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Yang, Jingjing and Khalil, Sana

School of Economics and Trade, Hunan University, China

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Jingjing Yang[a] & Sana Khalil[a]

[a] School of Economics and Trade, Hunan University, Changsha, China

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Do innovation dimensions matter in China's cross-regional income differences?

Jingjing Yang and Sana Khalil*

School of Economics and Trade, Hunan University, Changsha, China

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This paper studies the interlinks between innovation inputs and outputs and between innovation outputs and economic development. Using a panel data-set from 31 regions of China, we show that the difference in regional innovation output can be significantly explained by R&D manpower and expenditure, highly educated students, and public education spending, while GDP is linked to patent, high-tech export share, and new product sales. Our findings provide support for the use of government R&D subsidies and education rebate.

Keywords: innovation; R&D; education; patents; economic development

1. 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. China is currently going through economic transition where it runs the possibility of falling into a middle-income trap (World Bank 2012). The country is set to undergo major demographic transitions where its age dependency ratios will more than double over the next 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 the allocation of resources from agriculture sector to industrial sector have already been reaped and from this point onwards, continued capital accumulation may generate less growth due to decreasing returns to capital and labor. These issues signal toward alternative strategies that need to be taken to ensure China's smooth economic transition to higher-income level. This paper aims to answer the following questions: (1) has China's innovation efforts in inputs been translated into outputs? (2) if so, can innovation outputs ultimately improve economic growth?

This paper is structured as follows. The next section provides an overview of China's position in the global innovation landscape. This is followed by a review of the literature in Section 3 and a discussion of data and methodologies in Section 4. Section 5 presents estimation results and discussions, and the final section draws conclusions.

*Corresponding author. Email: sana.khalil@khi.iba.edu.pk

2. An Overview of China's Innovation

China is ranked the 35th out of 142 world economies according to Global Innovation Index (GII 2013) report[1] released jointly by Cornell University, USA, European Institute of Business Administration (INSEAD) and World Intellectual Property Organization (WIPO). Top five leaders in global innovation according to GII 2013 are Switzerland, Sweden, the United Kingdom (UK), Netherlands, and the United States (USA). In terms of global innovation input ranking, China is ranked the 46th but stands at the 25th for innovation output. Within the category of upper-middle-income countries, China is ranked the 1st for innovation output but the 6th in innovation input. The report also enlists China in the rank of eighteen emerging economies that are outperforming others in their respective income groups. In terms of patents, China is emerging as a powerhouse in filing with an increasing number of patents. However, public R&D and education expenditures seem to lag behind the average spending levels of advanced economies.

We now set the stage for a critical comparison of China's innovative capacities with respect to other countries (see Figures 1–5). For this purpose, we select Japan and South Korea as 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 show that China's public spending on education as a percentage of GDP (both current and capital) was around 1.4% in 1971. It remained almost stagnant over the years, later increasing to 1.9% in 1999. Comparing China's share of education expenditure in GDP with that of Japan's, Japanese public educational spending as a percent of GDP was 3.7% in 1971, and it rose to more than 5% over 1980s (the remarkable aspect is the "sustained" portion of education expenditure share in GDP at more than 5% over 1980–1989) before marginally declining over 1990s and finally closing at 3.7% in 2011. Japanese policy of high level of public spending for education seems quite congruent with Korean policy over the period of 1970–2011. In 1970, Korean government spent around 3.45% of its GDP on education. The figure increased to 6.5% in 1982, and then declined during the late 1980s. However, as of the years 2000–2011, an average of 4% of GDP was allocated to education by the Korean government.

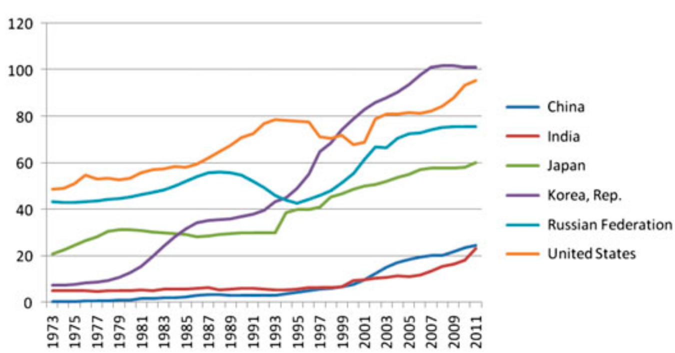

Figure 1. Higher education enrollment rate (%).
Note: Comparison of innovation indicators (Figures are drawn using data from World Bank database).

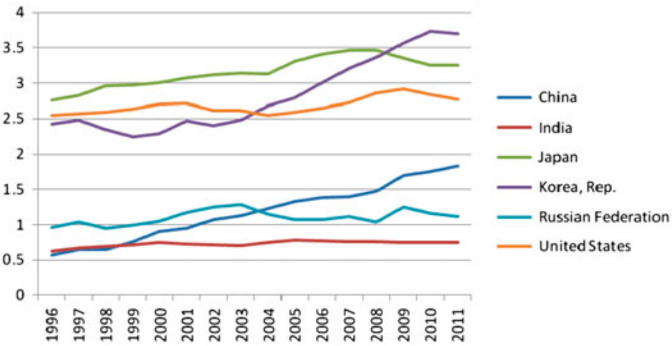

Figure 2. R&D expenditure (% of GDP).
Note: Comparison of innovation indicators (Figures are drawn using data from World Bank database).

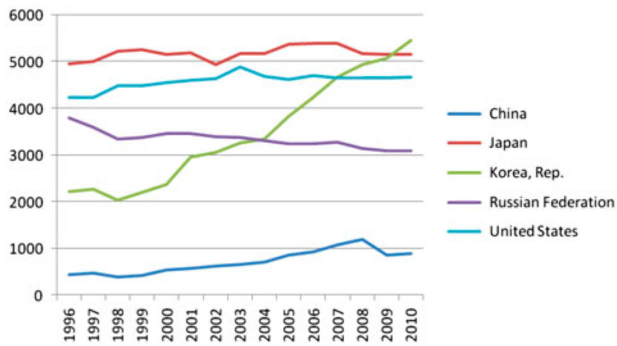

Figure 3. R&D personnel (per million people).
Note: Comparison of innovation indicators (Figures are drawn using data from World Bank database).

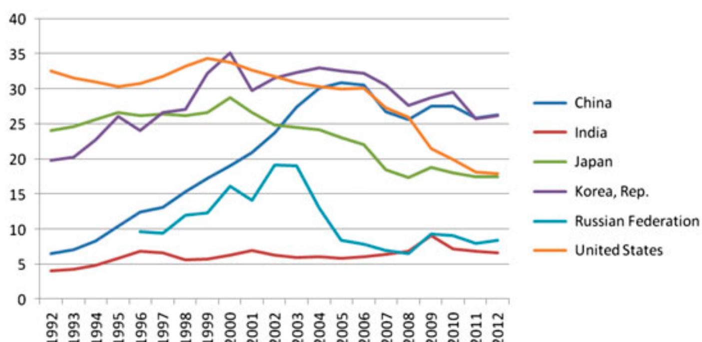

Figure 4. High-tech export share (% of manufactured exports).
Note: Comparison of innovation indicators (Figures are drawn using data from World Bank database).

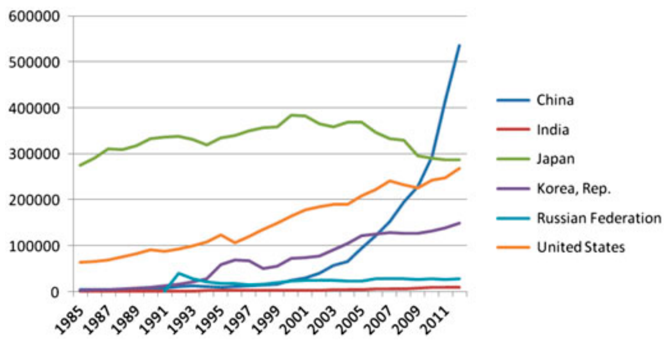

Figure 5. Number of patent applications filed by residents.
Note: Comparison of innovation indicators (Figures are drawn using data from World Bank database).

China's gross enrollment ratio for higher education (as percentage of total population) was very low (nearly .13) in 1970s but later increased manifolds to 7.95 in 2000 and then reached 26.79 in 2011 (see Appendix A and Figure 1) (which is a remarkable increase of 236% 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 of China. The gross enrollment ratio in higher education for Korea was 7.25 in 1971 and rose to 103.11 in 2011. Along the same line, gross enrollment ratio in higher education for Japan was 17.6 in 1971 and 50.74 in 2010. The comparative figures substantiate Korea's and Japan's advantages in highly educated stock of human capital and imply that China still has 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 to higher-income category, it cannot afford to overlook the role of highly educated stock of human capital in economic development.

We also compare other alternative measures of innovation in the analysis: high-tech export share in manufactured exports, the number of patents filed, R&D manpower, R&D expenditure, and tertiary enrollment. Two important findings are evident; China seems to have outshined other countries in terms of high-tech export share and patents but underperformed on the account of tertiary enrollment, R&D manpower, and R&D expenditure. In 2008, Japan and South Korea had the highest number of researchers in R&D which is as expected 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 found in 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. They 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, for China, the figures have been low. Although they were more than tripled from .56% in 1996 to more than 1.7% in 2010, they are still low compared to high-income countries. The R&D expenditure as a share of GDP was around 2.42% for Korea and 2.7% for Japan in 1996 which later rose to 3.73 and

3.26% in Korea and Japan, respectively, in 2010. Evidently, public policies of both countries seem to pay close attention not only to education (spending and enrollment ratios) but also to R&D manpower and investments.

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

Finally, patent applications filed by Chinese residents seem to have surpassed other countries. Patent filings through Patent Cooperation Treaty procedure were only 4065 for China in 1985 but increased sharply over the years, and as of 2011, there were 415,829 patent applications filed by Chinese residents. China's case is worthy of attention – as to how this achievement might have been translated into 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.

3. Innovation and its Dimensions

Studying the link between innovation and economic development faces a challenging task: how to measure innovation? How much innovation output a society can generate from its innovation inputs? We categorize overall innovation into innovative capacity – the *input dimension* (that measures the status of existing innovation inputs) and innovative performance – and hence the *output dimension* (which would reflect the current output from existing innovative activities and innovation inputs). 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. As far as inputs and outputs of innovation[2] are concerned, there seems to be a general consensus in the 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 (Basberg 1998; Griliches 1998; Hausman, Hall, and Griliches 1984; Patel and Pavitt 1994; Stern, Furman, and Porter 2002).

Referring to innovation indicators, various attempts to measure and compare the innovation activities of nations over time have translated into reports specifically centered on ranking innovation efforts. Arundel and Hollanders (2006); Hollanders and Van Cruysen (2008) and Archibugi, Denni, and Filippetti (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. Based on the extant literature (e.g. Archibugi, Denni, and Filippetti 2009; Arundel and Hollanders 2006; Hollanders and Van Cruysen 2008), our attempts to come up with comparable measures of innovation for our empirical analysis are translated into the categorization of overall innovation into input and output dimensions of innovation. Please see Appendix B for explanation.

4. Data and Methodology

Data were collected from National Bureau of Statistics of China[3], China Knowledge Resource Integrated Database (generally known in China as tongji.cnki.com)[4] and EPSnet.com.cn[5]. The main panel consists of 31 regions of China over 1981–2012. Following Stern et al. (2002), we specify the equations below that link innovation inputs and one innovation output (i.e. Patent) and the impact of innovation output on economic development:

$$\begin{aligned}\text{Patents}_{it} = {} & \alpha_0 + \alpha_1\text{EduExp}_{it-1} + \alpha_2\text{RDExp}_{it-1} + \alpha_3\text{HEGrads}_{it-1} + \alpha_4\text{STP}_{it-1} \\ & + \alpha_5\text{TradeOpen}_{it-1} + \alpha_6\text{PopGrowth}_{it-1} + \alpha_7\text{CapForm}_{it-1} + \gamma_i + \delta_t + \varepsilon_{it}\end{aligned}$$

where Patents_{it} is the number of patents which is 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), while ε_{it} is an error term. Definitions and explanations of the rest of the variables are given in Appendix A.

$$\begin{aligned}\text{PCGDP}_{it} = {} & \beta_0 + \beta_1\text{Patents}_{it-1} + \beta_2\text{HiTechExportShare}_{it-1} + \beta_3\text{TranValTech}_{it-1} \\ & + \beta_4\text{OutValNewPr}_{it-1} + \beta_5\text{TradeOpen}_{it-1} + \beta_6\text{PopGrowth}_{it-1} \\ & + \beta_7\text{CapForm}_{it-1} + \zeta_i + \tau_t + v_{it}\end{aligned}$$

where PCGDP_{it} is the per capita income for region i at time t, ζ_i and τ_t are controls used for region and time effects (captured by region and time dummies to control of region/time specific effects), while υ_{it} is an error term. Definitions of the rest of the variables can be consulted from Appendix A.

5. Estimation Results and Discussions

Table 1 presents correlation coefficients between various innovation indicators, along both input and output dimensions. It is clear these indicators are positively correlated, but the correlation coefficients vary in the range of .07 and .87. Table 2 presents descriptive statistics for variables to be estimated. The regression results for innovation output measured by the number of patents are presented in Table 3. In order to decide whether a simple OLS regression is more efficient than random-effects (RE) regression, we run the Lagrange Multiplier (LM) test with the test statistic being 67.74. Therefore, we can conclude that RE model is more appropriate than a simple OLS since there are significant differences across regions. In order to decide between fixed effects (FE) and RE estimation, we apply Hausman test, and the test statistic is 50.76 which is significant at 1% level, thereby validating that FE is the preferred model over RE model. Following FE estimation results in Table 3, it is clear that the share of highly educated graduates in population and the share of R&D expenditure in GDP are positively related to the number of patents, and these coefficients are significant at the 10% level.

Table 1. Correlation matrix: Input and output dimensions of innovation.

	lnEduExp	lnRDExpPub	lnHeGradsinPop	lnPatentInv	lnHiTechExportShare	lnOutValNewPr	lnTranValTech
lnEduExp				.87	.43	.38	.66
lnRDExpPub	.77			.80	.40	.59	.66
lnHeGradsinPop	.60	.54		.72	.17	.41	.43
lnSTPinPop	.45	.71	.82	.72	.07	.47	.77

Table 2. Descriptive statistics.

Variables	Observations	Mean	Standard deviation
lnEduExp	460	−3.4335	.4461
lnRDExpPub	745	−6.8833	1.0469
lnHeGradsinPop	482	−6.5469	.8795
lnSTPinPop	78	1.2148	.9780
lnSTPPriv	210	1.4933	.3655
lnRDExpPriv	212	.3472	.4196
lnCapFormRatio	978	−.8335	.3344
lnTradeOpen	861	−4.0733	1.5299
PopGrowth	990	2.0442	.6820
lnPCGDP	1003	1.4443	1.4443
lnPatent	448	4.996	1.8473
lnTranValTech	470	11.799	1.9296
lnHiTechExport-Share	300	−.3350	2.3099
lnOutValNewPr	211	2.460	.6992

The coefficient on the share of public education expenditure has a positive sign and is significant 1% level. The results reinforce the findings by Mansfield et al. (1977) that the externalities generated by the social and private rates of return of R&D investments can positively influence the pace of innovation. Stern et al. (2002) suggest that education and R&D investments boost the potential for and productivity of innovation. Overall, the *R*-squared values show that the explanatory variables included in the estimations can explain 82–86% of the variation in innovation output.

Table 4 illustrates fixed effects estimation results for determinants of innovation keeping in mind the high correlations between innovation input measures (the partial estimations are carried out to show the individual and combined effects when high multicollinearity is not a problem). Compared to the variation in patents highly explained by educated students, education and R&D expenditures, trade openness, population growth, and capital formation play a less significant role. 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 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). The share of science and technology personnel in population appears positively and significantly related to innovation output. 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 frontier. The link between human capital and innovation is identified 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. Trade openness seems to have a positive and significant effect on innovation output at 1% level. 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

Table 3. Determinants of innovation output (measured by patent).

	RE	FE	OLS	FE	FE	FE
lnEduExp	.6874*	.8179*	.7158*			
	(.116)	(.070)	(.031)			
lnRDExpPub	.1692*	.2087*	.2864*			
	(.032)	(.033)	(.065)			
lnHeGradsinPop	.4307* (.094)	.4020* (.068)	.4189* (.064)			
lnSTPinPop					2.067* (.425)	
lnSTPPriv				−.2586 (.172)		
lnRDExpPriv				.5808* (.218)		
lnTradeOpen						.5240* (.153)
PopGrowth						−1.999* (.132)
lnCapFormRatio						−.0839 (.020)
Adj. R^2	.85	.82	.86	.19	.27	.43
N	373	373	373	210	71	398

Note: *Robust standard errors* within parentheses.
***Significance at 10% confidence levels.
**significance at 5% confidence levels.
*Significance at 1% confidence levels.

Table 4. The role of innovation output dimensions in per capita income.

	RE	RE[a] (Full Model)	FE	FE[b] (Full Model)
lnPatents	.4086* (.026)	.3282* (.0295)	.6608* (.043)	.4576* (.051)
lnHiTechExportShare	.0130 (.021)	.0470** (.0208)	.0902** (.028)	.0727** (.025)
lnTranValTech	.0151 (.028)	.0380** (.0254)	.0902 (.036)	.0542* (.031)
lnOutValNewPr	.1598** (.046)	.1217** (.042)	.1491** (.051)	.1195** (.045)
PopGrowth		.0769 (.059)		−.0925 (.069)
lnCapFormRatio		.6672* (.136)		.6972* (.145)
lnTradeOpen		.1427* (.040)		.3481* (.080)
_cons	6.771* (.337)	15.438* (1.466)	3.457* (.45)	16.82* (1.92)
$\bar{R}^2$	.54	.65	.69	.79
N	210	210	210	210

Note: *Robust standard errors* within parentheses.
***Significance at 10% confidence levels.
**significance at 5% confidence levels.
*significance at 1% confidence levels.

relation (significant at 1% level) between population growth and innovation output; that is, for regions experiencing high population growth, the pace of innovation development would eventually be driven down.

In table 4 we 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, we 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, we found a test statistic of 67.74. Therefore, the null hypothesis was rejected 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, we applied 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, we found a test statistic of 50.76 which proved significant at 1% level thereby validating that fixed effects is the preferred model over random effects model since there are wide differences across regions. Thus, variations in the estimates provided in the table 4 (a,b) can partly be accounted in terms of large regional variations.

The results suggest that variations in innovation output can significantly explain China's cross-regional income differences. The indicators included in Table 4 seem to hold significant contribution toward regional income. Our results seem to bolster the idea that fiscal instruments aimed at building innovative capacity must not ignore interrelations between innovation input, output and per capita income. 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

Table 5. Treatment of endogeneity: IV estimation.

	2SLS	2SLS
lnPatents	.2066*** (.032)	.1661*** (.055)
lnHiTechExportShare	.1159*** (.020)	.1544*** (.034)
lnTranValTech		.0121 (.029)
lnOutValNewPr		.1492* (.093)
PopGrowth	−.1088* (.051)	−.0820 (.063)
lnCapFormRatio	.9438*** (.307)	.4966** (.248)
lnTradeOpen	.1766*** (.030)	.2307*** (.042)
R^2	.67	.70
N	347	347

Notes: *Robust standard errors* within parentheses.
Column 1: (Endogenous variables) lnTradOpen lnCapFormRatio lnPatentsGran lnHiTechExportShare.
Instruments: lnPopgrowth lag2lnTradOpen lag2lnCapFormRatio lag2lnPatentsGran lag2lnHiTechExportShare.
Column 2: (Endogenous variables) lnTradOpen lnCapFormRatio lnPatentsGran lnHiTechExportShare lnOutValNewPr lnTranValTech.
Instruments: Popgrowth lag2lnTradOpen lag2lnCapFormRatio lag2lnPatentsGran lag2lnHiTech ExportShare lag2lnOutValNewPr lag2lnTranValTech.
***Significance at 10% confidence levels.
**significance at 5% confidence levels.
*significance at 1% confidence levels.

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.

In Table 4 (columns a and b), we compare the fixed effects and random-effects estimation results. In order to decide whether a simple OLS regression is more efficient than random-effects regression, we run the 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, we found a test statistic of 67.74. Therefore, the null hypothesis was rejected concluding that random-effects regression 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, we applied 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, we found a test statistic of 50.76 which proved significant at 1% level thereby validating that fixed effects is the preferred model over random-effects model since there are wide differences across regions. Thus, variations in the estimates provided in the Table 4 (a,b) can partly be accounted in terms of large regional variations in main indicators of innovation.

5.1. Endogeneity and its treatment: IV estimation

Woolridge (2002, 285) specifies testing for strict exogeneity which is implemented by estimating the respective model (regression equation) using *lead* values of the variables. The test result indicates that the strict conditions of exogeneity are not met. Therefore, we use IV estimation for the treatment of endogeneity in our regression models. Due to data availability, it is quite hard to find suitable and reliable instrumental variables. We choose the most utilitarian approach and use twice-lagged values of the regressors as instruments in the first differenced model.

In Table 5, we treat all the regressors except population growth as endogenous and use two-stage least squares (2SLS) 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 significantly affect 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. 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.

6. Conclusion and policy implications

This paper emphasizes the idea that the current accumulation of innovation inputs would determine future innovation output which in turn determines economic prosperity. Our empirical exercises show that R&D manpower and investments, stock of students at higher education level, and public education expenditure can significantly explain the variations in cross-regional innovation output. Linking the overall innovation output with economic development, we find that the stock of patents, high-technology exports, transaction value in the technical market, and output value of new products can significantly attribute to the variations in cross-regional income levels. We put forward three unique and important findings: (1) trade openness has a positive impact on innovation output, (2) Population growth seems to have a negative relationship with innovation output; our 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.

Finally, this study can be considered as 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 we 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 our findings may lead to reassessment of the measurement of innovation, and the role of innovation efforts in economic development.

Acknowledgements

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Notes

1. GII 2013 can be accessed from World Intellectual Property Rights Organization (WIPO) website (http://www.wipo.int/econ_stat/en/economics/gii/).
2. See Acs, Anselin, and Varga (2002) for a discussion on innovation inputs and outputs.
3. http://www.stats.gov.cn/english/Statisticaldata/AnnualData/.
4. http://tongji.cnki.net/overseas/EngNavi/NaviDefault.aspx.
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Appendix A. Comparative landscape of innovation capacities

Country	High-tech exports[a] 2011	Patents[b] 2011	R&D personnel[c]	R&D expenditure[d]	Tertiary enrollment ratio (2012)[e]
South Africa	5.11	656	393 (2008)	.83 (2009)	NA
India	6.87	8841	135 (2005)	.75 (2007)	23.27
Russian Federation	7.97	26,495	3092 (2010)	1.16 (2010)	NA
Brazil	9.72	2705	703 (2010)	1.16 (2010)	NA
Japan	17.46	287,580	5180 (2010)	3.26 (2010)	59.9
United States	18.09	247,750	4673 (2007)	2.83 (2010)	95.33
Korea, Rep.	25.72	8018	5481 (2010)	3.74 (2010)	100
China	25.81	415,829	863 (2010)	1.76 (2010)	24.3

Source: Data are from the World Bank.
[a]High-tech exports (as % of manufactured exports).
[b]Number of patent applications filed by residents.
[c]R&D personnel (per million people).
[d]R&D expenditure (% of GDP).

Appendix B. Variable definitions and measurements

Variable	Measurement
lnPCGDP	log(gross regional output/total population)
lnPopGrowth	log(population growth rate)
lnTradeOpen	log((exports + imports)/ gross regional output)
lnCapFormRatio	log(gross capital formation/gross regional output)
Innovation input dimensions	
lnEduExp	log(government education spending/GDP)
lnRDExp-Pub	log(public R&D spending in institutions of higher education/GDP)
lnHeGradsinPop	log(higher education graduates/total population)
lnSTPinPop	log(science and technology personnel at public institutions/population)
lnSTPPriv	log(science and technology personnel/total number of employees)
lnRDExpPriv	log(private R&D expenditure/total revenue)
Innovation output dimensions	
lnPatent	log(patents)
lnPatentInv	log(invention patents)
lnPatentDesign	log(design patents)
lnPatentUtMod	log(utility models patents)
lnHiTechExportShare	log(high-tech exports/total manufacturing exports)
lnOutValNewPr	log(new product sales/ industrial output)
lnTranValTech	log(transaction value in technical market/ total value of transactions)

Sources: China Statistical Yearbook (coverage: 1980–2012); Educational Statistical Yearbook of China (coverage: 1987-2010); China Statistical Yearbook on Science and Technology (coverage: 1991-2011); China Statistical Yearbook on High-tech Industry (coverage: 2002–2011). (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).