent grants was -1,291 percent.

# Appendix

## Estimation of the Degree of Over- and Under-Achievement in USPTO Patent Grants

The first step in the estimation of the degree of over- and/or under-achievement is to predict what the number of USPTO patent grants would have been for each economy, based on its quantity of real R&D capital stock of that year, if the economy were operating on the overall linear regression line. Once the predicted number of USPTO patent grants is derived, it can be subtracted from the actual number of USPTO patent grants and then divided by the actual number of USPTO patent grants to arrive at a percentage over- or under-achievement. This is done for each economy for every year from 2000 to 2019. The results of these calculations are presented in Table A8-1 below.

**Table A8-1: Estimated Percentage Over- and Under-Achievements in USPTO Patent Grants, G-7 Countries, Mainland China, and 4 EANIEs (2000-2019)**

| | Canada | France | Germany | Italy | Japan | United Kingdom | United States | Mainland, China | Hong Kong, China | South Korea | Singapore | Taiwan, China |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2000 | 32.2 | -72.0 | -4.0 | -50.2 | 38.0 | -42.0 | 27.3 | -1,290.6 | 75.3 | 57.7 | 37.7 | 91.0 |
| 2001 | 31.4 | -66.8 | 2.1 | -54.7 | 39.3 | -33.7 | 25.9 | -876.4 | 79.1 | 56.4 | 46.6 | 91.3 |
| 2002 | 22.5 | -71.9 | -1.0 | -55.8 | 40.0 | -40.6 | 21.9 | -659.0 | 75.5 | 54.9 | 55.6 | 90.6 |
| 2003 | 17.5 | -84.5 | -2.6 | -63.7 | 39.1 | -51.8 | 19.8 | -767.0 | 76.4 | 52.5 | 51.7 | 89.4 |
| 2004 | 11.4 | -116.1 | -12.0 | -82.7 | 36.7 | -62.7 | 13.3 | -651.9 | 75.8 | 53.7 | 48.9 | 89.6 |
| 2005 | -9.2 | -160.6 | -37.2 | -128.6 | 23.9 | -81.1 | -1.2 | -794.2 | 69.0 | 48.1 | 25.6 | 86.7 |
| 2006 | 7.0 | -121.9 | -26.4 | -104.5 | 34.9 | -62.1 | 13.0 | -550.0 | 66.8 | 58.0 | 29.9 | 88.3 |
| 2007 | -4.7 | -148.2 | -43.4 | -138.6 | 25.4 | -80.4 | -2.0 | -566.3 | 65.1 | 56.3 | 18.1 | 86.5 |
| 2008 | -6.5 | -150.4 | -49.5 | -136.0 | 23.2 | -97.6 | -8.8 | -399.5 | 57.4 | 59.5 | 8.5 | 85.7 |
| 2009 | -2.0 | -157.3 | -53.0 | -145.0 | 24.8 | -96.6 | -6.7 | -338.6 | 52.4 | 61.4 | 4.7 | 84.9 |
| 2010 | 20.9 | -85.8 | -14.4 | -88.0 | 39.4 | -47.9 | 15.7 | -230.9 | 63.2 | 68.1 | 26.2 | 86.7 |
| 2011 | 21.8 | -86.3 | -22.2 | -83.7 | 40.2 | -50.8 | 13.8 | -231.8 | 59.3 | 66.4 | 26.6 | 86.4 |
| 2012 | 30.6 | -60.3 | -9.0 | -66.7 | 44.5 | -26.4 | 20.3 | -169.8 | 65.8 | 65.3 | 36.7 | 87.7 |
| 2013 | 37.6 | -45.1 | -0.7 | -44.4 | 45.0 | -14.9 | 25.9 | -150.4 | 64.2 | 64.9 | 31.7 | 87.2 |
| 2014 | 41.1 | -34.7 | 2.9 | -40.0 | 45.8 | -4.5 | 29.8 | -141.3 | 66.2 | 65.8 | 38.9 | 86.5 |
| 2015 | 37.9 | -40.4 | -0.1 | -42.1 | 43.0 | -7.8 | 26.0 | -147.8 | 63.9 | 65.4 | 35.8 | 86.0 |
| 2016 | 34.4 | -46.4 | -7.2 | -43.7 | 39.0 | -9.4 | 25.4 | -121.8 | 65.1 | 65.6 | 31.9 | 84.9 |
| 2017 | 37.0 | -40.4 | -4.6 | -44.1 | 38.1 | -8.9 | 26.9 | -99.3 | 65.6 | 65.2 | 29.2 | 84.0 |
| 2018 | 32.0 | -50.5 | -13.9 | -42.9 | 34.4 | -11.8 | 21.2 | -105.3 | 62.9 | 60.6 | 25.3 | 81.9 |
| 2019 | 41.2 | -36.9 | -3.5 | -29.4 | 40.8 | 2.6 | 29.7 | -73.5 | 67.5 | 61.0 | 31.4 | 81.6 |

Source: Authors' calculations.

## Chapter 9: Innovation at the Microeconomic Level

In Chapters 4, 5, 6 and 7, we have shown, visually through many charts and in simple linear regressions, that the quantity of real R&D capital stock of an economy has a positive and statistically significant effect on its numbers of patent applications and grants. This is found to be true for not only the domestic patent applications and grants in each economy in our study, but also the foreign patent applications and/or grants of the U. S. Patent and Trademark Office (USPTO), the European Patent Office (EPO) and the China National Intellectual Property Administration (CNIPA). In general, the higher the total quantity of real R&D capital stock in an economy is, the more domestic and international patent applications will be submitted by and patent grants awarded to its residents.

In this chapter, we examine data from selected individual Chinese and U.S. enterprises to see whether the same relation holds at the microeconomic level, that is, whether a higher number of patent grants are awarded to individual enterprises with higher quantities of real R&D capital stock. Cross-sectional U.S. firm-level data have been analysed by Hausman, Hall and Griliches (1984) and Hall, Griliches and Hausman (1986) in their pioneering studies on the relationship between the number of patent applications and R&D expenditure. We use a different approach: we assemble time-series data on the R&D expenditures of specific, selected Chinese and U.S. enterprises as well as the numbers of Chinese and U.S. patents granted to these enterprises. From the data on R&D expenditures, we construct estimates of the time series of the quantities of real R&D capital stock for each enterprise in 2019 U.S. dollars. Then we attempt to relate the annual numbers of Chinese and U.S. patent grants to each enterprise to the quantities of its real R&D capital stock in the previous year.

The specific Chinese enterprises that we have selected are China Petroleum and Chemical Corporation (Sinopec), Huawei Technologies Co., Ltd. (Huawei) and ZTE Corporation (ZTE). They have been consistently among the annual top ten Chinese recipients of CNIPA patent grants. The specific U.S. enterprises that we have selected are Apple Inc. (Apple), General Electric Company (GE), Hewlett-Packard Corporation (H-P),[5] International Business Machines Corporation (IBM), Microsoft Corporation (Microsoft) and Qualcomm, all well-known U.S. high-technology companies.

[5] The data for Hewlett-Packard Corporation are available up to 2015, after which it was split up into more than one successor corporation.

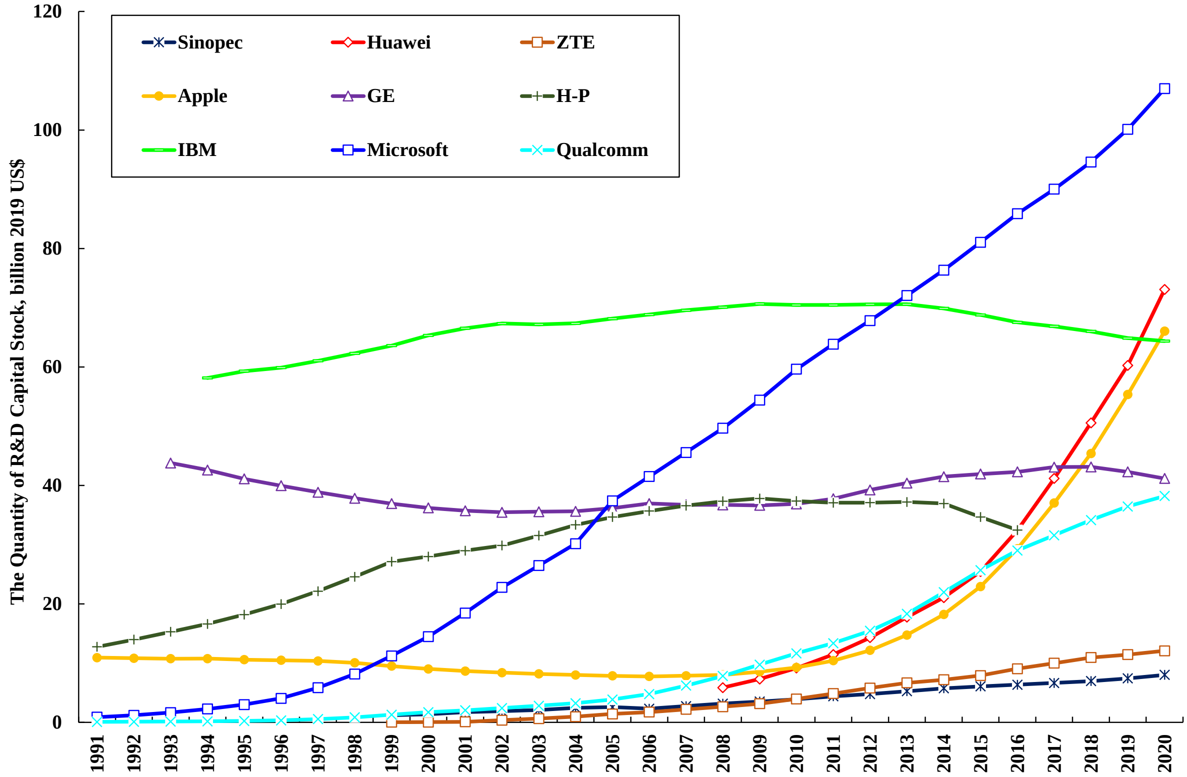
### The Quantities of Real R&D Capital Stock

First, we construct estimates of the time-series of the quantities of real R&D capital stock for each enterprise from its time-series of real R&D expenditures.[6] The quantity of real R&D capital stock is derived as the cumulative past R&D expenditures in 2019 U.S. dollars less a ten-percent depreciation per year.[7] In Chart 9-1, the quantities of real R&D capital stock of all the individual Chinese and U.S. enterprises under study are presented. As of 2020, Microsoft Corporation had the highest quantity of real R&D capital stock, followed by Huawei Technology Co., Ltd., and Apple Inc. IBM Corporation was the global leader until it was surpassed by Microsoft in 2013, and then by both Huawei and Apple in 2020. General Electric used to be number two but fell to fifth place in 2020. Qualcomm, whose real R&D capital stock had been rising fast, was in sixth place. ZTE and Sinopec still lagged behind the other enterprises significantly in terms of the quantity of real R&D capital stock.

[6] The R&D expenditures are converted into real R&D expenditures in national or regional currencies in 2019 prices using the GDP deflators of the respective economies. Annual GDP deflators are collected from International Financial Statistics (IFS) database and domestic official statistical sources. The real R&D expenditures in national or regional currencies are then converted to U.S. dollars, using the 2019 year-end exchange rates.

[7] The initial real R&D capital stock for each enterprise is estimated by dividing the real R&D expenditure in the first year that R&D expenditure data are available by the sum of the rate of growth of real R&D expenditure in the first five years and the annual rate of depreciation, assumed to be 10%.

**Chart 9-1: The Quantity of Real R&D Capital Stock, Selected Chinese and U.S. Enterprises**




Source: Authors' calculations. R&D expenditures for Chinese enterprises are collected from their annual reports (various years), supplemented by their financial reports from the Osiris Database. R&D expenditures for U.S. enterprises are collected from the U.S. Securities and Exchange Commission and the Orbis Americas database.

### The Number of Patent Grants

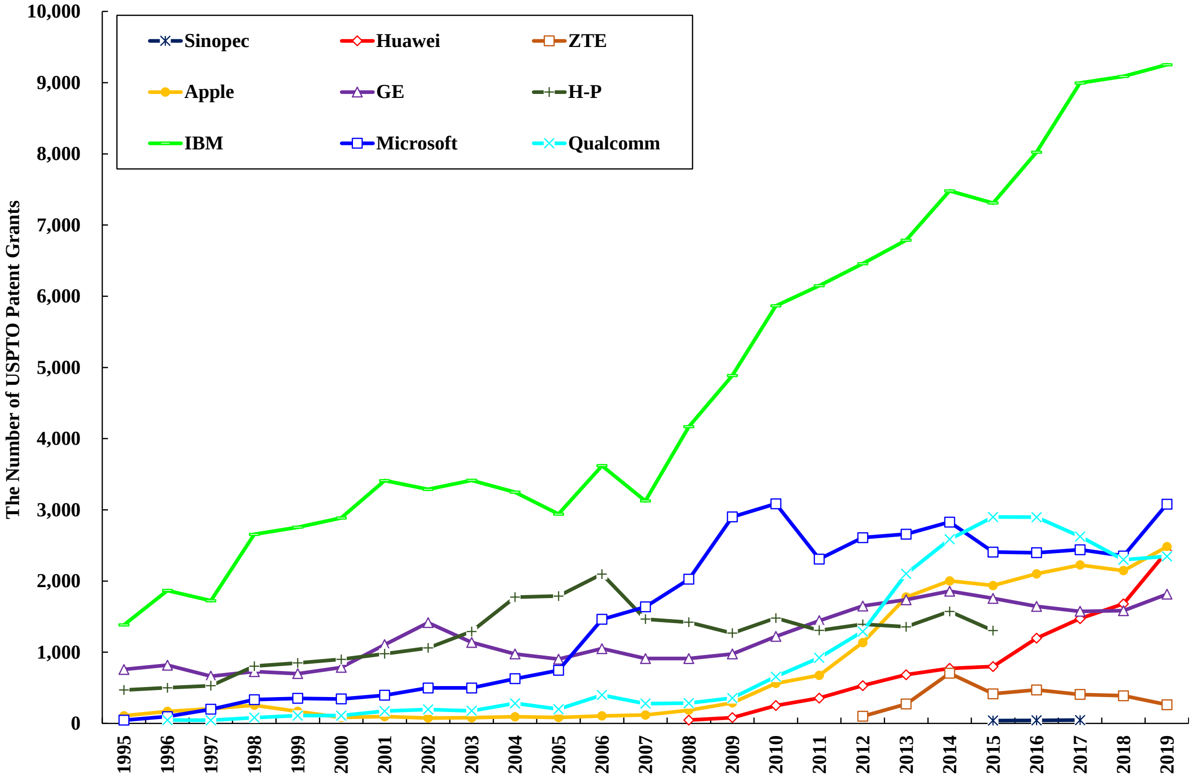
In Chart 9-2, the numbers of USPTO patent grants awarded to our selected enterprises are plotted against time. IBM Corporation had a commanding lead in the number of USPTO patent grants. In 2019, it was awarded 9,253 patents, compared to 3,080 for Microsoft. Huawei, in fourth place with 2,417 USPTO patent grants, was just behind Apple with its 2,483 patent grants. ZTE and Sinopec are at the bottom.[8]

However, we note that the number of USPTO patents awarded to Apple Inc. has been almost stationary over time, even though the quantity of its real R&D capital stock has been rising rapidly (see Chart 9-1). This is a little anomalous. We conjecture that the slowdown in the number of patent grants awarded to Apple is due to the slowdown in the number of patent

[8] The number of patent grants awarded to Sinopec is available for only three years. This does not necessarily mean that Sinopec received no USPTO patent grants in the other years, but the USPTO published patents grants to a given applicant separately only if the number of patent grants awarded in a given year is greater than or equal to forty.

applications submitted by Apple, and not necessarily due to a slowdown of the discoveries and inventions at Apple. There may possibly be two reasons for the slowdown in patent applications: disclosure avoidance or tax avoidance. Disclosure avoidance is a strategy sometimes used by a corporation to avoid alerting its competitors of its product development strategy and progress thereof. The corporation may forego patent applications altogether or may apply for patents at relatively obscure locations so as to avoid widespread dissemination of the disclosure. Tax avoidance is a strategy to vest the ownership of patents in a subsidiary in a low-tax jurisdiction, such as the Republic of Ireland, so as to reduce the profit or income tax payable on any potential royalties and license fees to be earned from the patents.

**Chart 9-2: The Number of USPTO Patent Grants, Selected Chinese and U.S. Enterprises**



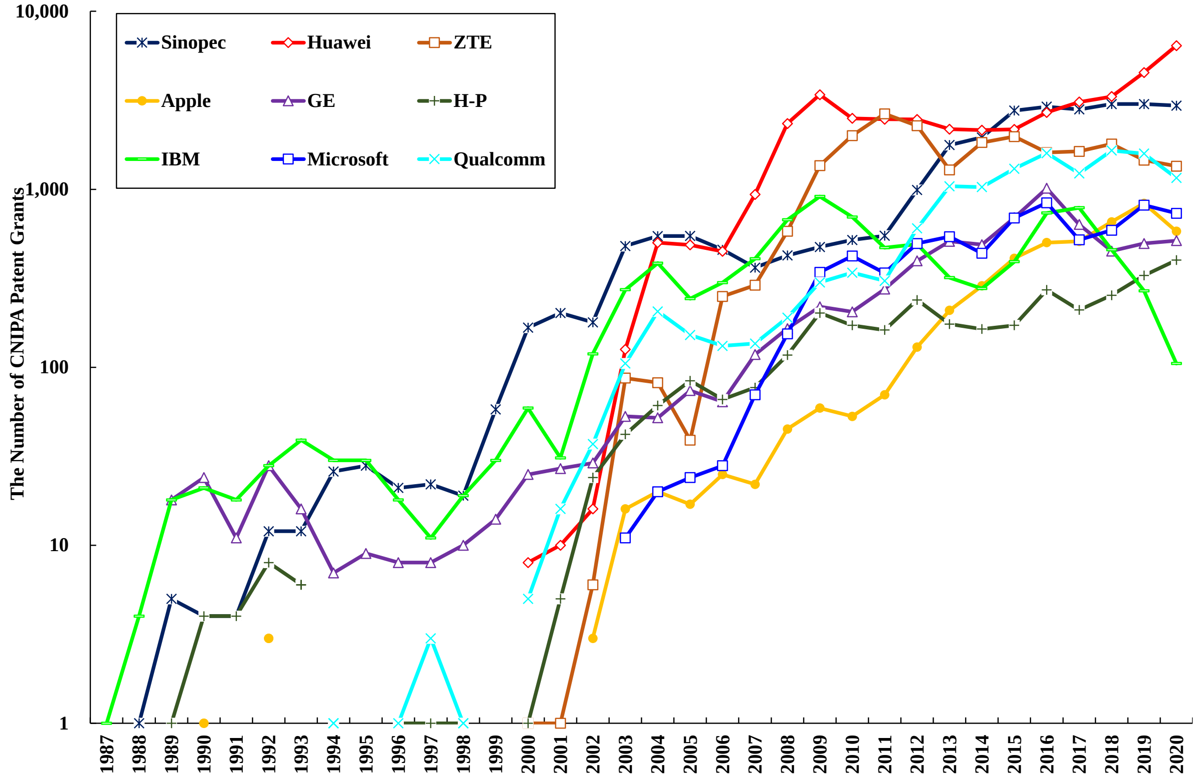

Source: USPTO.
Note: Organisations with less than 40 patent grants awarded are not separately listed on the USPTO website.

In Chart 9-3, the number of CNIPA patent grants awarded to our selected enterprises are plotted against time. It is clear that the numbers of CNIPA patent grants of all the selected enterprises, Chinese and U.S., have been rising rapidly over time, much more so than their respective numbers of USPTO patents.[9] In 2020, Huawei had the highest number of CNIPA patent grants (6,413), followed by Sinopec (2,954) and ZTE (1,348). Qualcomm had the

[9] The number of CNIPA patent grants awarded to IBM began to decline in 2017.

highest number of CNIPA patents among U.S. enterprises (1,158 in 2020), followed by Microsoft and Apple. For reasons not apparent, the number of CNIPA patent grants of IBM has been declining over time since 2017.

**Chart 9-3: The Number of CNIPA Patent Grants, Selected Chinese and U.S. Enterprises**




Source: Patsnap database (https://www.zhihuiya.com/).

We note an interesting but not unexpected phenomenon—for all of these enterprises, the numbers of their home patent grants have always been greater than the numbers of their foreign patent grants over our period of study. Thus, Sinopec, Huawei, and ZTE have had more CNIPA patent grants than USPTO patent grants awarded to them each year. Similarly, Apple, GE, H-P, IBM, Microsoft, and Qualcomm have had more USPTO patent grants than CNIPA patent grants awarded to them each year, with the exception of the years 2016-2019 for H-P.[10]

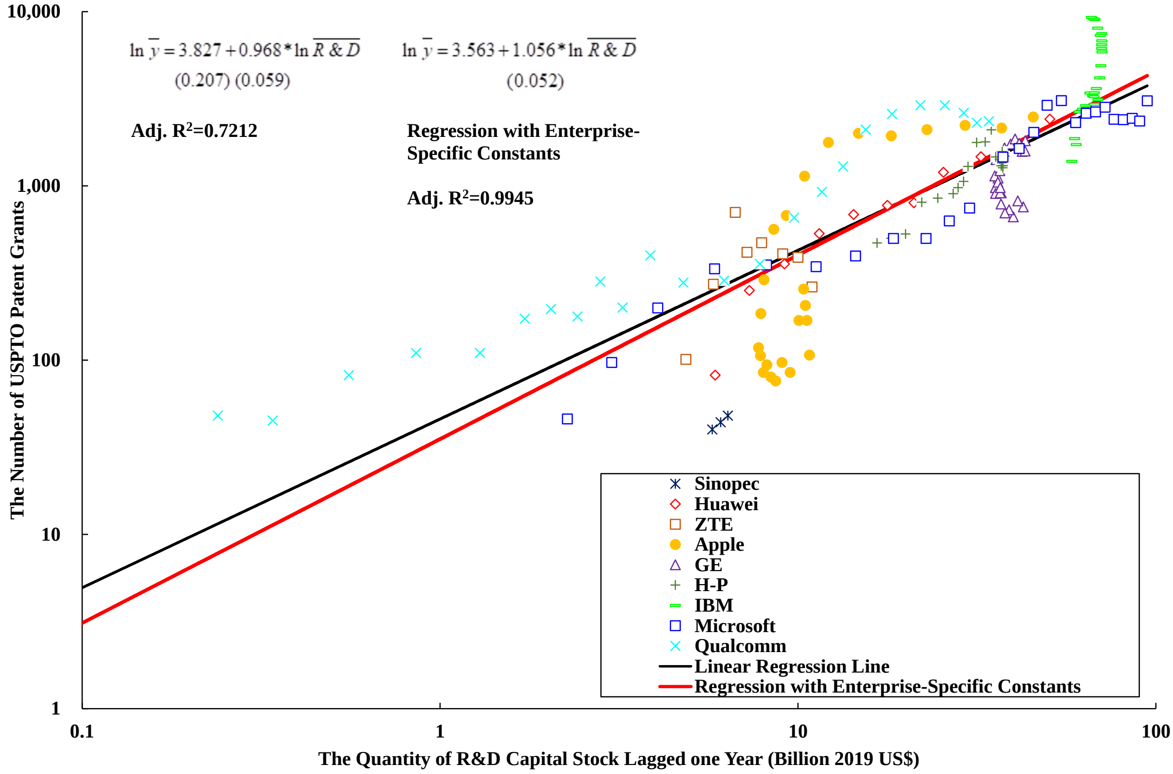
[10] See Tables A9-2 and A9-3 in the Appendix. By 2016, Hewlett-Packard Corporation has already been split into several independent entities and Mainland China has become the manufacturing hub for them.

**The Relationship between the Number of Patent Grants and the Quantity of Real R&D Capital Stock**

In Chart 9-4, the annual number of USPTO patent grants awarded to each enterprise is plotted against the quantity of its R&D capital stock in 2019 U.S. dollars of the previous year. We find the same positive relationship between the number of patent grants and the quantity of real R&D capital stock found at the macroeconomic level of an economy in the earlier chapters. The linear regressions, with and without enterprise-specific constants, both fit quite well and yield statistically significant coefficients.[11] The estimated elasticity of the number of USPTO patent grants with respect to the quantity of real R&D capital stock lies between 0.968 and 1.056, or approximately one, that is, a one-percent increase in the real R&D capital stock increases the number of USPTO patent grants by approximately one percent. However, IBM seems to be an outlier, and perhaps also GE. The problem appears to be that the quantity of its real R&D capital stock is no longer growing but the number of its patent grants keeps rising, resulting in a very steep enterprise-specific USPTO patent grant-real R&D capital stock line. One possible conjecture is that the rate of depreciation of 10 percent per annum may have been too high for these enterprises if a high proportion of their R&D expenditures were devoted to basic research, in which case a higher quantity of real R&D capital would have been implied.

[11] As might be expected, the linear regression with enterprise-specific constants fits much better. The red line in Chart 9-4 is drawn with a constant term set equal to the weighted average of all the enterprise-specific constants with the shares of the number of observations of each enterprise in the total number of observations as weights.

**Chart 9-4: The Number of USPTO Patent Grants and the Quantity of Real R&D Capital Stock, Selected Chinese and U.S. Enterprises**



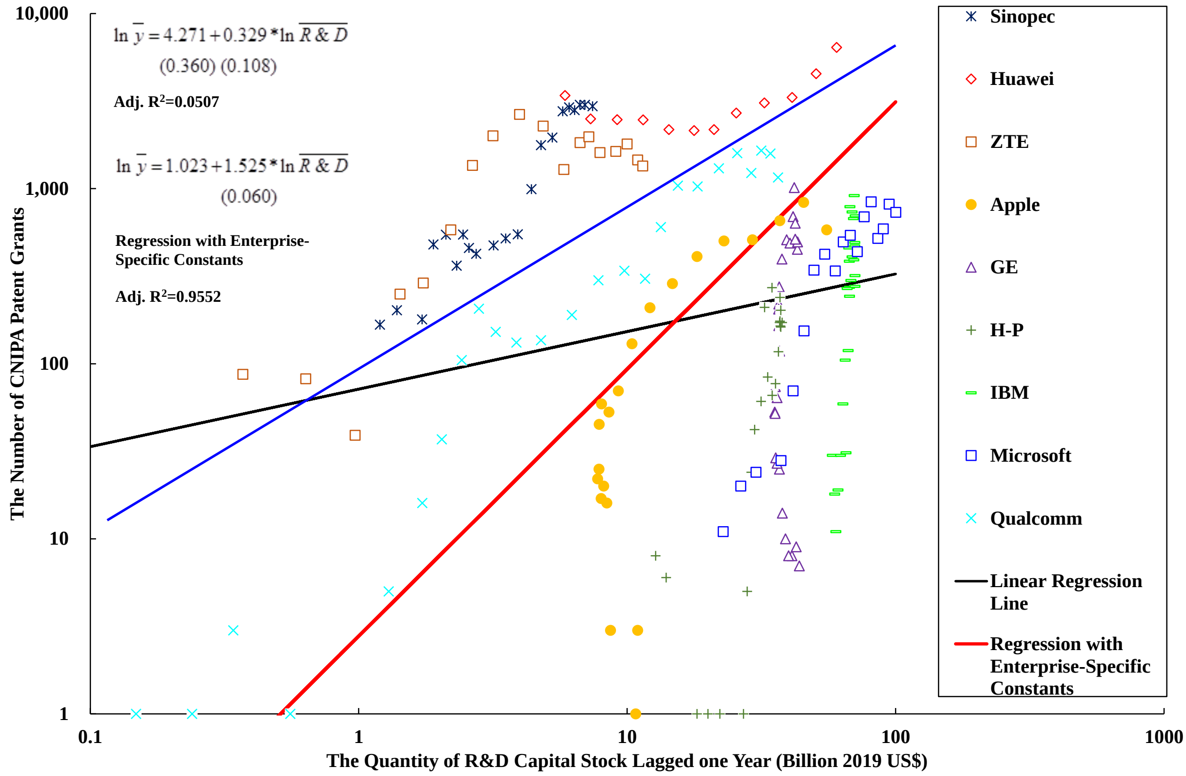

Source: Table A9-1 and Table A9-2.

In Chart 9-5, the annual number of CNIPA patent grants awarded to each enterprise is plotted against the quantity of its R&D capital stock in 2019 U.S. dollars of the previous year. However, the scatter diagram itself, unlike Chart 9-4, does not show a clear correlation between the number of CNIPA patent grants and the quantity of real R&D capital stock. The fit of the simple linear regression is poor, with an adjusted $R^2$ of only 0.0507, even though the estimated coefficient of the natural logarithm of the quantity of real R&D capital stock is positive and statistically significant. Yet the implied elasticity of the number of patent grants with respect to the quantity of real R&D capital stock is an implausibly low 0.329. We believe this low estimate is the result of the very diverse behaviour of the Chinese and U.S. enterprises. The linear regression with enterprise-specific constants fits much better, with an adjusted $R^2$ of 0.9552, but yields an incredibly high elasticity of 1.525 (the red line).[12] Moreover, it is also apparent from the scatter diagram that a straight line (the blue line) can be drawn so that the data points for all of the Chinese enterprises (except for one observation for ZTE in 2005) lie on one side and those of all U.S. enterprises lie on the other. This suggests that the experiences

[12] The red line in Chart 9-5 is drawn with a constant term set equal to the weighted average of all the enterprise-specific constants with the shares of the number of observations of each enterprise in the total number of observations as weights.

of the selected Chinese and U.S. enterprises with the CNIPA must have been quite different. We believe this may be due to the differences in the CNIPA patent application rates between the Chinese and U.S. enterprises.[13] At the economy-wide level, CNIPA grant rates for the U.S. (59% in 2019) have been consistently higher than those for Mainland China (26% in 2019).[14] Unfortunately, it has not been possible to find data on enterprise-specific CNIPA patent application rates. We note, however, that the appearance of the scatter of data points in Charts 9-4 and 9-5 for both IBM and GE are quite similar (the respective data points are on top of one another), even though they apply to different patent grants, USPTO and CNIPA, respectively. This suggests that perhaps the quantities of real R&D capital stocks of these two enterprises may have been under-estimated because of the possible over-depreciation of their basic research capital.

**Chart 9-5: The Number of CNIPA Patent Grants**
**and the Quantity of Real R&D Capital Stock, Selected Chinese and U.S. Enterprises**



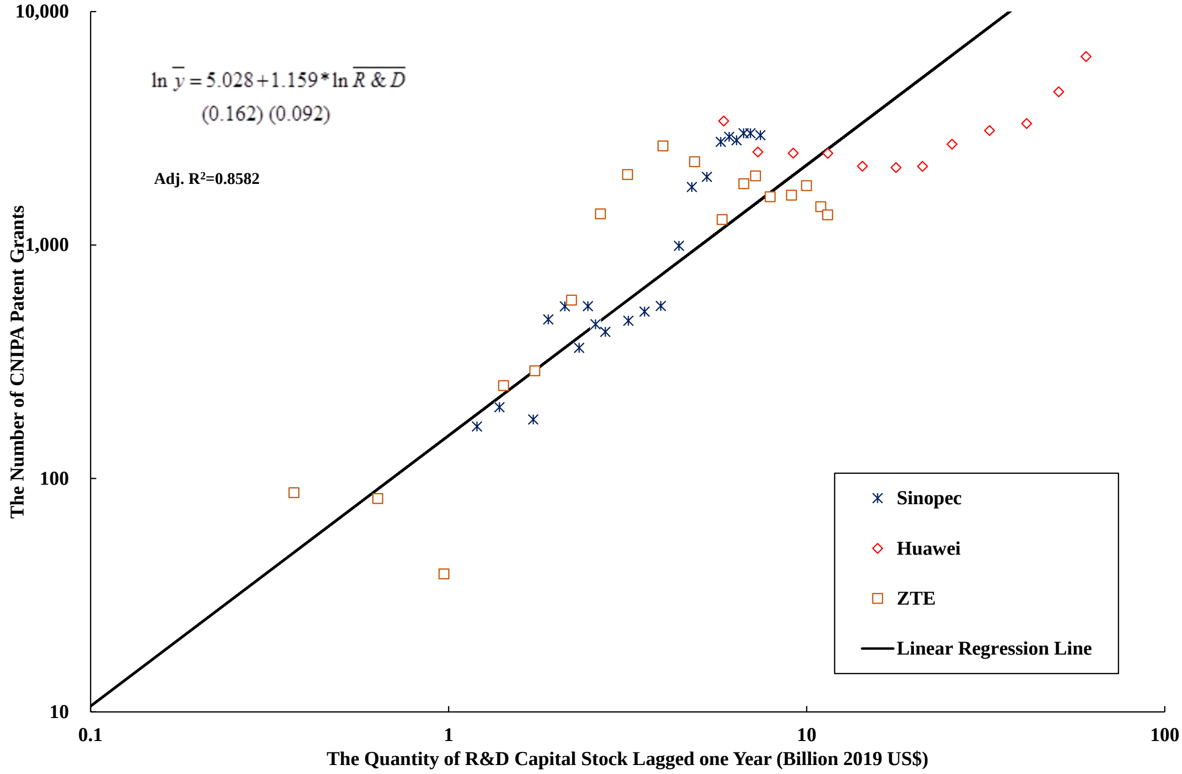

Source: Table A9-1 and Table A9-3.

In Charts 9-6 and 9-7, we present the data for the selected Chinese and U.S. enterprises separately. Chart 9-6 shows the same positive and monotonic effect of the quantity of real

[13] For U.S. enterprises, it may be necessary to strike a balance between the avoidance of disclosure and the need for intellectual property right protection.
[14] See Chapter 7.

R&D capital stock of a Chinese enterprise on the annual number of CNIPA patent grants awarded to it. The fit of the simple linear regression is good, with an adjusted $R^2$ of 0.8582. The estimated elasticity of 1.159 suggests the existence of a reasonable degree of economies of scale in real R&D capital at the enterprise level.

**Chart 9-6: The Number of CNIPA Patent Grants and the Quantity of Real R&D Capital Stock, Selected Chinese Enterprises**



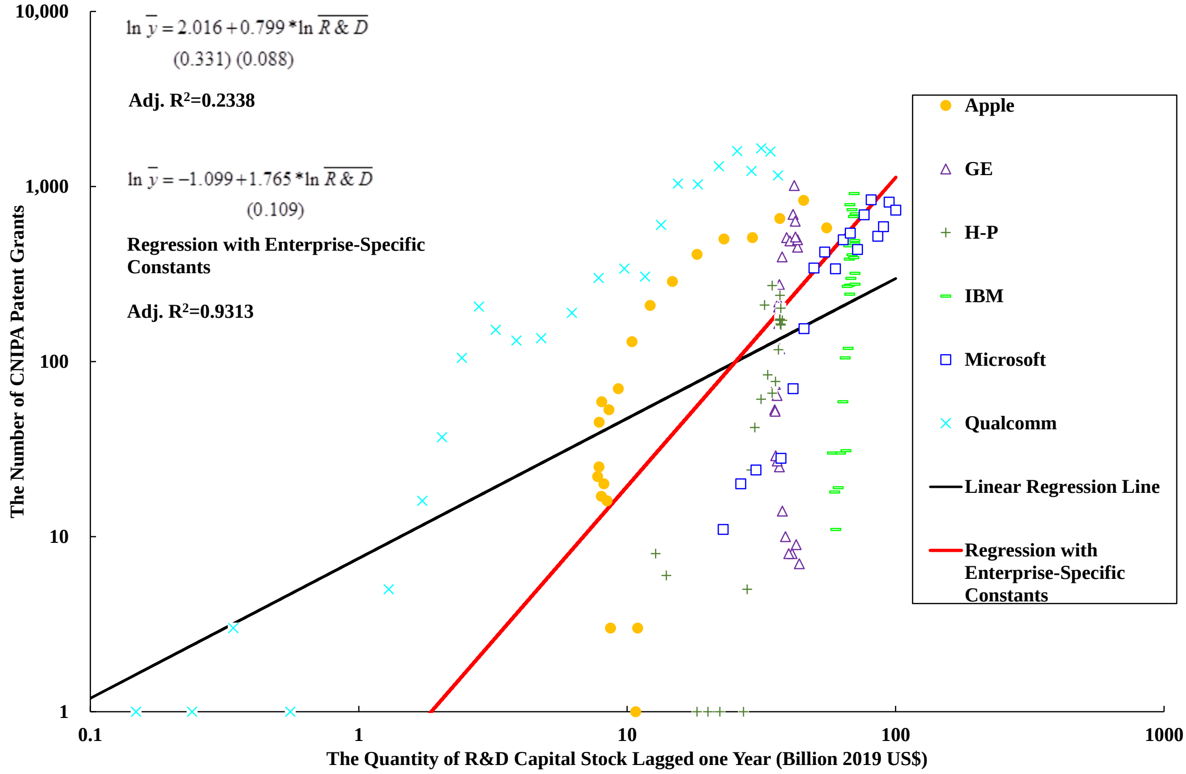

Source: Same as Chart 9-5.

In Chart 9-7, the data of only the U.S. enterprises are presented. The fit of the simple linear regression is not that good, with an adjusted $R^2$ of only 0.2338, even though the estimated coefficient of 0.799 is statistically significant. The fit of the linear regression with enterprise-specific constants is much better, with an adjusted $R^2$ of 0.9313 (the red line).[15] However, the estimated coefficient of 1.765 also implies an incredibly high degree of economies of scale. We believe this may be due to the possible over-depreciation of real basic research capital in a couple of the U.S. enterprises as well as the rapidly rising enterprise-specific patent application and patent grant rates over time. We note that the steep enterprise-specific CNIPA patent grant-real R&D capital lines in Chart 9-7 are not dis-similar to the

[15] Similar to the red lines in Charts 9-4 and 9-5, the red line in Chart 9-7 is drawn with a constant term set equal to the weighted average of all the enterprise-specific constants with the shares of the number of observations of each enterprise in the total number of observations as weights.

corresponding economy-specific lines in Chart 7-8 above. For U.S. enterprises, Mainland China is a large and rapidly growing new market and CNIPA patenting is a new game, leading to continuing large increases in patent applications (and patent grants), based in part on their reserve pools of not-yet-CNIPA-patented discoveries and inventions, which are not affected by the current levels of real R&D capital stock. As in Chapter 7 above, we do not believe that the actual elasticity of patent grants with respect to real R&D capital can be so high. The high estimate is probably an artifact of the rapid increases in the CNIPA patent application and patent grant rates of the selected U.S. enterprises.

**Chart 9-7: The Number of CNIPA Patent Grants and the Quantity of Real R&D Capital Stock, Selected U.S. Enterprises**




Source: Same as Chart 9-5.

**Summary**

From our analysis of the data from an admittedly limited number of Chinese and U.S. enterprises, the evidence suggests that there exists a positive and monotonic dependence of the number of patent grants on the quantity of the real R&D capital stock at the microeconomic level as at the macroeconomic level. In addition, there also appears to be some degree of economies of scale in the creation of patents from R&D activities at the enterprise level. However, there is also some evidence that real R&D capital may have a useful life beyond ten years, depending on the share of basic research in total R&D expenditures, the verification of which will have to await further study.

# Appendix

**Table A9-1: The Estimated Quantities of Real R&D Capital Stock, Selected Chinese and U.S. Enterprises (billion 2019 US$)**

| Chinese Enterprises | | | U.S. Enterprises | | | | | |
|---|---|---|---|---|---|---|---|---|
| China Petroleum and Chemical Corporation | Huawei Technologies Co., LTD. | ZTE Corporation | Apple Inc. | General Electric Company | Hewlett-Packard Corporation | International Business Machines Corporation | Microsoft Corporation | Qualcomm |
| | | | 10.933 | | 12.761 | | 0.888 | 0.088 |
| | | | 10.835 | | 13.982 | | 1.201 | 0.118 |
| | | | 10.756 | 43.790 | 15.287 | | 1.668 | 0.148 |
| | | | 10.764 | 42.597 | 16.629 | 58.147 | 2.268 | 0.178 |
| | | | 10.588 | 41.116 | 18.201 | 59.295 | 3.014 | 0.239 |
| | | | 10.489 | 39.962 | 19.980 | 59.885 | 4.057 | 0.341 |
| | | | 10.368 | 38.861 | 22.154 | 61.041 | 5.850 | 0.556 |
| | | | 10.063 | 37.829 | 24.584 | 62.296 | 8.170 | 0.856 |
| 1.200 | | 0.027 | 9.509 | 36.926 | 27.132 | 63.597 | 11.234 | 1.292 |
| 1.387 | | 0.053 | 9.020 | 36.201 | 28.008 | 65.335 | 14.480 | 1.724 |
| 1.723 | | 0.098 | 8.664 | 35.736 | 28.997 | 66.534 | 18.464 | 2.041 |
| 1.897 | | 0.370 | 8.403 | 35.470 | 29.857 | 67.329 | 22.783 | 2.421 |
| 2.112 | | 0.634 | 8.181 | 35.570 | 31.540 | 67.180 | 26.475 | 2.805 |
| 2.450 | | 0.970 | 8.004 | 35.627 | 33.354 | 67.371 | 30.167 | 3.237 |
| 2.574 | | 1.424 | 7.854 | 36.160 | 34.665 | 68.152 | 37.401 | 3.867 |
| 2.317 | | 1.740 | 7.756 | 36.946 | 35.683 | 68.844 | 41.496 | 4.780 |
| 2.738 | | 2.204 | 7.869 | 36.731 | 36.594 | 69.577 | 45.559 | 6.220 |
| 3.179 | 5.867 | 2.654 | 8.032 | 36.713 | 37.321 | 70.094 | 49.653 | 7.820 |
| 3.525 | 7.310 | 3.163 | 8.550 | 36.641 | 37.811 | 70.635 | 54.416 | 9.756 |
| 3.914 | 9.171 | 3.970 | 9.272 | 36.879 | 37.363 | 70.454 | 59.629 | 11.666 |
| 4.402 | 11.462 | 4.862 | 10.427 | 37.750 | 37.086 | 70.453 | 63.852 | 13.364 |
| 4.779 | 14.302 | 5.805 | 12.166 | 39.243 | 37.103 | 70.573 | 67.821 | 15.457 |
| 5.262 | 17.764 | 6.676 | 14.748 | 40.397 | 37.211 | 70.595 | 72.061 | 18.309 |
| 5.756 | 21.070 | 7.198 | 18.214 | 41.483 | 36.951 | 69.877 | 76.349 | 21.963 |
| 6.076 | 25.471 | 7.913 | 22.941 | 41.924 | 34.663 | 68.783 | 81.052 | 25.703 |
| 6.369 | 32.418 | 9.065 | 29.301 | 42.290 | 32.475 | 67.534 | 85.870 | 29.023 |
| 6.665 | 41.170 | 9.994 | 37.038 | 43.091 | | 66.861 | 90.013 | 31.590 |
| 6.966 | 50.556 | 10.946 | 45.404 | 43.133 | | 66.001 | 94.599 | 34.148 |
| 7.426 | 60.260 | 11.437 | 55.348 | 42.293 | | 64.873 | 100.122 | 36.456 |
| 8.028 | 73.077 | 12.089 | 66.030 | 41.179 | | 64.375 | 106.985 | 38.209 |

Sources: Authors' calculations. The values of R&D expenditures for Chinese and U.S. enterprises are collected from Osiris Publicly Listed Companies Worldwide Database.

## Table A9-2: The Number of USPTO Patent Grants, Selected Chinese and U.S. Enterprises

| | Chinese Enterprises | | | U.S. Enterprises | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | China Petroleum and Chemical Corporation | Huawei Technologies Co., LTD. | ZTE Corporation | Apple Inc. | General Electric Company | Hewlett-Packard Corporation | International Business Machines Corporation | Microsoft Corporation | Qualcomm |
| 1995 | | | | 107 | 758 | 470 | 1,383 | 46 | |
| 1996 | | | | 169 | 819 | 501 | 1,867 | 97 | 48 |
| 1997 | | | | 206 | 664 | 530 | 1,724 | 199 | 45 |
| 1998 | | | | 256 | 729 | 805 | 2,657 | 334 | 82 |
| 1999 | | | | 169 | 699 | 850 | 2,756 | 352 | 110 |
| 2000 | | | | 85 | 787 | 901 | 2,886 | 344 | 110 |
| 2001 | | | | 97 | 1,107 | 978 | 3,411 | 396 | 173 |
| 2002 | | | | 76 | 1,416 | 1,061 | 3,288 | 499 | 196 |
| 2003 | | | | 80 | 1,139 | 1,292 | 3,415 | 499 | 178 |
| 2004 | | | | 94 | 976 | 1,775 | 3,248 | 629 | 283 |
| 2005 | | | | 85 | 904 | 1,790 | 2,941 | 746 | 200 |
| 2006 | | | | 106 | 1,051 | 2,099 | 3,621 | 1,463 | 399 |
| 2007 | | | | 118 | 911 | 1,466 | 3,125 | 1,637 | 278 |
| 2008 | | 48 | | 185 | 911 | 1,422 | 4,169 | 2,026 | 286 |
| 2009 | | 82 | | 289 | 976 | 1,269 | 4,887 | 2,901 | 356 |
| 2010 | | 251 | | 563 | 1,222 | 1,480 | 5,866 | 3,086 | 657 |
| 2011 | | 356 | | 676 | 1,444 | 1,307 | 6,148 | 2,309 | 923 |
| 2012 | | 532 | 101 | 1,136 | 1,650 | 1,393 | 6,457 | 2,610 | 1,292 |
| 2013 | | 685 | 273 | 1,775 | 1,737 | 1,358 | 6,788 | 2,659 | 2,103 |
| 2014 | | 773 | 705 | 2,003 | 1,858 | 1,573 | 7,481 | 2,829 | 2,586 |
| 2015 | 40 | 799 | 416 | 1,937 | 1,756 | 1,304 | 7,309 | 2,408 | 2,900 |
| 2016 | 44 | 1,198 | 472 | 2,101 | 1,644 | | 8,023 | 2,398 | 2,897 |
| 2017 | 48 | 1,472 | 407 | 2,225 | 1,575 | | 8,996 | 2,440 | 2,626 |
| 2018 | | 1,680 | 389 | 2,147 | 1,584 | | 9,088 | 2,353 | 2,300 |
| 2019 | | 2,417 | 263 | 2,483 | 1,816 | | 9,253 | 3,080 | 2,348 |

Sources: USPTO (https://www.uspto.gov/web/offices/ac/ido/oeip/taf/reports_topo.htm).

## Table A9-3: The Number of CNIPA Patent Grants, Selected Chinese and U.S. Enterprises

| | Chinese Enterprises | | | U.S. Enterprises | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | China Petroleum and Chemical Corporation | Huawei Technologies Co., LTD. | ZTE Corporation | Apple Inc. | General Electric Company | Hewlett-Packard Corporation | International Business Machines Corporation | Microsoft Corporation | Qualcomm |
| 1987 | | | | | | | 1 | | |
| 1988 | 1 | | | | | | 4 | | |
| 1989 | 5 | | | | 18 | 1 | 18 | | |
| 1990 | 4 | | | 1 | 24 | 4 | 21 | | |
| 1991 | 4 | | | 0 | 11 | 4 | 18 | | |
| 1992 | 12 | | | 3 | 28 | 8 | 28 | | |
| 1993 | 12 | | | 0 | 16 | 6 | 39 | | |
| 1994 | 26 | | | 1 | 7 | 0 | 30 | | 1 |
| 1995 | 28 | | | 0 | 9 | 0 | 30 | | 0 |
| 1996 | 21 | | | 0 | 8 | 1 | 18 | | 1 |
| 1997 | 22 | | | 0 | 8 | 1 | 11 | | 3 |
| 1998 | 19 | 1 | | 0 | 10 | 1 | 19 | | 1 |
| 1999 | 58 | 0 | | 0 | 14 | 0 | 30 | | 0 |
| 2000 | 167 | 8 | 1 | 0 | 25 | 1 | 59 | | 5 |
| 2001 | 202 | 10 | 1 | 0 | 27 | 5 | 31 | | 16 |
| 2002 | 179 | 16 | 6 | 3 | 29 | 24 | 119 | | 37 |
| 2003 | 480 | 126 | 87 | 16 | 53 | 42 | 273 | 11 | 105 |
| 2004 | 546 | 501 | 82 | 20 | 52 | 61 | 385 | 20 | 206 |
| 2005 | 547 | 487 | 39 | 17 | 74 | 84 | 243 | 24 | 152 |
| 2006 | 458 | 448 | 250 | 25 | 64 | 66 | 299 | 28 | 132 |
| 2007 | 363 | 935 | 289 | 22 | 118 | 77 | 407 | 70 | 136 |
| 2008 | 425 | 2,342 | 581 | 45 | 165 | 117 | 674 | 154 | 190 |
| 2009 | 474 | 3,400 | 1,359 | 59 | 219 | 202 | 912 | 342 | 300 |
| 2010 | 519 | 2,503 | 2,004 | 53 | 205 | 172 | 699 | 422 | 340 |
| 2011 | 548 | 2,475 | 2,657 | 70 | 275 | 162 | 470 | 339 | 306 |
| 2012 | 992 | 2,469 | 2,276 | 130 | 396 | 239 | 492 | 496 | 603 |
| 2013 | 1,772 | 2,177 | 1,286 | 209 | 510 | 175 | 319 | 542 | 1,040 |
| 2014 | 1,958 | 2,149 | 1,832 | 287 | 489 | 164 | 277 | 437 | 1,029 |
| 2015 | 2,767 | 2,172 | 1,978 | 410 | 693 | 172 | 392 | 690 | 1,305 |
| 2016 | 2,910 | 2,704 | 1,609 | 502 | 1,013 | 272 | 736 | 840 | 1,596 |
| 2017 | 2,809 | 3,092 | 1,634 | 510 | 634 | 210 | 788 | 520 | 1,228 |
| 2018 | 3,013 | 3,318 | 1,797 | 656 | 450 | 254 | 458 | 589 | 1,651 |
| 2019 | 3,012 | 4,530 | 1,459 | 834 | 496 | 328 | 269 | 815 | 1,586 |
| 2020 | 2,954 | 6,413 | 1,348 | 581 | 515 | 400 | 105 | 733 | 1,158 |

Sources: Patsnap database (https://analytics.zhihuiya.com/search/input#/simple).

## Chapter 10: The Econometric Models

The annual numbers of patent applications submitted and patent grants received by an economy is a useful indicator of its degree of success in Research and Development (R&D) activities because a patent application or grant must have been based on some underlying original discovery or invention. We begin with the assumption that there exist functions, possibly specific to each individual economy, relating the annual numbers of patent applications to the annual quantities of real Research and Development (R&D) capital stock, which may be taken to be a measure of the capacity of each economy for conducting R&D and achieving successful outcomes at any given time. In turn, the annual numbers of patent grants awarded to each economy may depend on its annual numbers of patent applications, appropriately lagged (the average lag will be assumed to be one year in this study). These functions will be referred to as the "patent application production functions" and the "patent grant production functions" respectively. Indirectly, the annual numbers of patent grants are also functions of the lagged annual quantities of real R&D capital stock.

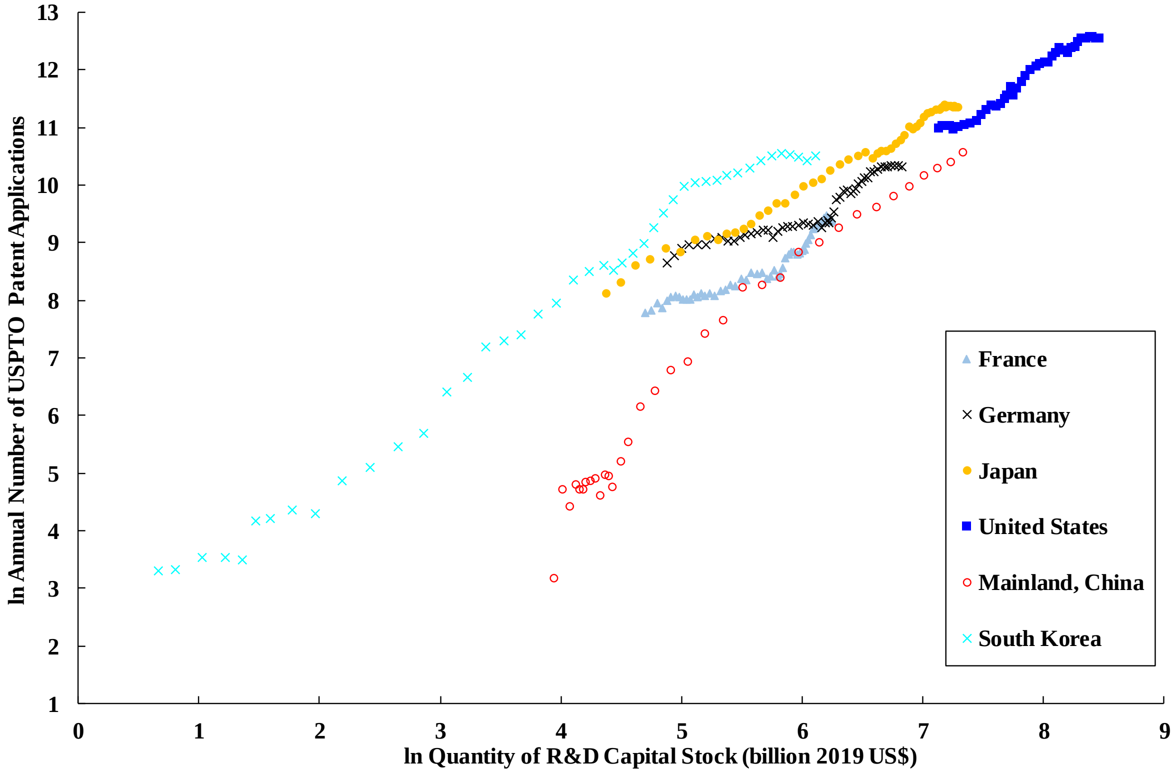
There is of course no a priori reason why the same functional relationships should apply to both domestic and foreign patent applications and grants across all the economies included in our study. This is especially true for domestic patent applications and grants, because the domestic propensities to apply for as well as to grant patents may depend very much on the domestic conditions, cultures, customs, markets, policies, practices, procedures and standards, in addition to the domestic capacities for R&D, proxied by the quantities of their respective real R&D capital stocks. For a variety of reasons that are discussed in Chapter 3, the domestic patent application behaviour and the USPTO patent application behaviour can be quite different in some economies, especially in the ones with relatively small home markets, and often do not depend solely on the qualities and quantities of the outcomes of their respective R&D activities. However, for the United States Patent and Trademark Office (USPTO) patent applications and grants, it is more plausible for the same functional relationships to hold across economies, since the U.S. market itself is important for almost all economies and the same procedures and standards have been and are used by the USPTO to assess the quality of the patent applications received from applicants in different parts of the world.

As a result of these considerations, we shall focus our econometric analysis on only USPTO patent applications and grants and not the respective domestic patent applications and grants. Even then, the propensity to apply for a USPTO patent, given an original discovery or invention of a certain quality, may still vary significantly across economies and change over time for different reasons. In particular, this is especially likely to be true for economies in which the annual numbers of domestic patent applications are smaller than their annual numbers of USPTO patent applications. It is reasonable to assume that if a discovery or invention is good enough for a USPTO patent application, it should be good enough, in terms of quality, for a domestic patent application. Moreover, the cost of application, and subsequent maintenance if granted, of a USPTO patent is in general much more expensive than that of a domestic patent, which should bias the application in favour of a domestic patent. However, as Chart 5-4 in Chapter 5 shows, for six of the twelve economies included in our study—Canada, Hong Kong (China), Italy, Singapore, Taiwan (China), and the U.K., the annual number of USPTO patent applications has exceeded the annual number of domestic applications quite regularly. Thus, the patent applications of these economies, both domestic and foreign, must have been subject to considerations extraneous to the intrinsic quality of their discoveries or inventions, and their annual numbers are therefore potentially biased indicators of their degrees of R&D success. Our econometric analysis will therefore be restricted to USPTO patent applications and grants of the six economies in which the annual numbers of domestic patent applications exceed the annual numbers of USPTO patent applications, that is, Mainland China, France, Germany, Japan, South Korea and the U.S. Moreover, in order to assure comparability and consistency of the data over time and across economies, we have used only the data between certain years for the different economies in the analyses in this Chapter and Chapter 11. The beginning and ending years of the data used for each economy in these two chapters are presented in Appendix Table A10-1.

### A Model for USPTO Patent Applications

First, we formulate a model for USPTO patent applications. In Chart 10-1, the natural logarithm of the annual number of USPTO patent applications of each of the six economies is plotted against the natural logarithm of the respective quantity of real R&D capital stock in each year. Chart 10-1 provides prima facie evidence that there exists a stable, positive relationship between the annual number of USPTO patent applications and the quantity of real R&D capital stock, across the six economies and over time. However, there appears to be some divergence among the economies, especially between the developed economies on the one hand and the developing and newly industrialised economies of East Asia on the other.

**Chart 10-1: The Natural Logarithm of the Annual Number of USPTO Patent Applications versus the Natural Logarithm of the Quantity of Real R&D Capital Stock**




Source: Authors' calculations. Data on the numbers of USPTO patent applications are from Table A5-1 and data on the quantity of real R&D capital stocks from Table A3-2.

In general, the number of USPTO patent applications in the ith economy in year t, $YA_{USit}$, may be taken to be a measure of the outcome resulting from R&D activities in that year. It may be expressed as a function of $K_{it}$, the quantity of real R&D capital stock in the ith economy in year t. Thus,

$$YA_{USit} = F_i(K_{it}), \qquad (10\text{-}1)$$

where $F_i(K_{it})$ is the "patent application production function" that relates the annual number of USPTO patent applications to the quantity of real R&D capital stock in the ith economy in that year. Note that the function $F_i(.)$, subscripted by i, may vary with the particular economy, but is assumed not to vary over time.

We assume, however, that after an economy-specific and time-varying transformation, $YA_{USit}$, the measured annual number of USPTO patent applications, may be converted into an "efficiency-equivalent" or "quality-equivalent" number of USPTO patent applications, $YA^*_{USit}$, that is comparable across economies. Thus, for example, it is possible that one USPTO patent application submitted by a U.S. resident is equivalent to two USPTO patent applications submitted by a Chinese resident in terms of quality, or vice versa. However, $YA^*_{USit}$ is not directly observable. It is assumed that $YA^*_{USit}$ is related to the directly observable $YA_{USit}$ by an economy- and time-specific augmentation factor $A_{AUSi}(t)$:

$$YA^*_{USit} = A_{AUSi}(t) YA_{USit} . \quad (10\text{-}2)$$

More specifically, $A_{AUSi}(t)$, the patent application augmentation factor of the ith economy, is assumed to take the constant exponential form, so that:

$$YA^*_{USit} = A_{AUSi}\exp(c_{USi}t)\, YA_{USit}, \qquad (10\text{-}3)$$

where $A_{AUSi}$ and $c_{USi}$ are constants that may vary with i, that is, they depend on the specific economy. $A_{AUSi}$ may be identified as the augmentation level parameter and $c_{USi}$ as the augmentation rate parameter of the patent application augmentation factor of the ith economy. $A_{AUSi}$ is a positive constant that may be greater than, equal to, or less than one, and is the "efficiency-equivalent" conversion ratio of the USPTO patent applications of the ith economy at t=0; and $c_{USi}$ is a constant that may be greater than, equal to, or less than zero, and is the rate of change of the "efficiency-equivalent" conversion ratio of the ith economy per unit time. We note that, without loss of generality, for one economy, $A_{AUSi}$ can be taken to be unity; this is equivalent to choosing that economy's number of patent applications at t=0 to be the numeraire.

Similarly, the measured quantity of real R&D capital stock of the ith economy, $K_{it}$, may also be converted into an "efficiency-equivalent" or "quality-equivalent" quantity of real R&D capital stock, $K^*_{it}$ , that is also comparable across economies. Specifically, it is assumed that:

$$K^*_{it} = A_{Ki}(t) K_{it} = A_{Ki}\exp(c_{Ki}\, t)\, K_{it}, \quad (10\text{-}4)$$

where $A_{Ki}$ and $c_{Ki}$ are constants that may be identified as respectively the constant capital augmentation level and rate parameters that may vary with the particular economy. We also note that, without loss of generality, for one economy, $A_{Ki}$ can be taken to be unity (so that $\ln A_{Ki}$=0); this is equivalent to choosing that economy's quantity of real R&D capital stock at t=0 to be the numeraire.

Since both the "efficiency-equivalent" quantities of patent applications, $YA^*_{USit}$'s, and real R&D capital stocks, $K^*_{it}$'s, are supposedly comparable across economies, we can assume that they are related by a common production function $F$(.) that applies across economies:

$$YA^*_{USit} = F(K^*_{it}), \qquad (10\text{-}5)$$

where $F(.)$ is the so-called "meta-production function".[16] What this means is that if we can measure the outputs and the inputs of each economy appropriately, so that they are "efficiency-equivalent" or "quality-equivalent", they can be related by the same functional relationship across economies. In our empirical implementation, it is assumed that the function $F(.)$ in equation (10-5) takes the transcendental logarithmic form, introduced by Christensen, Jorgenson and Lau (1971), so that:

$$\ln YA^*_{USit} = \ln A_0 + \alpha_K \ln K^*_{it} + \frac{1}{2} \mathrm{B}_{KK} (\ln K^*_{it})^2. \qquad (10\text{-}6)$$

By substituting equation (10-3) into equation (10-6), we obtain:

$$\ln YA_{USit} + \ln A_{AUSi} + c_{USi}\mathrm{t} = \ln A_0 + \alpha_K \ln K^*_{it} + \frac{1}{2} \mathrm{B}_{KK} (\ln K^*_{it})^2. \qquad (10\text{-}7)$$

By substituting equation (10-4) into equation (10-7), and re-arranging, we obtain:

$$\ln YA_{USit} = -\ln A_{AUSi} - c_{USi}\mathrm{t} + \ln A_0 + \alpha_K (\ln A_{Ki} + c_{Ki}\,\mathrm{t} + \ln K_{it})$$
$$+ \frac{1}{2} \mathrm{B}_{KK} (\ln A_{Ki} + c_{Ki}\,\mathrm{t} + \ln K_{it})^2 \qquad (10\text{-}8)$$
$$= (-\ln A_{AUSi} + \ln A_0 + \alpha_K \ln A_{Ki} + \frac{1}{2} \mathrm{B}_{KK} (\ln A_{Ki})^2) + (\alpha_K + \mathrm{B}_{KK} \ln A_{Ki}) \ln K_{it}$$
$$+ (-c_{USi} + (\alpha_K + \mathrm{B}_{KK} \ln A_{Ki}) c_{Ki})\mathrm{t} + \mathrm{B}_{KK}\, c_{Ki} \ln K_{it}.\mathrm{t} + \frac{1}{2} \mathrm{B}_{KK} (\ln K_{it})^2 + \frac{1}{2} \mathrm{B}_{KK}\, c_{Ki}^2\, \mathrm{t}^2 .$$
$$(10\text{-}9)$$

Equation (10-9) may be simplified into:

$$\ln YA_{USit} = A^*_{AUSi} + (\alpha_K + \mathrm{B}_{KK} \ln A_{Ki}) \ln K_{it} + c^*_{USi}\mathrm{t} + \mathrm{B}_{KK}\, c_{Ki} \ln K_{it}.\mathrm{t} + \frac{1}{2} \mathrm{B}_{KK} (\ln K_{it})^2$$
$$+ \frac{1}{2} \mathrm{B}_{KK}\, c_{Ki}^2\, \mathrm{t}^2 , \qquad (10\text{-}10)$$

where

$$A^*_{AUSi} \equiv (-\ln A_{AUSi} + \ln A_0 + \alpha_K \ln A_{Ki} + \frac{1}{2} \mathrm{B}_{KK} (\ln A_{Ki})^2); \text{ and}$$

$$c^*_{USi} \equiv (-c_{USi} + (\alpha_K + \mathrm{B}_{KK} \ln A_{Ki})\, c_{Ki}). \qquad (10\text{-}11)$$

We note that the two parameters, $A^*_{AUSi}$ and $c^*_{USi}$, are unconstrained across economies, since $\ln A_{AUSi}$ and $c_{USi}$ are free to assume any value for each economy, but $\alpha_K$ and $\mathrm{B}_{KK}$ must be identical across economies.

Equation (10-10) is written entirely in terms of directly observable variables $YA_{USit}$ and $K_{it}$ rather than the unobservable variables $YA^*_{USit}$ and $K^*_{it}$, and hence can be directly estimated from the empirical data. However, we note that in equation (10-10), the square of

[16] However, this assumption of the existence of a meta-production function can and will be explicitly tested statistically.

the coefficient of the fourth term, $\ln K_{it}$.t, divided by the coefficient of the fifth term, $\frac{1}{2}(\ln K_{it})^2$, must be equal to the coefficient of the sixth term, $\frac{1}{2}t^2$. This is a direct consequence of the meta-production function model and implies a nonlinear restriction on these parameters for each economy, which will be referred to as the "First Necessary Condition" for the validity of the meta-production function model.

Moreover, equation (10-10) further implies that the coefficients of the fifth term, $\frac{1}{2}(\ln K_{it})^2$, $B_{KK}$'s, should be identical across all economies. This is the second necessary condition for the validity of the meta-production function model. These latter cross-economy restrictions will be referred to as the "Equality" restrictions. The "Equality" hypothesis is tested across all economies that satisfy the first necessary condition, with the restrictions implied by the "First Necessary Condition" as the maintained hypothesis. If both the "First Necessary Condition" and the "Equality" restrictions are accepted, the validity of the meta-production function model is confirmed, and these restrictions will be imposed in the further estimation of the model.

In principle, equation (10-10) can be directly estimated individually or jointly for all six economies. However, in order to minimise the possibility of serial correlation of the stochastic disturbance terms, equation (10-10) is estimated in its first-differenced form in the empirical implementation. Lagging equation (10-10) by one period, we have:

$$\ln YA_{USi(t-1)} = A^*_{AUSi} + (\alpha_K + B_{KK}\ln A_{Ki})\ \ln K_{i(t-1)} + c^*_{USi}(t-1) + B_{KK}\, c_{Ki}\ \ln K_{i(t-1)}.(t-1) + \frac{1}{2}B_{KK}(\ln K_{i(t-1)})^2 + \frac{1}{2}B_{KK}\, c^2_{Ki}\,(t-1)^2\,. \qquad (10\text{-}12)$$

Subtracting equation (10-12) from equation (10-10), we obtain:

$$\ln YA_{USit} - \ln YA_{USi(t-1)} = c^*_{USi} + (\alpha_K + B_{KK}\ln A_{Ki})(\ln K_{it} - \ln K_{i(t-1)}) + B_{KK}\, c_{Ki}\,(\ln K_{it}.t - \ln K_{i(t-1)}.(t-1)) + \frac{1}{2}B_{KK}((\ln K_{it})^2 - (\ln K_{i(t-1)})^2) + B_{KK}\, c^2_{Ki}\, t - \frac{1}{2}B_{KK}\, c^2_{Ki}$$

$$= c^{**}_{USi} + (\alpha_K + B_{KK}\ln A_{Ki})(\ln K_{it} - \ln K_{i(t-1)}) + B_{KK}\, c_{Ki}\,(\ln K_{it}.t - \ln K_{i(t-1)}.(t-1)) + B_{KK}\, c^2_{Ki}\, t + \frac{1}{2}B_{KK}((\ln K_{it})^2 - (\ln K_{i(t-1)})^2), \qquad (10\text{-}13)$$

where $c^{**}_{USi} \equiv c^{*}_{USi} - \frac{1}{2}\mathrm{B}_{KK}\, c^{2}_{Ki} \equiv (-c_{USi} + (\alpha_K + \mathrm{B}_{KK}\ln A_{Ki})\, c_{Ki}) - \frac{1}{2}\mathrm{B}_{KK}\, c^{2}_{Ki}$. Equation (10-13) is then the actual basic estimating equation for the model of USPTO patent applications. We note that there are five terms on the right-hand-side of equation (10-13). They are the constant term, $(\ln K_{it} - \ln K_{i(t-1)})$, $(\ln K_{it}.\mathrm{t} - \ln K_{i(t-1)}.(\mathrm{t}-1))$, t, and $\frac{1}{2}((\ln K_{it})^2 - (\ln K_{i(t-1)})^2)$. However, not all of the coefficients of the different terms are independent. The square of the coefficient of $(\ln K_{it}.\mathrm{t} - \ln K_{i(t-1)}.(\mathrm{t}-1))$, $\mathrm{B}_{KK}\, c_{Ki}$, divided by the coefficient of $\frac{1}{2}((\ln K_{it})^2 - (\ln K_{i(t-1)})^2)$, $\mathrm{B}_{KK}$, must be equal to the coefficient of the time trend, $\mathrm{B}_{KK}\, c^{2}_{Ki}$. These nonlinear restrictions are precisely the equivalent of the "First Necessary Condition" in equation (10-10) in the first-differenced form.

Equation (10-13) may first be estimated without imposing any restrictions on the parameters. This may be referred to as the "Unconstrained Model". In this unconstrained form, equation (10-13) is linear in all its parameters. The "First Necessary Condition", which implies one restriction per economy, may then be individually tested for all of the six included economies. If this restriction is rejected for any economy, that economy cannot be included in the same meta-production function model as the other economies. Equation (10-13) may then be estimated jointly for all six included economies after heteroscedastic adjustments[17], both with and without the six restrictions implied by the "First Necessary Condition". The difference in the sum of squares of residuals between the unconstrained and the restricted estimation, divided by the relevant degrees of freedom, is asymptotically distributed as a $\chi^2$ variable. A large value of the $\chi^2$ variable implies rejection of the null hypothesis being tested.

Subject to the acceptance of the joint test for the "First Necessary Condition", we proceed to test the "Equality" hypothesis of identical $\mathrm{B}_{KK}$'s across all economies, conditional on this joint hypothesis. If both tests are accepted, the validity of the meta-production function model is confirmed. We then proceed to test whether $\mathrm{B}_{KK} = 0$. $\mathrm{B}_{KK} = 0$ implies that the elasticity of the annual number of USPTO patent applications with respect to the quantity of real R&D capital stock is a constant that is identical across economies. There is a question of how many restrictions are implied by the hypothesis of $\mathrm{B}_{KK} = 0$. In principle, it is only a restriction on a single parameter, because only $\mathrm{B}_{KK}$ is involved. However, assuming the

[17] The heteroskedastic adjustments are made using the estimated standard errors of the stochastic disturbance terms of equation (10-13) for the individual economies.

validity of the meta-production function model, with 6 economies, there are 19 independent parameters in equation (10-13). With the restriction of $B_{KK}$= 0, there are only 7 independent parameters left to be estimated, so that the effective number of restrictions is actually 12 (19-7). We shall test this hypothesis as if it consists of 12 restrictions.

If the hypothesis of $B_{KK}$ = 0 is rejected, we proceed to test the following specific hypotheses on the other parameters: (1) identical $c_{Ki}$'s across economies; (2) identical $A_{Ki}$'s across economies (implying $\ln A_{Ki}$=0, all i, since $A_{Ki}$ =1 for the numeraire economy); and (3) identical $c_{USi}$'s across economies. However, if the hypothesis of $B_{KK}$ = 0 cannot be rejected, the parameters of the USPTO patent application and real R&D capital augmentation factors may not be identifiable, and these additional hypotheses (1) through (3) cannot be tested. Thus, the hypothesis of $B_{KK}$ = 0 is pivotal to our further analysis.

Subject to the outcomes of these tests, the implied restrictions accepted are imposed on the six economies. We can then make use of the restricted parameter estimates of equation (10-13) to recover the economy-specific USPTO patent application augmentation rate parameters, $c_{USi}$'s, for all six economies.[18] However, the recovery of the economy-specific USPTO patent application augmentation level parameters, $A_{AUSi}$'s, requires the use of the non-first-differenced equation (10-10). From equations (10-10) and (10-11), we have:

$$\ln YA_{USit} - (\alpha_K + B_{KK}\ln A_{Ki})\ln K_{it} - c^*_{USi}t - B_{KK}c_{Ki}\ln K_{it}.t - \tfrac{1}{2}B_{KK}(\ln K_{it})^2 - \tfrac{1}{2}B_{KK}c^2_{Ki}t^2$$
$$= A^*_{AUSi},$$
$$= -\ln A_{AUSi} + \ln A_0 + \alpha_K\ln A_{Ki} + \tfrac{1}{2}B_{KK}(\ln A_{Ki})^2. \qquad (10\text{-}14)$$

Or,

$$\ln YA_{USit} - (\alpha_K + B_{KK}\ln A_{Ki})\ln K_{it} - c^*_{USi}t - B_{KK}c_{Ki}\ln K_{it}.t - \tfrac{1}{2}B_{KK}(\ln K_{it})^2$$
$$- \tfrac{1}{2}B_{KK}c^2_{Ki}t^2 - \alpha_K\ln A_{Ki} - \tfrac{1}{2}B_{KK}(\ln A_{Ki})^2$$
$$= -\ln A_{AUSi} + \ln A_0. \qquad (10\text{-}15)$$

Equation (10-15) may be used to generate estimates for the $A_{AUSi}$'s by substituting the estimated values of the parameters on the left-hand-side and then running a regression with only economy-specific constant terms on the right-hand-side.[19]

[18] On the assumption that $B_{KK}$ is not equal to zero.
[19] We should bear in mind that $A_{AUSi}$ = 1 for the numeraire economy.

If $B_{KK}$ = 0, then equation (10-10) reduces to:

$$\ln YA_{USit} = A^{*}_{AUSi} + c^{*}_{USi}\mathrm{t} + \alpha_K \ln K_{it},$$

$$= (-\ln A_{AUSi} + \ln A_0 + \alpha_K \ln A_{Ki}) + (-c_{USi} + \alpha_K c_{Ki})\mathrm{t} + \alpha_K \ln K_{it}, \quad (10\text{-}16)$$

in which case it is clearly not possible to separately identify the level and the rate parameters of the USPTO patent application and the real R&D capital augmentation factors for each economy. And our first-differenced estimating equation (10-13) reduces to:

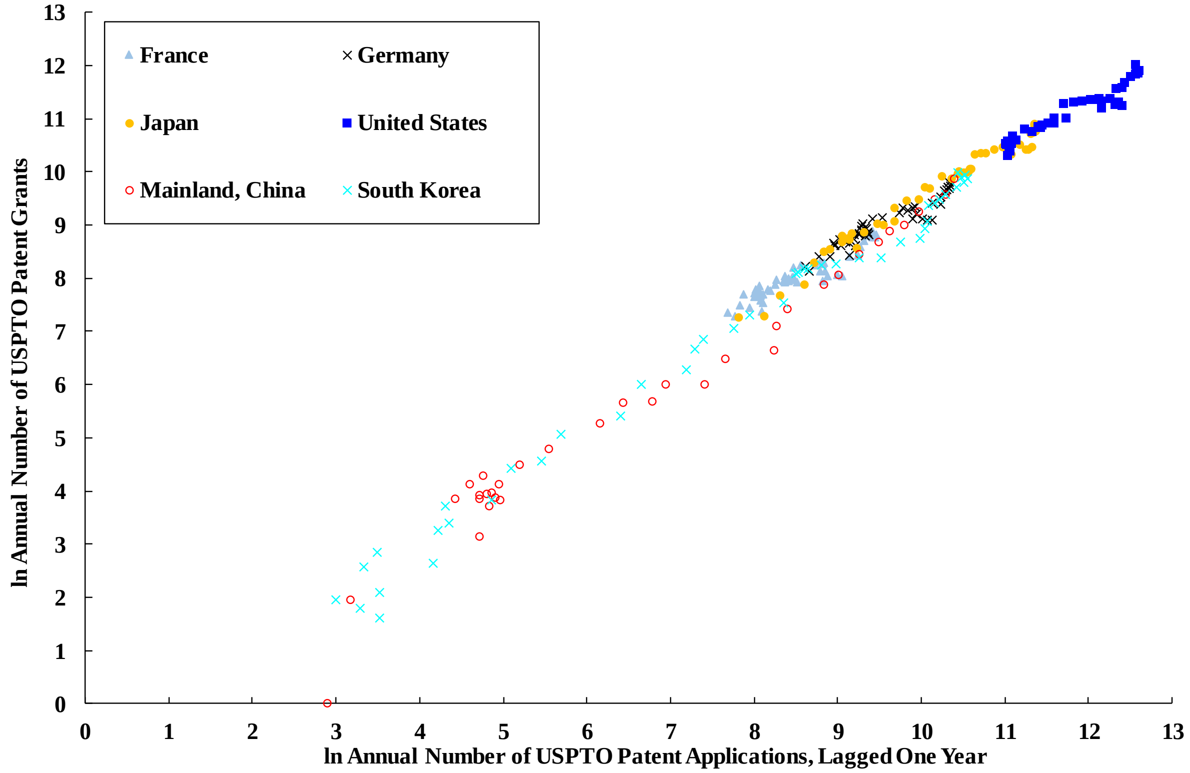
$$\ln YA_{USit} - \ln YA_{USi(t-1)} = c^{*}_{USi} + \alpha_K(\ln K_{it} - \ln K_{i(t-1)}), \quad (10\text{-}17)$$

from which $c^{*}_{USi}$ (= $-c_{USi} + \alpha_K c_{Ki}$) can be estimated.

### A Model for USPTO Patent Grants

Next, we derive a model for USPTO patent grants. In Chart 10-2, the natural logarithm of the annual number of USPTO patent grants is plotted against the natural logarithm of the annual number of USPTO patent applications, lagged one year, for all six economies. Chart 10-2 also provides prima facie evidence that there is a stable and positive relationship between the annual number of USPTO patent grants and the annual number of USPTO applications, lagged one year, across economies and over time.

**Chart 10-2: The Natural Logarithm of the Annual Number of USPTO Patent Grants versus the Natural Logarithm of the Annual Number of USPTO Patent Applications, Lagged 1 Year**




Source: Authors' calculations. Data on the numbers of USPTO patent applications and grants are from Table A5-1 and Table A5-2 respectively.

We begin with the assumption that the number of USPTO patent grants awarded to the ith economy in year t, $YG_{USit}$ , may be expressed as a function of $YA_{USi(t-1)}$, the number of USPTO patent applications from the ith economy in year (t-1). Thus,

$$YG_{USit} = F_i(YA_{USi(t-1)}), \qquad (10\text{-}18)$$

where $F_i(K_{it})$ is the "patent application production function" that relates the annual number of USPTO patent grants to the annual number of USPTO patent applications in the previous year. Moreover, we assume that there also exist economy-specific and time-varying transformations such that $YG_{USit}$, the measured annual number of USPTO patent grants, may be converted into an "efficiency-equivalent" or "quality-equivalent" annual number of USPTO patent grants, $YG^*_{USit}$ , that is comparable across economies. More specifically,

$$YG^*_{USit} = A_{GUSi}(\text{t})\, YG_{USit}, \qquad (10\text{-}19)$$

where $A_{GUSi}(\text{t})$ is the patent grant augmentation factor of the ith economy. $A_{GUSi}(\text{t})$ is assumed to take the constant exponential form, so that:

$$YG^*_{USit} = A_{GUSi}\exp(c_{GUSi}\text{t})\, YG_{USit}. \qquad (10\text{-}20)$$

We already have, from equation (10-3) above, the conversion factor between the measured number of USPTO patent applications and the "efficiency-equivalent" number of USPTO patent applications:

$$YA^{*}_{USit} \;= A_{AUSi}\exp(c_{USi}\mathrm{t})\, YA_{USit}. \qquad (10\text{-}3)$$

As the "efficiency -equivalent" numbers of both USPTO patent grants and patent applications are available, we assume that there exists a common USPTO patent grant production function linking the "efficiency-equivalent" numbers of patent grants and patent applications, lagged one year, for all six economies:

$$YG^{*}_{USit} = F(YA^{*}_{USi(t-1)}). \qquad (10\text{-}21)$$

In our empirical implementation, it is assumed that the function $F$(.) in equation (10-21) also takes the transcendental logarithmic form, so that:

$$\ln YG^{*}_{USit} \;= \ln G_{US0}+\alpha_{GUSA}\ln YA^{*}_{USi(t-1)} +\tfrac{1}{2}\mathrm{B}_{GUSKK}(\ln YA^{*}_{USi(t-1)})^{2}. \qquad (10\text{-}22)$$

Substituting equations (10-20) and (10-3) into equation (10-22), we obtain:

$$\ln YG_{USit} = -\ln A_{GUSi} - c_{GUSi}\mathrm{t} + \ln G_{US0}+\alpha_{GUSA}(\ln A_{AUSi}+c_{USi}(\mathrm{t}\text{-}1) + \ln YA_{USi(t-1)})$$
$$+\tfrac{1}{2}\mathrm{B}_{GUSKK}(\ln A_{AUSi}+c_{USi}(\mathrm{t}\text{-}1) + \ln YA_{USi(t-1)})^{2} \qquad (10\text{-}23)$$
$$= (-\ln A_{GUSi} + \ln G_{US0}+\alpha_{GUSA}(\ln A_{AUSi} - c_{USi})+\tfrac{1}{2}\mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi})^{2})$$
$$+ (\alpha_{GUSA}+\mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi}))\ln YA_{USi(t-1)}$$
$$+ (-c_{GUSi}+ (\alpha_{GUSA}+\mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi}))c_{USi})\mathrm{t} + \mathrm{B}_{GUSKK}c_{USi}\ln YA_{USi(t-1)}.\mathrm{t}$$
$$+\tfrac{1}{2}\mathrm{B}_{GUSKK}(\ln YA_{USi(t-1)})^{2} + \tfrac{1}{2}\mathrm{B}_{GUSKK}c^{2}_{USi}\mathrm{t}^{2}. \qquad (10\text{-}24)$$

Equation (10-24) may be simplified into:

$$\ln YG_{USit} = A^{*}_{GUSi} + c^{*}_{GUSi}\mathrm{t} + (\alpha_{GUSA} + \mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi}))\ln YA_{USi(t-1)}$$
$$+\mathrm{B}_{GUSKK}c_{USi}\ln YA_{USi(t-1)}.\mathrm{t} +\tfrac{1}{2}\mathrm{B}_{GUSKK}(\ln YA_{USi(t-1)})^{2} + \tfrac{1}{2}\mathrm{B}_{GUSKK}c^{2}_{USi}\mathrm{t}^{2}, \qquad (10\text{-}25)$$

where

$$A^{*}_{GUSi} \equiv (-\ln A_{GUSi}+ \ln G_{US0}+\alpha_{GUSA}(\ln A_{AUSi} - c_{USi})+\tfrac{1}{2}\mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi})^{2}); \text{ and}$$
$$c^{*}_{GUSi} \equiv (-c_{GUSi}+ (\alpha_{GUSA}+\mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi}))c_{USi}). \qquad (10\text{-}26)$$

As before, for one economy, $A_{GUSi}$ can be chosen to be unity, and hence $\ln A_{GUSi}$ = 0 for that economy. This is equivalent to measuring all the USPTO patent grants using this economy's number of USPTO patent grants at t=0 as the numeraire.

However, equation (10-25) should not be estimated solely on its own, because the annual number of USPTO patents granted to each economy also depends on the total patent grant rate of the USPTO, $g_t$, which fluctuates over time. There are two possible ways to measure the USPTO total patent grant rate: the first is the total number of patents granted divided by the total number of applications submitted, appropriately lagged, and the second is the total number of patents granted to non-U.S. applicants, divided by the total number of applications submitted by non-U.S. applicants, also appropriately lagged. This variable controls for the changes in the behavior and practices, if any, of the USPTO over time. In Chapter 5, we have found that the USPTO grant rate fluctuates significantly over time, thus affecting the number of patent grants awarded to the applicants independently of their numbers of patent applications (see Chart 5-10). However, Chart 5-11, which presents the same intertemporal fluctuations in the USPTO grant rates, also shows that there is virtually no difference between the two alternative measures of the USPTO total patent grant rate since 1977. We shall therefore use only the total success rate for all economies in our empirical analysis. The model of USPTO patent grants in equation (10-25), with the addition of the USPTO total grant rate variable in its natural logarithmic form, $\ln g_t$, is jointly estimated for all six economies in our study. Thus,

$$\ln YG_{USit} = A^*_{GUSi} + c^*_{GUSi}\mathrm{t} + (\alpha_{GUSA} + \mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi}))\ln YA_{USi(t-1)} + \mathrm{B}_{GUSKK}c_{USi}\ln YA_{USi(t-1)}.\mathrm{t} + \frac{1}{2}\mathrm{B}_{GUSKK}(\ln YA_{USi(t-1)})^2 + \frac{1}{2}\mathrm{B}_{GUSKK}c^2_{USi}\mathrm{t}^2 + \delta_i \ln g_t. \quad (10\text{-}27)$$

Equation (10-27) is then the basic estimating equation. As before, for one economy, $A_{GUSi}$ can be chosen to be unity, and hence $\ln A_{GUSi}$= 0. This is equivalent to measuring all the USPTO patent grants using this economy's number of USPTO patent grants at t=0 as the numeraire. However, we should also note that if both the USPTO patent application and grant production functions are estimated for the same economy, there are potentially additional restrictions between the parameters of the USPTO patent application production function in equation (10-9) and the USPTO patent grant production function in equation (10-24) as the parameters $\ln A_{AUSi}$ and $c_{USi}$ should be identical between the two equations for each economy.

In order to minimise the possibility of serial correlation of the stochastic disturbance terms, equation (10-27) is estimated in its first-differenced form. Lagging equation (10-27) by one period, we have:

$$\ln YG_{USi(t-1)} = A^{*}_{GUSi} + c^{*}_{GUSi}(\mathrm{t}-1) + (\alpha_{GUSA} + \mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi}))\ln YA_{USi(t-2)}$$
$$+ \mathrm{B}_{GUSKK}c_{USi}\ln YA_{USi(t-2)}\,.\,(\mathrm{t}\text{-}1) + \frac{1}{2}\mathrm{B}_{GUSKK}(\ln YA_{USi(t-2)})^2 + \frac{1}{2}\mathrm{B}_{GUSKK}c^2_{USi}(\mathrm{t}\text{-}1)^2$$
$$+ \delta_i \ln g_{(t-1)}. \qquad (10\text{-}28)$$

Subtracting equation (10-28) from equation (10-27), we obtain:

$$\ln Y\,G_{USit} - \ln Y\,G_{USi(t-1)}$$
$$= c^{*}_{GUSi} + (\alpha_{GUSA} + \mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi}))(\ln YA_{USi(t-1)} - \ln YA_{USi(t-2)})$$
$$+\mathrm{B}_{GUSKK}c_{USi}(\ln YA_{USi(t-1)}.\,\mathrm{t} - \ln YA_{USi(t-2)}\,.\,(\mathrm{t}\text{-}1))$$
$$+\frac{1}{2}\mathrm{B}_{GUSKK}((\ln YA_{USi(t-1)})^2 - (\ln YA_{USi(t-2)})^2) + \mathrm{B}_{GUSKK}c^2_{USi}\mathrm{t}$$
$$-\frac{1}{2}\mathrm{B}_{GUSKK}c^2_{USi} + \delta_i\,(\ln g_t - \ln g_{(t-1)})$$
$$= c^{**}_{GUSi} + (\alpha_{GUSA} + \mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi}))(\ln YA_{USi(t-1)} - \ln YA_{USi(t-2)})$$
$$+\mathrm{B}_{GUSKK}c_{USi}(\ln YA_{USi(t-1)}.\,\mathrm{t} - \ln YA_{USi(t-2)}\,.\,(\mathrm{t}\text{-}1))$$
$$+\frac{1}{2}\mathrm{B}_{GUSKK}((\ln YA_{USi(t-1)})^2 - (\ln YA_{USi(t-2)})^2)$$
$$+ \mathrm{B}_{GUSKK}c^2_{USi}\,\mathrm{t} + \delta_i\,(\ln g_t - \ln g_{(t-1)}), \qquad (10\text{-}29)$$

where $c^{**}_{GUSi} \equiv (-c_{GUSi} + (\alpha_{GUSA} + \mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi}))c_{USi}) - \frac{1}{2}\mathrm{B}_{GUSKK}c^2_{USi}$ . Equation (10-29) is then the actual estimating equation for the model of USPTO patent grants.

Again, the first step is to test jointly the nonlinear restrictions implied by the “First Necessary Condition” of the meta-production function model, followed by a test for the “Equality” restrictions across the six economies, conditional on the “First Necessary Condition”. If both tests are accepted, the validity of the meta-production function model is confirmed. We then proceed to test whether $\mathrm{B}_{GUSKK} = 0$. $\mathrm{B}_{GUSKK} = 0$ implies that the elasticity of the annual number of USPTO patent grants with respect to the annual number of USPTO patent applications is a constant that is identical across economies. There is a question of how many restrictions are implied by the hypothesis of $\mathrm{B}_{GUSKK} = 0$. In principle, it is only a restriction on a single parameter; however, assuming the validity of the meta-production function model, with 6 economies, there are 25 independent parameters in equation (10-29). With the restriction of $\mathrm{B}_{GUSKK} = 0$, there are only 13 independent parameters left to be estimated, so that the effective number of restrictions is actually 12 (25-13). We shall test this hypothesis as if it consists of 12 restrictions.

Conditional on the validity of the meta-production function model, we also test the hypothesis of identical $\delta_i$'s across economies. This hypothesis implies that fluctuations in the USPTO total grant rate affect the degree of success of the patent applications of all economies equally.

If the hypothesis of $\mathrm{B}_{GUSKK}$ = 0 is rejected, we proceed to test the following specific hypotheses on the other parameters: (1) identical $c_{USi}$'s across economies; (2) identical $A_{AUSi}$'s across economies (implying $\ln A_{AUSi}$=0, all i, since $A_{AUSi}$ =1 for the numeraire economy); and (3) identical $c_{GUSi}$'s across economies. However, if the hypothesis of $\mathrm{B}_{GUSKK}$ = 0 cannot be rejected, the USPTO patent application and patent grant augmentation factors may not be identifiable, and these additional hypotheses (1) through (3) cannot be tested. Thus, the hypothesis of $\mathrm{B}_{GUSKK}$ = 0 is also pivotal to our further analysis.

Subject to the outcomes of these tests, the implied restrictions accepted are imposed on the six economies. We can then make use of the restricted parameter estimates of equation (10-29) to recover the economy-specific USPTO patent grant augmentation rate parameters, $c_{GUSi}$'s, for all the economies.[20] However, the recovery of the economy-specific USPTO patent grant augmentation level parameters, $A_{GUSi}$'s, requires the use of the non-first-differenced equation (10-27). From equations (10-27) and (10-26), we have:

$$\begin{aligned}
&\ln YG_{USit} - c^*_{GUSi}\mathrm{t} - (\alpha_{GUSA} + \mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi}))\ln YA_{USi(t-1)} \\
&\quad - \mathrm{B}_{GUSKK} c_{USi} \ln YA_{USi(t-1)}.\mathrm{t} - \tfrac{1}{2}\mathrm{B}_{GUSKK}(\ln YA_{USi(t-1)})^2 - \tfrac{1}{2}\mathrm{B}_{GUSKK} c^2_{USi}\mathrm{t}^2 - \delta_i \ln g_t. \\
&\quad = A^*_{GUSi} \\
&\quad = -\ln A_{GUSi} + \ln G_{US0} + \alpha_{GUSA}(\ln A_{AUSi} - c_{USi}) + \tfrac{1}{2}\mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi})^2.
\end{aligned}$$

(10-30)

Or,

$$\begin{aligned}
&\ln YG_{USit} - c^*_{GUSi}\mathrm{t} - (\alpha_{GUSA} + \mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi}))\ln YA_{USi(t-1)} \\
&\quad - \mathrm{B}_{GUSKK} c_{USi} \ln YA_{USi(t-1)}.\mathrm{t} - \tfrac{1}{2}\mathrm{B}_{GUSKK}(\ln YA_{USi(t-1)})^2 - \tfrac{1}{2}\mathrm{B}_{GUSKK} c^2_{USi}\mathrm{t}^2 - \delta_i \ln g_t \\
&\quad -\alpha_{GUSA}(\ln A_{AUSi} - c_{USi}) - \tfrac{1}{2}\mathrm{B}_{GUSKK}(\ln A_{AUSi} - c_{USi})^2 \\
&\quad = -\ln A_{GUSi} + \ln G_{US0}. \qquad (10\text{-}31)
\end{aligned}$$

[20] On the assumption that $\mathrm{B}_{GUSKK}$ is not equal to zero.

Equation (10-31) may be used to generate estimates for the $A_{GUSi}$'s by substituting the estimated values of the parameters on the left-hand-side and then running a regression with only economy-specific constant terms on the right-hand-side.[21]

Finally, it is also worth noting that if $\mathrm{B}_{GUSKK} = 0$, then equation (10-27) reduces to:

$$\ln YG_{USit} = A^{*}_{GUSi} + c^{*}_{GUSi}\,\mathrm{t} + \alpha_{GUSA} \ln YA_{USi(t-1)} + \delta_i \ln g_t, \qquad (10\text{-}32)$$

$$= (-\ln A_{GUSi} + \ln G_{US0} + \alpha_{GUSA}(\ln A_{AUSi} - c_{USi})) + (-c_{GUSi} + \alpha_{GUSA} c_{USi})\mathrm{t} + \alpha_{GUSA} \ln YA_{USi(t-1)} + \delta_i \ln g_t. \; (10\text{-}33)$$

Equation (10-33) shows clearly that the level and rate parameters of the patent application and patent grant augmentation factors cannot be uniquely identified. Our first-differenced estimating equation (10-29) reduces to:

$$\ln Y\, G_{USit} - \ln Y\, G_{USi(t-1)} = c^{*}_{GUSi} + \alpha_{GUSA}(\ln YA_{USi(t-1)} - \ln YA_{USi(t-2)}) + \delta_i\, (\ln g_t - \ln g_{(t-1)}). \qquad (10\text{-}34)$$

Equation (10-33) shows clearly that $A_{GUSi}$, $A_{AUSi}$, $c_{GUSi}$ and $c_{USi}$ cannot be separately identified if $\mathrm{B}_{GUSKK} = 0$. Thus, it is also no longer possible to separately identify the USPTO patent application and patent grant augmentation factors for each economy. However, equation (10-34) can be used to generate estimates of the $c^{*}_{GUSi}$'s and to test whether they are equal across economies. Once estimates of the $c^{*}_{GUSi}$'s are available, equation (10-32) can be used to generate estimates of the $A^{*}_{GUSi}$'s and to test whether they are equal across economies.

**The Empirical Implementation**

In the empirical implementation, the U.S. is always chosen to be the numeraire economy, so that the numbers of USPTO patent applications and grants and the quantities of the real R&D capital stocks are all measured relative to the U.S. quantities at t=0. Thus, for the U.S., $A_{AUSi} = A_{GUSi} = A_{Ki} = 1$; and hence $\ln A_{AUSi} = \ln A_{GUSi} = \ln A_{Ki} = 0$.

First, we must test whether the meta-production function model is suitable for the analysis of USPTO patent applications and patent grants. This is done in two steps. In step one, we test the nonlinear restrictions referred to as the "First Necessary Condition". The joint hypothesis that all of these nonlinear restrictions on the coefficients hold for all included

[21] We should bear in mind that $A_{GUSi} = 1$ for the numeraire economy.

economies is directly tested for both USPTO patent applications and patent grants.[22] If the test for the "First Necessary Condition" is accepted, then we proceed to step two, to test the hypothesis of "Equality" of the $B_{KK}$'s (and similarly that of the $B_{GUSKK}$'s), across all economies, conditional on the "First Necessary Condition", separately for patent applications and patent grants. If this "Equality" hypothesis is also accepted for a model, then the validity of the meta-production function assumption is confirmed for that model.

Subject to the acceptance of the validity of the meta-production function model, the hypotheses of a zero coefficient for the second-order term in the translog production functions ($B_{KK}$ and $B_{GUSKK}$) are separately tested. In addition, if the hypothesis of a zero second-order term is rejected, we also test respectively the hypotheses that the rate and level parameters of the real R&D capital augmentation factors, the USPTO patent application augmentation factors, and the USPTO patent grant augmentation factors are identical across economies.[23] For the model of USPTO patent grants, we also test the equality of the $\delta_i$'s, the effects of the USPTO total grant rate, across economies.

For the hypotheses testing, we set an overall level of significance of 0.1 (10%) each for the tests of the USPTO patent application and patent grant models, which means that the probability of our falsely rejecting a hypothesis when it is true is less than or equal to 10 percent. Because of the central importance of the meta-production function model within our analysis, within the 10%, we assign a level of significance of 0.05 (5%) to the tests of its validity, divided equally between the two hypotheses necessary for its validity, the "First Necessary Condition" and the "Equality" restrictions. The remaining 0.05 (5%) is allocated over specific hypotheses on the parameters at 0.01 (1%) each.

Conditional on the validity of the meta-production function model, the first specific hypothesis to be tested is whether the second-order coefficient of the translog production function is zero. This is an important hypothesis, because, depending on its outcome, it will determine how our analysis should proceed. We assign a level of significance of 0.01 (1%) to

[22] To carry out this joint test, we need to estimate the coefficients of all selected economies in the form of a pooled regression. For the pooled regression, the data of the different economies are adjusted for heteroscedasticity, using the estimated standard errors of the unrestricted regression of the basic estimating equation of each model for each individual economy.

[23] Note that in the event of a zero coefficient for the second-order term in the translog production function ($B_{KK}$ or $B_{GUSKK}$), the parameters of the real R&D capital, patent application and patent grant augmentation factors cannot be separately identified, and consequently hypotheses on these parameters cannot be tested.

this hypothesis. If this hypothesis cannot be rejected, then it is not possible to identify the parameters of the augmentation factors and we shall have to terminate the sequence of tests. If this hypothesis is rejected, then for the patent applications model, we proceed to test the following additional hypotheses: (1) identical capital augmentation rates; (2) identical capital augmentation levels; and (3) identical patent application augmentation rates. Each of these hypotheses is tested, conditional on the validity of the meta-production function model. For the model of USPTO patent grants, we proceed to test the following additional hypotheses: (1) identical patent application augmentation rates; (2) identical patent application augmentation levels; and (3) identical patent grant augmentation rates. In addition, we also test the hypothesis of the equality of the coefficients of the USPTO total grant rate across economies. The levels of significance for each of the specific tests on the parameters are set at a uniform 0.01 (1%) each. We proceed to estimate the parameters and separately test the hypotheses for each of the two models in succession below.

**The Model for USPTO Patent Applications**

First, we estimate the model for USPTO patent applications in equation (10-13) for the six economies. We begin our analysis by testing the implied nonlinear restrictions of the joint hypothesis of the "First Necessary Condition" for the six economies. There are six restrictions, one per economy. This joint hypothesis cannot be rejected at a level of significance of 0.025. (We also test this hypothesis for each of the six economies individually. It turns out that none of these individual tests of the "First Necessary Condition" can be rejected at any reasonable level of significance. The detailed results are presented in Appendix Table A10-2.) Conditional on the acceptance of the joint test of "First Necessary Condition", the hypothesis of "Equality", that is, identical $B_{KK}$'s across all economies, is also tested. With six economies, there are five restrictions. The hypothesis of "Equality" also cannot be rejected at a level of significance of 0.025, thus confirming the validity of the meta-production function model for USPTO patent applications. The test results are reported in Table 10-1.

Given the validity of the meta-production function model for USPTO patent applications, we proceed to test whether $B_{KK}$=0, conditional on the meta-production function model. The hypothesis of $B_{KK}$= 0, with its implied 12 restrictions, cannot be rejected at the 0.01 level of significance. But $B_{KK}$=0 implies that the level and rate parameters of the USPTO patent application and the real R&D capital stock augmentation factors, $A_{AUSi}$, $c_{USi}$, $A_{Ki}$, and $c_{Ki}$ cannot be uniquely identified and therefore hypotheses about them cannot be tested.

With $B_{KK}$= 0, we proceed to estimate equation (10-17):

$$\ln YA_{USit} - \ln YA_{USi(t-1)} = c^*_{USi} + \alpha_K\left(\ln K_{it} - \ln K_{i(t-1)}\right), \quad (10\text{-}17)$$

where $c^*_{USi} \equiv (-c_{USi} + \alpha_K c_{Ki})$ and test whether the $c^*_{USi}$'s are equal across economies,[24] and if so, whether they are equal to zero. At a level of significance of 0.01, the hypothesis of equality of the $c^*_{USi}$'s cannot be rejected. In addition, the hypothesis of a common zero $c^*_{US}$ for all six economies also cannot be rejected at a level of significance of 0.01. With the $c^*_{USi}$'s being set equal to zero, we can estimate the $A^*_{AUSi}$'s from a re-arranged version of equation (10-16):

$$\ln YA_{USit} - c^*_{US}t - \alpha_K \ln K_{it} = \ln YA_{USit} - \alpha_K \ln K_{it} = A^*_{AUSi}, \qquad (10\text{-}35)$$

into the left-hand-side of which the known estimated values of the parameter $\alpha_K$ is plugged. We also test whether the $A^*_{AUSi}$'s are equal across economies,[25] and if so, whether they are equal to zero. However, we note that $A^*_{AUSi} \equiv (-\ln A_{AUSi} + \ln A_0 + \alpha_K \ln A_{Ki})$, which means that neither $A_{AUSi}$ nor $A_{Ki}$ can be uniquely identified. At a level of significance of 0.01, the hypothesis of equality of the $A^*_{AUSi}$'s can be rejected. These test results are also reported in Table 10-1.

**Table 10-1: Tests of Hypotheses, USPTO Patent Applications**

| Maintained Hypothesis | Tested Hypothesis | Level of Significance | Critical Value | Test Statistic | p-Value | Accept/Reject |
|---|---|---|---|---|---|---|
| Unconstrained | First Necessary Condition | 0.025 | 2.4593 | 1.6230 | 0.1412 | Accept |
| First Necessarty Condition | Equality of $B_{KK}$'s | 0.025 | 2.6165 | 1.7759 | 0.1182 | Accept |
| Meta-Production Function | $B_{KK} = 0$ | 0.01 | 2.2537 | 2.1972 | 0.0123 | Accept |
| Meta-Production Function with $B_{KK}$=0 | Equality of $C^*_{USi}$'s | 0.01 | 3.0851 | 1.3055 | 0.2618 | Accept |
| Meta-Production Function with $B_{KK}$=0 and identical $C^*_{USi}$'s | $C^*_{USi}$'s = 0 | 0.01 | 6.7273 | 0.5728 | 0.4498 | Accept |
| Meta-Production Function with $B_{KK}$=0 and $C^*_{US}$ = 0 | Equality of $A^*_{AUSi}$'s | 0.01 | 3.0849 | 117.3548 | 0.0000 | Reject |

Notes: $c^*_{USi} \equiv (-c_{USi} + \alpha_K c_{Ki})$; $A^*_{AUSi} \equiv (-\ln A_{AUSi} + \ln A_0 + \alpha_K \ln A_{Ki})$.

[24] Note that equality of the $c^*_{USi}$'s does not imply the equality of the $c_{USi}$'s.
[25] Similarly, the equality of the $A^*_{AUSi}$'s does not imply the equality of the $A_{USi}$'s.

We impose all the restrictions implied by the meta-production function model and all the accepted hypotheses and re-estimate all the parameters for the model of USPTO patent applications. The results are presented in Table 10-2.

**Table 10-2: Estimated Parameters of the USPTO Patent Application Production Functions**

| Parameter | Estimate | Standard Error | t-statistic | P-value |
|---|---|---|---|---|
| $C^{*}_{US}$ | 0.000 | N.A. | N.A. | N.A. |
| $\alpha_K$ | 1.132 | 0.087 | 13.004 | [.000] |
| $A^{*}_{AUSi}$'s | | | | |
| France | 2.217 | 0.067 | 33.048 | [.000] |
| Germany | 2.717 | 0.067 | 40.500 | [.000] |
| Japan | 3.156 | 0.067 | 47.049 | [.000] |
| United States | 2.971 | 0.076 | 38.945 | [.000] |
| Mainland, China | 1.028 | 0.083 | 12.449 | [.000] |
| South Korea | 3.325 | 0.074 | 45.156 | [.000] |

Table 10-2 shows that for a given quantity of real R&D capital stock, South Korea has the highest annual number of USPTO patent applications, followed by Japan; and Mainland, China has the lowest annual number, other things being equal. This may be due, in part, to the significantly lower USPTO patent application rate of Mainland China.

### The Model for USPTO Patent Grants

For the model of USPTO patent grants, we estimate equation (10-29) for all six economies. Again, we first test the "First Necessary Condition" jointly for all the included economies. This hypothesis cannot be rejected at a level of significance of 0.025. (We also test this hypothesis for each of the six economies separately. The p-values of these tests indicate that this hypothesis cannot be rejected for all six economies at any reasonable level of significance. The detailed results are presented in Appendix Table A10-3.) Conditional on the joint hypothesis of the "First Necessary Condition", the hypothesis of "Equality", that is, identical $\mathrm{B}_{GUSKK}$'s across the six economies, is tested. This hypothesis also cannot be rejected at a level of significance of 0.025, confirming the validity of the meta-production function model for USPTO patent grants. The test results are reported in Table 10-3.

Given the validity of the meta-production function model for USPTO patent grants, we proceed to test the hypothesis that $\mathrm{B}_{GUSKK}=0$.[26] The hypothesis of $\mathrm{B}_{GUSKK}=0$ cannot be rejected at a level of significance of 0.01. These results are reported in Table 10-3.

Subject to the validity of the meta-production function model, we also test whether the $\delta_i$'s are identical across economies. The equality of the $\delta_i$'s across economies implies that the effects of changes in the USPTO total grant rates affect the annual numbers of patent grants of all economies equally. This hypothesis cannot be rejected at a level of significance of 0.01.

With $\mathrm{B}_{GUSKK}=0$, it is not possible to identify the level and rate parameters of the USPTO patent grant and patent application augmentation factors, and hence to test hypotheses on them. We therefore proceed to estimate equation (10-34):

$$\begin{aligned}\ln Y\,G_{USit} - \ln Y\,G_{USi(t-1)} &= c^*_{GUSi} + \alpha_{GUSA}(\ln YA_{USi(t-1)} - \ln YA_{USi(t-2)}) \\ &\quad + \delta_i\ (\ln g_t - \ln g_{(t-1)}), \qquad (10\text{-}34)\end{aligned}$$

where $c^*_{GUSi} \equiv (-c_{GUSi} + \alpha_{GUSA} c_{USi})$. We test the hypothesis of the equality of the $c^*_{GUSi}$'s across economies in equation (10-34),[27] and if so, whether they are equal to zero. At a level of significance of 0.01, the hypothesis of equality of the $c^*_{GUSi}$'s cannot be rejected. However, the hypothesis of a common zero $c^*_{GUS}$ for all six economies can be rejected at a level of significance of 0.01. With the estimated $c^*_{GUS}$, we estimate the $A^*_{GUSi}$'s from a re-arranged version of equation (10-32), in which we have set $\delta_i = \delta$ in accordance with our test results:

$$\ln YG_{USit} - c^*_{GUS}\,\mathrm{t} - \alpha_{GUSA} \ln YA_{USi(t-1)} - \delta\ \ln g_t = A^*_{GUSi}. \qquad (10\text{-}36)$$

We plug into the left-hand-side of equation (10-36) the known estimated values of the parameters, $c^*_{GUS}$, $\alpha_{GUSA}$ and $\delta$, and run the regression on economy-specific constant terms. We also test whether the $A^*_{GUSi}$'s are equal across economies,[28] and if so, whether they are equal to zero. At a level of significance of 0.01, the hypothesis of equality of the $A^*_{GUSi}$'s can be rejected. These test results are also reported in Table 10-3.

[26] We note that if $\mathrm{B}_{GUSKK}=0$, the USPTO grant and application augmentation factors are not identifiable, and hypotheses on their level and rate parameters cannot be tested.
[27] Note that equality of the $c^*_{GUSi}$'s does not imply the equality of the $c_{GUSi}$'s.
[28] Similarly, the equality of the $A^*_{GUSi}$'s does not imply the equality of the $A_{GUSi}$'s.

**Table 10-3: Tests of Hypotheses, USPTO Patent Grants**

| Maintained Hypothesis | Tested Hypothesis | Level of Significance | Critical Value | Test Statistic | p-Value | Accept/Reject |
|---|---|---|---|---|---|---|
| Unconstrained | First Necessary Condition | 0.025 | 2.4606 | 0.2816 | 0.9453 | Accept |
| First Necessarty Condition | Equality of $B_{GUSKK}$'s | 0.025 | 2.6177 | 1.4033 | 0.2236 | Accept |
| Meta-Production Function | $B_{GUSKK}$=0 | 0.01 | 2.2554 | 1.0567 | 0.3976 | Accept |
| Meta-Production Function | Equality of $\delta_i$'s | 0.01 | 3.0900 | 0.1513 | 0.9795 | Accept |
| Meta-Production Function with $B_{GUSKK}$=0 | Equality of $C^*_{GUSi}$'s | 0.01 | 3.0867 | 2.2195 | 0.0527 | Accept |
| Meta-Production Function with $B_{GUSKK}$=0, and identical $C^*_{GUSi}$'s | $C^*_{GUSi}$'s = 0 | 0.01 | 6.7293 | 15.2893 | 0.0001 | Reject |
| Meta-Production Function with $B_{GUSKK}$=0, identical $\delta_i$'s and identical $C^*_{GUSi}$'s | Equality of $A^*_{GUSi}$'s | 0.01 | 3.0849 | 112.2517 | 0.0000 | Reject |

Notes: $c^*_{GUSi} \equiv (-c_{GUSi} + \alpha_{GUSA} c_{USi})$; $A^*_{GUSi} \equiv (-\ln A_{GUSi} + \ln G_{US0} + \alpha_{GUSA}(\ln A_{AUSi} - c_{USi}))$.

The final estimation is done with all the restrictions on the parameters implied by the meta-production function model and the accepted hypotheses imposed. The results are presented in Table 10-4.

**Table 10-4: Estimated Parameters of the USPTO Patent Grant Production Functions**

| Parameter | Estimate | Standard Error | t-statistic | P-value |
|---|---|---|---|---|
| $C^*_{GUS}$ | 0.032 | 0.008 | 3.950 | [.000] |
| $\alpha_{GUSA}$ | 0.402 | 0.087 | 4.621 | [.000] |
| $\delta$ | 1.196 | 0.141 | 8.496 | [.000] |
| $A^*_{GUSi}$'s | | | | |
| France | -1.509 | 0.105 | -14.368 | [.000] |
| Germany | -0.936 | 0.105 | -8.910 | [.000] |
| Japan | -0.504 | 0.105 | -4.798 | [.000] |
| United States | 0.189 | 0.119 | 1.580 | [.114] |
| Mainland, China | -3.223 | 0.129 | -24.943 | [.000] |
| South Korea | -2.516 | 0.115 | -21.832 | [.000] |

Table 10-4 shows that for a given annual number of USPTO patent applications, lagged one year, the United States has the highest annual number of USPTO patent grants, followed by Japan; and Mainland, China has the lowest, other things being equal. This may be due, in part, to the significantly lower USPTO patent application rate of Mainland, China.

### Summary of the Estimation Results

From equation (10-33), the annual number of USPTO patent grants of the ith economy in year t is given by:

$$\ln YG_{USit} = A^*_{GUSi} + c^*_{GUS}\,t + \alpha_{GUSA} \ln YA_{USi(t-1)} + \delta \ln g_t. \qquad (10\text{-}37)$$

From equation (10-16), the annual number of USPTO applications of the ith economy in year t is given by:

$$\ln YA_{USit} = A^*_{AUSi} + \alpha_K \ln K_{it}. \qquad (10\text{-}38)$$

Finally, by combining equations (10-37) and (10-38), we have:

$$\begin{aligned}\ln YG_{USit} &= A^*_{GUSi} + c^*_{GUS}\,t + \delta \ln g_t + \alpha_{GUSA} \ln YA_{USi(t-1)} \\ &= A^*_{GUSi} + c^*_{GUS}\,t + \delta \ln g_t + \alpha_{GUSA}(A^*_{AUSi} + \alpha_K \ln K_{i(t-1)}) \\ &= A^*_{GUSi} + \alpha_{GUSA}A^*_{AUSi} + c^*_{GUS}\,t + \delta \ln g_t + \alpha_{GUSA}\alpha_K \ln K_{i(t-1)}. \qquad (10\text{-}39)\end{aligned}$$

It is interesting to compare the estimated values of ($A^*_{GUSi} + \alpha_{GUSA}A^*_{AUSi}$), calculated from Tables 10-2 and 10-4, across the six economies. This is done in Table 10-5:

**Table 10-5: Estimated Values of the Economy-Specific Constants in the USPTO Patent Grants Production Functions**

| Economy | $A^*_{GUSi}$ | $\alpha_{GUSA}$ | $A^*_{AUSi}$ | $A^*_{GUSi} + \alpha_{GUSA}\,A^*_{AUSi}$ |
|---|---|---|---|---|
| **France** | **-1.509** | **0.402** | **2.217** | **-0.618** |
| **Germany** | **-0.936** | **0.402** | **2.717** | **0.156** |
| **Japan** | **-0.504** | **0.402** | **3.156** | **0.764** |
| **United States** | **0.189** | **0.402** | **2.971** | **1.382** |
| **Mainland, China** | **-3.223** | **0.402** | **1.028** | **-2.810** |
| **South Korea** | **-2.516** | **0.402** | **3.325** | **-1.180** |

The last column of Table 10-5 also shows that for a given quantity of real R&D capital stock of the preceding year, the United States has the highest annual number of USPTO patent grants, followed by Japan, and Mainland, China the lowest, other things being equal. This may also be due, in part, to the significantly lower USPTO patent application rate of Mainland China.

This completes our estimation of the econometric models of USPTO patent applications and patent grants. We note that the final model yields statistically significant estimates of the parameters. The analysis and interpretation of the empirical results will be presented in Chapter 11 below.

## Appendix

**Table A10-1: The Beginning and Ending Years of the Data for the Six Economies in Chapters 10 and 11**

| Economy | Beginning Year | Ending Year |
|---|---|---|
| France | 1967 | 2019 |
| Germany | 1967 | 2019 |
| Japan | 1967 | 2019 |
| U.S. | 1979 | 2019 |
| Mainland, China | 1985 | 2019 |
| South Korea | 1976 | 2019 |

**Table A10-2: Economy-Specific Tests of the First Necessary Condition for the Validity of the Meta-Production Function Model, USPTO Patent Applications (Six Economies)**

| Economy | Test Statistic | p-Value | Accept/Reject |
|---|---|---|---|
| France | 1.6022 | 0.2117 | Accept |
| Germany | 0.0492 | 0.8254 | Accept |
| Japan | 0.0612 | 0.8057 | Accept |
| U.S. | 0.7689 | 0.3864 | Accept |
| Mainland, China | 0.0308 | 0.8618 | Accept |
| South Korea | 2.5009 | 0.1219 | Accept |

**Table A10-3: Economy-Specific Tests of the First Necessary Condition for the Validity of the Meta-Production Function Model, USPTO Patent Grants (Six Economies)**

| Economy | Test Statistic | p-Value | Accept/Reject |
|---|---|---|---|
| France | 0.3943 | 0.5331 | Accept |
| Germany | 0.5151 | 0.4765 | Accept |
| Japan | 0.5486 | 0.4626 | Accept |
| U.S. | 0.0110 | 0.9171 | Accept |
| Mainland, China | 0.2697 | 0.6075 | Accept |
| South Korea | 0.3485 | 0.5585 | Accept |

## Chapter 11: The Research Findings

The econometric analysis in Chapter 10 indicates that, at the economy level, there appears to be a "Law of Innovation" that is common to the six economies analysed. Innovation, measured in terms of the annual numbers of United States Patent and Trademark Office (USPTO) patent applications and patent grants, appears to depend on the quantity of real investment in Research and Development (R&D) and in particular on the quantity of the accumulated real R&D capital stock, in a similar and statistically significant, though not completely identical, manner across the six economies in our study—Mainland China, France, Germany, Japan, South Korea, and the U.S., all economies with their numbers of domestic patent applications exceeding their numbers of USPTO patent applications.

On the whole, the meta-production function models for the USPTO patent applications and patent grants fit the data of all the included economies reasonably well, except for China (see below). We have not attempted to model the domestic patent application and grant behaviour of our selected economies because the diversity in their propensities to apply for and to award patents makes it virtually impossible for a single meta-production function model to capture it adequately.

From the results of our estimation of the econometric models in Chapter 10 above, we can calculate the values of the elasticities of the annual number of USPTO patent applications with respect to the quantity of real R&D capital stock as well as the elasticities of the annual number of USPTO patent grants with respect to the lagged annual number of USPTO patent applications, and ultimately the elasticities of the annual number of USPTO patent grants with respect to the lagged quantity of real R&D capital stock of the individual economies. According to equation (10-37), the annual number of USPTO patent grants of the ith economy at year t, $\ln YG_{USit}$, is given by:

$$\ln YG_{USit} = A^{*}_{GUSi} + c^{*}_{GUS}\,t + \alpha_{GUSA} \ln YA_{USi(t-1)} + \delta \ln g_t$$

$$= A^{*}_{GUSi}{}^{[29]} + \underset{(0.008)^{[30]}}{0.032}\,t + \underset{(0.087)}{0.402} \ln YA_{USi(t-1)} + \underset{(0.141)}{1.196} \ln g_t, \quad (11\text{-}1)$$

where the estimated values of the parameters and their standard errors are taken from Table 10-4, which have incorporated all the restrictions implied by the accepted hypotheses.

[29] The estimates of the $A^{*}_{GUSi}$'s of specific economies are presented in Table 10-4.
[30] Numbers in parentheses are estimated standard errors.

Differentiating equation (11-1) partially with respect to $\ln YA_{USi(t-1)}$, we obtain the elasticity of the annual number of USPTO patent grants with respect to the annual number of USPTO patent applications in the previous year of the ith economy, holding the year, t, and the USPTO total patent grant rate constant:

$$\frac{\partial \ln YG_{USit}}{\partial \ln YA_{USi(t-1)}} = \alpha_{GUSA} = 0.402. \qquad (11\text{-}2)$$

Thus, all six economies have the same estimated elasticity. Differentiating equation (11-1) partially with respect to time, t, we obtain the rate of growth of the annual number of USPTO patent grants, holding the annual number of USPTO patent applications in the previous year of the ith economy and the USPTO total patent grant rate constant. The rate of growth also turns out to be the same for all six economies:

$$\frac{\partial \ln YG_{USit}}{\partial \mathrm{t}} = c^*_{GUS} = 0.032 \text{ or } 3.2\%. \qquad (11\text{-}3)$$

The annual number of USPTO patent applications of the ith economy in year t, $\ln YA_{USit}$ , is, according to equation (10-38), given by:

$$\ln YA_{USit} = A^*_{AUSi} + c^*_{US}\mathrm{t} + \alpha_K \ln K_{it}$$

$$= A^*_{AUSi}{}^{31} + \underset{(0.087)}{1.132} \ln K_{it}. \qquad (11\text{-}4)$$

Differentiating equation (11-4) partially with respect to $\ln K_{it}$, we obtain the elasticity of the annual number of USPTO patent applications with respect to the quantity of real R&D capital stock, holding t constant:

$$\frac{\partial \ln YA_{USit}}{\partial \ln K_{it}} = \alpha_K = 1.132. \qquad (11\text{-}5)$$

Thus, all six economies also have the same estimated elasticity. Differentiating equation (11-4) partially with respect to t, holding the quantity of real R&D capital stock constant, we obtain zero:

$$\frac{\partial \ln YA_{USit}}{\partial \mathrm{t}} = 0. \qquad (11\text{-}6)$$

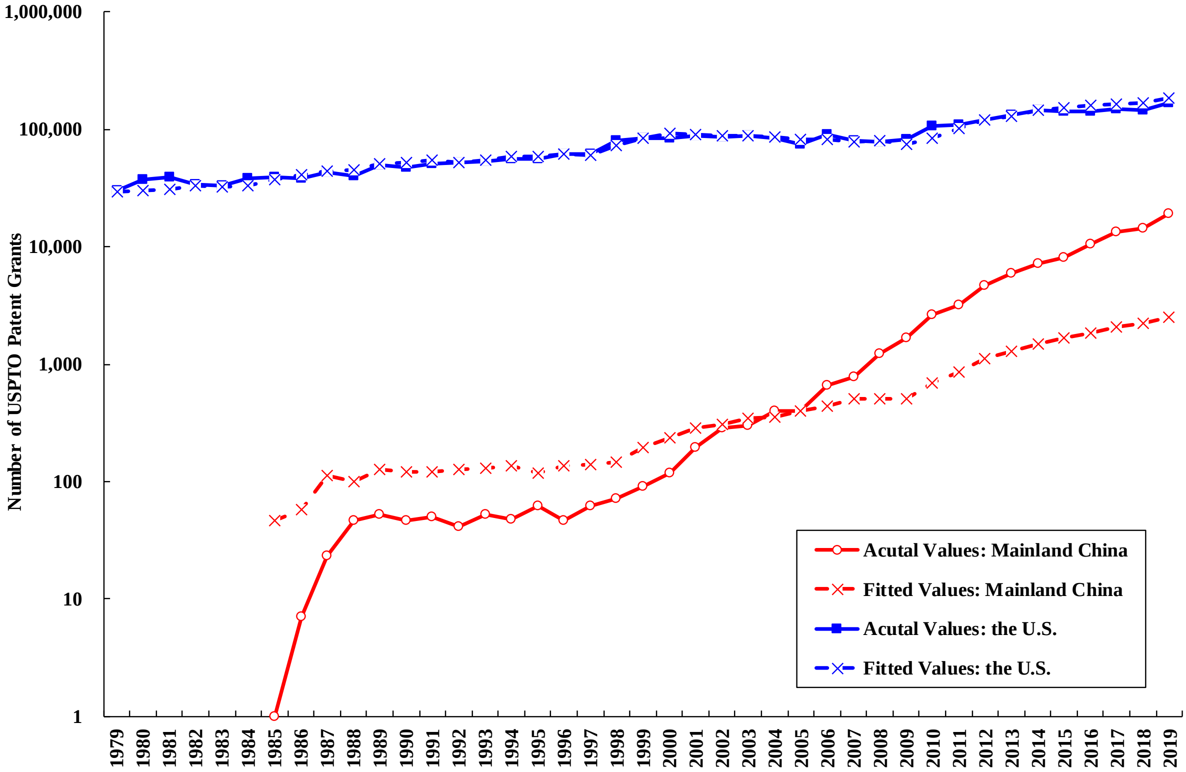
This implies that there is no autonomous growth in the annual number of USPTO applications without the growth of the quantity of the real R&D capital stock.

It is of interest to see how well equations (11-1) and (11-4) fit the actual data. In Chart 11-1, the actual and fitted values of the annual numbers of USPTO patent grants of both

[31] The estimates of the $A^*_{USi}$'s of specific economies are taken from Table 10-2.

Mainland China and the U.S. (from equation (11-1)) are plotted against time. The goodness of fit of the annual number of USPTO patent grants of the U.S. is excellent. However, the goodness of fit of the annual number of USPTO patent grants of Mainland China is quite poor. There is significant over-estimation before 2004 and significant under-estimation since. We believe this is due to the abrupt change in the annual rate of growth of the number of USPTO patent grants awarded to Mainland China, from virtually zero to an average of over 26%, beginning in1996. Even the addition of an economy-specific time-trend term in equation (11-1) would not have been able to reflect this.

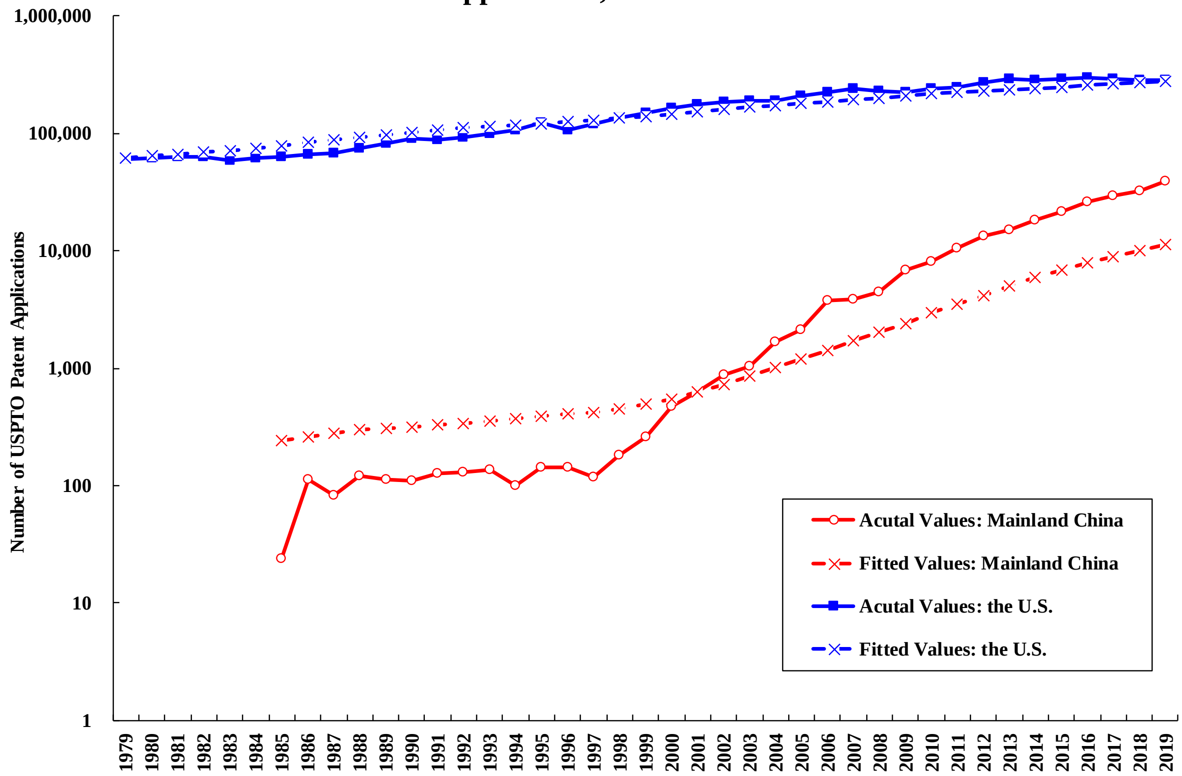
**Chart 11-1: The Actual and Fitted Values of the Annual Numbers of USPTO Patent Grants, Mainland China and the U.S.**




Source: Data on the actual values of annual numbers of USPTO patent grants are from Table5A-2 and the fitted values are based on authors' calculations.

In Chart 11-2, the actual and fitted values of the annual numbers of USPTO patent applications of both Mainland China and the U.S. (from equation (11-4)) are plotted against time. The goodness of fit of the annual number of USPTO patent applications of the U.S. is not bad, but there is a systematic bias—over-estimation before 1997 and under-estimation thereafter. The goodness of fit of the annual number of USPTO patent applications of Mainland China is just as poor as its annual number of USPTO patent grants in Chart 11-1. There is significant over-estimation before 2001 and significant under-estimation since. We believe this is also due to the very abrupt and rapid rise in the number of USPTO patent applications from Mainland China beginning in the late 1990s as well as the absence of an economy-specific time trend term in equation (11-4).

**Chart 11-2: The Actual and Fitted Values of the Annual Number of USPTO Patent Applications, Mainland China and the U.S.**



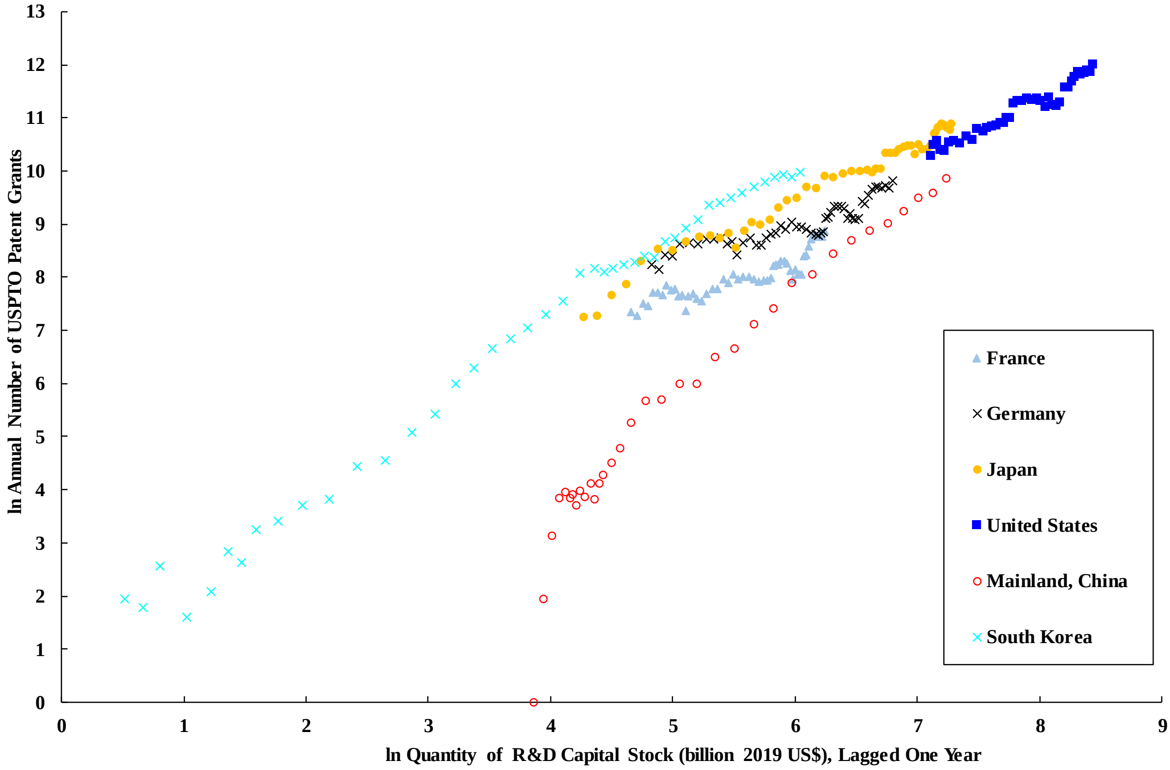

Source: Data on actual values of annual numbers of USPTO patent grants are from Table5A-1 and the fitted values are based on authors' calculations.

Actually, the annual number of USPTO patent grants awarded to the ith economy is indirectly a function of the quantity of real R&D capital stock, lagged one year. It is, according to equation (10-39), given by:

$$\ln YG_{USit} = (A^*_{GUSi} + \alpha_{GUSA} A^*_{AUSi}) + c^*_{GUS}\mathrm{t} + \delta \ln g_t + \alpha_{GUSA}\alpha_K \ln K_{i(t-1)}. \quad (11\text{-}7)$$

In Chart 11-3, the natural logarithm of the annual number of USPTO patent grants is plotted against the natural logarithm of the quantity of real R&D capital stock, lagged one year. Chart 11-3 provides prima facie evidence that there exists a stable, positive relationship between the annual number of USPTO patent grants of the ith economy and its lagged quantity of real R&D capital stock, across economies and over time. However, the relationship appears stronger and more similar for the developed economies than for Mainland China and South Korea.

**Chart 11-3: The Natural Logarithm of the Annual Number of USPTO Patent Grants versus the Natural Logarithm of the Quantity of Real R&D Capital Stock, Lagged One Year**




Source: Authors' calculations. Data on the annual numbers of USPTO patent grants are from Table A5-2 and data on the quantities of R&D capital stocks are from Table A3-2.

Differentiating equation (11-7) partially with respect to $\ln K_{i(t-1)}$, we obtain the elasticity of the annual number of USPTO patent grants with respect to the quantity of real R&D capital stock of the previous year of the ith economy, holding the year t and the USPTO total patent grant rate constant:

$$\frac{\partial \ln YG_{USit}}{\partial \ln K_{i(t-1)}} = \alpha_{GUSA}\alpha_K = 0.402 \times 1.132 = 0.455. \qquad (11\text{-}8)$$

Once again, all six economies also have the same estimated elasticity. Differentiating equation (11-7) partially with respect to t, we obtain the rate of growth of the annual number of USPTO patent grants of the ith economy, holding the quantity of its lagged real R&D capital stock and the USPTO total grant rate constant:

$$\frac{\partial \ln YG_{USit}}{\partial t} = c^*_{GUS} = 0.032 \text{ or } 3.2\%. \qquad (11\text{-}9)$$

More specifically, we find that, on average, a ten-percent increase in the quantity of real R&D capital stock of the preceding year increases the annual number of USPTO patent grants by 4.55 percent, that is, an elasticity of 0.455. In addition, a ten-percent increase in the quantity of real R&D capital stock increases the annual number of USPTO patent applications grants by 11.32 percent, that is, an elasticity slightly greater than one. Overall, it confirms the importance of investment in R&D for the occurrence of innovation.

However, there is a question on the disparity between these two estimated elasticities, granted that they actually refer to different things. One would have expected that the elasticity of the annual number of patent grants with respect to the annual number of patent applications should be closer to one. One possible explanation for the relatively low estimated elasticity may be due to the fact that in equation (10-37) (and equation (11-1)), only the annual number of USPTO patent applications lagged one year is included on the right-hand-side. In actual fact, the number of patent grants in a given year may also depend on the number of patent applications submitted more than one year ago. In order to try to address this issue, we augment equation (11-1) as:

$$\ln YG_{USit} = A^{*}_{GUSi} + c^{*}_{GUS}\,t + \alpha_{GUSA} \ln YA_{USi(t-1)} + \alpha_{GUSA1} \ln YA_{USi(t-2)} + \delta\, \ln g_t, \qquad (11\text{-}10)$$

adding an independent variable, the number of USPTO patent applications lagged two years. Lagging equation (11-10) by one period and subtracting it from equation (11-10), we obtain:

$$\ln YG_{USit} - \ln YG_{USi(t-1)} = c^{*}_{GUS} + \alpha_{GUSA}(\ln YA_{USi(t-1)} - \ln YA_{USi(t-2)})$$
$$+ \alpha_{GUSA1}(\ln YA_{USi(t-2)} - \ln YA_{USi(t-3)}) + \delta\, (\ln g_t - \ln g_{(t-1)}), \qquad (11\text{-}11)$$

which is then estimated. Plugging these estimated parameters into equation (11-10), and moving everything except the economy-specific constant terms to the left-hand-side, we can obtain new estimates of the $A^{*}_{GUSi}$'s. The estimated results are presented in Table 11-1.

**Table 11-1: The Estimated Parameters of Equation (11-11)**

| Parameter | Estimate | Standard Error | t-statistic | P-value |
|---|---|---|---|---|
| $C^*_{GUS}$ | **0.016** | **0.008** | **1.879** | **[.060]** |
| $\alpha_{GUSA}$ | **0.296** | **0.082** | **3.635** | **[.000]** |
| $\alpha_{GUSA1}$ | **0.516** | **0.081** | **6.337** | **[.000]** |
| $\delta$ | **1.252** | **0.135** | **9.260** | **[.000]** |
| $A^*_{GUSi}$ **'s** | | | | |
| **France** | **-4.558** | **0.041** | **-111.180** | **[.000]** |
| **Germany** | **-4.391** | **0.041** | **-107.112** | **[.000]** |
| **Japan** | **-4.223** | **0.041** | **-103.012** | **[.000]** |
| **United States** | **-4.098** | **0.047** | **-87.680** | **[.000]** |
| **Mainland, China** | **-5.227** | **0.051** | **-103.103** | **[.000]** |
| **South Korea** | **-4.984** | **0.045** | **-110.556** | **[.000]** |

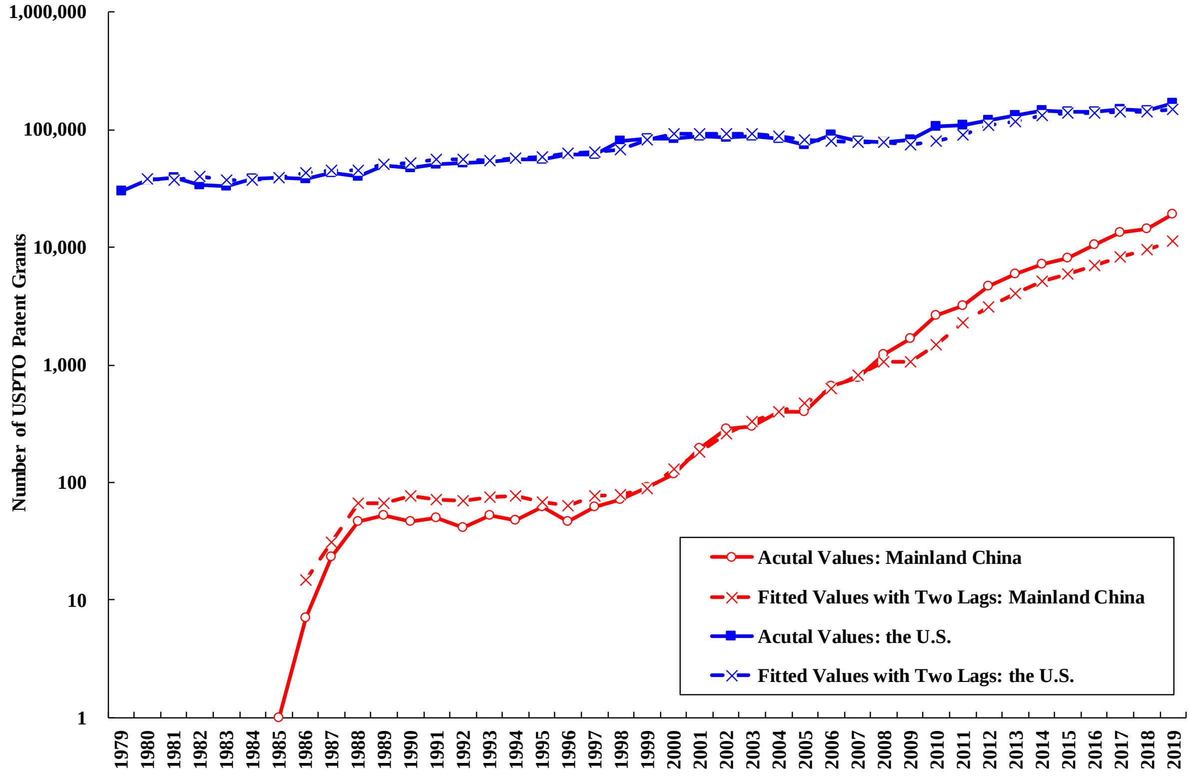
Substituting the estimated parameters in Table 11-1 into equation (11-10), we obtain:

$$\ln YG_{USit} = A^*_{GUSi}{}^{32} + \underset{(0.008)^{33}}{0.016}.\mathrm{t} + \underset{(0.082)}{0.296}\ln YA_{USi(t-1)} + \underset{(0.081)}{0.516}\ln YA_{USi(t-2)} + \underset{(0.135)}{1.252}\ln g_t. \quad (11\text{-}12)$$

Using equation (11-12), we construct a Chart 11-4, presenting both the actual and fitted values of the annual numbers of USPTO patent grants for both Mainland China and the U.S. A comparison of Chart 11-1 and Chart 11-4 shows a much-improved fit of the annual number of USPTO patent grants for Mainland China[34] and the same excellent fits for the U.S.

[32] The estimates of the $A^*_{GUSi}$'s of specific economies are taken from Table 11-1.
[33] Numbers in parentheses are estimated standard errors.
[34] Even though there is over-estimation before 1998 and under-estimation after 2008.

**Chart 11-4: The Actual and Fitted Values of the Annual Numbers of USPTO Patent Grants, Mainland China and the U.S. with Estimated Parameters from Table 11-1**




Combining equations (11-10) and (11-4), we obtain:

$$\ln YG_{USit} = A^{*}_{GUSi} + c^{*}_{GUS}\,\mathrm{t} + \alpha_{GUSA} \ln YA_{USi(t-1)} + \alpha_{GUSA1} \ln YA_{USi(t-2)} + \delta\ \ln g_t,$$

$$= A^{*}_{GUSi} + c^{*}_{GUS}\mathrm{t} + \alpha_{GUSA}(A^{*}_{AUSi} + 1.132 \ln K_{i(t-1)}) + \alpha_{GUSA1}(A^{*}_{AUSi} + 1.132 \ln K_{i(t-2)})$$

$$+ \delta\ \ln g_t$$

$$= (A^{*}_{GUSi}{}^{35} + (\alpha_{GUSA} + \alpha_{GUSA1})A^{*}_{AUSi}{}^{36}) + \underset{(0.008)^{37}}{0.016}.\mathrm{t}$$

$$+ \underset{(0.087)}{1.132} \times (\underset{(0.082)}{0.296} \ln K_{i(t-1)} + \underset{(0.081)}{0.516} \ln K_{i(t-2)}) + \underset{(0.135)}{1.252}\ \ln g_t. \qquad (11\text{-}13)$$

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[35] The estimates of the $A^{*}_{GUSi}$'s of specific economies are taken from Table 11-1.
[36] The estimates of the $A^{*}_{USi}$'s of specific economies are taken from Table 10-2.
[37] Numbers in parentheses are estimated standard errors.

In steady state, $K_{i(t-1)} = K_{i(t-2)} = K_i$, so that the partial derivative of $\ln YG_{USit}$ with respect to $K_i$, that is, the elasticity of the annual number of USPTO patent grants with respect to the real R&D capital stock, is given by $(\alpha_{GUSA} + \alpha_{GUSA1}) \times 1.132 = (0.296 + 0.516) \times 1.132 = 0.919$. slightly less than one.[38] Differentiating equation (11-13) with respect to t, we obtain:

$$\frac{\partial \ln YG_{USit}}{\partial \mathrm{t}} = c^{*}_{GUS} = 0.016 \text{ or } 1.6\%. \qquad (11\text{-}14)$$

This is the autonomous rate of growth of the number of USPTO patent grants, holding all other variables constant. However, we believe this reflects the residual effects of patent applications submitted more than two years ago.

**The Economies of Scale of R&D**

R&D is an activity that is believed to exhibit inherent economies of scale. Doubling the R&D resources is believed to more than double the probability of a discovery or invention, since it is then possible to pursue the same objective from two or more different directions. However, it may also create competition for the scarce R&D resources, such as R&D manpower and critical equipment, which may in some cases lower the probability of a discovery or invention. We estimate below the degree of local returns to scale in real R&D capital stock among the economies in our study. Given a production function Y = F(X), where Y is the quantity of output and X is a vector of quantities of inputs, the existence of economies of scale implies that F(λX) > λF(X), for any positive scalar λ, λ>1, that is, any expansion of the quantities of inputs will result in a more than proportionate increase in the quantity of output. The degree of local returns to scale at X is given by $\frac{\partial \ln \mathrm{F}(\lambda \mathrm{X})}{\partial \ln \lambda}\ _{\lambda=1}$. If X is a scalar variable, then $\frac{\partial \ln \mathrm{F}(\lambda \mathrm{X})}{\partial \ln \lambda}\ _{\lambda=1} = \frac{\partial \ln \mathrm{F}(\lambda \mathrm{X})}{\partial \ln \mathrm{X}}\ _{\lambda=1} = \frac{d \ln \mathrm{F}(\mathrm{X})}{d \ln \mathrm{X}}$.

Thus, the degree of local returns to scale in the production of USPTO patent applications from real R&D capital stock is given by the elasticity in equation (11-5), 1.132, indicating a slightly increasing returns to scale. The degree of local returns to scale in the production of USPTO patent grants from real R&D capital stock from equation (11-8), is given by the elasticity, 0.455. Taken by itself, there appear to be significantly decreasing returns to

[38] We believe this number would be even closer to one if we had included a third lagged number of USPTO patent applications in equation (11-10).

scale. However, using the estimation results of in Table 11-1, the annual number of USPTO patent grants is indirectly a function of the quantities of the real R&D capital stocks, lagged one and two years respectively, as in equation (11-13). In steady state, the elasticity of the annual number of USPTO patent grants with respect to the quantity of real R&D capital stock is estimated to be 0.919, indicating slightly decreasing returns to scale. There does not appear to be any evidence of significant increasing returns to scale to investment in R&D.

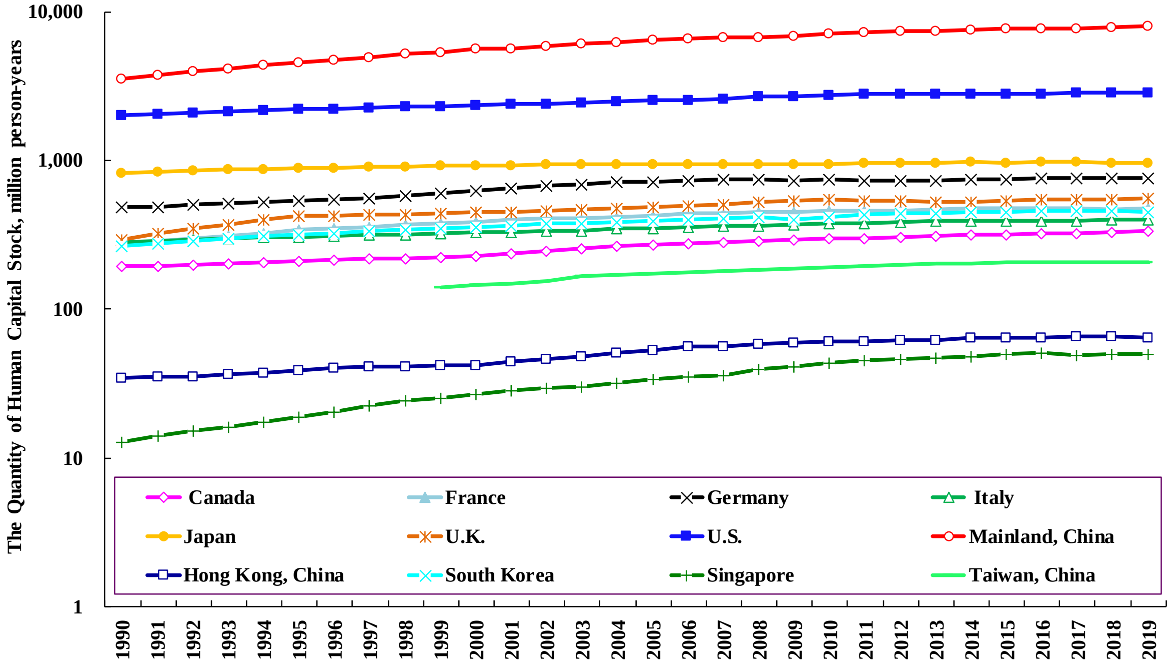
## Chapter 12: Complementary Inputs to R&D Capital

In addition to real R&D capital, complementary inputs, such as R&D researchers, are needed to produce innovation. Complementary inputs are also needed, in addition to real R&D capital, in order to produce real GDP in an economy. What are some complementary inputs to real R&D capital? At the microeconomic level, there are, of course, the R&D researchers and the physical R&D infrastructure, such as structures and equipment. However, we should note that R&D expenditure per se already includes the total cost of the human resources employed in the R&D activities as well as the investment in R&D-related structures and equipment. Thus, only the current-period R&D manpower input should be considered a complementary input in R&D activities to avoid double-counting.

At the macroeconomic level, within an aggregate production function framework, there are of course the conventional inputs of production: tangible capital, labour, and human capital. Human capital, in particular, should be complementary to R&D capital, since R&D activities must be carried out and its results applied and implemented by educated (including some highly educated), experienced, and skilled workers. In Chart 12-1, the quantity of human capital of each economy in our study, measured as the total number of person-years of schooling (including tertiary education) among the working-age population, defined as those aged between 15 and 64, are presented. However, as comparable data on the mean years of schooling of the working-age population are not readily available across economies, instead, we use the mean years of schooling achieved by people aged 25 and above and multiply it to the total working-age population. This is likely to result in a downward bias in our estimates of the total quantity of human capital, especially for economies with a rapidly expanding educational system at the primary and secondary levels.[39] Chart 12-1 shows that Mainland China has the highest total quantity of human capital, primarily on the basis of its large population, followed by the U.S. and Japan.

[39] Typically, the number of years of schooling changes very little over time for an individual aged 25 and above.

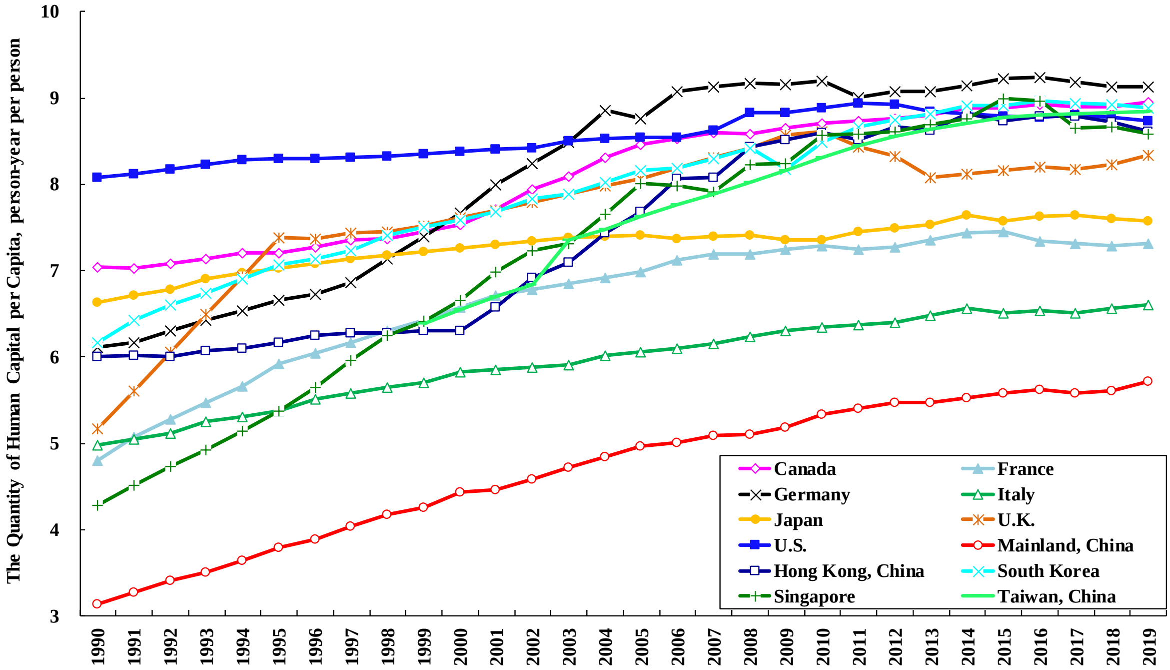
**Chart 12-1: The Quantity of Human Capital (Total Person-Years of Education), G-7 Countries, Mainland China, and 4 EANIEs**




Source: Data are collected from Human Development Reports, United Nations Development Programme, and the Directorate General of Budget, Accounting and Statistics, Taiwan, China.

In Chart 12-2, we compare the quantities of human capital across the economies in our study on a per capita basis. Chart 12-2 shows that the U.S. was the leader in terms of human capital per capita until 2003, when it was overtaken by Germany. As of 2019, Germany remained the leader, followed by Canada, South Korea and Taiwan, China. The U.S. fell to fifth place. Mainland China is in the last place among our economies. Despite significant increases in the total number of person-years of education for Mainland China in recent decades, the quantity of Chinese human capital in per capita terms is still relatively low, especially because our measurement includes only the school-years of those aged 25 and above and hence cannot reflect the huge expansion of the tertiary education sector in Mainland China in the past decade or so. It will take another couple of decades before the quantity of Mainland Chinese human capital per capita can catch up to the level of the G-7 economies.

**Chart 12-2: The Quantity of Human Capital per Capita,
G-7 Countries, Mainland China, and 4 EANIEs (person-years per person)**



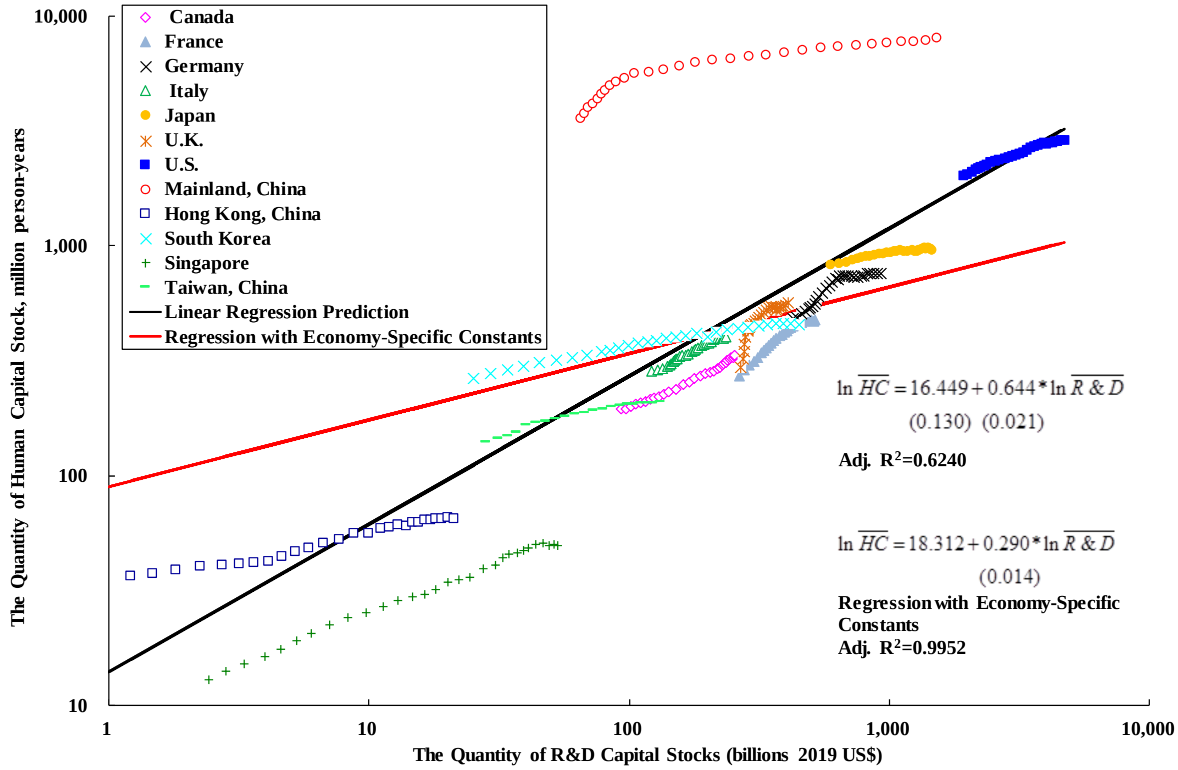

Source: Same as Chart 12-1.

In Chart 12-3, we plot a scatter diagram between the total quantity of human capital, measured in terms of person-years of education, and the quantity of real R&D capital stock in the same year. Chart 12-3 shows a very diverse scatter. The ratio of human capital to real R&D capital varies greatly across economies and over time. If they were constant across economies, the scatter points should all lie on the same straight line. However, Chart 12-3 clearly shows that, overall, the quantities of human capital and real R&D capital are positively correlated—the more real R&D capital, the more human capital, and vice versa. The G-7 economies as a group do appear to have similar elasticities of human capital with respect to R&D capital. Among the East Asian economies other than Japan, there is a wide spread, with Mainland China having the highest ratio of human capital to R&D capital and Singapore the lowest. The goodness of fit of the simple linear regression of the natural logarithm of the quantity of human capital on the natural logarithm of the quantity of real R&D capital is relatively poor (the black line), reflecting the significant diversity among the economies, but the linear regression with economy-specific constants has a much better fit (the red line).[40] The elasticity of human capital with respect to R&D capital does not seem to vary significantly

[40] The red line in Chart 12-3 is drawn with a constant term set equal to the weighted average of all the economy-specific constants with the shares of the number of observations of each economy in the total number of observations as weights.

across economies, and a ten-percent increase in the real R&D capital of an economy is associated with an approximately three-percent increase in its human capital.

**Chart 12-3: A Scatter Diagram between the Quantity of Human Capital and the Quantity of Real R&D Capital Stock, G-7 Countries, Mainland China, and 4 EANIEs**

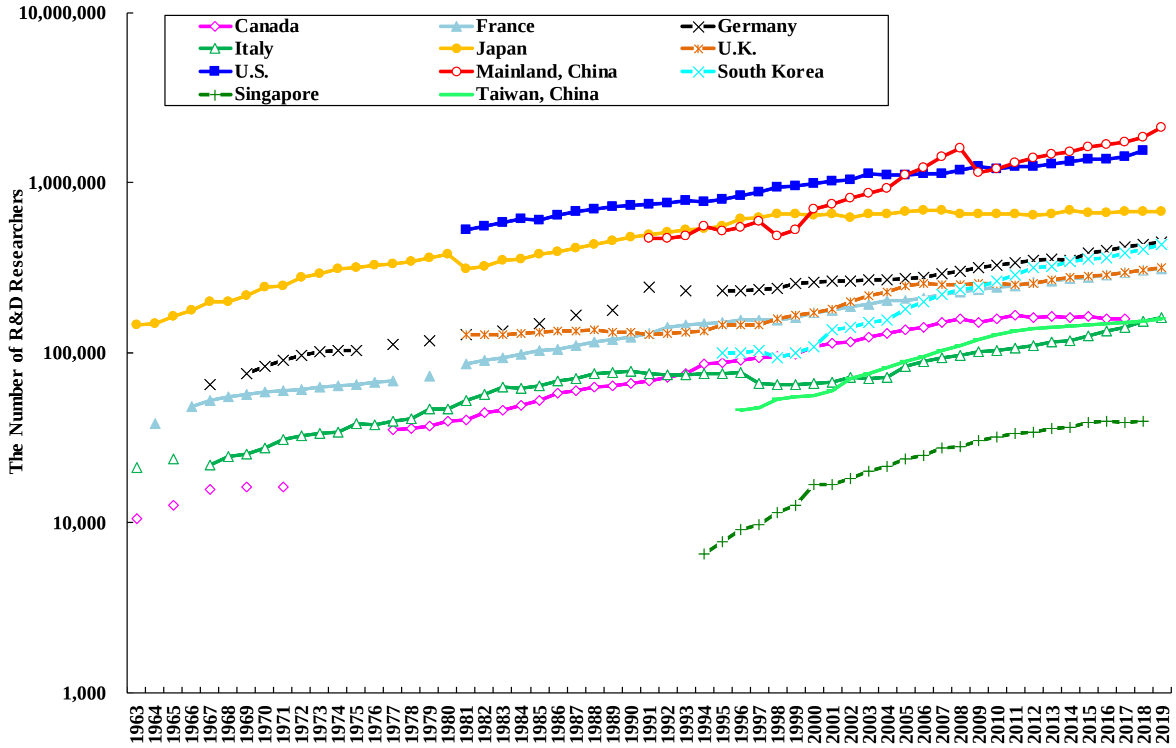



Source: Data are collected from Human Development Reports, United Nations Development Programme, and the Directorate General of Budget, Accounting and Statistics, Taiwan, China. The quantities of R&D capital stocks are from Table A3-2.

At a more microeconomic level, the number of R&D researchers in an economy is important, because these are the actual people who have to carry out the R&D activities. However, R&D researchers per se constitute only a small proportion of the scientists and engineers in an economy. In Chart 12-4, the total number of R&D researchers, including researchers in (1) natural sciences and engineering,[41] (2) social science, humanities, and the arts, and (3) not elsewhere classified, are presented and compared across economies.[42] The number of R&D researchers does not include other R&D personnel such as technicians and other support staff. Traditionally, the U.S. had the highest number of R&D researchers. However, Mainland, China has been catching up very fast and has overtaken the U.S. in 2010.

[41] Data for ONLY the number of scientists and engineers are not readily available.
[42] Data for Hong Kong, China are not readily available.

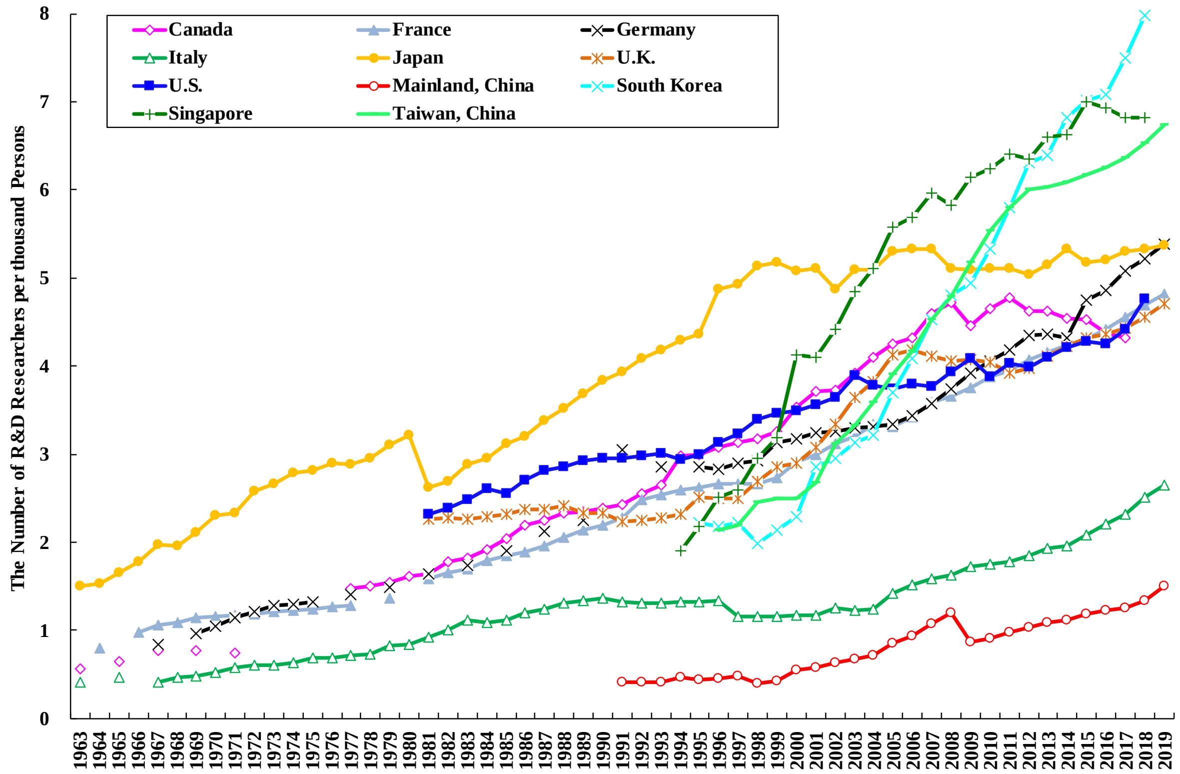
**Chart 12-4: The Number of R&D Researchers, G-7 Countries, Mainland China, and 3 EANIEs**




Source: The number of R&D researchers are collected from Main Science and Technology Indicators, OECD.

In Chart 12-5, we compare the number of R&D researchers of the economies in our study on a per capita basis. Chart 12-5 shows that despite significant increases in the total number of R&D researchers in Mainland China, the number of Mainland Chinese R&D researchers is still low in per capita terms. In fact, it is the lowest in our sample of economies, due, in part, to its large population. It will probably take decades before the number of Chinese R&D researchers per capita can catch up to the level of the G-7 economies.

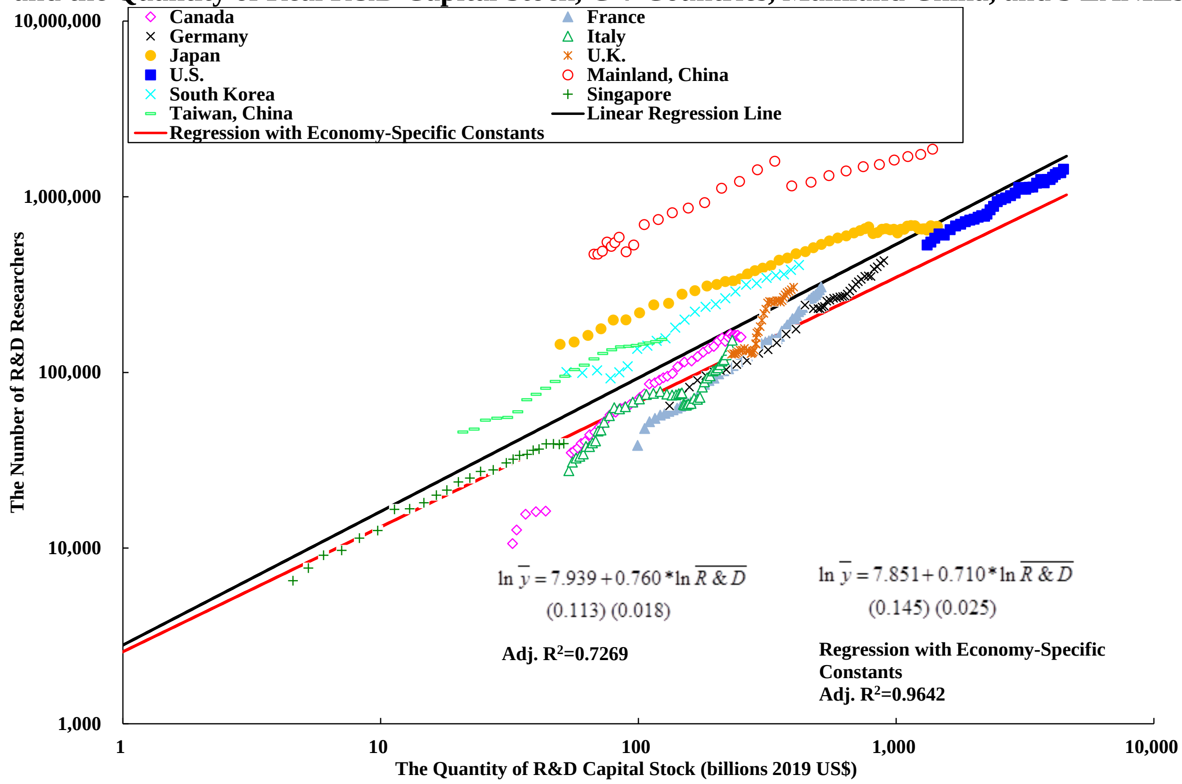
**Chart 12-5: The Number of R&D Researchers per Capita, G-7 Countries, Mainland China, and 3 EANIEs**




Source: Authors' calculations. The number of R&D researchers are collected from Main Science and Technology Indicators, OECD. The population data are from International Financial Statistics (Canada, France, Germany, Italy, Japan, South Korea, Singapore and U.K.), World Development Indicators (U.S.), and the local statistical agencies (Mainland China, Hong Kong, China and Taiwan, China).

In Chart 12-6, we plot a scatter diagram between the total number of R&D researchers and the quantity of real R&D capital stock in the same year. Chart 12-6 shows that overall, the number of R&D researchers and the quantity of real R&D capital stock are positively correlated. Moreover, the correlation appears to be tighter than that between human capital and real R&D capital in Chart 12-3, which is what should be expected. The elasticity of the number of R&D researchers with respect to the quantity of real R&D capital is approximately greater than 0.7, that is, a ten-percent increase in real R&D capital is likely to result in a more-than-seven-percent increase in the number of R&D researchers. However, Mainland China appears to have a lower real R&D capital to R&D researcher ratio than all the other economies. This may perhaps be due in part to the lower cost of R&D labour relative to real R&D capital in Mainland China.

**Chart 12-6: A Scatter Diagram between the Number of R&D Researchers and the Quantity of Real R&D Capital Stock, G-7 Countries, Mainland China, and 3 EANIEs**



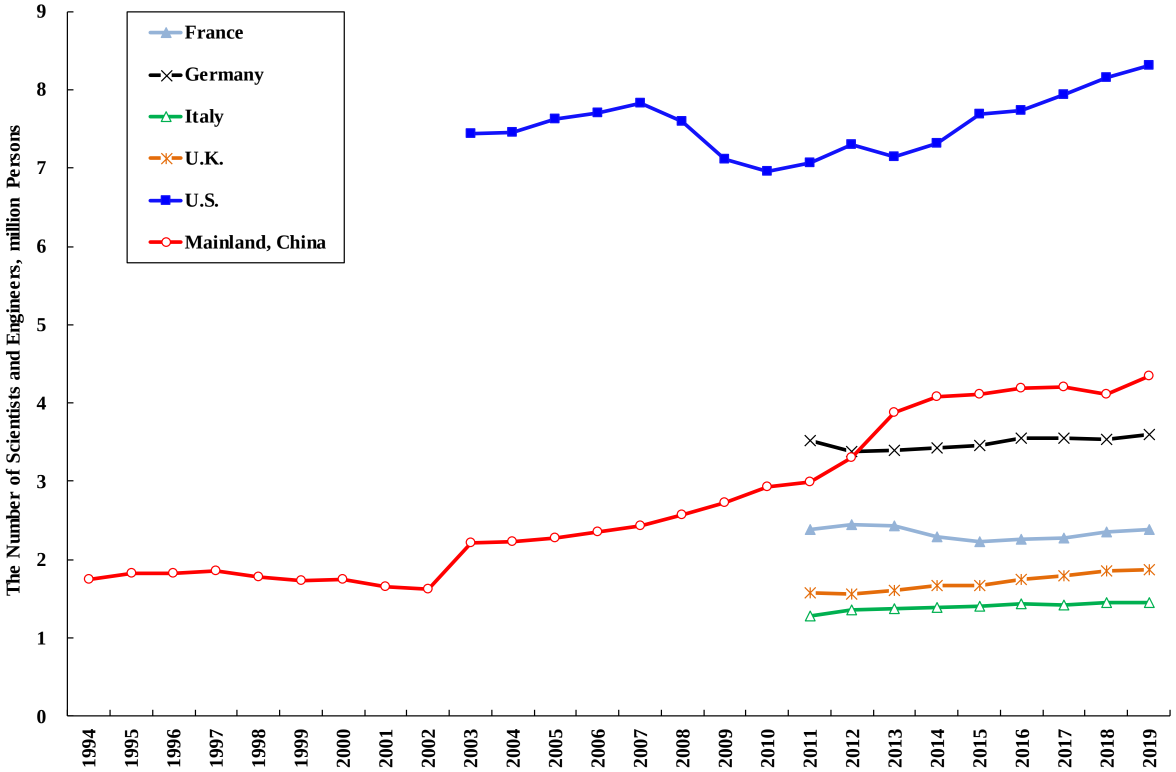

Sources: The number of R&D researchers are collected from Main Science and Technology Indicators, OECD. The quantities of R&D capital stocks are from Table A3-2.

An important determinant of whether innovation can enhance the actual rate of technical progress of an economy is its total number of scientists and engineers, because these are the people who have to implement the discoveries and inventions in actual manufacturing and other productive activities downstream from R&D. In fact, the proportion of scientists and engineers directly engaged in R&D activities is probably a small percentage of the total. In Chart 12-7, the total numbers of scientists and engineers of selected economies in our sample are compared.[43] Chart 12-7 shows that the U.S. has by far the highest number of scientists and engineers, followed by Mainland China and Germany.[44]

[43] Unfortunately, it is not possible to compare the number of scientists and engineers across all the economies in our sample because the data are not readily available for some of them.

[44] The definition of "scientists and engineers" in Chinese statistics may not be exactly the same as that used by the International Labour Organization. However, we believe they are broadly comparable.

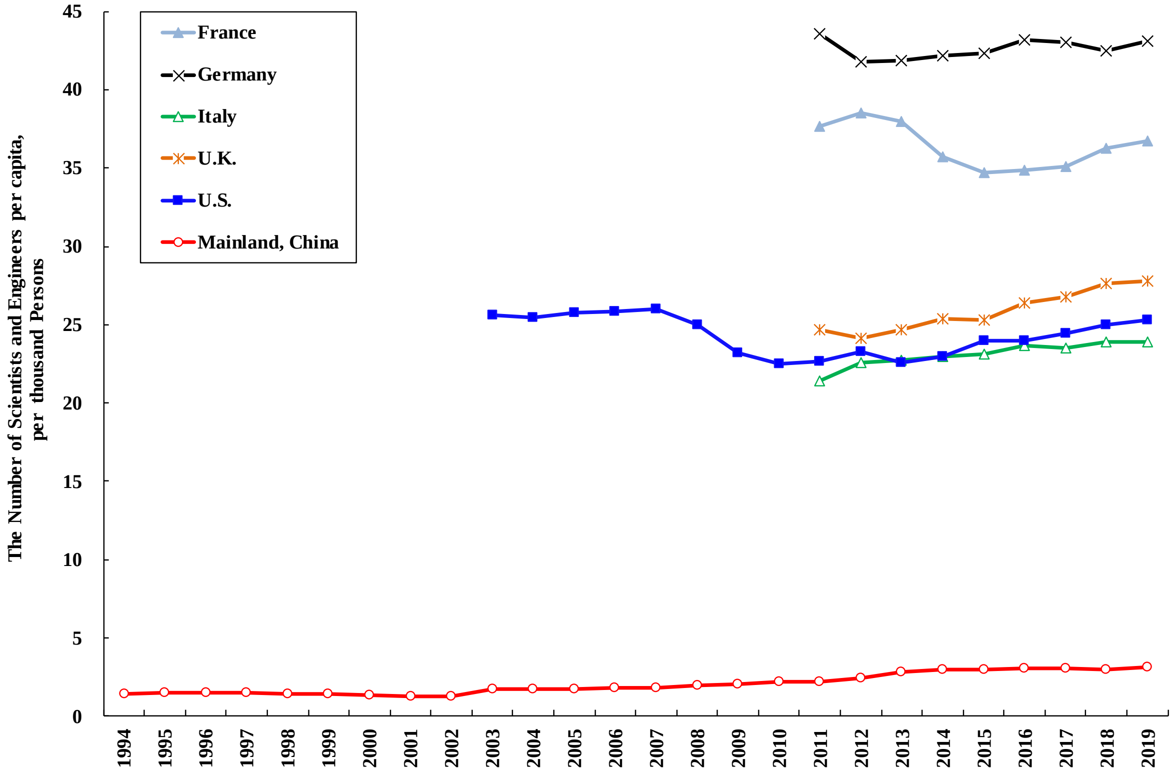
**Chart 12-7: The Number of Scientists and Engineers, Selected Economies**




Sources: Labour Statistics (ISCO level 2), International Labour Organization; Chinese Labour Statistical Yearbook.

In Chart 12-8, we compare the number of scientists and engineers of selected economies in our sample on a per capita basis. Chart 12-8 shows that Germany has the highest number of scientists and engineers per capita, followed by France. We believe that the U.S. has a relatively low number of scientists and engineers per capita among the developed economies mainly because of its relatively smaller manufacturing sector. The number of Mainland Chinese scientists and engineers in per capita terms is still low despite significant increases in its total number of scientists and engineers in the recent decade. It will take decades before the number of Chinese scientists and engineers per capita can catch up to the levels of the developed economies.

**Chart 12-8: The Number of Scientists and Engineers per Capita, Selected Economies**




Sources: Same as Chart 12-7.

## Chapter 13: Other Indicators of Innovation Success

In Chapters 3, 4, 5, 6 and 7, we have examined two major indicators of the innovation output of an economy at the macroeconomic level—the total numbers of patent applications to and patent grants from domestic and foreign patent offices—and shown that they depend positively and monotonically on the quantities of real R&D capital stock, defined as the cumulative total real R&D expenditures less the depreciation of an assumed ten percent per year. In Chapter 8, we have also developed several other indicators of relative success in innovation, again at the macroeconomic level.

There are of course other possible indicators of innovation output at the economy-wide level, for example, the total number of articles published in professional and scientific journals, the number of frequently cited published journal articles, the frequency of major scientific awards such as the Nobel Prize, and the annual value of income from licence fees and royalties. It is not possible to undertake an exhaustive examination of all of these alternative indicators of innovation output, but some of them will be briefly discussed in turn below.

### The Number of Published Articles in Professional Journals

When a new and original discovery or invention is made, it is likely that the first public disclosure is through a research paper authored by the discoverer(s) or inventor(s). The research paper, after being peer-reviewed and confirmed to be valid, is then published as an article in a professional journal. Thus, the publication of such an article should also be considered as an output of R&D activities and an indicator of innovation success. In Chart 13-1, the time-series of the number of scientific and engineering articles published in professional journals by authors who are residents of a given economy included in our study between 2000 and 2018 are presented.[45] [46] These articles include those published in the following fields: physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering and technology, and earth and space sciences. The journals are limited to those that are

[45] The numbers of scientific and engineering articles for G-7 countries, Mainland China, Singapore, and South Korea are taken from the World Development Indicators (WDI) database of the World Bank. Data for Taiwan, China are collected from Science & Engineering Indicators, U.S. National Science Foundation. Data on Hong Kong, China are not readily available.

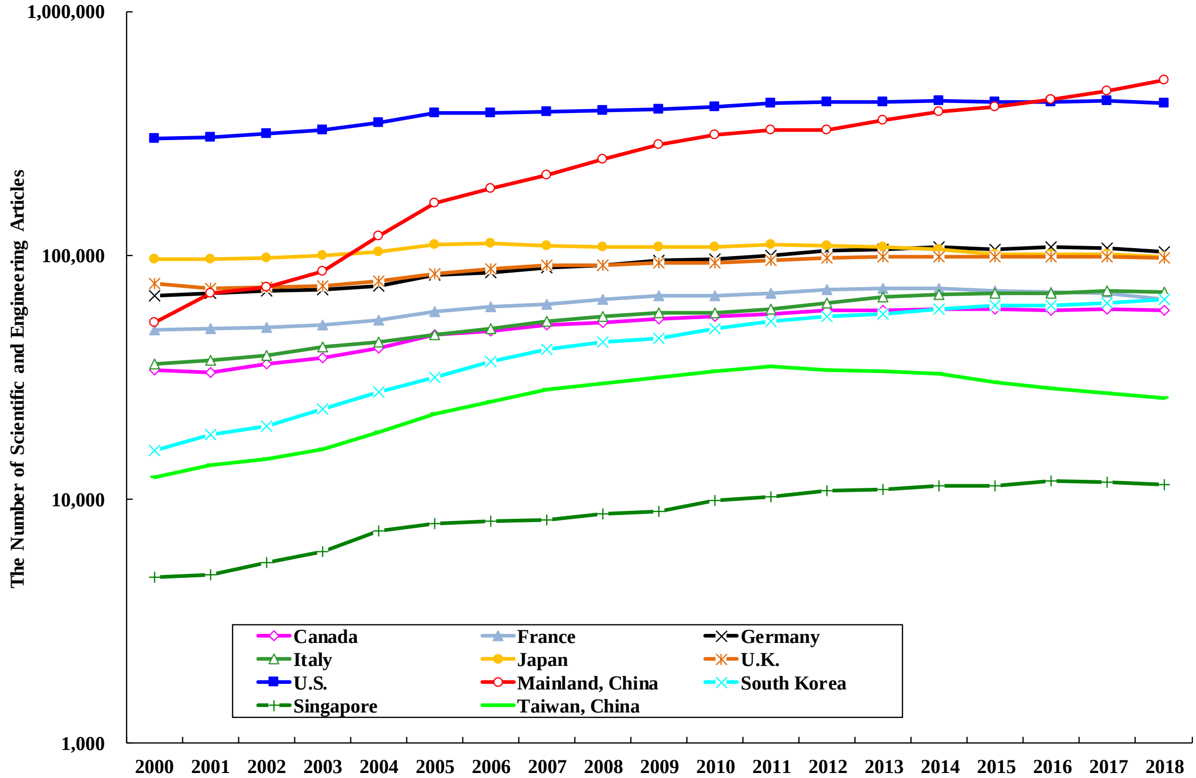
[46] Counts are based on fractional assignments; articles with authors from different economies are allocated proportionately to each economy.

abstracted in the Institute for Scientific Information's Science Citation Index (SCI) and Social Sciences Citation Index (SSCI).

Chart 13-1 shows that in 2000, the United States was far and away the leader in the annual number of published scientific and engineering articles, with more than 300,000. In contrast, China had only 53,000 articles. Japan, the U.K., and Germany were in the second, third and fourth places, respectively. However, the number of articles authored by Mainland Chinese residents began to increase rapidly, and China overtook first Japan in 2004 and then the U.S. in 2016 to take the lead in the total number of published scientific and engineering articles. In 2018, Chinese authors published 530,000 articles compared to the 420,000 of the U.S. authors, with Germany in a distant third place with 104,000 articles. Japan used to be the second most prolific publisher of scientific and engineering articles until it was overtaken by China in 2004 and Germany in 2014. In last place in 2018 was Singapore.[47] Over the period 2000-2018, the number of scientific and engineering articles grew in every economy in our study at rates ranging from 0.1% per annum for Japan to 12.8% per annum for Mainland China, with an average of 4.0%. The number of articles from the U.S. grew at 1.8% per annum. For the world as a whole, the number of articles grew at 4.8% per annum. The rapid growth of the number of articles from Mainland China inevitably crowded out potential articles from the rest of the world. In fact, between 2014 and 2018, the numbers of articles from Canada, France, Germany, Japan, the U.K., the U.S. and Taiwan, China all declined.

[47] Comparable figures on the number of articles published by residents of Hong Kong, China are not readily available.

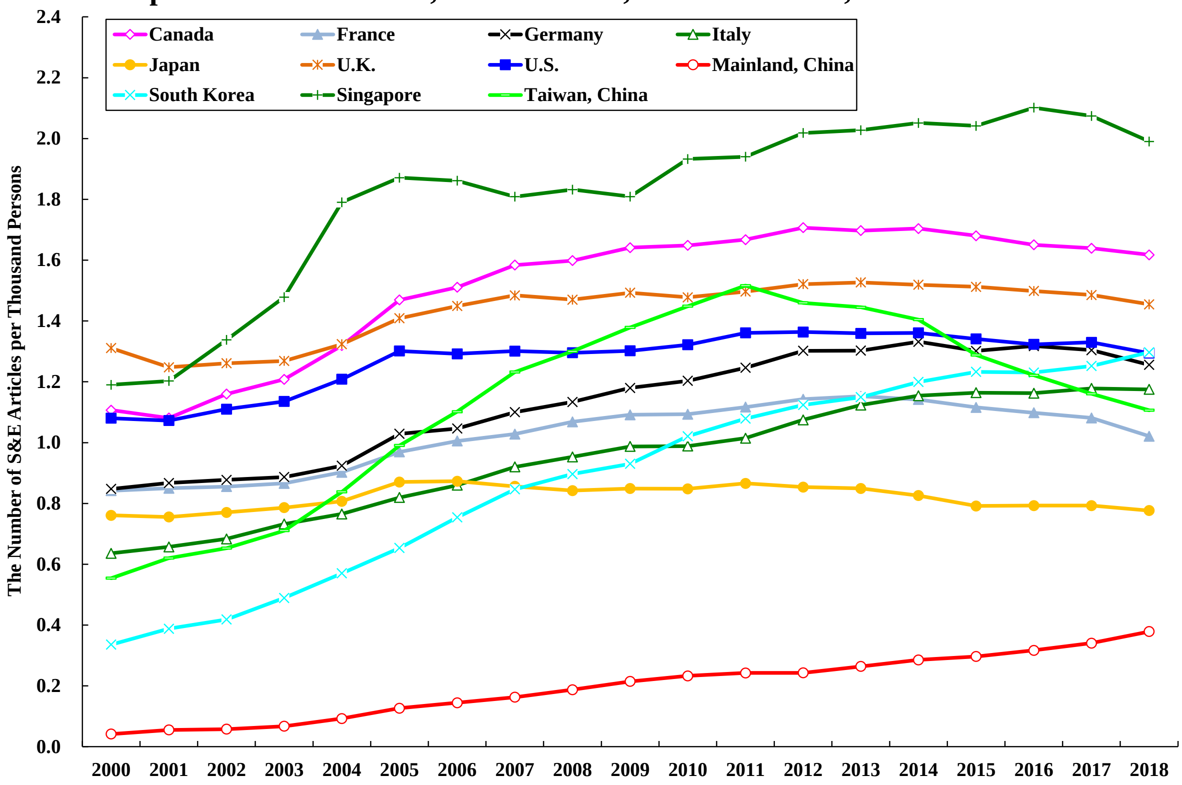
**Chart 13-1: The Number of Scientific and Engineering Articles in Professional Journals, G-7 Countries, Mainland China, and 3 EANIEs**




Sources: World Development Indicators and Science & Engineering Indicators, U.S. National Science Foundation.

In Chart 13-2, the numbers of scientific and engineering articles in professional journals published by authors resident in a given economy per thousand persons each year are compared across the economies in our study. Surprisingly, Singapore is the leader among the economies included in our study, followed by Canada and the U.K. The U.S. falls into the middle of the group. Equally surprisingly, Japan is in the next to the last place. Mainland China, with only one third of the number of articles per capita as the U.S., is in the last place in part because of its large population.

**Chart 13-2: The Number of Scientific and Engineering Articles in Professional Journals per Thousand Persons, G-7 Countries, Mainland China, and 3 EANIEs**

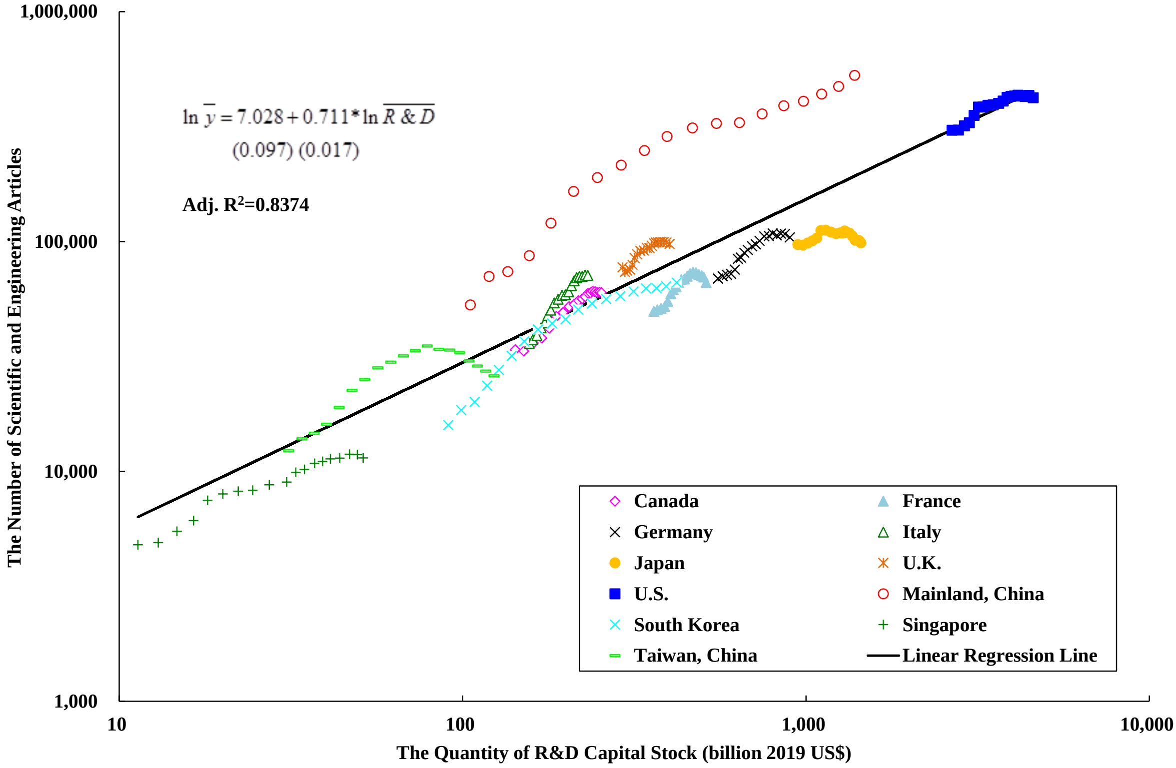



Sources: The numbers of scientific and engineering articles are from World Development Indicators and Science & Engineering Indicators, U.S. National Science Foundation. The population data are from International Financial Statistics (Canada, France, Germany, Italy, Japan, South Korea, Singapore and U.K.), World Development Indicators (U.S.) and the local statistical agencies (Mainland China, Hong Kong, China and Taiwan, China).

In Chart 13-3, the number of scientific and engineering articles in professional journals published by authors resident in a given economy each year is plotted against the quantity of its real R&D capital stock. Not surprisingly, the number of articles also bears a positive relationship to the quantity of real R&D capital stock. The higher the quantity of real R&D capital stock, the higher is the number of scientific and engineering articles published in professional journals. However, as pointed out above, since the mid-2010s, the numbers of published articles have been declining for Canada, France, Germany, Japan, the U.K., the U.S., and Taiwan, China, even as the total for the world has continued to increase. This may be explained in part by the large increases in the number of article submissions and publications by authors from Mainland China, which have in effect crowded out those authors from other economies. This is evidenced by the dips at the ends of the economy-specific number of articles-quantity of real capital stock lines. Nevertheless, the overall positive relationship between the number of published articles and the quantity of real R&D capital stock is unmistakeable. The linear regression yields a statistically highly significant coefficient of

0.711, which can be interpreted as the elasticity of the annual number of articles with respect to the quantity of real R&D capital. We believe the relatively low estimate of the elasticity may have been caused by the decline in the number of articles in most of the economies beginning in the mid-2010s. China does appear to be an over-achiever in Chart 13-3.[48]

**Chart 13-3: A Scatter Diagram between the Numbers of Scientific and Engineering Articles and the Quantities of Real R&D Capital Stock, G-7 Countries, Mainland China, and 3 EANIEs**




Sources: World Development Indicators; Science & Engineering Indicators, U.S. National Science Foundation; and Table A3-1.

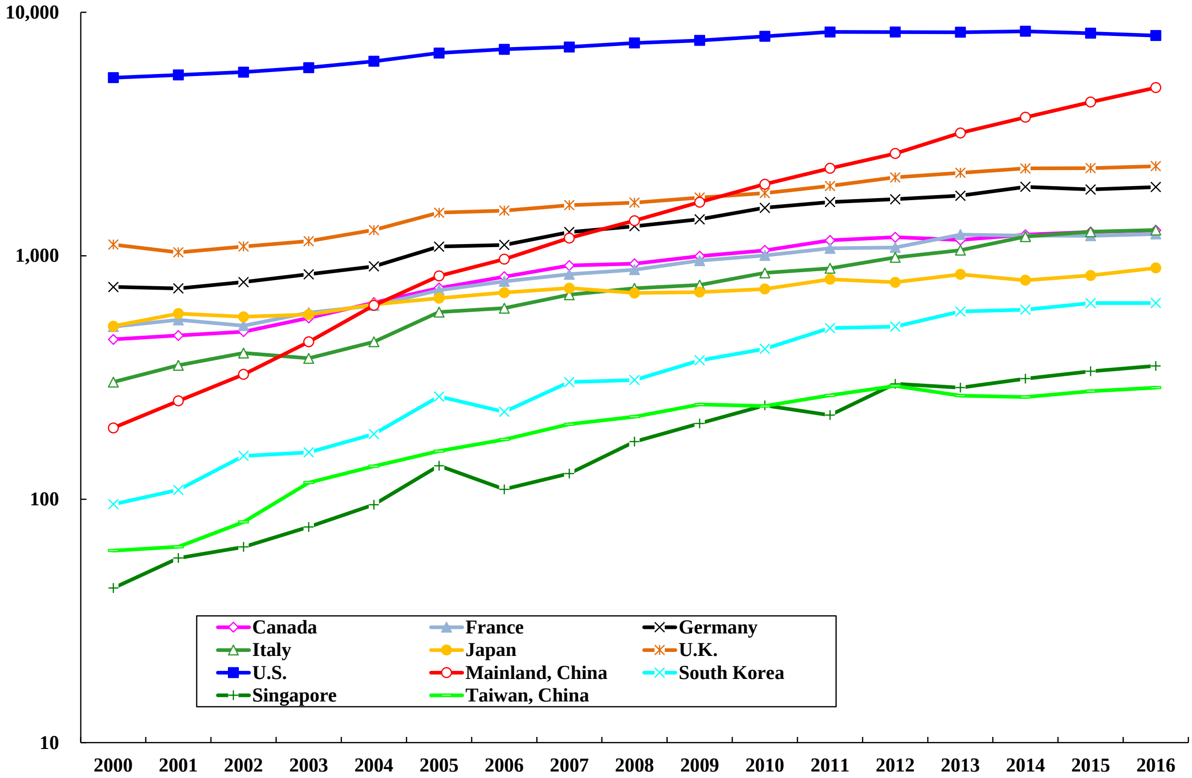
## The Number of Frequently Cited Articles

However, not all published articles are of equal quality or importance. The highest-quality articles are often the most frequently cited. In Chart 13-4, we present time-series data on the number of "top 1-percent most cited science and engineering articles" published by the residents of each economy in our study. The U.S. has been and continues to be the leader in the number of "top 1-percent most cited science and engineering articles". However, China has made great progress since 2000, overtaking Italy in 2003, France in 2004, Japan and Canada

[48] In some Chinese universities, there is a publication requirement for the completion of master and Ph. D. degrees. Having high quality publications which are cited in SSCI and SCI is also a requirement for obtaining tenured academic positions in most Chinese universities and research institutes. This may explain, in part, the surge in the number of Chinese published articles.

in 2005, Germany in 2008 and the U.K. in 2010, to reach the second place with just below 5,000 articles, compared to the just above 8,000 for the U.S. It is of interest to note that with the exception of China, the numbers of frequently cited articles of the other East Asian economies, including Japan, are relatively low.

**Chart 13-4: The Number of Top 1% Most Cited S&E Articles in the Scopus Database, G-7 Countries, Mainland China, and 3 EANIEs**



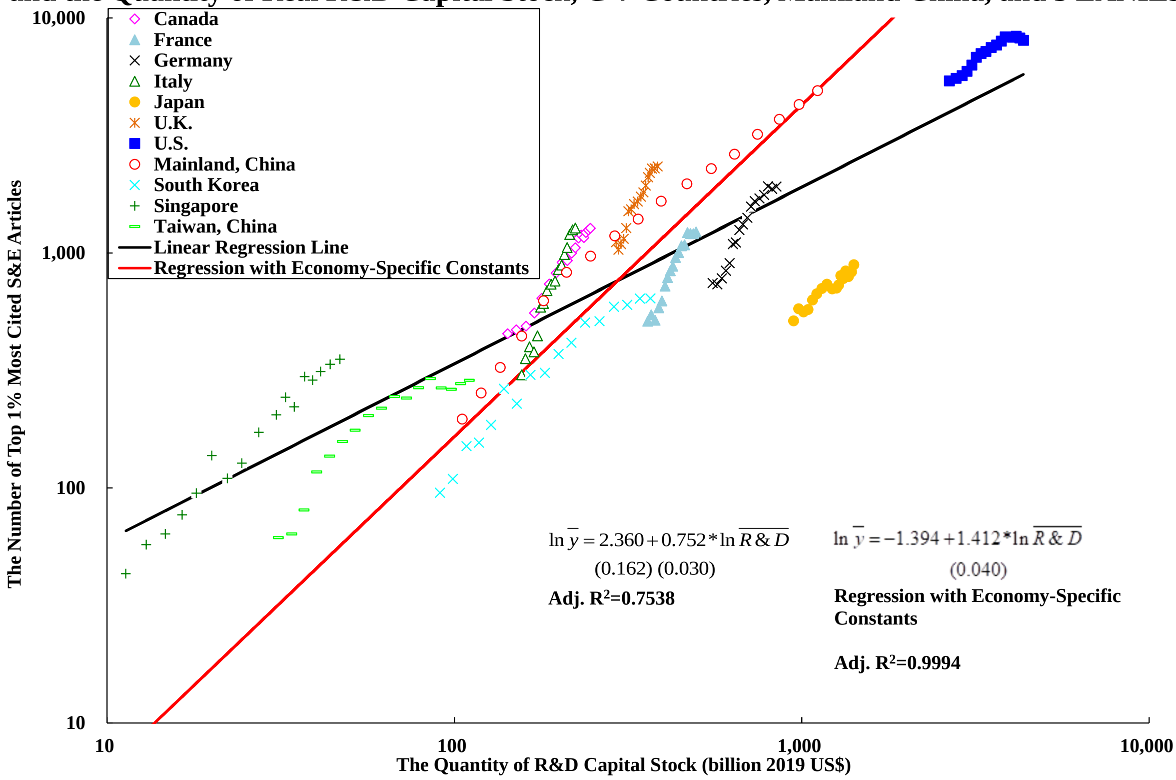

Source: Authors' Calculations. Data are collected from Table S5a-2 and Table S5a-35, Science & Engineering Indicators, U.S. National Science Foundation.

In Chart 13-5, the number of top 1% most cited Science and Engineering articles published in professional journals written by authors resident in each economy each year is plotted against the quantity of its real R&D capital stock. Once again, the number of top 1% most cited S&E articles also has a positive relationship to the quantity of real R&D capital stock. The higher the quantity of real R&D capital stock, the higher is the number of top 1% most cited S&E articles. Two separate linear regression lines, one with economy-specific constant terms (the red line)[49] and one without (the black line), are plotted in Chart 13-5. They both show a significant positive relationship between the number of top 1% most cited articles

[49] The red line in Chart 13-5 is drawn with a constant term set equal to the weighted average of all the economy-specific constants with the shares of the number of observations of each economy in the total number of observations as weights.

and the quantity of real R&D capital stock. However, the linear regression with economy-specific constants (the red line) has a much better overall fit (Adjusted $R^2$ of 0.9994) and an estimated elasticity of the number of most cited articles with respect to the real R&D capital stock of 1.41, indicating substantial economies of scale once economy-specific factors are controlled.

**Chart 13-5: A Scatter Diagram between the Number of Top 1% Most-Cited S&E Articles and the Quantity of Real R&D Capital Stock, G-7 Countries, Mainland China, and 3 EANIEs**



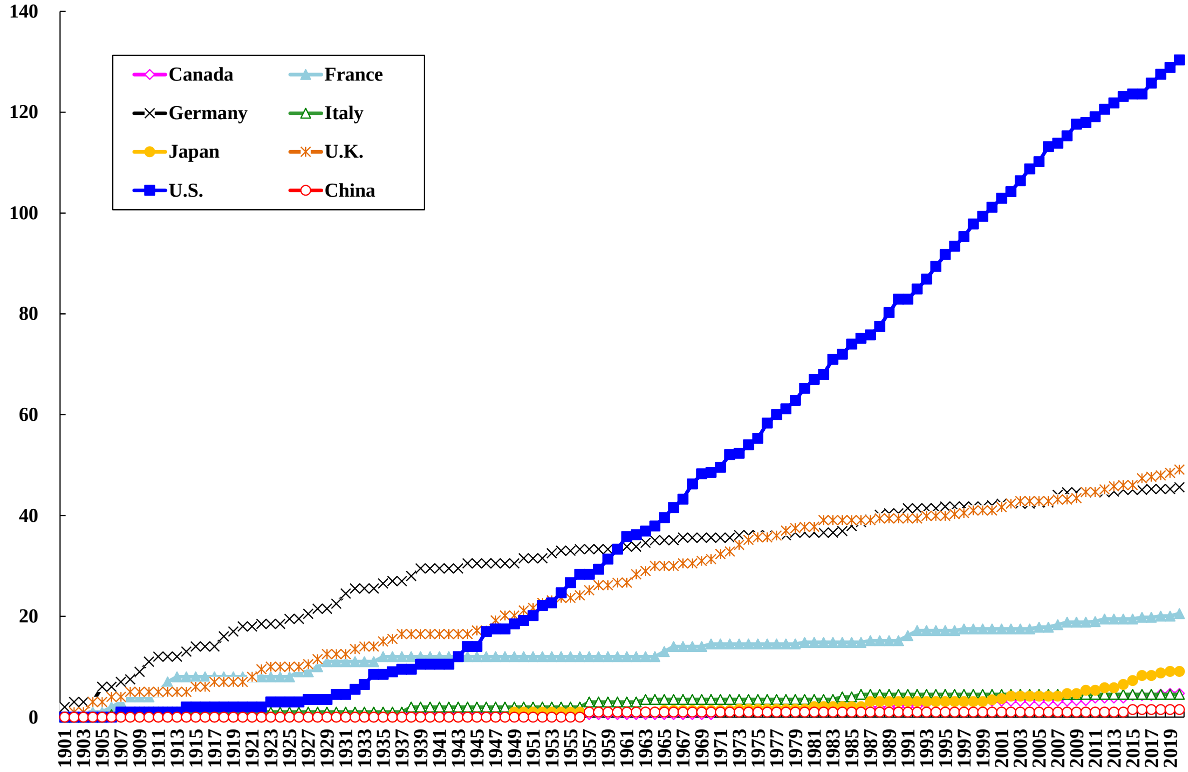

Sources: Data on the number of top 1% most cited S&E articles are the same as Chart 13-4. Data on the quantity of R&D capital stock are from Table A3-2.

### The Number of Nobel Prizes in Chemistry, Physics, and Physiology or Medicine

Major scientific awards given for important original discoveries and inventions are also good indicators of innovation output. There are many such awards. We choose to look at the Nobel Prizes in the physical and life sciences, that is, the Nobel Prizes in Chemistry, Physics, and Physiology or Medicine. In Chart 13-6, the cumulative total number of Nobel Prizes received by the nationals of the G-7 countries and China (Mainland only) are presented. (There has been no Nobel Prize in the physical and life sciences awarded to the residents of the 4 EANIEs.)

Chart 13-6 shows that as of 2020, the United States has the highest cumulative number of Nobel Laureates, 130.4, in the physical and life sciences.[50] In fact, it has had a commanding lead since 1961. It is followed by the U.K., with 49.1 Laureates, and Germany, with 45.6 laureates. China has only 1.5 Laureates. The gap between the U.S. and the other G-7 countries plus China is large. In fact, the cumulative number of U.S. Nobel Laureates is just shy of the combined total of the other G-7 countries and China, 135.

**Chart 13-6: The Cumulative Number of Nobel Prizes in Chemistry, Physics and Physiology or Medicine, G-7 Countries and China**

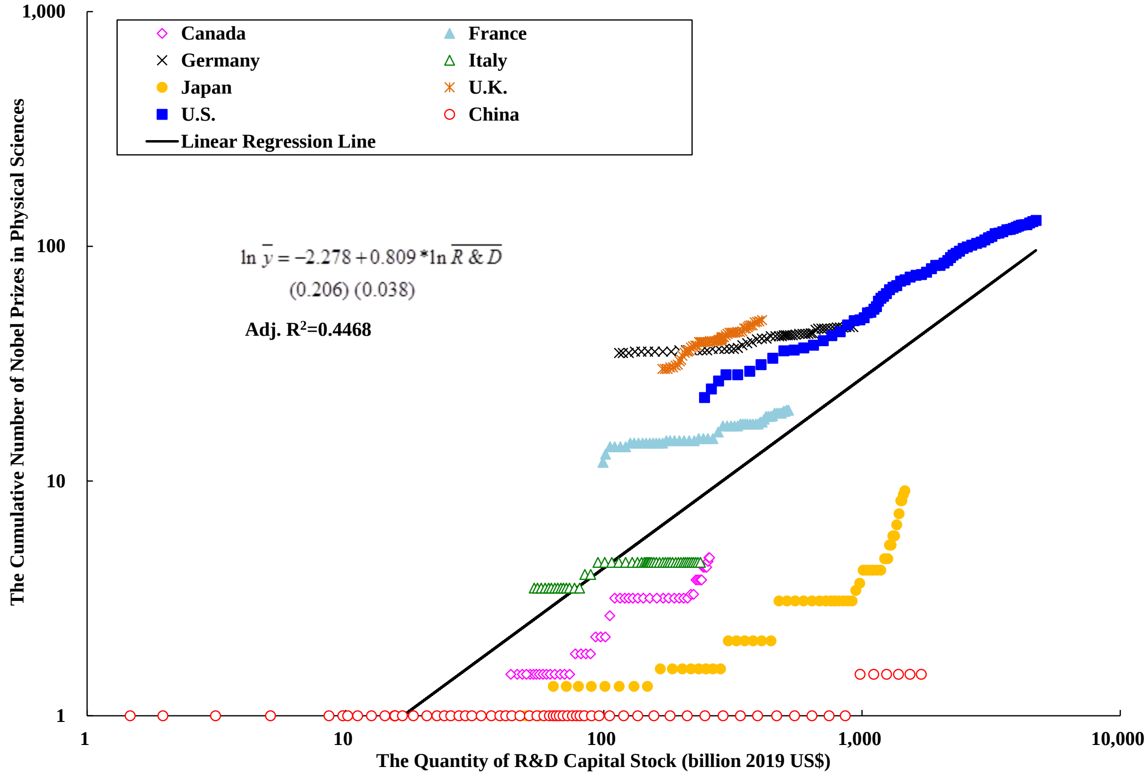



Source: Derived from Nobel Prize website.

In Chart 13-7, the cumulative total number of Nobel Prizes in the physical and life sciences received by the nationals of the G-7 countries and China each year is plotted against the quantity of its real R&D capital stock. The relationship is also positive: the higher the quantity of real R&D capital stock of an economy, the higher is its cumulative number of Nobel Laureates. The linear regression line is also statistically significant. However, there appears to be a large gap between the "over-achievers" of the U.S., the U.K., Germany, and France on the one hand and the "under-achievers" of Canada, Italy, Japan and China on the other.

[50] The number of prizes are fractional because each Nobel Prize can be shared by as many as three laureates each year.

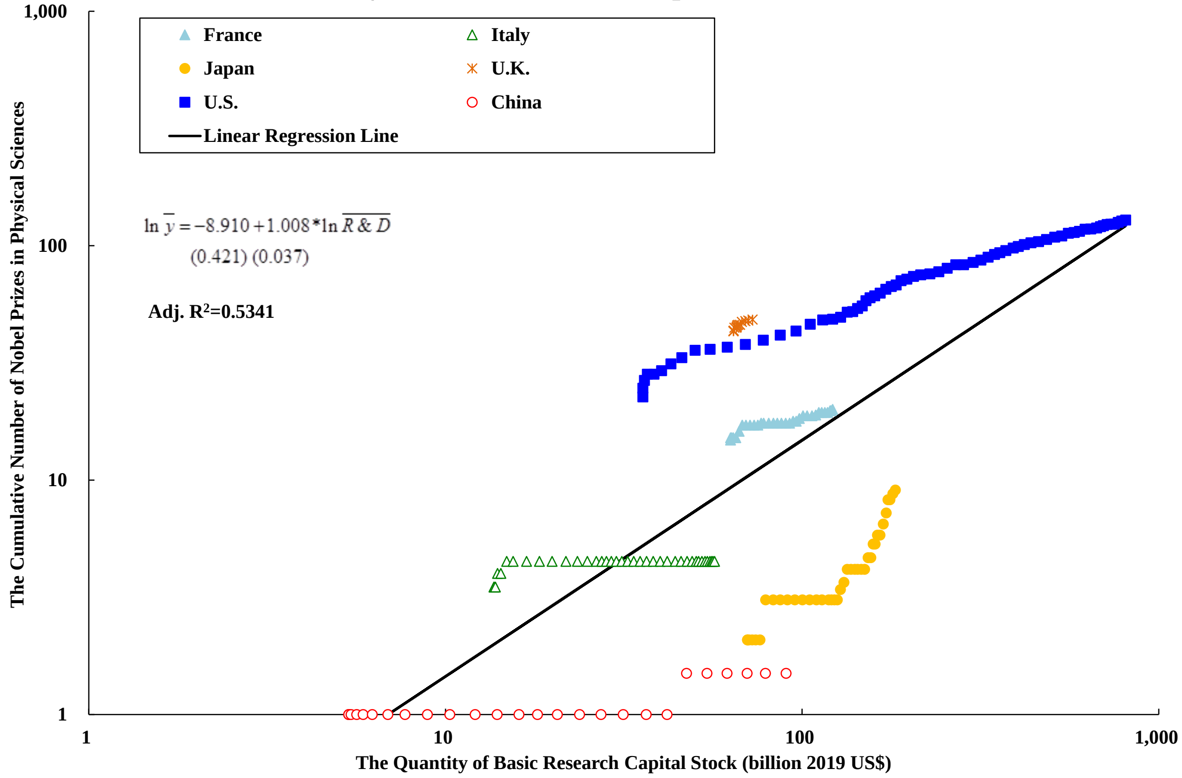
**Chart 13-7: A Scatter Diagram between the Cumulative Number of Nobel Prizes in Physical Sciences and the Quantity of Real R&D Capital Stock, G-7 Countries and China**




Source: Chart 13-6 and Table A3-1.

Alternatively, we can also draw a scatter diagram between the cumulative number of Nobel Prizes and the quantity of real basic research capital stock each year. This is presented in Chart 13-8 below. (Unfortunately, data on basic research expenditures are not readily available for Canada and Germany.) The relationship is also positive: the higher the quantity of real basic research capital stock of an economy, the higher is its cumulative number of Nobel Laureates. In fact, the goodness of fit of the linear regression of the number of Laureates on the quantity of real basic research capital stock (Adjusted $R^2$=0.5341) is better than the one on the quantity of real R&D capital stock (Adjusted $R^2$=0.4468), which shows that basic research is probably a more important determinant of break-through scientific discoveries.

**Chart 13-8: A Scatter Diagram between the Cumulative Number of Nobel Prizes in Physical Sciences and the Quantity of Real Basic R&D Capital Stock, G-7 Countries and China**




Sources: Chart 13-6 and Table A3-4.

On the basis of this cursory examination of other indicators of innovation success, we can conclude that they are all positively and monotonically related to the quantity of real R&D capital stock. The connection between innovation and R&D is always present, no matter how innovation is measured.

Finally, while in principle, the value of licence fees and royalties received is also a good indicator of innovation success, it is in practice quite difficult to collect such data in a comprehensive way. In addition to domestic revenue from licence fees and royalties, there can also be significant foreign revenue from license fees and royalties. However, these fees and royalties are sometimes booked to tax havens for tax avoidance reasons. Furthermore, whatever data available are often not disaggregated to the level of the individual economies by either origin or destination. It will have to await a further study in itself.

## Chapter 14: Conclusions and Directions for Further Research

Are There Laws of Innovation? Our investigations, as reported in Chapters 1 through 13 above, allow us to answer unequivocally: Yes, there are "Laws of Innovation"! This is certainly true at the economy-wide level. Innovation is found not to be accidental or fortuitous. It is also not manna from heaven. It is basically the outcome of research and development (R&D) activities conducted in an economy over a long period of time. The more an economy invests in R&D, the more innovation success it will be able to generate over time, and the more sustainable its economic growth will become.

We have established that the numbers of patent applications and grants are useful measures of innovation output. We have also established that the quantity of real R&D capital stock is a useful measure of innovation input. Moreover, a positive and monotonic relationship between innovation output and innovation input has also been consistently and repeatedly identified and confirmed with empirical data. Specifically, the positive relationship between the number of patent applications submitted by and patent grants awarded to the residents of an economy and the quantity of its real R&D capital stock has been empirically established for different economies and different patent granting agencies (including the United States Patent and Trademark Office (USPTO), European Patent Office (EPO) and China National Intellectual Property Administration (CNIPA)), and at both the macroeconomic and microeconomic levels.

Our investigations also show that the number of patent grants by a foreign patent authority (for example, USPTO, EPO and CNIPA), as opposed to the number of domestic patent grants, is a more reliable indicator of the relative success in innovation across economies. However, on balance, it also appears that the number of USPTO patent grants is probably a more reliable indicator to use because its economy-specific grant rates appear to be quite consistent and uniform across different economies and exhibit no obvious biases.

Through our econometric analysis of USPTO patent applications and grants in Chapters 10 and 11 for the six economies with more domestic patent applications than USPTO patent applications,[51] consisting of Mainland China, France, Germany, Japan, South Korea and the

[51] It is reasonable to assume that if a discovery or invention is good enough for a USPTO patent application, it should be good enough, in terms of quality, for a domestic patent application. Moreover, the cost of application, and subsequent maintenance if granted, of a USPTO patent is, in general, much more expensive than that of a

U.S., we have also rigorously established that the positive relationship between the number of patent applications and patent grants and the quantity of real R&D capital stock is actually quite similar across the different economies. In fact, one cannot reject the hypothesis that they are identical. Thus, the common "Laws of Innovation" appear to apply across economies. The estimated elasticity of the number of USPTO patent grants awarded to an economy with respect to the quantity of its lagged real R&D capital stock is 0.92.[52] It means, on average, a 1 percent increase in the quantity of the real R&D capital stock of an economy increases its annual number of USPTO patent grants by 0.92 percent, indicating the existence of some slight decreasing returns to scale.[53] However, we believe that the R&D enterprise on balance exhibits approximately constant returns to scale. In any case, we should bear in mind that the quantity of real R&D capital stock is the cumulative total of a decade of R&D investments and cannot be changed significantly either upwards or downwards overnight.

Other indicators of innovation success, such as publications in professional journals and frequency of citations, also show a similar relationship with the quantity of real R&D capital stock. In particular, our analysis of the Nobel Prizes in the physical and life sciences identifies investment in basic research as an important determinant of cumulative success in Nobel Prizes in the long run.

It would be interesting to extend our econometric model for the analysis of USPTO patent applications and grants to include EPO patent applications and grants and CNIPA patent application and grants. Like the USPTO, the EPO and the CNIPA are likely to maintain more consistent and uniform standards and procedures in their assessment of the quality of the patent applications, at least insofar as foreign applicants are concerned.

Another interesting question is whether there exist cross-economy externalities in R&D. What we have in mind is whether a higher quantity of real R&D capital stock in one economy can raise the R&D output, for example, patent grants, in another economy. We believe this is not only possible, but quite likely, given the large volume of published professional and scholarly articles and educational exchanges. However, this effect may be difficult to identify

domestic patent. Thus, when a USPTO patent application is submitted without concurrently submitting a domestic patent application, considerations extraneous to the quality of the discovery or invention must have been involved. In this case, the number of patent applications is a biased indicator of innovation success.

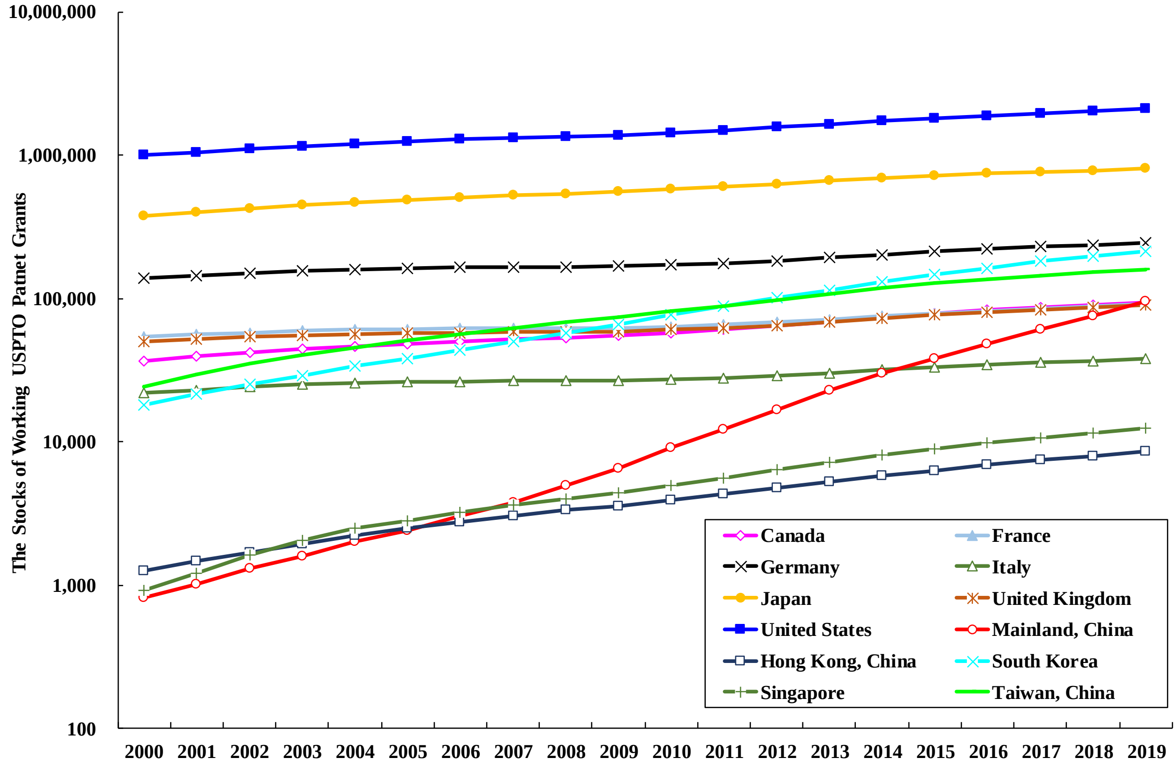
[52] See Chapter 11.

[53] An elasticity of one indicates constant returns to scale.

and quantify empirically. Perhaps one can begin with a study of cross-economy collaboration in R&D as revealed in publications in professional and scientific journals.

Yet another interesting question is the relative distribution of the stocks of working USPTO patents across the economies included in our study.[54] A patent grant is typically valid for 20 years from the date of application (not the date of the patent grant). Thus, at any given time, the stock of working patents may be approximately estimated by the cumulative total number of patent grants over the previous 19 years, on the assumption that it takes, on average, one year from the date of application for a patent grant to be approved. The estimated time-series of the stocks of working USPTO patents of each economy in our study between 2000 and 2019 are presented in Chart 14-1. Chart 14-1 shows that the U.S. has consistently had the largest stock of working USPTO patents. Japan is in second place. Even though the other East Asian economies, including China, have been catching up fast, but it is likely to take a while before they reach the same level as the developed economies.

**Chart 14-1: The Stock of Working USPTO Patent Grants,**
**The G-7 Countries, Mainland China, and 4 EANIEs**

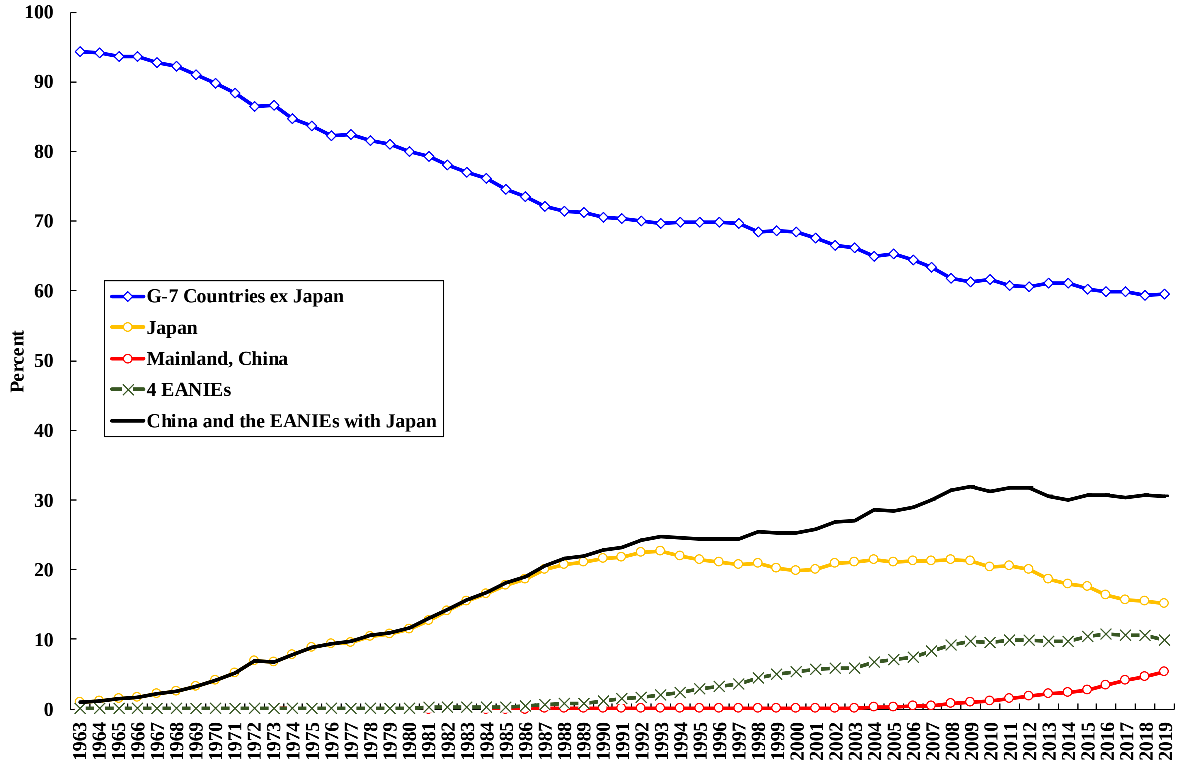



Source: Authors' calculations. The number of USPTO patent grants are from Table A5-2.

[54] It is also possible to look at patents granted by other patent offices. However, judging from the economy-specific USPTO patent application success rates, it appears that the USPTO has maintained uniform standards for all economies, including the U.S. itself.

Our investigations also reveal the rising importance of East Asian economies other than Japan, especially Mainland China, in the creation of patents worldwide. In Chart 14-2, we compare the share of total number of USPTO patent grants accounted for by the G-7 countries without Japan, and those of China and the EANIEs with Japan.[55] We refer to the group of G-7 countries without Japan as "G-7 Countries ex Japan" and China and the EANIEs with Japan as "East Asian economies". The share of G-7 Countries ex Japan has fallen from a peak of almost 95% in 1963 to just below 60% in 2019, while the share of East Asian economies has risen from less than 1% in 1963 to almost 31% in 2019. It is clear that, over time, the centre of gravity of innovation has been gradually shifting from the developed to the developing economies, and also from European and North American economies to East Asian economies. It is, however, noteworthy that the share of Japan has also been declining since the early 1990s and the rate of increase of the share of the four EANIEs seems to have plateaued. It will probably take another couple of decades before the share of East Asian economies in USPTO patent grants can rise above 40%, but it will likely do so on the strength of USPTO patent applications from Mainland China.

**Chart 14-2: The Distribution of USPTO Patent Grants, G-7 Countries ex Japan, Japan, Mainland China, and 4 EANIEs**

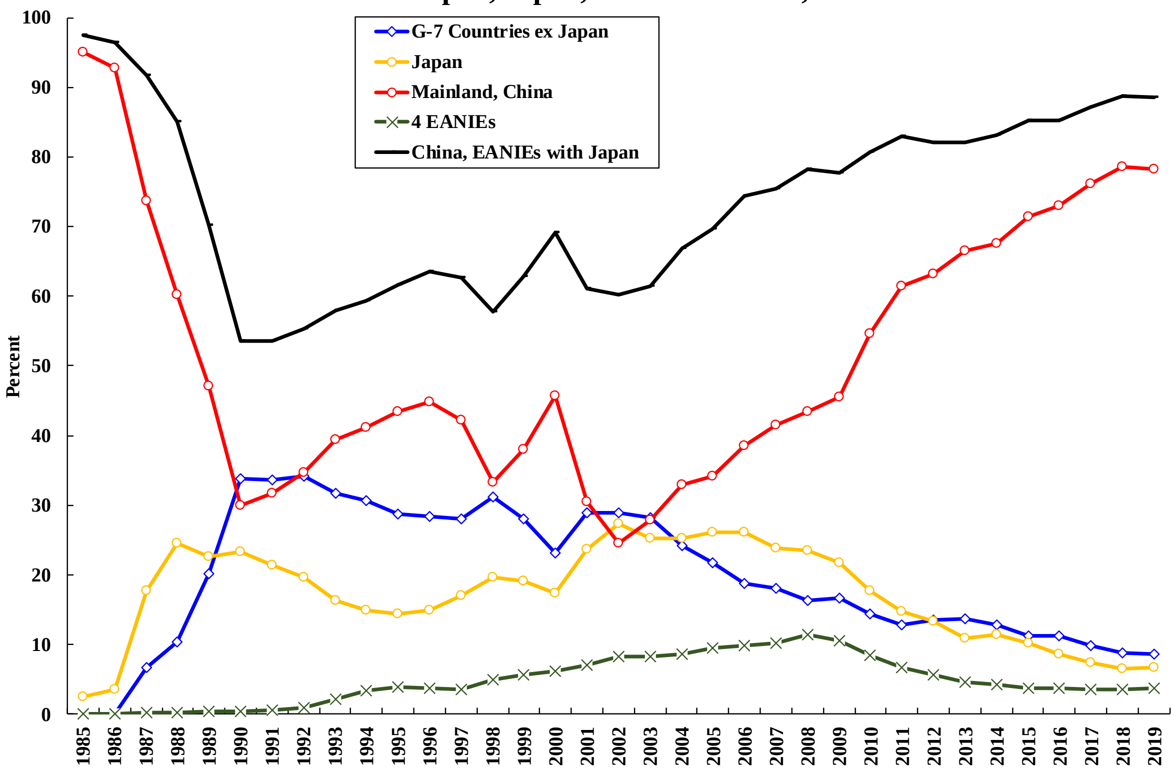



Sources: Table A5-2.

[55] Japan may also be considered an East Asian economy, along with China and the 4 EANIEs.

For the sake of comparison, we also look at the distribution of CNIPA patent grants between the "G-7 Countries ex Japan" and the East Asian economies, consisting of Mainland China, Japan and the 4 EANIEs. In Chart 14-3, we compare the shares of the total number of CNIPA patent grants accounted for by these two groups of economies. Chart 14-3 shows that, in 2019, G-7 Countries ex Japan accounted for less than 10% of CNIPA patent grants and East Asian economies accounted for almost 90%, with 78% from Mainland China itself. We believe this is due, in part, to the low CNIPA patent application rates from economies outside of Mainland China. As the patent application rates from other economies rise, the share of G-7 Countries ex Japan should also begin to rise, perhaps ultimately to 30%. This is not inconsistent with the hypothesis that the centre of gravity of innovation will continue to shift from European and North American economies to East Asian economies.

**Chart 14-3: The Distribution of CNIPA Patent Grants, G-7 Countries ex Japan, Japan, Mainland China, and 4 EANIEs**




Source: China Statistical Yearbook, various years.

Finally, it remains to be established that the quantity of the working stock of patent grants of an economy can have a positive effect on its rate of technical progress or equivalently the rate of growth of its total factor productivity. One possible alternative approach is to use our estimated time-series of quantities of real R&D capital stocks as a variable input in the estimation of aggregate production functions in addition to the conventional inputs of tangible capital, labour and human capital. While these are all worthwhile research initiatives, they are beyond the scope of this study and will have to be taken up in other studies in the future.

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