AN ANALYSIS OF DYNAMIC ECONOMETRIC RELATIONSHIP BETWEEN R&D INPUT AND INNOVATIVE OUTPUT IN CHINA

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Abstract: This paper is a further step toward closing the analytical gap in the extensive literature on the results of government and enterprises R&D efficiency on the innovative output by treating government R&D funding and enterprises R&D investment as inputs, considering patents and academic publications as outputs during 1990-2009 in China, which dynamics are adequately captured by the cointegration tests, error-correction models and Granger-causality tests. The empirical results evidently identified the long-lasting relationship between different R&D investment rate elasticity of respective innovative output, and the short-run rate elasticity and impact of government and enterprises R&D investment were smaller and statistically weaker than the long-run, while the Granger-causality tests were performed to determine the causal relationship between R&D inputs and outputs, the lag length tests were performed to facilitate the cointegration analysis, which indicated that both the government funding and enterprises investment had unidirectional granger relationships with scientific publication and patent application, however, the relationships between government funding and respective innovative output were stronger than enterprises investment, while the effect of enterprises investment on patent application was more direct and effective. Furthermore, the results also showed that it took two years for government funding, as for the enterprises investment it only took one year, which would have a significant impact on respective innovative output in China.

Keywords: Error Correction Model, Government Funding, Enterprises Investment, Patent application, Scientific Literature

Introduction

Since the resources allocated to the generation of new knowledge are limited, they should be used as efficiently as possible, it is both necessary and prudent for China to efficiently utilize the scarce resources devoted to R&D, for utilizing R&D resources inefficiently tend to be penalized with a growth discount. Therefore, the empirical work on this subject continues with renewed vigor, in good part result from the fact that the problem is being approach in very different ways with theoretical models whose specifications and estimation methods are not the same.

However, as the impact of irrational factors in China self-renovation developing process, it seems clear that a full understanding of the impact and dynamics of R&D investment efficiency requires one to find out what relationship between different investment sources and their respective fruits of R&D. Therefore, this paper devotes to research on financial input in R&D has proceeded towards the extreme of measurement without classical theory, we believe that what is likely to prove most fruitful at this juncture is the provision of more structural guidance in making sense of the empirical findings. This paper conceptually and empirically examines whether, and how much the effectiveness of government R&D funding and enterprises R&D investment differs systematically between contractions and expansions. The task set for this paper is therefore to examine the causal relationship between R&D productivity and different funding sources and the time that it takes those investments to have impact on output.

Data description

The starting point for analytical lengths should be R&D input and other fruits of R&D data of good quality. The data source that serves as the base of information is the China Statistical Yearbook on Science and Technology edited by State Statistical Bureau and Ministry of Science and Technology. To measure the presumed technological impact of R&D funding on innovative output, data on R&D funding which serve as inputs, are taken from the ongoing numbers of researches, and we distinguish between R&D funding contributed by the government and by business enterprises, because such differentiation

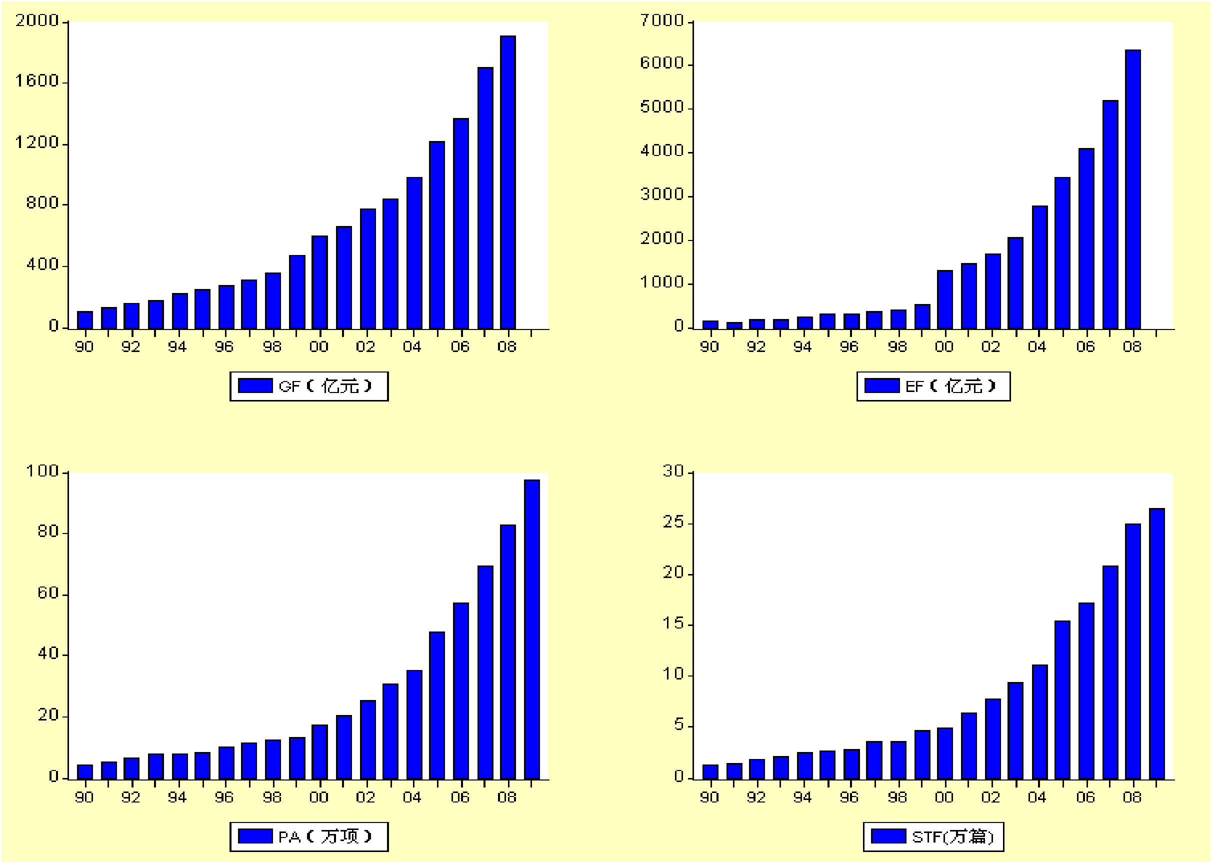

Figure 1: Total Number of Dependent Variables and Independent Variable

provides a more detailed picture taking into account the distribution of R&D specific funding sources when measuring R&D efficiency. Used to analyze the number of patent applications received the number of input-output relationship between innovation began in the 1960s [1, 2], study abroad [3-11] show that the number of patent applications received was to evaluate the output of a valid indicator of technological activity output. Although similar to the co-author and language discrimination, there is a problem [12, 13], but in the mainstream research [14-23], the number of papers and quality assessment of scientific and technological activities is still an important indicator of output.Based on the above, we construct scientific publication only using the Chinese papers catalogued by SCI,ISTP and EI, as well as the patent application as direct fruit of R&D would be satisfactorily justifies the research productivity.

Central to our exercise is the construction of these indicators aggregates by year, counts are built by covering four variables according to their priority date between 1990-2009. Figure 1 summarizes the input-output combinations. As indicated in the first two columns in Figure 1, the gross China government funding successively increased while the enterprise investment had a big leap, and the proportion of enterprise investment was over 50% in 2000 and was impressively up to 69.82% in 2008. On the other hand, the innovative output mounted up, the accumulative ratio of patents and scientific publications growth was 18.09% and 17.45%.

The series extends from 1990 to 2009, while reasonable accuracy of these data deserves further attention. 1990 was the first year for which the survey of China Statistics on Science and Technology was fully implemented, which could not achieve perfect reporting, especially the difficulty to measure the activity as research and development. Figure 2 and 3 show that the estimating structural models provides an excellent framework to apply the data information of R&D funding figures of 2009, which was also with comparable 2008 figures. In addition, the data were subjected to verification before use, figure 4 illustrates the standard correction was to replace the annual R&D funding figures with their replaced ones deflated by the ratio of RPI deflators using 1978 as the base year.

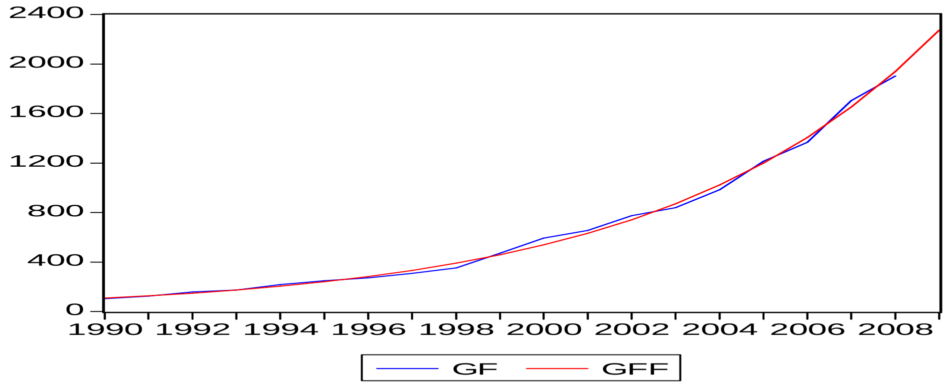

Figure2: The Estimating Structural Models of Government Funding

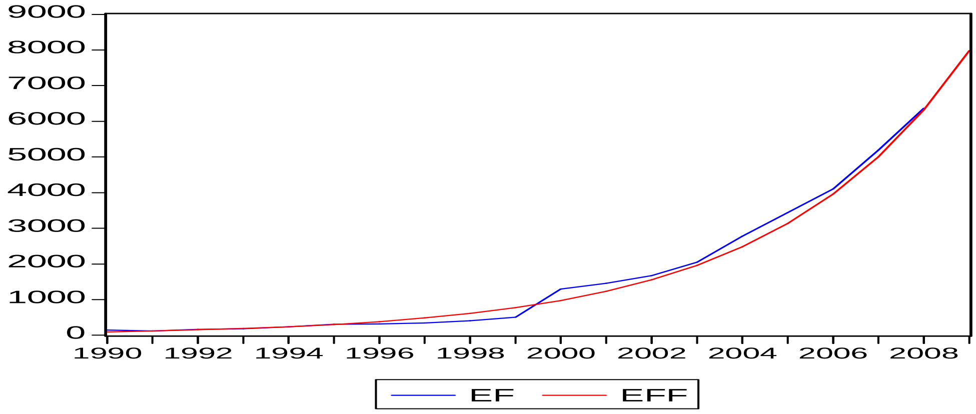

Figure 3: The Estimating Structural Models of Enterprise Funding

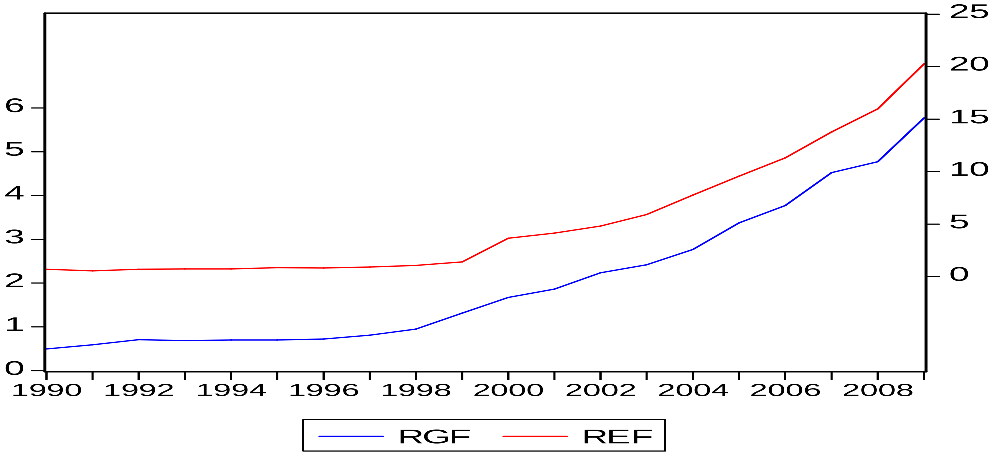

Figure 4: The Adjusting trends of Government Funding and Enterprise Funding

Empirical Analysis

Unit root test

Following the methodology used in earlier works in the literature we test for the stationarity for the four variables of LRGF, LREF, LSTF and LPA. Figure 5 reports that these series is rather smooth, having dominant long swings, which could roughly figure out the non-stationary, therefore, OLS estimates with the levels of these variables may give misleading estimates of standard errors and other summary statistics.

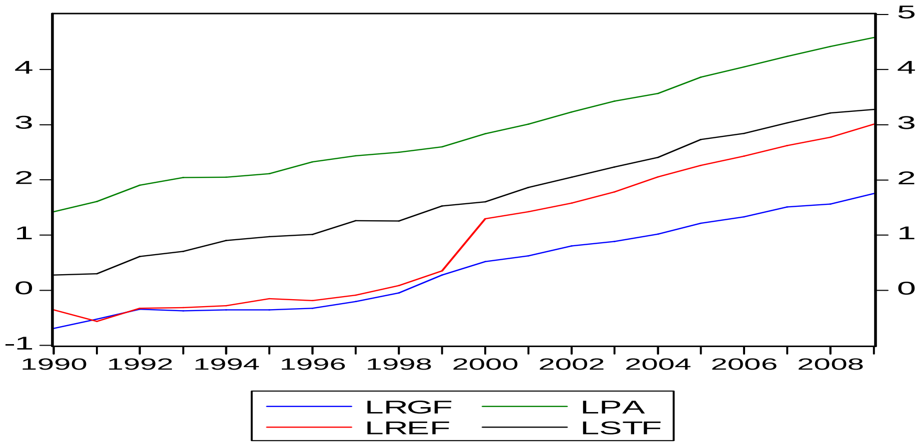

Figure 5: The Stationarity of the Four Variables

Conventional unit root test statistics based on ADF, which shows that the unit root null cannot be rejected for the levels of the variables, implying that all the levels of the variables are non-stationary. The unit roots test results for the variables are reported in Table 4. Our unit root tests below show that the four variables are non-stationary in their levels but stationary in their first differences, because the p values for the first difference of these variables are all significant at the 5% level and reject the unit root null. Namely, it can be seen that variables are in all cases non-stationary, with their first difference being stationary or I(0).

Table 1: Tests for Unit Roots: Levels and First Differences of Variables with Intercepts and Linear Trends

Variables	Level/First Difference	Lag Length	ADF Test Statistic	Test critical values (5% level)	Stationary
RGF	Level	4	0.587631	-3.759743	Non- Stationary
LRGF	Level	3	-3.709977	-3.7332	Non- Stationary
	First difference	0	-7.963482	-3.040391	Stationary
REF	Level	0	2.3498024	-3.673616	Non- Stationary
LREF	Level	0	-2.561204	-3.673616	Non- Stationary
	First difference	0	-3.2505	-3.040391	Stationary
STF	Level	4	-2.685383	-3.759743	Non- Stationary
LSTF	Level	3	-2.902232	-3.7332	Non- Stationary
	First difference	3	-3.313693	-3.081002	Stationary
PA	Level	0	4.594843	-4.532598	Non- Stationary
LPA	Level	2	-1.938958	-3.065585	Non- Stationary
	First difference	0	-4.121709	-3.040391	Stationary

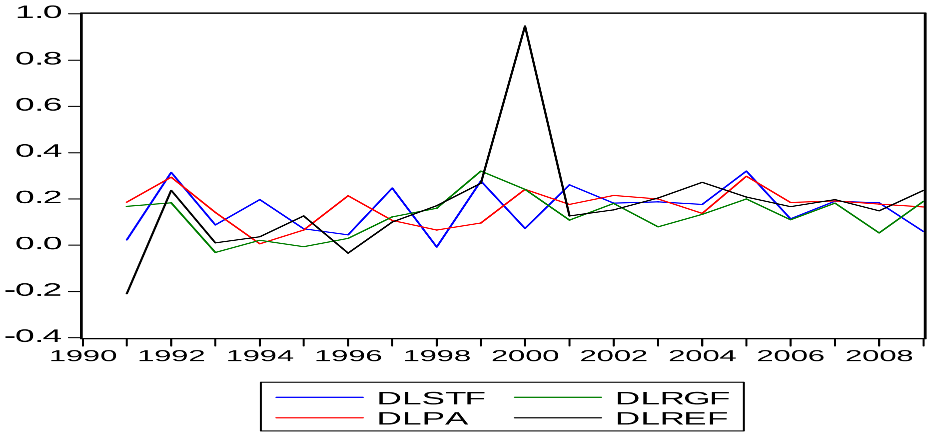

Figure 6: The First Differences of the Four Variable

Error correction model

One of the major benefits of cointegration is that it allows a single formulation that combines in one model the short-run dynamics and the long-run relationship between the variables. If all the variables are found to be I (1), the Engel-Granger (EG) two step procedure can be used to find if they are cointegrated, which is the simplest cointegration test for a bivariate model. The first step is a static OLS regression, because the first differences are stationary, if the error term would be I(0) which could satisfy the standard classical assumptions, and OLS can be used to estimate equation. A preliminary estimate of equation using the simple OLS procedure and partial adjustment mechanism would give promising results.

Study is divided into two steps: first, take LPA and LSTF as the dependent variable respectively, LRGF and LREF as explanatory variables, the regression model is estimated using OLS regression, and get the following equation:

$$LY_t = \alpha_0 + \alpha_1 LX_t + \varepsilon_t \qquad (1)$$

LY_t	LX_t	α_0	α_1	R^2	DW
$LSTF_t$	$LRGF_t$	1.207806936 (0.038480)	1.202301599 (0.043513)	0.976967	0.669008
LPA_t	$LRGF_t$	2.420604591 (0.038379)	1.189401902 (0.043398)	0.976597	0.516358
$LSTF_t$	$LREF_t$	0.9729719244 (0.060242)	0.7551364367 (0.038456)	0.955399	0.79384
LPA_t	$LREF_t$	2.188844336 (0.060816)	0.7464612353 (0.038822)	0.953573	0.602392

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DW test results show that the equation residuals have a strong first-order autocorrelation. Consider adding an appropriate lag, lnY and lnX the distributed lag model are as follows:

$$LY_t = \alpha_0 + \alpha_1 LY_{t-1} + \alpha_2 LX_t + \alpha_3 LX_{t-1} + \varepsilon_t \qquad (2)$$

	LY_t	LY_{t-1}	LX_t	LX_{t-1}	α_0	α_1	α_2	α_3	R^2	DW
M2	*LPA* $_t$	*LPA* $_{t-1}$	*LRGF* $_t$	*LRGF* $_{t-1}$	0.821977 (0.223904)	0.712763 (0.092002)	0.240432 (0.157667)	0.122947 (0.194809)	0.996638	2.002197
M4	*LPA* $_t$	*LPA* $_{t-1}$	*LREF* $_t$	*LREF* $_{t-1}$	0.621001 (0.153694)	0.77416 (0.071298)	0.153087 (0.069039)	0.027949 (0.072178)	0.996588	2.109297

$$LY_t = \alpha_0 + \alpha_1 LY_{t-1} + \alpha_2 LY_{t-2} + \alpha_3 LX_t + \alpha_4 LX_{t-1} + \alpha_5 LX_{t-2} + \varepsilon_t \qquad (3)$$

	LY_{t-2}	LX_{t-2}	α_0	α_1	α_2	α_3	α_4	α_5	R^2	DW
M1	*LSTF* $_{t-2}$	*LRGF* $_{t-2}$	0.657328 (0.150229)	0.101625 (0.19441)	0.538795 (0.199725)	0.267059 (0.221551)	0.109088 (0.35776)	0.078818 (0.247766)	0.996579	2.216558
M3	*LSTF* $_{t-2}$	*LREF* $_{t-2}$	0.542462 (0.095859)	0.091593 (0.182002)	0.599673 (0.182002)	0.123658 (0.082478)	0.060541 (0.107617)	0.064713 (0.077257)	0.99643	2.294406

In the second stage, this overtly general specification is reduced into a parsimonious dynamic adjustment equation, using the variable deletion tests by ensuring that the overall summary statistics do not become significant and reject the null that the residuals satisfy the underlying classical assumptions. Namely, a test for stationarity of the residuals, using an Augmented Dickey–Fuller test, with the critical values adjusted to account for the fact that the cointegrating coefficients have been estimated.

Table 2: The ADF Test Result of the Residuals

Variables	**Level**	**Lag Length**	**ADF Test Statistic**	**Test critical values (5% level)**	**Stationary**
Ec1	Level	2	-4.162694	--1.962813	Stationary
Ec2	Level	0	-2.9649	-1.96017	Stationary
Ec3	Level	1	-2.768954	-1.961409	Stationary
Ec4	Level	0	-2.989964	-1.960171	Stationary

After determining the cointegration relationship estimated error correction term ECM, which reflects the short-term fluctuations in the degree of deviation from the long-run equilibrium relationship shown in Table 3. Engle-Granger two-step model parameter estimates obtained with good statistical properties.

Table 3: The Summary of the ECM Models

	M_1	M_2	M_3	M_4
C	-0.11844 (0.090352)	-0.00146 (0.057106)	-0.00556 (0.093848)	-0.02084 (0.051722)
$\Delta LSTF_{t-1}$	0.625555 (0.344282)		0.132998 (0.304426)	
$\Delta LSTF_{t-2}$	0.950048 (0.276221)		0.578543 (0.275506)	
ΔLPA_{t-1}		0.723902 (0.334769)		0.994766 (0.291625)
$\Delta LRGF_{t}$	0.475622 (0.19429)	0.245962 (0.191273)		
$\Delta LRGF_{t-1}$	0.185781 (0.195219)	0.121092 (0.215033)		
$\Delta LRGF_{t-2}$	-0.43242 (0.238635)			
$\Delta LREF_{t}$			0.154229 (0.099966)	0.158341 (0.072189)
$\Delta LREF_{t-1}$			0.048355 (0.082894)	-0.06418 (0.069168)
$\Delta LREF_{t-2}$			0.0746 (0.074438)	
EC_{t-1}	-1.99548 (0.492663)	-1.01307 (0.424052)	-1.3835 (0.515679)	-1.276 (0.385816)
R^2	0.786532	0.49626	0.682096	0.554811
$R^2_{Adj.}$	0.658452	0.341263	0.491354	0.417829
DW	1.819229	1.826159	1.807296	1.96131
Probability(F-test)	0.0063	0.049005	0.036981	0.023927

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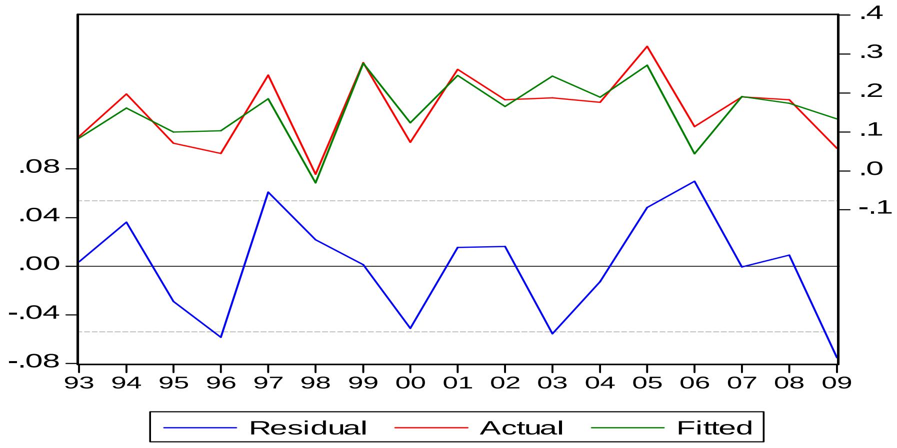

Figure 7: The Trend Chart of M1 Model

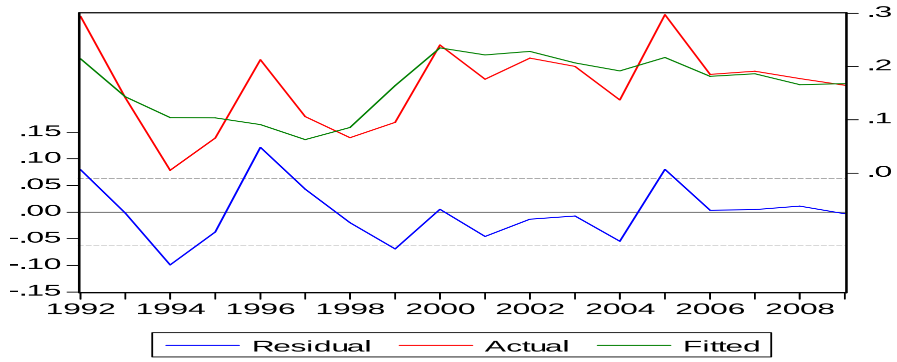

Figure 8: The Trend Chart of M2 Model

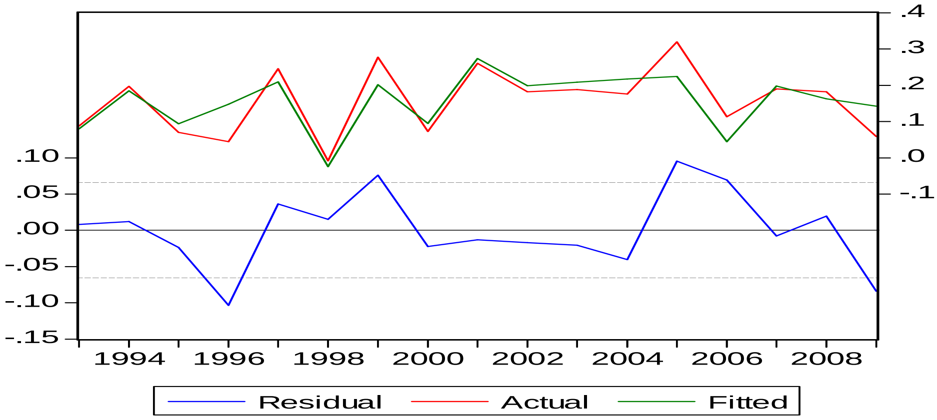

Figure 9: The Trend Chart of M3 Model

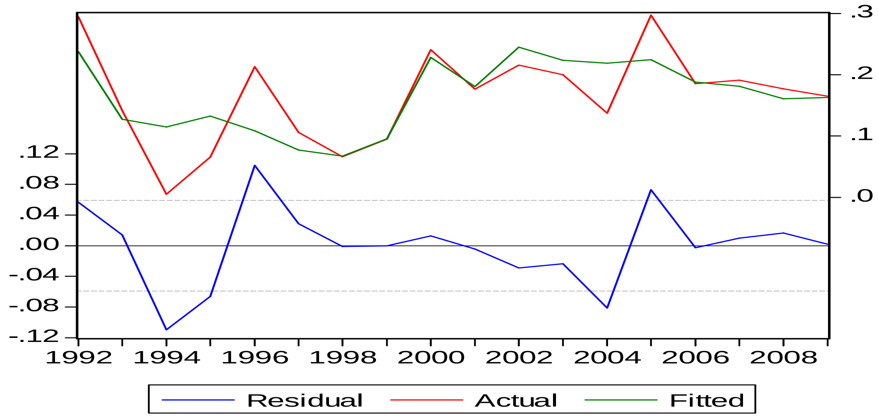

Figure 10: The Trend Chart of M4 Model

Causality tests results

Although cointegration says nothing about the direction of the causal relationship between the variables, if two variables are found to be cointegrated, it follows that there must be Granger causality in at least one direction. Causality tests are based on the test proposed by Granger (1981). As the Granger causality test is very sensitive to the lag order, according to the principles of A IC and SC, the test results is showed in table:

Table 4: The Result of Granger-Causality Test

Null Hypothesis:	Lag Length	F-Statistic	Probability	Reject/Do not reject hypothesis
LRGF does not Granger Cause *LSTF*	2	6.06219	0.01380	Reject
LSTF does not Granger Cause *LRGF*		3.46134	0.06235	Do not reject
LREF does not Granger Cause *LSTF*	2	4.86489	0.02647	Reject
LSTF does not Granger Cause *LREF*		1.24258	0.32076	Do not reject
LPA does not Granger Cause *LRGF*	2	1.98495	0.17690	Do not reject
LRGF does not Granger Cause *LPA*		4.13018	0.04087	Reject
LPA does not Granger Cause *LREF*	1	2.50128	0.13332	Do not reject
LREF does not Granger Cause *LPA*		6.58194	0.02074	Reject

Conclusions

This article investigated the causal relationship between government-enterprises investment and innovative output in China. Results of the empirical analysis evidently identifies that a steady equilibrium relationship exists among the government funding, enterprises investment, scientific publication and patent application. Seen from the long-run equilibrium relation (1) (2) (3), the long-run rate elasticity among the government funding, enterprises investment and scientific publication are respectively 1.2653 and 0.8062; and the long-run rate elasticity among government funding, enterprises investment and patent application are 1.2651 and 0.8016.

In the error correction model, the variable error correction term shows that the annual government funding and enterprises investment for the number of papers and patent applications are accepted error rate of non-equilibrium growth rate this year to make amendments, and the error correction term coefficient represents the adjustment speed. Seen from the long and the short-run rate elasticity and impact of government and enterprises R&D investment were smaller and statistically weaker than the long-run, while the Granger-causality tests were performed to determine the causal relationship between R&D inputs and outputs, the lag length tests were performed to facilitate the cointegration analysis, which indicated that both the government funding and enterprises investment had unidirectional granger relationships with scientific publication and patent application, however, the relationships between government funding and respective innovative output were stronger than enterprises investment, while the effect of enterprises investment on patent application was more direct and effective. Furthermore, the results also showed that it took two years for government funding, as for the enterprises investment it only took one year, which would have a significant impact on respective innovative output in China.

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