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Sana Khalil

School of Economic And Trade, Hunan University (North Campus), Changsa, Hunan, China

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ARTICLE

A CURIOUS CASE OF CHINA

Sana Khalil

School of Economics and Trade, Hunan University

(North Campus), Changsha, Hunan, China

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Abstract

China seems well-positioned in terms of innovation output; nonetheless, have underperformed with regards to innovation input which presents a very curious case for study. I investigate the determinants of China's cross-regional innovation output and link the variations in innovation output with the level of economic development. Using panel dataset from 31 regions of China, I show that the differences in China's regional innovation output can significantly be explained by variations in R&D manpower and expenditure, share of highly educated students, and public education spending. Additionally, domestic patent stock, high-tech export share and output value of new products are positively and significantly linked with economic prosperity. Overall, a 1% increase in innovation output translates into a rise in per capita income of between 0.01 to 0.49 percent with patent stock being the highest contributor. My findings imply that the arguments against government R&D subsidies and education rebates seem implausible at best.

JEL Codes: O11, O31, O32, O34

Key Words: Innovation, Economic Development, Per Capita Income, R&D, Patents, Higher Education

Introduction

This paper attempts to look into the complex queries encompassing the concept of innovation, the dilemma of quantifying overall innovation efforts and investigating the role of these efforts in explaining the variations in the level of economic development across Chinese regions.

Although new growth theories do highlight the role of innovation efforts in economic development, quantifying the amount of innovation efforts being carried out in a society poses a serious challenge. This is why there is only a modicum of empirical literature on the contribution of innovation toward growth and development. Understanding the conditions that influence the pace of innovation is a precondition to design suitable policies in order to expedite economic transition (as in case of china, the challenge of its economic transition from upper-middle income category to high-income category has become the crux of economic debates over past few years).

I don't intend to challenge the theories underlying the concepts of innovation and economic development; therefore, I will not attempt to review the plethora of theoretical literature on the respective concepts. Rather, what I present here is an empirical investigation into China's cross-regional innovation output and in per capita income levels (used as an indicator of economic development) with an explicit interest to study (1) policy instruments

aimed at building innovative capacity, (2) proximate determinants of regional innovation, and (3) role of innovation dimensions in China's cross-regional income variations.

Motivation for conducting this study originates from three explicit factors; first, China is currently going through an economic transition phase where it runs the possibility of falling into a middle-income trap (World Bank, 2013). China is set to undergo major demographic transitions where its old age dependency ratios will more than double over upcoming two decades which will result in slower expansion of its working-age population. To add fuel to fire, China's total factor productivity has also started declining since much of the productivity gains due to allocation of resources from agriculture sector to industrial sector have already been reaped and from this point onwards, continued capital accumulation will generate less growth due to decreasing returns to capital and labor.

These issues signal toward alternative measures that need to be taken to ensure China's smooth economic transition from its current status to higher-income level. Which is why I was keen to focus on the question that if China is able to improve its cross-regional innovation efforts, be it innovation input or innovation output, can it ultimately improve its level of economic development?

This paper is structured as follows; the next section briefly highlights China's possibility of falling into a middle-income trap and its position in global innovation landscape, second section provides an overview of the literature, third section furnishes data and estimation methodology, section four presents estimation results and discussion while section five concludes the paper highlighting various policy implications of this study.

A curious case of China

Is China on the verge of a middle-income trap?

China is safely considered a unique example in the economic history¹ whereby a country, despite growing tremendously for 4 decades with an average growth rate of 7%, still had a comparatively lower per capita income level than other countries with similar growth patterns (for example, Korea and Japan grew stably with an average of 7% over 3 decades and were able to translate that tremendous growth into higher per capita income levels). This leads us to the question why china's per capita income levels seem to have lagged behind compared to other countries with similar growth patterns. According to the World Bank classifications in table A, China currently stands in the category of upper-middle-income nations with a per capita income level of \$7958. Rising from per capita income level of \$7958 to \$12616 would be a quantum jump for China's economy. Transition from upper-middle-income level to higher-income level seems daunting due to a number of factors. According to World Bank (2013) estimates, China's GDP growth rate would gradually decline from an average 8.5 percent in 2011-2015 to around 5 percent over 2026-2030. Labor growth (growth of labor force) and labor productivity growth will slow down from 0.3 and 8.3 percentage points (over 2011-2015) to -0.4 and 5.5 percentage points respectively (over 2026-2030²).

¹ Only China and Singapore have achieved this feat so far, while Singapore is the only country to have grown with an average rate of 5% over last 5 decades.

² The data quoted in this part comes from the World Bank and the Development Research Center of the State Council, P. R. China, 2013, *China 2030: Building a Modern, Harmonious, and Creative Society*, Washington, DC: World Bank.

Table A: World Bank Income Classifications³ (2012):

Lower-middle-income economies	Upper-middle-income economies	High-income economies
India (\$3340)	Brazil (\$10264)	United States (\$45335)
	China (\$7958)	Korea, Rep. (\$27990)
	South Africa (\$9860)	Japan (\$31425)
		Russian Federation (\$15177)
Low-income economies (\$1,035 or less)		
Lower-middle-income economies (\$1,036 to \$4,085)		
Upper-middle-income economies (\$4,086 to \$12,615)		
High-income economies (\$12,616 or more)		

Notes to table A: Figures are given in 2005 constant U.S. dollars at PPP.

Two factors are set to constrain China's current spree of rapid economic growth; first, the contribution from labor is set to decline due to a slower expansion of its working-age population (which is estimated to be eventually negative from 2015 onwards), second, total factor productivity growth, which has been a source major of China's past growth (Brandt and Zhu, 2010; Young, 2003), will decline significantly since much of the productivity gains due to reallocation of resources from agriculture to industry have already been reaped. From this point onwards, continued capital accumulation will ineluctably generate less growth due to decreasing returns to capital and labor. Meanwhile, China is set to undergo major demographic transition whereby old age dependency ratios will more than double in upcoming two decades and the size of its labor force will shrink. Overall, Chinese economy seems to have already reaped the benefits from first-generation policy initiatives and gains from second-generation policy measures are more likely to have less impact on growth.

Using growth accounting framework, Lee and Hong (2012) base their growth projections on total factor productivity (TFP) growth, estimated through growth drivers such as capital to labor ratio, saving rates, stock of patents, years of schooling, openness and demographic variables, and project a growth rate of 6.1 to 7 percent for 2011-2020 and 5 to 6.2 percent for 2021-2030. The authors suggest a slower growth of growth drivers: labor force growth, growth in educational attainment, growth of capital stock and TFP growth. Slower growth is indicated to result from the convergence of capital to labor ratio, TFP to advanced-economic levels while slower growth of educational attainment is expected once enrollment ratios reach reasonably higher levels due to ageing population.

Since China's major growth drivers are expected to slow-down before it can complete its transition from current level to upper-income level, the focus needs to be shifted on the alternative measures of economic development. What I suggest here is that China's

³ (Detailed classification of other countries can be accessed at http://data.worldbank.org/about/country-classifications/country-and-lending-groups#Lower_middle_income)

future needs to be viewed from a development perspective rather than growth aspect since the general economic tradition does agree that economic growth is not a necessary equivalent of economic development. The gargantuan variations in the level of economic development across Chinese regions require balanced structural transformation and policy instruments if China is to rise up to a higher income status.

Global innovation landscape: where does China stand?

China is ranked 35th out of 142 world economies according to Global Innovation Index (GII 2013) report⁴ released jointly by Cornell University, USA, European Institute of Business Administration (INSEAD) and World Intellectual Property Organization (WIPO). Stressing the role of a good policy mix catering to multiple fronts such as infrastructures, institutions, skills, linkages with global markets and business community, the GII 2013 report attaches great significance to the key roles played by innovation in driving economic prosperity.

Top five leaders in global innovation according to GII 2013 are Switzerland, Sweden, United Kingdom (UK), Netherlands and United States of America (USA). In terms of global innovation input rankings, China ranks 46th (Singapore is ranked 1st in this sub-category) while Japan and South Korea rank at 14th and 16th respectively (USA ranks 3rd in this regard). China seems better positioned in terms of innovation output ranking standing at 25th position; USA ranks 12th, Korea 24th and Japan 33rd respectively (Switzerland has the top position in this sub-category). Within its own income category of upper-middle-income, China ranks 1st in innovation output but 6th in innovation input while 3rd in terms of efficiency ratio (efficiency ratios indicate how much innovation output a country is getting for its innovation inputs); Malaysia dominates the upper-middle-income category with top ranks both in overall innovation index and innovation input sub-index while 2nd in innovation output sub-index.

The report also enlists China in the rank of eighteen emerging economies that are outperforming others in their respective income groups. In term of patents, China is emerging as a driver of growth in filings with an increasing share of global patents. However, public R&D and education expenditures seem to lag behind average spending levels of advanced economies. Implications from global innovation rankings substantiate the idea that although China may be outperforming its counterparts in innovation output, in terms of innovation input it seems to have underperformed within its income group.

In the following parts of this section, I would set the stage for a critical comparison of China's innovative capacities with respect of other countries. For this purpose, I select three benchmark examples of high income countries; USA, Japan and South Korea. The latter two can serve as good benchmarks since both are Asian countries and have gone through rapid growth phases like China. Other four countries are constituents of BRICS (Brazil, Russia, India, China and South Africa) nations which can be seen as going through an almost similar growth contour as China.

For public investments in education, the World Bank data shows that China's public spending on education as a percentage of GDP (both current and capital) was around 1.4 percent in 1971. It remained almost stagnant over the years, later increasing to 1.9 percent in 1999. Comparing China's share of education expenditure in GDP with that of Japan's, it's not surprising to note that the Japan maintained a handsome figure over a significantly long

⁴ GII 2013 can be accessed from World Intellectual Property Rights Organization (WIPO) website at http://www.wipo.int/econ_stat/en/economics/gii/

period. Japanese public educational spending as a percent of GDP was 3.7 percent in 1971 which rose to more than 5 percent over 1980s (the remarkable aspect is the “sustained” portion of education expenditure share in GDP at more than 5 percent over 1980-989) ,declined marginally over 1990s and finally closed at 3.7 percent in 2011. Japanese policy of higher public spending for education seems quite congruent with Korean policy of higher education spending over a long period of 1970-2011. In 1970, Korean government spent around 3.45 percent of its GDP on education which incremented to 6.5 percent in 1982, declining later during the late 1980s. However, as of the years 2000-2011, the figures again gained momentum and an average of 4 percent of GDP was allocated to education by the Korean government over 2000-2011; as of 2011 the figure reported was 5 percent.

China’s gross enrollment ratio for higher education (as percentage of total population) was very low (nearly 0.13) in 1970s but later increased manifolds to 7.95 in 2000; the figure continued incrementing thereafter to reach at 26.79 in 2011 (which is a remarkable increase of 236 percent over a short span of eleven years). Comparing China’s performance in terms of highly educated stock of students with Korea’s, Korea seems to be far ahead than China; the gross enrollment ratio in higher education for Korea was 7.25 in 1971 which rose to 103.11 in 2011. On the same lines, Japanese figures are encouraging but do lag behind Korean figures; gross enrollment ratio in higher education for Japan was 17.6 in 1971 and 50.74 in 2010. The comparative figures substantiate Korea’s advantage in terms of highly educated stock of human capital and imply that China still needs a long way to go to build its stock of highly educated students. Given the current challenge concerning China’s economic transition from upper-middle-income category to higher-income category, it can’t afford to overlook the role of highly educated stock of human capital in catching up with the high-income nations.

Table B: Comparative landscape of innovation capacities

Country	High technology exports 2011	Patents (residents) 2011	Researchers in R&D (2010)	R&D expenditure (2010)	Tertiary enrollment ratios, gross (2012)
South Africa	5.11	656.00	393 (2008)	0.83 (2009)	NA
India	6.87	8841.00	135 (2005)	0.75 (2007)	23.27
Russian Federation	7.97	26495.00	3092	1.15861	NA
Brazil	9.72	2705.00	703	1.16042	NA
Japan	17.46	287580.00	5180	3.25806	59.9
United States	18.09	247750.00	4673 (2007)	2.83408	95.33
Korea, Rep.	25.72	8018.00	5481	3.73781	100
China	25.81	415829.00	863	1.75899	24.3
Source: The World Bank					

Notes to table B: High technology exports (as % of manufactured exports); Number o patent applications filed by residents; Researchers in R&D (per million people); R&D expenditure (as a% of GDP).

In table B I include other alternative measures of innovation in my comparative analysis; high technology export share in manufactured exports, patent filings, R&D

manpower and expenditure and tertiary enrollment ratios. Two important findings are evident in table B; China seems to have outshined other countries in terms of high technology export share and patent filings but underperformed on the account of tertiary enrollment ratios, R&D manpower and expenditure. In the year 2008 Japan and South Korea had the highest number of researchers in R&D which is quite understandable since both countries have maintained comparatively higher stocks of highly educated students than China. Why is the stock of highly educated students or R&D manpower so important? The answer can be best explained by Papageorgiou and Perez-Sebastian (2006) who use the cases of South Korea and Japan as examples of “development miracles” to argue that while Japanese growth over 1963-1987 mainly stemmed from faster physical capital accumulation, South Korea derived its faster pace of economic development from higher human capital accumulation. The authors suggest that R&D becomes more productive with the growth of average schooling as a higher human capital level enables workers to efficiently use ideas and fosters technology acquisition.

In terms of R&D expenditure (both public and private) share in GDP, for China, the figure has been quite low (which although more than tripled from 0.56 percent in 1996 to more than 1.7 percent in 2010 but is still very low compared to the R&D expenditure shares of high income countries included in the table). Comparing that figure with Korean and Japanese figures, the R&D expenditure shares were around 2.42 percent for Korea and 2.7 percent for Japan in 1996 which later rose to 3.73 and 3.26 percentage points respectively in 2010. Evidently, public policies of both countries seem to associate great importance not only to education (spending and enrollment ratios) but also to R&D manpower and investments.

Comparing high-technology exports shares in total manufactured exports, for China, the figures seem to bode well. High-tech export share was merely 6.4 percent in 1992 which skyrocketed over the years to clinch a gigantic proportion of more than 25.8 percent in 2011. USA has the second highest share of 18% in table B while Japan has the third highest share of 17% which is still very handsome.

Finally, in terms of Intellectual Property Rights System (IPRS) filings, Patent applications filed by Chinese residents seem to have surpassed other countries. Patent filings through Patent Cooperation Treaty procedure were only 4,065 for China in 1985 but his figure incremented sharply over the years and as of 2011 there were 415,829 (or 0.41 million) patent applications filed by Chinese residents. Moving from a meager figure of 4065 to 0.41 million over a period of 26 years, China's case is worthy of attention- as to how this marvelous achievement might have been translated into its exemplary economic performance and its implications for China's economic development.

Overall, a comparison of innovation capacities shows that, Korea and Japan in their initial and later phases of economic development carried out tremendous innovation efforts reflected not only in their policy instruments-investments in R&D and education but also visible in their strong bases of highly educated students and R&D manpower. Matching China's domestic innovation indicators with its rankings on the global innovation front, one aspect becomes crystal clear; policy instruments need to be targeted toward accumulating innovation inputs for spurring future innovation output and economic development. For China to join the ranks of advanced countries (belonging to higher income levels and innovation leaders), strong policies aimed at speeding its pace of innovation are of dire need.

Literature: what we know and don't know Innovation and its determinants

Given the dilemma of quantifying the amount of innovation efforts being carried out in a society, studying the link between innovation and economic development poses a challenging task. In order to refresh our understanding of innovation, let's turn to Schumpeter (1939) for a while. Schumpeter (1939) translates technological change as the introduction of new products (inventions) and innovation in production processes and management methods. Hence, the Schumpeterian technological change is related to the genesis of brand new

scientific and technological ideas, and development of “marketable” novelties. From this perspective, one could think of innovation having two faces; a side that is “intangible”-new scientific and technological ideas that might be in raw forms and not necessarily materialized into measurable output, as well as a side that is “tangible”- the outcome from the intangible scientific and technological ideas that have been processed into some material output. Consequently, one might think of these two sides of innovation as interrelated. Therefore, when we talk about innovation in this paper I would be referring to the composite of tangible and intangibles sides of innovation.

Whether innovation is something tangible or intangible is not that big a problem as quantifying the innovation outcome; that is, when we think about comparing the outcomes from innovation efforts we ineluctably run into a dilemma as how to measure innovation. Once we have dealt with the measurement problems, we can further investigate into the query that how much innovation output a society can generate from its innovation inputs. Given the lack of consensus on a set of reliable and holistic innovation indicators, I deem it necessary to categorize overall innovation efforts into innovative performance-hence the *output dimension* (which would reflect the current output from existing innovative activities and innovation inputs), and innovative capacity-the *input dimension* (that measures the status of existing innovation inputs). This type of differentiation is important both for theoretic and analytical purposes. From a theoretical perspective⁵, innovative performance can be viewed as output resulting from existing research and knowledge, while innovative capacity can be thought of as inputs or engines that drive future research and knowledge. Stern et al. (2002) define “national innovative capacity” as a country’s ability to commercially produce a flow of innovative technology over a substantial period. Factors that determine the pace of innovation (number of patents) are R&D investment and manpower, aggregate policy choices concerning IPRS and trade openness and the role of academic sector in the genesis of research efforts. Thus, a country’s patenting productivity depends on its knowledge “stock”-which concerns both the investments and manpower. As far as inputs and outputs of innovation⁶ are concerned, there seems to be a general consensus in literature on the categorization. R&D expenditures and manpower are primarily taken as input while patents are treated as the output resulting from innovation inputs (Stern et al., 2002; Hausman et al., 1984; Basberg, 1987; Patel and Pavitt, 1994; Griliches, 1998). The actual innovation output is considered to reflect not only the outcome of current innovation inputs but also a contribution to the existing inputs (Nelson and Winter, 1982). Thus, innovative performance can be defined as current output of innovation efforts (for example, number of patents granted and number of R&D projects completed by private sector), while innovation capacity is about the stocks of knowledge and human capital or economic incentives (for example, the pool of students in education, education expenditure and R&D expenditure) which a country can devote to research and knowledge creation at any stage during its growth transition process. From an analytical perspective, an empirical investigation into the determinants of innovation requires measurable and comparable indicators. Dividing overall innovation activities of a country into separate input-output dimensions would not only help in understanding the multidimensional links between innovation indicators but also addressing the problem of multicollinearity. Since many of the innovation indicators are highly correlated, it is highly essential to set separate dimensions for them so that each indicator captures and measures a separate process underlying innovation. Due to an overlap within each dimension of innovation- inputs and outputs; separating the individual effects of each would be almost impossible (Hagedoorn and Cloodt 2003). If we include a set of multiple innovation indicators within each dimension, analysis with a “low noise” empirical model would be a challenging task. Consequently, a general norm in literature is to employ one or two indicators (either from input side or output

⁵ See Romer (1990)

⁶ See Acs et.al, (2002) for a discussion on innovation inputs and outputs

side) instead of a set of multiple indicators to study the effect of innovation efforts on growth. As my study is concerned with both dimensions of innovation, what I do is to calculate the statistical overlap within/between innovation inputs and outputs and then decide their inclusion in the analysis based upon the strength of their overlap. Finally, whether one indicator is adequate or a multiple set is required (to measure innovative capacity or innovative performance) depends on the strength of each indicator in explaining the variations in their resulting impacts (Hagedoorn and Cloudt 2003).

Referring to innovation indicators, it is only recently that innovation indicators can increasingly be seen becoming a sort of medal table for the global race of innovation. Countries seem to take pride in their standings as “innovators” rather than “imitators”. Various attempts to measure and compare the innovation activities of nations over time have translated into reports specifically centered on ranking innovation efforts. Arundal and Hollanders (2006), Hollanders and Van Cruysen (2008) and Archibugi et al., (2009) provide encouraging developments in this regard. Providing an assessment of innovation indicators that encompass structural conditions, creation of knowledge, firm-level innovations, throughputs and outputs, reports from these authors present innovation scoreboards against which they rank different countries and regions which helps us understand the global innovation landscape.

Given the circumstances whereby the problem of measuring innovation efforts in a country have not been thoroughly solved (Acs et.al, 2002), my attempts to come up with comparable measures of innovation for my empirical analysis are translated in the categorization of overall innovation efforts into input and output dimensions of innovation in table C. Table C largely draws on Arundal and Hollanders (2006), Hollanders and Van Cruysen (2008) and Archibugi et al., (2009) keeping in mind the tradition put forward by other studies on innovation.

Table C: Measuring Innovation

Input dimensions
<i>Human capital</i>
-Higher education enrollment ratio (share in total population)
-R&D personnel at public institutions (share in total population)
-R&D personnel employed by private enterprises (share in employment)
<i>Investment in knowledge creation</i>
<i>Fiscal instruments</i>
-Public R&D expenditure (as % of GDP)
-Public education expenditure (as % of GDP)
Output dimensions
<i>Intellectual property</i>
-Number of Patents, trademarks and design registrations
<i>Competitiveness and success of innovation</i>
-Share of high technology exports in total exports (as % of total exports)
-Share of new products introduced (output value of new products as a percentage of total gross output)
<i>Technical activity</i>
-Transactions carried out in technical market

Higher Education

Although there are compelling reasons to believe that investment in education enhances growth, empirical evidence doesn't necessarily support this conclusion. It is also unclear that what level of education would contribute most toward a country's economic performance- primary, secondary or tertiary education. Moreover, the literature on the positive link between education and growth is generally based upon the argument that more education leads to an improved labor force and therefore higher productivity; as a more educated labor force is easier to train, has better work habits, and can resolve complex tasks. The 'new' growth theories, for example, suggest that the developing nations can catch up with the advanced economies if they have a stock of skilled labor to develop new technologies or imitate foreign technology. Education is considered to increase output via two channels: more education imparts necessary skills to labor thereby enhancing the capacity of the labor force; and it augments the workers' capacity to innovate thereby improving workers' productivity (since with better education workers' can learn new methods of using existing technology, create new technology or imitate foreign technology. Thus, the intuition behind 'new' growth theories emphasize the role of education in improving the quality of labor force, enhancing technological advancements and generating long-term externalities (Mankiw et al., 1992). The externalities generated by a better educated labor force are better explained by Agenor, Canuto, and Jelenic (2012) who use the term "knowledge network externalities" to suggest that a higher proportion of workers with higher levels of education would have a positive effect on the performance of all the workers involved in innovation activities. Such "knowledge network externalities are essential in developing a caliber to understand existing technology and reap the benefits out of prevailing knowledge. Thus, it can be suggested that, in the cases of countries at low levels of development, a combination of "knowledge spillover" and "learning-by-doing" effect would increase the marginal productivity gains. From this perspective, tertiary education may contribute more toward economic development and growth than primary and secondary education levels.

For practical examples of countries, which benefited tremendously from an increased stock of highly educated human capital, we can turn to the special case of Korea's smooth transition from middle- to high-income level which is generally linked with its expansion of human capital stock at secondary and tertiary education levels. Korea stands as an example of a country which successfully avoided the possibility of falling into a middle-income trap by capitalizing on the returns to higher education (Eichengreen, Park and Shin, 2013). On the other hand, the cases of Malaysia and Thailand along with other Latin American countries, which failed to graduate into upper income levels after reaching middle-income stage, have been linked with their failures to upgrade and develop high quality human capital to keep up their increasing growth rates (Eichengreen, Park and Shin, 2013; Woo, 2009). The lack of highly educated workers undermines innovation and research activities which constrains the gains from productivity improvements and exploitation of knowledge externalities. At micro level, the pool of highly educated workers is considered to enhance the "absorptive capacity"⁷ of a firm to gain from knowledge externalities from innovation and other R&D activities (Cohen and Levinthal, 1989). Investment in human capital, therefore, stands as a crucial factor in determining per capita output. Along the same lines, Mankiw et al. (1992) find that investment in human capital along with other two variables namely population growth and investments in physical capital account for 80 per cent of the variations in per capita income across countries.

Papageorgiou (2003) differentiates between overall education and higher education efforts; his empirical findings suggest that higher education is more important for the technological progress of a country than lower education levels as post-primary education

⁷ The term "absorptive capacity was first identified by Cohen and Levinthal (1989).

contributes mainly to technology adoption and innovation while primary education is more important in the production of final output. When viewed from this point of view, for a country moving up on its *innovation possibility frontier*, higher education can be considered the relevant level of education most important in developing a competitive human capital base for technology adoption and innovation. Applying China's case here, China's transition from middle-income to higher-income group would, in one way or the other, would rely on its stock of highly educated human capital that can concoct its future socio-economic landscape.

Research and Development (R&D)

Most studies apply R&D investment choices to firm-level decisions rather than to public policy options; that is, we find enormous literature on the role of R&D efforts on firm productivity and other spill-over effects but fewer studies seem to be centered on the role of public policy options concerning R&D investments. The role of R&D expenditure and manpower in economic growth is generally viewed to be channeled through its effects on TFP growth. For example Griffith et al., (2004) use panel study on firm level data from OECD countries and provide empirical evidence on the positive and statistically significant effect of R&D (captured by business expenditure on R&D) and human capital on the rates of TFP growth. Two faces of R&D are evident; its positive effect on innovation output and its impact on technology transfer. Thus R&D supports TFP growth by stimulating innovation and facilitating the imitation of others' discoveries-termed as "*absorptive capacity*" or technology transfer. Thus, countries that lag behind on the productivity frontier can catch-up with innovator countries by heavily investing in R&D.

In debates concerning economic transition, R&D expenditure and manpower seem to have taken the front seat. Agenor, Canuto, and Jelenic (2012) stress the role of government R&D expenditure in enhancing innovation efforts and moving up the national learning curve. Relating government R&D investments with the creation of incentives for innovations, the authors suggest that at a micro level (at firm-level) these "incentives" for innovations could be constrained by "imitation trap" whereby productivity and wages are relatively low (during initial developmental stage). Therefore, market failures may lead to underinvestment in private R&D activities thereby creating a rationale for government funding of research and development. Since transition to upper-income levels increasingly depends on innovation efforts, public support of R&D activities turns axiomatic.

Even if we assumed that R&D efforts have a positive role in productivity improvements and economic development, the story does not end here. The next investigation centers on the query as how to mobilize public policy instruments to channel R&D efforts toward economic development and growth i.e. whether public policy instruments are more efficient than private policy instruments. Arguments concerning the role of private R&D versus public R&D efforts suggest that R&D efforts generate knowledge spillovers that private businesses may not take into account thus government intervention is a much needed factor (Grossman and Helpman, 1993).

The debate on the choice of policy options concerning R&D efforts does not end here. The next dilemma is how to channelize policy instruments with regards to R&D efforts. Public funding of R&D could be channelized through i) funding of R&D activities at public research institutions and universities, or ii) subsidizing the R&D efforts of private firms (David et al., 2000; Svensson 2008). Promoting R&D via private organizations (through government subsidies for R&D activities) may entail limitations as the conflict of interests (firm-interests versus social-interests) may lead to biased R&D decisions; companies may choose projects that guarantee higher private return (rather than social return) with higher returns in short-term (David et al., 2000). Thus, leaving the incentives for R&D activities totally on the discretion of private sector could prove quite tricky in its outcomes. At firm level (when R&D activities are financed by the firm itself), however, returns on publicly

funded and privately funded R&D activities could be congruent. A handful of studies have directly compared the returns on publicly-funded R&D and privately-funded R&D and find that there is no major difference in return between returns on both types of R&D at the firm level (Griliches, 1998).

At an aggregate level, the link between government funded R&D activities (at universities and other public institutions) and economic growth has been connected through the concepts of “knowledge transfer” and “knowledge externalities” (Agenor, Canuto, and Jelenic, 2012). That is, the public R&D efforts expedite knowledge transfer and result in positive spill-over on other economic fundamentals; i.e. productivity and foreign direct investment (FDI). Guellec and Van (2004), for example, link government funded R&D activities at universities and research institutions with productivity growth implying that public support of R&D activities through public institutions serves as a comparatively better tool to enhance economic performance (since public institutions can afford to lay more emphasis on social return than private return while private institutions may not afford that luxury). From this perspective, role of government R&D expenditure in determining per capita income can be of great significance in the discussion concerning economic transitional dynamics. Using cross country data, Perez-Sebastian (2000) focuses on the transitional dynamics of the R&D-based growth model and contends that the role of public R&D in innovation and imitation can account for growth ‘miracles’. During the growth transition, technology imitation can be an important source of TFP growth at the beginning, but innovation serves as a dominating factor later on (Perez-Sebastian, 2007).

Intellectual property rights system and inventions

As mentioned by Schumpeter (1939), scientific knowledge and ideas result in production of marketable novelties. Unless the inventor is able to gain substantial benefits out of such inventions, there won't be any incentive to innovate. Intellectual property rights system (IPRS) render monopolistic power (and benefits) to the developer of new knowledge or product to be the sole seller of the new product or idea. In the absence of IPRS, the developer of new ideas would lack the legal protection against imitators who could easily reproduce the acquired ideas and sell them thereby eroding the incentives for innovators to create new ideas. A patent gives legal right to the inventor to solely exploit commercial benefits from his or her invention over a given period of time. It also facilitates the entry of small and medium enterprises (SMEs) in the market by protecting them against the cost and time between invention stage and market entry of the invention. Nordhaus (1969) mentions that the number of innovations grows as the legal protection granted to the innovator increases since the externalities generated due to the innovation are greatly internalized-thus diffusion of innovation leads to further innovations. Empirical studies generally find support the positive relation between IPRS and innovation considering patents as key drivers of innovation (Levin et al., 1987; Merges and Nelson, 1991).

While there is no general consensus on what actually should be considered as an “invention” and how to measure it, keeping in line with the prevalent tradition, I provide a perspective toward this issue by using number of patents as a measure of new inventions made in a society. Limitations that accompany with this approach cannot be easily casted aside. Although patents may not reflect the true effects of firm-level innovations or other technological innovations, they may provide a standard measure of inventions being made in a society over a given time period.

Role of inventions is highly essential in its spill-over effects on higher productivity and economic growth. Intellectual property rights (patents), in this regard, serve as means to generating incentives for firms and individuals to innovate which in turn translate into development of high quality work force (as the learning curve from these incentives would keep rising eventually imparting knowledge into the work force). Role of patents is generally

linked with “innovation sales” (Hall and Mairesse, 2006) and incentives to engage firms and individuals with increased innovation efforts (Agenor, Canuto, and Jelenic (2012).

Technology catch-up based on imitation requires generally lower level of skills and countries in their initial phase can grow rapidly by copying the technology from advanced economies. However, once the development process heats-up, sustained growth would require innovation rather than imitation to preclude the possibilities of productivity slow-down. Also, once the economy heats-up, the old drivers of growth start wearing out; this turns the role of innovations as a requisite rather than a luxury.

Data and methodology

Data collection and sources

I aimed at investigating past 30 years of China’s economic development and set out to collect data from 31 regions of China over 1980-2012 (encompassing the latest available years). However, my peregrination encountered tremendous setbacks on data availability. Data on regional indicators of innovation for china is not easily available and even if accessed from multiple sources, the coverage is modicum at best. Thus, the data collection not only entails resorting to multiple sources for data collection but also a compromise on time dimension. I resorted to National Bureau of Statistics of China⁸, China Knowledge Resource Integrated Database (generally known in China as tongji.cnki.com)⁹ and EPSnet.com.cn accessed from Hunan University Library¹⁰. My main panel consists of 31 regions of China over 1981-2012 (for data on innovation indicators, only higher education could be traced back to 1980s). Nevertheless, the limitations on data availability on certain innovation indicators necessitated formation of smaller panels taking into account the available years.

Data on R&D activities of large and medium enterprises is collected from China Statistical Yearbook on Science and Technology (coverage: 1991-2011) which provides data on R&D from 2002 to 2008. Data on high-tech industry comes from China Statistics Yearbook on High Technology Industry (coverage: 2002-2011) which does provide historical data enabling us to cover high-tech exports from 1998-2007. Data on education has been matched with Educational Statistics Yearbook of China (Coverage: 1987-2010). Rest of the data comes from National Bureau of Statistics of China.

Empirical Set-up

My empirical strategy is twofold; firstly, I study the link between innovation input and output dimensions, secondly, I investigate the role of innovation output in China’s cross-regional income variations.

Link between innovation input and output dimensions

I resort to a rather simple-to-understand specification (roughly matched with Stern et al., 2002) for the empirical investigation of the links between innovation input and output dimensions. Following equation specifies the link between innovation input and output dimensions for my empirical analysis;

$$\text{InvOutput}_{it} = \alpha + \beta_1 \text{InvInput}_{it-1} + \beta_2 \text{Controls}_{it-1} + \varepsilon_{it-1} \quad (1)$$

Where, InvOutput_{it} is a measure of innovation output dimension from table C, InvInput_{it-1} is a measure of innovation input dimension from table C (detailed definitions of

⁸ <http://www.stats.gov.cn/english/Statisticaldata/AnnualData/>

⁹ <http://tongji.cnki.net/overseas/EngNavi/NaviDefault.aspx>

¹⁰ <http://www.epsnet.com.cn/Sys/Login.aspx?ReturnUrl=%2fSys%2fOlap.aspx>

each measure are provided in exhibit A in the appendix), $Controls_{it-1}$ is a vector of various controls including trade openness measured as (Exports + Imports/ GDP), gross capital formation ratio measured as (Gross capital formation/ GDP), population growth rate, time and region effects, i and t are region and time trends respectively; while ε_{it-1} is an error term.

Based on Eq. 1, my empirical model is as follows;

$$Patents_{it} = \alpha\beta_1 EduExp_{it-1} + \beta_2 RDExp_{it-1} + \beta_3 HEGrads_{it-1} + \beta_4 STP_{it-1} + \beta_5 TradeOpen_{it-1} + \beta_6 PopGrowth_{it-1} + \beta_7 CapForm_{it-1} + \gamma_i \delta_t + \varepsilon_{it-1}$$

Where, $Patents_{it}$ is the stock of patents used as a proxy to measure innovation output for region i at time t , γ_i and δ_t are controls used for region and time effects (captured by region and time dummies to control of region/time specific effects), while ε_{it-1} is an error term. Definitions and explanations of the rest of the variables are given in Exhibit A.

Link between innovation output and economic development

The following model investigates the impact of innovation output on economic development in a panel dataset of 31 regions of China over 1980-2012.

$$PCGDP_{it} = \alpha + \beta_1 InvOutput_{it-1} + \beta_2 Controls_{it-1} + \varepsilon_{it-1} \quad (2)$$

Where, $PCGDP_{it}$ is per capita income is used as a proxy to measure the level of economic development (keeping in line with the general tradition in Economics, we use per capita income levels as a proxy for the level of economic development), $InvOutput_{it}$ is the measure of innovation output dimension (from Eq. 1) from table C (detailed definitions of each measure are provided in exhibit A), $Controls_{it}$ is a vector of various controls including trade openness, gross capital formation ratio, population growth rate and time and region effects. Region and time trends are denoted by i and t respectively; while ε_{it} is an error term.

Based on Eq. 2, the regression model is given as follows;

$$PCGDP_{it} = \alpha\beta_1 Patents_{it-1} + \beta_2 HiTechExportShare_{it-1} + \beta_3 TranValTech_{it-1} + \beta_4 OutValNewPr_{it-1} + \beta_5 TradeOpen_{it-1} + \beta_6 PopGrowth_{it-1} + \beta_7 CapForm_{it-1} + \gamma_i \delta_t + \varepsilon_{it-1}$$

Where, $PCGDP_{it}$ is the per capita income for region i at time t , γ_i and δ_t are controls used for region and time effects (captured by region and time dummies to control of region/time specific effects), while ε_{it-1} is an error term. Definitions of the rest of the variables can be consulted from Exhibit A.

In this paper, I try to capture the effect of the existing stock of knowledge as reflected by innovation inputs (my study would safely contain itself to the “measurable” aspect of the existing stock of knowledge) and empirically investigate the roles played by inventions, stock of highly educated students, R&D manpower and expenditure and public education spending in explaining the variations in per capita income levels. Measures such as R&D efforts, patents and the stock of highly educated human capital are generally associated with “national technological efforts” (Lall, 1992). However, measuring technological efforts of a country for an empirical exercise is challenging due to the “intangible” components associated with the concept of innovation. Nevertheless, studies generally use proxies to remedy that issue. A few studies forward suggestions for measuring a country’s innovative capacity or technological efforts through number of patents. Furman and Hayes (2004), for example, use number of patents to measure the innovative capacity of countries and find large variations in inventions across countries at similar income levels suggesting that the link between patents and income could vary due to country-specific parameters.

There are various issues concerning the proxies of innovation generally used so far in the literature. For example, although the numbers of patents and patent counts have largely been employed as proxies for measuring innovation output of a country, a number of studies highlight the limitations and disadvantages of using patents as a measure of total innovative capacity (Stern et al., 2002; Eaton and Kortum, 1998; Dosi, Pavitt and Soete, 1990). For example, the tendency to apply for IPRS may reflect variations in industrial composition (that is, a region may have a large pharmaceutical sector and thereby a larger share of patents) or differences in rules and institutions concerning Intellectual Property Rights (IPRS). Though I don't profess to have overcome these limitations entirely, I do address such concerns by introducing alternative measures of innovation (such as high technology export share, transaction value in technical market and output value of new products) in my analysis. The conventional alternatives such as the number of scientific publications are not applicable in my case due to data availability issues. Intuition for including high technology export share, transaction value in technical market and output value of new products as other measures of innovation output comes from Stern et al., (2002) who suggest that high-technology industrial success (that can largely be reflected through high technology exports, number of transactions in technical market and output of new products) could be considered a result of innovation efforts and therefore a significant measure of innovation output. Inclusion of the transaction value in the technical market and output value of new products in the empirical exercise would help capture the success of firm-level innovations thereby capturing the "economic success" of innovation. This strategy is supported by Hollanders and Van Cruysen (2008) who validate the inclusion of "economic effects" of innovation that are captured by employment, exports and sales due to innovation efforts.

Reasons to include the shares of higher education graduates and science and technology personnel and investments on education and R&D in the analysis are underlined by the empirical findings that innovation-oriented human capital and investments can be considered key elements of the public innovation infrastructure commonly available to everyone in an economy (Stern et al., 2002). This "common innovation infrastructure" not only creates a potential for *post-hoc* innovations but also raises the productivity of the current innovation efforts and thereby has a substantially positive role in economic development.

Considering the suggestions by the recent strand of literature that the social rates of return to the role of innovation in growth and catch-up in per capita income levels have been underestimated by studies that generally apply the case of USA (United States of America) only (Griffith et.al; 2004), this study contributes by reassuming the role of innovation in economic development using China's regional case.

Although, the standard neoclassical theory seems to undermine the role of innovation efforts as it treats technological progress as an exogenous factor in output expansion; it rather emphasizes on capital accumulation as the main driver of economic growth (Romer, 1990). Latter studies, however, consider innovation as an engine of productivity growth and technological progress (Romer, 1990, Aghion and Howitt, 1992). What I like most about Romer (1990) model is that it views research as a continuous activity and treats research sector as a commercial sector that employs human capital and the existing stock of knowledge to produce new knowledge. Hence, the output produced by a researcher (in terms of a new design or product) is determined by applied inputs; human capital and existing stock of knowledge (that is, the existing stock of knowledge plays a crucial role in determining the productivity of researchers). Moreover, taking Schumpeterian perspective on innovation (1939) into account, where he argues that innovation-oriented market power can provide better solutions and results than Adam Smith's invisible hand or price competition

(since in Schumpeterian economy the innovator reaps Schumpeterian rents¹¹ which creates incentive for future innovations and continuous learning), we can think of intellectual property rights or a patent as something that maximizes Schumpeterian rent.

Exhibit A: Definitions of the variables

Variable	Full Variable Name	Notes to the variable	Measured as
lnPCGDP	Log of GDP per capita		Gross regional output/total population

Innovation input dimens

lnEduExp	Log of government education spending		Education Expenditure/GDP
lnRDExp-Pub	Log of Public R&D expenditure	Public expenditure on R&D in Institutions of Higher Education	Public R&D expenditure/GDP
lnHeGradsinPop	Log of share of higher education graduates in population	Total Graduates of Regular Institutions of Higher Education	Higher education graduates/total population
lnSTPinPop	Log of share of science and technology personnel (S&T)in population-public	Science and technology personnel at public institutions	Science and technology personnel/ population
lnSTPPriv	Log of share of S&T personnel in employment-private	S&T Personnel as a Percentage of Total Employed Persons-private	Science and technology personnel/ Total employed persons
lnRDExpPriv	Log of private R&D expenditure	Expenditure on R&D as a percentage of total revenue from the sale of products	Private R&D expenditure/Total revenue

Innovation output dimension

Variable	Full Variable Name	Notes to the variable	Measured as
lnPatent	Log of total domestic patents	(Domestic)	
lnPatentInv	Log of total domestic invention patents		
lnPatentDesign	Log of total domestic design patents		

¹¹ Schumpeterian rent is the rent earned by the innovator during the time period between introduction of an innovation and its successful diffusion. Successful innovations may be imitated soon in time, but until any imitations can occur, the innovator can reap Schumpeterian rents.

InPatentUtMod	Log of total domestic utility models patents		
IHiTechExportShare	Log of high technology export share in total manufactured exports		High technology export share/ total manufactured exports
IOutValNewPr	Log of share of output value of new products	Output value of new products as a percentage of gross industrial output	Output value of new products/ Gross industrial output
ITranValTech	Log of transaction value in technical market		Transaction value in technical market/ total Transactions

Other control variables

InPopGrowth	Log of population growth		Population growth rate
InTradeOpen	Log of total trade share in GDP		(Exports +Imports)/ GDP
InCapFormRatio	Log of gross capital formation ratio		Gross capital formation/ GDP

Sources of Data¹²: China Statistical Yearbook (panel data derived for 1980-2012); Educational Statistics Yearbook of China (coverage: 1987-2010); China Statistical Yearbook on Science and Technology (coverage: 1991-2011); China Statistics Yearbook on High Technology Industry (coverage: 2002-2011)

An advantage of using panel data is that it allows us to control for unobserved differences across regions thus accounting for individual heterogeneity. However, a strong statistical overlap between innovation indicators reflected by high correlations among them would render the model noisy. Thus, the chances are that the results could be redundant in the face of multicollinearity. In order to remedy that issue it's essential to detect the presence of multicollinearity and its strength in influencing the estimations. A widely used formal method of detecting multicollinearity is via analysis of Variance Inflation Factors (VIF). VIFs tell us how much of the variances in the estimated regression coefficients are inflated due to collinearity. In this study I would use the rule of thumb that a $VIF(\beta_i) > 10$ would reflect high multicollinearity (Kutner; 2004). Variance Inflation Factors in table 9 follow the rule of thumb by Kutner (2004) and show that for my estimations the general rule of thumb is satisfied; $VIF(\beta_i) < 10$ reflecting that results are not plagued by multicollinearity. Additionally, the VIF values for partial and full model estimations also favor the estimations under partial model rather than full model.

Correlations and descriptive statistics are provided in tables 1 (a), (b), (c) and (d). Table 1(a) shows correlation coefficients for the variables. Share of highly educated graduates and science and technology personnel in population are highly correlated with each other (with a correlation coefficient of 0.82 between each other). Therefore, multicollinearity could be a problem if I include both variables simultaneously in the regression equations (subsequently, I enter both indicators of innovation input dimensions separately to compare

¹² Websites accessed are national Bureau of Statistics of China (<http://www.stats.gov.cn/english/>), China Knowledge Resource Integrated Database (<http://tongji.cnki.net/>) and EPS.net.com (<http://www.epsnet.com.cn/Sys/Login.aspx?ReturnUrl=%2fSys%2fOlap.aspx>)

their explanatory powers and significance in relation with per capita income). Similar condition applies with the correlation between higher education expenditure and R&D expenditure; therefore, I would decide their inclusion in the full model based upon collinearity tests and analysis of VIFs. In table 2, interesting correlations are found when I calculate correlation coefficients of innovation inputs against constituents of total patents granted (domestic); namely inventions, designs and utility models. Human factor of innovation input (higher education enrollment rate and number of science and technology personnel) show a strong correlation only with inventions (which is quite logical since other two constituents of patents i.e. utility models and designs require specialized training and skill sets rather than just higher education). What I did next was to delve into this finding and repeat the correlations replacing the share of higher education graduates with the graduates of specialized courses. Remarkably, my expectation, that I would find a stronger link between graduates of specialized courses and all constituents of patents, was met with a pleasant surprise. The new correlation coefficients for graduates of specialized courses were 0.52, 0.63, 0.62 and 0.45 against total patents granted, inventions, designs and utility models respectively. This signals toward a stronger link between graduates of specialized courses and number of patents granted for domestic designs and utility models; however, a weaker link with respect to inventions as compared to the much stronger correlation between higher education graduates and inventions. Since my study focuses on inventions (which relates more closely to innovation dimensions), I would thereby select total inventions (domestic) and share of higher education graduates in population for the rest of my study.

Estimation results and discussion

In Table 3, I fit the model for determinants of innovation (using number of domestic invention patents as the dependent variable) with Prais-Winsten (PW) estimation method which can take care of the observed or unobserved serial correlation. The coefficients that are significant in OLS, by far do not differ from PW estimates, which is not surprising. Theoretically speaking; statistically insignificant coefficients are expected to change markedly. Standard errors in second column are higher since PW standard errors account for serial correlation. R-squared for both OLS and PW estimates are same (which shows that variables in table 3 can explain 82 percent of the variation in per capita income) although it comes from the regression of transformed dependent and independent variables in case of PW estimation; while in OLS it is based on the regression of untransformed dependent and independent variables. The results in Table 3, therefore, show that the coefficients are not merely driven by any serial correlation whether observed or unobserved. Results in column 1 and 2 of table 3 confirm that there is almost no change in the magnitude and significance of the explanatory variables under OLS and PW estimations. All three determinants of innovation i.e. public education spending share in GDP (measured as Education Expenditure/GDP), R&D expenditure share (measured as public R&D Expenditure/GDP) and stock of highly educated students (measured as higher education graduates/total population) appear significant at 1 % and 5% levels.

In table 4 I present fixed effects and random effects estimation results for the determinants of innovation using number of domestic invention patents as the dependent variable. In order to decide whether a simple OLS regression is more efficient than random-effects regression, I run the Lagrange Multiplier (LM) test. LM test applies the null hypothesis which treats the variances across entities as zero assuming no significant differences across units and therefore no panel effect. Running Breusch and Pagan LM test in table 4, I find a test statistic of 67.74. Therefore, I can reject the null hypothesis concluding that Random-effects is more appropriate than a simple OLS since there are significant differences across regions. In order to decide between fixed effects and random effects estimation for determinants of innovation, I apply Hausman test. Hausman test determines whether the errors are correlated with the regressor terms thus treating random-effects model

as the preferred model compared to fixed-effects in the null hypothesis. Applying Hausman test, I find a test statistic of 50.76 which is significant at 1% level thereby validating that fixed effects is the preferred model over random effects model since there are wide differences across regions.

FE estimation results in table 4 indicate that the share of highly educated graduates in population and share of R&D expenditure in GDP are positively related to number of domestic invention patents and are significant at 1% and 5% levels. The coefficient on the share of public education expenditure enters with a positive sign and is significant 1% level. On average, if share of education expenditure in GDP increases by 1%, number of invention patents would increase by 0.82 percent, all else equal. In addition, one percent change in R&D expenditure share of GDP increases the number of domestic invention patents by around 0.21 percent. The results seem to reinforce the findings by Mansfield et al., (1977) that the externalities generated by the social and private internal rates of return of R&D investments can positively influence the pace of innovation. On the same lines, Stern et al., (2002) suggest that education and R&D investments boost the potential for and productivity of innovation. Finally, a one percent increase in highly educated share of students in population raises the number of domestic invention patents by 0.40%, *ceteris paribus*. Overall, the R-squared values show that the explanatory variables included in the estimations can explain 82 to 86 percent of the variation in innovation output.

Note that I have not added other indicators of innovation input dimensions in table 4. That is, since the VIFs (presented in table 9) and collinearity tests favored partial estimations rather than full model estimation, I present partial estimations for other innovation inputs under FE estimation in table 5.

Table 5 illustrates fixed effects estimation results for determinants of innovation keeping in mind the high correlations between explanatory variables (the partial estimations are carried out to show the individual and combined effects when high multicollinearity is not a problem). Compared to 82 of the variation in number of inventions explained by highly educated students, education and R&D expenditures, variation explained by trade openness, population growth and capital formation Ratio (share in GDP) is nearly 43 percent.

Results in column 2 of table 5 show that the stock of highly educated students (share in population), public education spending (share in GDP) and R&D expenditure (share in GDP) have a positive and significant impact on innovation output. Public R&D investments (coefficient=0.21) seem to have a positive effect on innovation output which is significant at 1% level. Theoretically speaking, public R&D investments enhance the innovative process by improving the common innovation infrastructure. On the other hand, private R&D spending can be considered a direct reflection on innovation environment of a nation's industrial clusters (Stern et al., 2002). In table 5, the positive and significant roles of public and private R&D spending in innovation seem to reinforce this concept. Coefficients on public education spending and share of highly educated students are 0.82 and 0.40 respectively.

Column 3 of the table 5 shows that share of science and technology personnel in population appears positively and significantly related to innovation output; once percent increase in the share of science and technology personnel in population leads to nearly 2.1 percent increase in number of invention patents. These results are in line with the findings by Acemoglu and Ziliboti (2001) who suggest that a region lacking highly educated human capital would lack absorptive capacity; that is, it would have greater difficulties to implement technologies in order to move up on its innovation possibility frontier. The link between human capital and innovation is reinforced by a number of studies; for example, Nelson and Phelps (1966) suggest that variations in human capital levels determine cross-country difference in technology adoption. Thus, there is a strong connection between technological

change and human capital. On the same line, Hall and Jones (1999) detect a strong correlation between human capital and total factor productivity.

The coefficients in column 4 of table 5 show that Trade openness seems to have a positive and significant effect on innovation output at 1% level; one percent increase in trade openness raises the innovation output by 0.52 percent. This is quite consistent with the findings of Stern et al., (2002) who propose a positive role of trade openness in increasing the pace of innovation. A quite remarkable finding here is the negative relation (significant at 1% level) between population growth and innovation output; one percent increase in population growth reduces the innovation output by 1.99 percent. This finding is very crucial not only with respect to the literature but also development of public policies; that is, for regions experiencing high population growth, the pace of innovation development would eventually be driven down by their high population growth rates. A convergence in innovation capacities would be vitiated by population growth.

In Table 6 I present panel data fixed effects (FE) and random effects (RE) estimation results using per capita income as the dependent variable. Fixed effects model can account for unobserved heterogeneity across regions through transformation of variables. On the other hand, random effects model can deal with the serial correlation in disturbance term (Wooldridge, 2002).

For fixed effects estimation, R^2 reported is of within (regression), while for random effects, I report overall R^2 . Significance of Wald Chi-Square statistic (testing for random effects) shows the overall fit of the model for partial and full models under RE estimations. The overall model is jointly statistically significant at 1% confidence level according to Wald test statistic and the full model can predict 65% ($R^2 = 0.65$) of the variations compared to 54% in partial model which is pretty decent. Under RE estimation, the signs of the independent variables remain robust to the inclusion of control variables; however, the significance levels differ slightly as all the variables except population growth (which enters with a positive sign) appear statistically significant at 1% and 5% levels of significance.

Choice of RE or FE estimation is determined by the Hausman test which shows that FE estimation is preferred over RE estimation as cross-regional differences are quite large. A more encouraging aspect of the full model under FE estimation is that, all the independent variables except population growth (which enters with a negative sign in line with conventional logic) appear statistically significant at 1%, 5% and 10% significance levels while the R^2 rises to 79%.

After controlling for population growth, openness to trade, and capital formation (that can account for differences in institutional factors and infrastructure), I find that all the constituents of innovation output dimension in my model are positively and significantly related to per capita income. The results suggest that variations in innovation output can significantly explain China's cross-regional income differences. Overall, the results seem to confirm the strong link between innovation output and economic development.

Table 7 shows positive and significant correlations between innovation output dimension and per capita income. In table 7, all output dimensions appear significantly and positively related to per capita income. What is the significance of these results? The results are an effort to show that fiscal instruments aimed at building innovative capacity must not ignore interrelations between innovation input, output and per capita income. That is to say, although the impact of R&D and higher education on economic development may not be completely purged of reverse causalities, one needs to take into account the complementary aspects of innovation dimensions; the link between innovation input dimension and economic development can make more sense via its direct impact on innovation output dimension which in turn affects economic development. Thus, considering innovation outputs as channels that transmit the impact of innovation inputs to enhance economic development may

help minimize the ambiguity manifested in empirical studies concerning the overall link between innovation and development. Government spending, if viewed from this perspective, needs to be balanced toward enhancing all input dimensions of innovation which can in turn augment innovation output and therefore per capita income.

Endogeneity and its treatment: IV estimation

Woolridge (2002; pp. 285) specifies testing for strict exogeneity which is implemented by estimating the respective model (regression equation) using *lead* values of the variables. Following this test, I found that the regression equations do not meet the strict conditions of exogeneity. Therefore, I decided to use IV estimation for the treatment of endogeneity in my regression models. Due to data availability problems (for China's regional innovation indicators) it is quite hard to find suitable and reliable instrumental variables; and as I could not afford the risk of using less reliable instruments. I chose the most utilitarian approach for my case also provided by Woolridge (2002, pp. 567) to use twice-lagged values of the regressors as instruments in the first differenced model.

In table 8, I treat all the regressors except population growth as exogenous by using their twice-lagged values as instruments in two-stage least square (2SLS) instrumental variable estimation. Wald Chi-Square test statistic validates the significance of the IV estimation results at 1% level. The signs on the coefficients are robust to IV estimation under 2SLS. Patents, high-tech export share, population growth rate, capital formation ratio and trade openness can explain 70 percent of the variations in cross-regional per capita income. As far as the response of new indicators of innovation to IV estimation is concerned, output value of new products (market success of innovation efforts) seems to have done well; the sign remains positive and the coefficient is significant at 10% level. On the other hand, transaction value in the technical market seems to respond weakly to IV estimation; the coefficient remains positive but insignificant at conventional levels (1%, 5% and 10%).

Overall, the newly introduced indicators of innovation output dimension (namely, transaction value in technical market and output value of new products) stand robust to OLS, RE and FE estimations while output value of new products seems robust to IV-estimation (instrumental variable estimations also help address the endogeneity concerns in part) methods as well; which is a good news as I expect that new dimensions of innovation would help refine further studies on the role of innovation in betterment of an economy. As mentioned earlier, application of transaction value in technical market and output value of new products would help capture the success of firm-level innovations thereby capturing the "economic success" of innovation. This kind of feat is supported by Hollanders and Van Cruysen (2008) who validate the inclusion of "economic effects" of innovation that are captured by employment, exports and sales due to innovation efforts.

Conclusion and policy implications

I build this study on the argument that innovation has played a greater role in China's regional economic development than generally credited to. Investigating the determinants of innovation output dimension, I show that the stock of highly educated graduates, public education expenditure, R&D manpower and investments (which I categorize under innovation input dimension) significantly explain around 82% to 86% of the variations in China's cross-regional innovation output (measured by the stock of patents). Additionally, the variations in China's cross-regional income levels (differences in economic development levels) can mostly be explained by the stock of patents and high technology export share. Out of the other two measure of innovation output namely output value of new products and transaction value in the technical market, the former does perform well as indicators of innovation output under various estimation methods while the later shows a comparatively weaker correlation.

With respect to the role of trade openness, capital formation and population growth rate in determining the innovation output, I put forward three unique and important findings that are quite rare (though not extinct) in the literature; (1) trade openness has a positive impact on innovation output, (2) Population growth seems to have a negative relationship with innovation output; my findings suggest that convergence in innovation capacities could be vitiated by population growth, and (3) the correlation between capital formation ratio and innovation output appears quite weak for China's regional case.

This paper emphasizes the idea that current accumulation of innovation inputs would determine future innovation output. From this perspective, China's underperformance on the accumulation of innovation inputs does not augur well for its transition from current income status to higher-income level. My empirical exercises show that R&D manpower and investments, stock of students at higher education level, public education expenditure can significantly explain the variations in cross-regional innovation output. Linking the overall innovation output with economic development, I find that the stock of patents, high-technology exports, transaction value in the technical market and output value of new products can significantly be attributed to the variations in cross-regional income levels. My findings suggest that a 1% increase in innovation output indicators is found to translate into a rise in per capita income of between 0.01 to 0.49 percent; patent stock being the highest contributor.

Although there is *prima facie* positive theoretical link between innovation and economic development, I argue that the magnitude and nature of this link differs significantly by the dimension that each innovation indicator represents i.e. innovation output dimension and innovation input dimension. Within innovation input dimension, education expenditure share in GDP and the share of science and technology personnel in population seem to exert strongest impact on cross-regional income differences in China. This link and magnitude of correlation is further manifested by the comparatively stronger positive connection between the education expenditure share in GDP and the number of invention patents; same finding applies to the share of science and technology personnel in population and the number of invention patents. It could be inferred that education expenditure share in GDP and the share of science and technology personnel in population can explain cross-regional income differences in China through their subsequent effects on the number of new invention-patents. Overall, innovation input dimensions exhibit strong explanatory powers to explain variations in both innovation output dimensions and per capita income levels.

As of innovation output dimension, the number of patents seems to exhibit a stronger positive correlation with per capita income level compare to its peers of this dimension i.e. share of high technology exports, output value of new products and the share of transaction value in technical market in overall sales transactions. Within the category of patents, number of invention-patents, compared to the utility models and design-patents, appears to be strongly correlated with the share of education expenditure in GDP and the share of science and technology personnel in population.

Views concerning government appropriations of education and R&D expenditures often seem to consider singular measures of innovation therefore ostracizing them from a whole group or dimension that each innovation indicator represents i.e. innovation input dimension and innovation output dimension. Strong correlations between innovation input and output dimensions suggest kaleidoscopic connections within/across each dimension (and in turn with per capita income) which need not to be confused with all-inclusive indicators of innovation. Thus, policies aimed at spurring innovation and economic development need to take into account the nature and implications of individual innovation dimension rather than all-inclusive indicators of innovation. That is, the opponents of government R&D subsidies or fiscal appropriations of education need to understand that these fiscal instruments may not spur economic development singly but may still affect those very determinants of economic

development which are generally and axiomatically unchallenged; from this perspective, the arguments against education rebates or R&D subsidies seem genuinely implausible.

Analysis of China’s domestic performance in terms of innovation efforts suggest that strong policy instruments need to be targeted toward accumulating innovation inputs for spurring future innovation output and economic development. For China to join the ranks of advanced countries (belonging to higher income levels and innovation leaders), strong policies aimed at speeding its pace of innovation are of dire need.

Finally, this study can be considered an attempt toward quantifying China’s cross-regional innovation efforts in terms of innovation input-output dimensions which are linked with economic development. The newly introduced indicator of innovation output dimension in this paper (namely, output value of new products) stands robust to OLS, FE and IV-estimation methods which is a good news as I expect that the introduction of alternative measures of innovation would not only help streamline future studies on the role of innovation but also acknowledge the credit it deserves in promoting economic progress. Additionally, implications of my findings may lead to reassessment of the measurement of innovation, and the role of innovation efforts in economic development.

Appendix

Tables

Table 1 (a): Correlation Matrix: Input and output dimensions of innovation

	lnPatentInv	lnEduExp	lnRDEExpPub	lnHeGrads-inPop	lnSTPinPop
lnPatentInv	1.00				
lnEduExp	0.87	1.00			
lnRDEExp-Pub	0.80	0.77	1.00		
lnHeGrads-inPop	0.72	0.60	0.54	1.00	
lnSTPin-Pop	0.72	0.45	0.71	0.82	1.00

Table 1 (b): Correlations between input and output dimensions of innovation

	lnPatentInv	lHiTechExport-Shar	lOutValNewPr	lTranValTech
lnEduExp	0.89*	0.4316*	0.3808*	0.6635*
lnRDEExpPub	0.79*	0.4056*	0.5905*	0.6635*
lnHeGrads-inPop	0.81*	0.1720	0.4131*	0.4308*
lnSTPinPop	0.72*	0.0706	0.4684**	0.7673*

*** Significance at 10%, ** significance at 5 % and * significance at 1% confidence levels.

Table 1 (c): Correlation between innovation output, capital formation, trade openness and population growth

	lnPatentInv	lnCapForm-Ratio	lnTradeOpen	lnPopGrowth
lnPatentInv	1.00			
lnCapForm-Ratio	0.012	1.00		
lnTradeOpen	0.142	0.344	1.00	
PopGrowth	-0.6735	-0.1141	-0.4089	1.00

Table 1 (d): Descriptive Statistics

Variables	Observations	Mean	Standard Deviation
lnEduExp	460	-3.4335	0.4461
lnRDEExpPub	745	-6.8833	1.0469
lnHeGrads- inPop	482	-6.5469	0.8795
lnSTPin- Pop	78	1.2148	0.9780
lnSTPPriv	210	1.4933	0.3655
lnRDEExpPriv	212	0.3472	0.4196
Variables	Observations	Mean	Standard Deviation
lnCapFormRatio	978	-0.8335	0.3344
lnTradeOpen	861	-4.0733	1.5299
PopGrowth	990	2.0442	0.6820
lnPCGDP	1003	1.4443	1.4443
lnPatent	448	4.996	1.8473
lnTranValTech	470	11.799	1.9296
lnHiTechExport-Share	300	-0.3350	2.3099

Table 2: Correlations between constituents of total patents granted and innovation inputs

	lnPatent	lnPatentInv	lnPatentDesign	lnPatentUtMod
lnEduExp	0.88	0.89	0.87	0.88
lnRDEExp	0.81	0.79	0.70	0.86
lnHeGrads-inPop	0.50	0.81	0.36	0.30
lnSTPinPop	0.45	0.72	0.52	0.27

Table 3: Determinants of innovation: OLS and PW estimations

	(1) OLS lnPatentInv	(2)PW lnPatentInv
lnEduExp	0.8179* (0.070)	0.818* (0.088)
lnRDExp	0.2087* (0.033)	0.209** (0.099)
lnHeGrads- inPop	0.4020* (0.068)	0.4021** (0.127)
_cons	-2.355*** (0.901)	-2.355 (1.38)
Adj. R ²	0.82	0.82
N	373	373

t statistics within parentheses; *** Significance at 10%, ** significance at 5 % and * significance at 1% confidence levels; F(3, 259) = 419.17; Prob > F = 0.0000

Table 4: Determinants of innovation: OLS, RE and FE estimations

	(1) RE lnPatentInv	(2) FE lnPatentInv	(3) OLS lnPatentInv
lnEduExp	0.6874* (0.116)	0.8179* (0.070)	0.7158* (0.031)
lnRDExp	0.1692* (0.032)	0.2087* (0.033)	0.2864* (0.065)
lnHeGrads- inPop	0.4307* (0.094)	0.4020* (0.068)	0.4189* (0.064)
_cons	-0.1500 (0.901)	-2.355*** (0.901))	-1.742** (0.825)
Adj. R ²	0.85	0.82	0.86
N	373	373	373

t statistics within parentheses; *** Significance at 10%, ** significance at 5 % and * significance at 1% confidence levels

Diagnostic tests:

1. Hausman test statistic (H)= 50.76*
2. Lagrange Multiplier (LM)= 67.74*

Table 5: Determinants of innovation: partial estimations under fixed effects

	(1) FE	(2) FE	(3) FE	(4) FE
	lnPatent	lnPatent	lnPatent	lnPatent
lnEduExp	0.8179* (0.070)			
lnRDExpPub	0.2087* (0.033)			
lnHeGrads-inPop	0.4020* (0.068)			
lnSTPin-Pop			2.067* (0.425)	
lnSTPPriv		-0.2586 (0.172)		
lnRDExpPriv		0.5808* (0.218)		
lnTradeOpen				0.5240* (0.153)
PopGrowth				-1.999* (0.132)
lnCapForm-Ratio				-0.0839 (0.020)
_cons	-2.355*** (0.901)	5.1517* (0.3079)	2.864* (0.515)	10.555* (0.602)
Adj. R ²	0.82	0.19	0.27	0.43
N	373	210	71	398

t statistics within parentheses; *** Significance at 10%, ** significance at 5 % and * significance at 1% confidence levels

Table 6: Role of Innovation output dimensions in Per Capita Income: FE, RE

	(1)RE lnPCGDP	(2)RE ^a lnPCGDP (Full Model)	(3)FE lnPCGDP	(4)FE ^b lnPCGDP (Full Model)
lnPatents	0.4086* (0.026)	0.3282* (0.0295)	0.6608* (0.043)	0.4576* (0.051)
lnHiTech- ExportShare	0.0130 (0.021)	0.0470** (0.0208)	0.0902** (0.028)	0.0727** (0.025)
lnTranValTech	0.0151 (0.028)	0.0380** (0.0254)	0.0902 (0.036)	0.0542* (0.031)
lnOutValNew- Pr	0.1598** (0.046)	0.1217** (0.042)	0.1491** (0.051)	0.1195** (0.045)
PopGrowth		0.0769 (0.059)		-0.0925 (0.069)
lnCapFormRatio		0.6672* (0.136)		0.6972* (0.145)
lnTradeOpen		0.1427* (0.040)		0.3481* (0.080)
_cons	6.771* (0.337)	15.438* (1.466)	3.457* (0.45)	16.82* (1.92)
R ²	0.54	0.65	0.69	0.79
N	210	210	210	210

estimations

t statistics within parentheses; *** Significance at 10%, ** significance at 5 % and * significance at 1% confidence levels

Diagnostic tests:

1. Hausman test statistic for models in RE^a and FE^b(H)= 41.22*
2. Wald Chi Square= 338.29 * (for RE estimates in column 1; partial model)
3. Wald Chi Square= 476.12*(for RE estimates in column 2; full model)

Table 7: Role of Innovation output dimensions in Per Capita Income: FE estimations

	(1) FE lnPCGDP	(2) FE lnPCGDP	(3) FE lnPCGDP	(4) FE lnPCGDP
lnPatents	0.492 * (.0317)			
lnHiTech- ExportShare		0.2043 ** (0.058)		
lnTranVal- Tech			0.1356** (0.051)	
lnOutVal- NewPr				0.0345* (0.083)
Adj. R ²	0.41	0.044	0.016	0.089
N	373	373	465	211

t statistics within parentheses; *** Significance at 10%, ** significance at 5 % and * significance at 1% confidence levels

Table 8: Treatment of endogeneity: IV estimation under 2SLS

	(1) IV 2SLS lnPCGDP	(2) IV 2SLS lnPCGDP
lnPatents	0.2066*** (0.032)	0.1661*** (0.055)
lnHiTech- ExportShare	0.1159*** (0.020)	0.1544*** (0.034)
lnTranVal- Tech		0.0121 (0.029)
lnOutVal- NewPr		0.1492* (0.093)
PopGrowth	-0.1088* (0.051)	-0.0820 (0.063)
lnCapFormRatio	0.9438*** (0.307)	0.4966** (0.248)
lnTradeOpen	0.1766*** (0.030)	0.2307*** (0.042)
_cons	19.68*** (2.782)	16.917*** (2.043)
R ²	0.67	0.70
N	347	347

t statistics within parentheses; *** Significance at 10%, ** significance at 5 % and * significance at 1% confidence levels

Column 1: (Instrumented) lnTradOpen lnCapFormRatio lnPatentsGran lnHiTechExportShare
Instruments: lnPopgrowth lag2lnTradOpen lag2lnCapFormRatio lag2lnPatentsGran lag2lnHiTechExportShare

Column 2: (Instrumented) lnTradOpen lnCapFormRatio lnPatentsGran lnHiTechExportShare lnOutValNewPr lnTranValTech

Instruments: Popgrowth lag2lnTradOpen lag2lnCapFormRatio lag2lnPatentsGran lag2lnHiTechExportShare lag2lnOutValNewPr lag2lnTranValTech

Diagnostic test: Wald Chi-square (column 1) =254.42*

Wald Chi-square (column 2) = 151.59*

Table 9: Variance Inflation Factors (VIF)

(VIF: Innovation output and per capita income: full model)

Variable	VIF	1/VIF
laglHiTech~e	3.49	0.286916
laglPatent~v	3.29	0.303502
laglTradOpen	3.07	0.326041
laglTranVa~h	2.52	0.396749
laglPopgro~h	2.19	0.457665
laglOutVal~r	1.61	0.622652
laglCapFor~o	1.29	0.777404
Mean VIF	2.49	

(VIF: Innovation output and per capita income: partial model)

(VIF: Determinants of innovation: full model)

Variable	VIF	1/VIF
laglPatent~v	2.73	0.366261
laglTranVa~h	2.36	0.423020
laglHiTech~e	1.36	0.733093
laglOutVal~r	1.29	0.772738
Mean VIF	1.94	

Variable	VIF	1/VIF
lag1STPinPop	7.97	0.125431
lag1HEGrad~p	7.29	0.137267
lag1EduExp~o	5.64	0.177350
lag1Popgro~h	5.32	0.188028
lag1TradOpen	3.11	0.321340
lag1RDEExpPub	2.99	0.334076
lag1CapFor~o	1.54	0.647707
Mean VIF	4.84	

(VIF: Determinants of innovation: Partial model)

Variable	VIF	1/VIF
lag1EduExp~o	3.27	0.305782
lag1RDEExpPub	2.57	0.388921
lag1HEGrad~p	1.99	0.502857
Mean VIF	2.61	

(VIF: Determinants of innovation: Partial model)

Variable	VIF	1/VIF
lag1Popgro~h	1.18	0.845283
lag1CapFor~o	1.13	0.881744
lag1TradOpen	1.10	0.906222
Mean VIF	1.14

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Don't 'manage' culture, celebrate it as a source of different ideas. Ashok Soota

David Olive & Gita Piramal, *The Quotable Tycoon: A treasury of business quotations*, Page 51